

# Projected increases in near-surface air temperature over Ontario, Canada: a regional climate modeling approach

Xiuquan Wang · Guohe Huang · Jinliang Liu

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**Abstract** As the biggest economy in Canada, the Province of Ontario is now suffering many consequences caused by or associated with global warming, such as frequent and intense heat waves, floods, droughts, and wind gust. Planning of mitigation and adaptation strategies against the changing climate, which requires a better understanding of possible future climate outcomes over the Province in the context of global warming, is of great interest to local policy makers, stakeholders, and development practitioners. Therefore, in this study, high-resolution projections of near-surface air temperature outcomes including mean, maximum, and minimum daily temperature over Ontario are developed, aiming at investigating how the global warming would affect the local climatology of the major cities as well as the spatial patterns of air temperature over the entire Province. The PRECIS modeling system is employed to carry out regional climate ensemble simulations driven by the boundary conditions of a five-member HadCM3-based perturbed-physics ensemble

(i.e., HadCM3Q0, Q3, Q10, Q13, and Q15). The ensemble simulations are then synthesized through a Bayesian hierarchical model to develop probabilistic projections of future temperature outcomes with consideration of some uncertain parameters involved in the regional climate modeling process. The results suggest that there would be a consistent increasing trend in the near-surface air temperature with time periods from 2030s to 2080s. The most likely mean temperature in next few decades (i.e., 2030s) would be  $[-2, 2]^\circ\text{C}$  in northern Ontario,  $[2, 6]^\circ\text{C}$  in the middle, and  $[6, 12]^\circ\text{C}$  in the south, afterwards the mean temperature is likely to keep rising by  $\sim 2^\circ\text{C}$  per 30-years period. The continuous warming across the Province would drive the lowest mean temperature up to  $2^\circ\text{C}$  in the north and the highest mean temperature up to  $16^\circ\text{C}$  in the south. In addition, the spread of the most likely ranges of future outcomes shows a consistent widening trend from 2030s to 2080s, implying that long-term climate change is more difficult to predict than near-term change because many more uncertain or unknown factors may continue to emerge during the long-term simulation.

X. Wang  
Institute for Energy, Environment and Sustainable Communities,  
University of Regina, Regina, SK S4S 0A2, Canada  
e-mail: xiuquan.wang@gmail.com

G. Huang (✉)  
Institute for Energy, Environment and Sustainability Research,  
UR-NCEPU, University of Regina, Regina, SK S4S 0A2, Canada  
e-mail: huang@iseis.org

G. Huang  
Institute for Energy, Environment and Sustainability Research,  
UR-NCEPU, North China Electric Power University,  
Beijing 102206, China

J. Liu  
Department of Earth and Space Science and Engineering,  
York University, Toronto, ON M3J 1P3, Canada

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## 1 Introduction

Global warming induced by the increasing concentration of greenhouse gases (GHGs) in the atmosphere is driving many significant and harmful changes to our climate, health, and surrounding environment in various forms (IPCC 2014; Rosenzweig 2007; Yohe et al. 2007), such as frequent and intense heat waves (e.g., Beniston

2004; Fouillet et al. 2006), heavy precipitation and flooding (e.g., Christensen and Christensen 2003; Leung and Qian 2009), severe and widespread droughts (e.g., Hanson and Weltzin 2000; Nicholls 2004), accelerating sea level rise (e.g., Church and White 2006; Rignot et al. 2011), as well as growing risks to public health, biodiversity, food supplies (e.g., Botkin et al. 2007; Diaz 2006; Game et al. 2011; La Sorte and Jetz 2010; Lobell et al. 2011; Martens 2002; Schmidhuber and Tubiello 2007). Global warming usually has serious worldwide implications, however, the climate change impacts associated with global warming on different nations or communities may vary considerably by region in terms of the type and magnitude of local effects. Planning of mitigation and adaptation strategies to climate change therefore requires a nationwide or regionalized planning and decision making behavior, though the international consensus and collaboration are fundamental and indispensable towards combating the changing climate (Adger et al. 2009; Neil Adger et al. 2005).

Assessing the potential impacts of climate change at regional scales can provide a scientific basis for decision making on mitigation and adaptation policies, thus is of great interest to local decision makers, stakeholders, as well as development practitioners. A thorough assessment of the local climate change effects is based upon a good understanding of what kind of a climate is expected in future, which in turn leads to the development of the projections of future climate at regional scales. With the advancement of numerical modeling and simulation, global climate models (GCMs) has been widely used to project future climate under different emission scenarios (Nakicenovic 2000; Van Vuuren et al. 2011). Because the spatial resolution of GCM outputs is typically too coarse for regional impact studies, further downscaling is required for deriving regional climate details from the coarse-resolution outputs (Giorgi et al. 1993a, b; Maurer et al. 2007; Wang et al. 2014b). Downscaling techniques are usually classified into two categories: (1) dynamical downscaling through nesting fine-resolution regional climate models (RCMs) into GCMs, and (2) statistical downscaling involving the development of quantitative relationships between large-scale atmospheric variables and local weather variables such as temperature and precipitation (Hewitson and Crane 1996; Wilby and Wigley 1997). Statistical downscaling approaches are usually referred to as black-box models and widely used in the climate research communities because of their easier implementation and lower computational requirements in comparison with dynamical ones (e.g., Christensen et al. 2007; Feddersen and Andersen 2005; Ghosh and Mujumdar 2008; Khan et al. 2006; Maurer and Hidalgo 2008; Wang et al. 2013; Wilby et al. 2004). Nevertheless, statistical downscaling methods have many limitations and are

subject to a number of widely-known assumptions on the underlying probabilistic model, parameter stability, as well as temporal dependence which are not always satisfied (Estrada et al. 2013). By contrast, RCMs are developed using the same laws of physics as described in GCMs to account for the sub-GCM grid scale processes with more regional details (such as mountain ranges, coastal zones, inland waters, and details of soil properties) in a physically-based way (Feser et al. 2011). By nesting RCMs into GCMs, dynamical downscaling can be used to develop the improved simulation of the local climate system with provision of a large number of climate variables at fine spatial scales, and is thus increasingly attracting the attention of climate impact researchers in recent years (e.g., Caldwell et al. 2009; Castro et al. 2005; Chan et al. 2014; Fujihara et al. 2008; Gao et al. 2013; Gao and Giorgi 2008; Kamamitsu et al. 2010; Nobre et al. 2001; Rockel et al. 2008; Sánchez et al. 2004; Wang et al. 2014b).

In the past few decades, extraordinary changes have taken place to the climatology over the Province of Ontario where people are seeing more frequent and intense weather anomalies including heat waves, floods, droughts, and wind gust, as well as shorter duration of ice cover on and fluctuating water levels in the Great Lakes, leading to a large number of weather-related catastrophes accompanied by massive losses of life and tremendous socio-economic damages (MoE 2011a). In response to these changes, the Government of Ontario has been taking prudent steps to protect its public health, economy, and communities from the harmful effects of climate change (MoE 2011b). The realization of such an adaptation initiative mainly depends upon how well we know and how confident we are about the potential impacts of a changing climate in the context of Ontario. Therefore, as an extension of the previous work of Wang et al. (2014a), we will investigate in this study how the near-surface air temperature (at 1.5 m above sea level) over Ontario would be influenced by the global warming through a regional modeling approach. Specifically, we adopt the PRECIS modeling system which is driven by the boundary conditions of a perturbed-physics ensemble of HadCM3 to carry out ensemble simulations to the regional climate of Ontario. A Bayesian hierarchical model proposed by Wang et al. (2014a, b) is then employed to help develop the probabilistic projections of future near-surface air temperatures (including mean, maximum, and minimum daily temperatures). Following that, the most likely estimates and uncertain ranges of future temperature outcomes at 17 major cities are first calculated and analyzed in detail, and then the similar analyses are extended to all PRECIS grid cells over the entire Province with the purpose of providing decision makers or policy makers with helpful information for assessing the potential effects of climate change in the context of Ontario.

## 2 Data and methods

### 2.1 Observations of current climate

The observed data for maximum and minimum daily temperature (hereinafter referred to as  $T_{\max}$  and  $T_{\min}$ ) is obtained from the 10-km gridded climate dataset provided by the National Land and Water Information Service (NLWIS), Agriculture and Agri-Food, Canada. The NLWIS dataset is interpolated from daily Environment Canada climate station observations through a thin plate smoothing spline surface fitting method as implemented by ANUSPLIN V4.3 (NLWIS 2007). Mean daily temperature (or  $T_{\text{mean}}$ ) on each 10-km grid is estimated by the average of  $T_{\max}$  and  $T_{\min}$ . Observations from the NLWIS dataset are available for the period of 1961–2003, here we extract the data for 1961–1990 (hereinafter referred to as baseline period) to represent the observations of current climate in the context of Ontario. The NLWIS dataset is further regridded to the 25-km grids specified by the PRECIS model such that the undermentioned validation and probabilistic analysis can be conducted at the same spatial resolution.

### 2.2 Regional climate modeling

In this study, the PRECIS regional climate modeling system developed at the UK Met Office Hadley Centre is employed to develop high-resolution climate projections for the Province of Ontario. The PRECIS system is a flexible, easy-to-use and computationally inexpensive RCM designed to provide detailed climate scenarios (Wilson et al. 2011). It can be applied easily to any area of the globe to generate detailed climate change projections, with the provision of a simple user interface as well as a visualization and data-processing package. The PRECIS is able to run at two different horizontal resolutions: 50 and 25 km, with 19 vertical levels using a hybrid coordinate system (a combination of  $\sigma$ -coordinate and pressure-based coordinate); and its output variables are available at various temporal scales (i.e., annual, seasonal, monthly, daily, and hourly). To help explore the uncertainties associated with the climate system modeling, here we use a HadCM3-based perturbed physics ensemble (named QUMP, denoted by HadCM3Q0-16) forced by the SRES A1B emissions scenario as boundary conditions to drive the PRECIS ensemble simulations (Bellprat et al. 2012). The QUMP dataset consists of 17 members and is developed by the Hadley Centre to allow users to generate an ensemble of high-resolution regional climate projections (McSweeney et al. 2012). Fully downscaling the QUMP dataset with PRECIS would require very large inputs of computing resources, data storage, and data analyses (McSweeney and Jones

2010). In order to explore the range of uncertainties while minimizing these requirements, we choose 5 members (i.e., HadCM3Q0, Q3, Q10, Q13, and Q15) from the QUMP dataset according to the Hadley Centre's recommendation (see <http://www.metoffice.gov.uk/precis/qump>). In this study, the PRECIS model is run at its highest spatial resolution (i.e., 25 km). There are ~ 1,800 25-km grid points over the entire Province (see Fig. 1). Thus, the spatial variability of local climatology in the context of Ontario can be simulated in detail.

### 2.3 Probabilistic projections of future climate

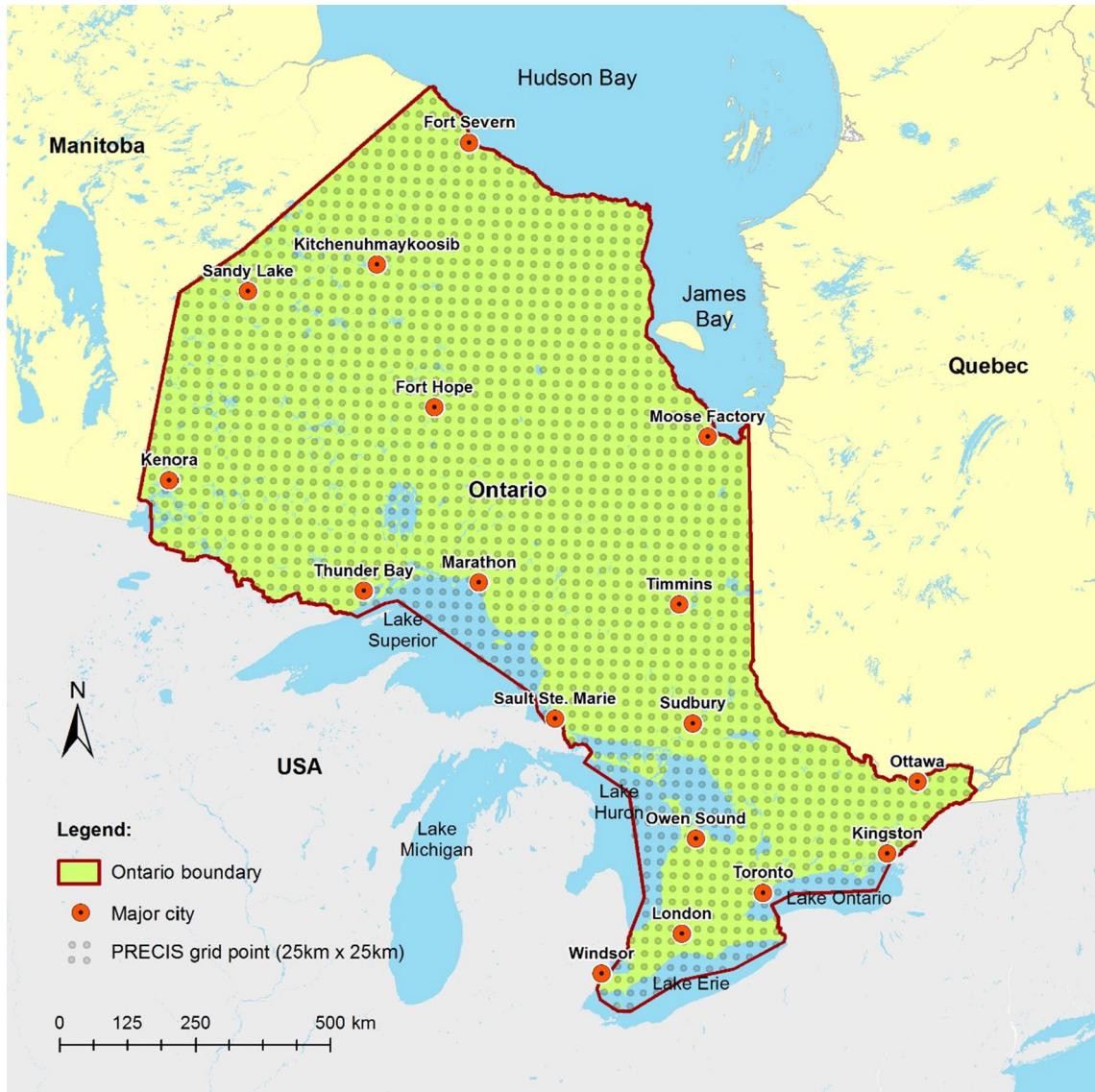
Forecasts of future climate change with current state-of-the-art climate models are often subject to many uncertainties due to our incomplete understanding of the climate system in terms of its complicated physical processes and natural variability (Allen et al. 2000; Murphy et al. 2004; Stainforth et al. 2005). It is necessary to utilize results from ensemble modeling approaches to project future climate change because no single model can be powerful enough to tackle the uncertainties all at once (Greene et al. 2006; Harris et al. 2013; Houghton et al. 2001; Watterson and Whetton 2011). Projections of future climate change are usually presented in a probabilistic way based upon a variety of statistical methods (e.g., Giorgi and Mearns 2002, 2003; Tebaldi et al. 2005; Xu et al. 2010), such that more helpful information for climate change impact studies and decision making can be obtained reasonably given that none of the model projections for future climate can be validated at this stage. In the paper of Wang et al. (2014a), a Bayesian hierarchical model has been proposed to help develop probabilistic projections of future climate change based on the PRECIS ensemble simulations. Here we adopt the same Bayesian model to develop future climate scenarios. Specifically, the future temperature scenarios (denoted as  $T_{\text{future}}$ ) can be expressed as follows:

$$T_{\text{future}} = T_{\text{obs}} + \Delta_{\text{sim}} \quad (1)$$

where  $T_{\text{obs}}$  means the observed temperature for current climate which can be obtained directly from the NLWIS dataset, and  $\Delta_{\text{sim}}$  indicates the projected change in mean temperature by the PRECIS ensemble simulations. According to Wang et al. (2014a),  $\Delta_{\text{sim}}$  is a random variable that can be represented by the difference between the true value of future climate (denoted as  $v$ ) and that of current climate (denoted as  $\mu$ ), as follows:

$$\Delta_{\text{sim}} = v - \mu \quad (2)$$

where  $v$  and  $\mu$  are subject to a number of unknown parameters which are treated as random variables with uninformative prior distributions. Posterior distributions for  $v$  and  $\mu$  can be derived through Bayesian inference



**Fig. 1** Major cities and 25-km PRECIS grid points in Ontario, Canada

theory. Assumptions on the non-informative priors of all unknown parameters and the derivation of their posteriors can be found in the Appendix A of Wang et al. (2014a). The posterior distributions for  $\nu$  and  $\mu$  are expressed as follows:

$$\mu \sim N\left( \frac{\sum_{i=1}^n [\lambda_i x_i - \theta \beta \lambda_i (y_i - \nu - \beta x_i)] + \lambda_0 x_0}{\lambda_0 + \sum_{i=1}^n \lambda_i (1 + \theta \beta^2)}, \frac{1}{\lambda_0 + \sum_{i=1}^n \lambda_i (1 + \theta \beta^2)} \right) \quad (3)$$

$$\nu \sim N\left( \frac{\sum_{i=1}^n \lambda_i [y_i - \beta(x_i - \mu)]}{\sum_{i=1}^n \lambda_i}, \frac{1}{\theta \sum_{i=1}^n \lambda_i} \right) \quad (4)$$

where  $n$  means the total number of members in the PRECIS ensemble;  $x_i$  and  $y_i$  represent the simulated temperature means for current and future climate by the  $i$ th PRECIS run;  $x_0$  indicates the biased observations of mean temperature for current climate with consideration of random errors (e.g., measurement and sampling) and systematic errors due to different measurement platforms and practices (Wang et al. 2014a). The remaining parameters (i.e.,  $\lambda_0$ ,  $\lambda_i$ ,  $\beta$ ,  $\theta$ ) are adopted to reflect various uncertainties associated with the PRECIS ensemble simulations, and their definitions are detailed in the paper of Wang et al. (2014a). An empirical estimate of the posterior distribution for  $\Delta_{sim}$  can be obtained through a Gibbs-based Markov chain Monte Carlo (MCMC) implementation to the proposed model, thus the probabilistic projections for  $T_{future}$  can be generated according to Eq. (1).

**Table 1** Major cities in the Province of Ontario

| No. | City name                       | Longitude | Latitude | Population <sup>a</sup> |
|-----|---------------------------------|-----------|----------|-------------------------|
| 1   | Toronto                         | 79°23'W   | 43°39'N  | 2,615,060               |
| 2   | Ottawa                          | 75°41'W   | 45°24'N  | 883,391                 |
| 3   | London                          | 81°15'W   | 42°59'N  | 366,151                 |
| 4   | Windsor                         | 83°03'W   | 42°18'N  | 210,891                 |
| 5   | Kingston                        | 76°30'W   | 44°14'N  | 123,363                 |
| 6   | Thunder Bay                     | 89°14'W   | 48°25'N  | 108,359                 |
| 7   | Sault Ste. Marie                | 84°20'W   | 46°31'N  | 75,141                  |
| 8   | Timmins                         | 81°20'W   | 48°29'N  | 43,165                  |
| 9   | Owen Sound                      | 81°00'W   | 44°34'N  | 21,688                  |
| 10  | Sudbury                         | 81°00'W   | 46°29'N  | 21,196                  |
| 11  | Kenora                          | 94°29'W   | 49°46'N  | 15,348                  |
| 12  | Marathon                        | 86°23'W   | 48°43'N  | 3,353                   |
| 13  | Moose Factory <sup>b</sup>      | 80°36'W   | 51°16'N  | 2,458 <sup>c</sup>      |
| 14  | Sandy Lake <sup>b</sup>         | 93°20'W   | 53°04'N  | 1,861                   |
| 15  | Fort Hope <sup>b</sup>          | 87°54'W   | 51°34'N  | 1,144 <sup>d</sup>      |
| 16  | Kitchenuhmaykoosib <sup>b</sup> | 89°53'W   | 53°49'N  | 904                     |
| 17  | Fort Severn <sup>b</sup>        | 87°38'W   | 56°00'N  | 334                     |

<sup>a</sup> Mostly obtained from the 2011 Census of Population released by Statistics Canada, available at: <http://www12.statcan.gc.ca/census-recensement/2011/dp-pd/index-eng.cfm>

<sup>b</sup> Indian reserve

<sup>c</sup> Derived from other data source: <http://www.wakenagun.ca/Adobe/moosefactory.pdf>

<sup>d</sup> Obtained from the 2006 Census of Population released by Statistics Canada, available at: <http://www12.statcan.gc.ca/census-recensement/2006/index-eng.cfm>

## 2.4 Interpretation of probabilistic projections

Probabilistic projections assign a probability to the different possible outcomes for future climate, instead of giving a single answer, to help with making robust adaptation decisions (Murphy et al. 2009). Due to the imperfection of climate models, we only can give plausible distribution for future climate outcomes. We cannot provide an absolute probability to describe the occurrence of each possible outcome. Instead we talk about the probability of future projections being less than or greater than a certain value. Following the approach used in UK Climate Projections science report—UKCP09 (Murphy et al. 2009), we employ the cumulative distribution function (CDF) in this study to define the probability of future temperature projections being less than or greater than a given amount. Specifically, we use a cumulative probability of 90 % to describe probabilistic projections by saying that the projected temperature is very likely to be less than or very unlikely to be greater than a given value; we use a cumulative probability of 10 % to indicate very likely to be greater than or very unlikely to be less than; and we define the value with a cumulative

probability of 50 % as the central estimate of future projections (also known as the median of the distribution) (Murphy et al. 2009; Wang et al. 2014a). For convenience, we use the term of probability rather than cumulative probability in the rest of this article.

## 3 Results

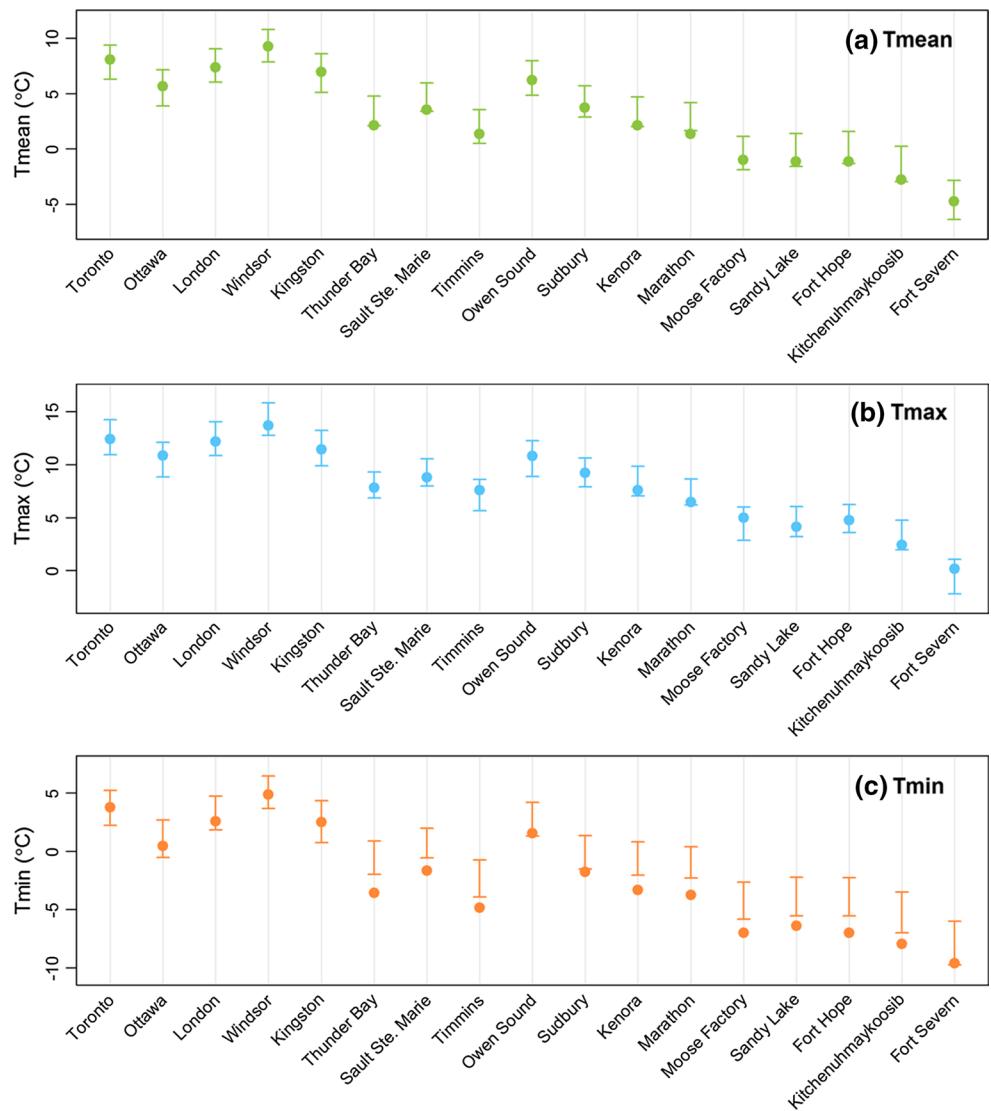
### 3.1 PRECIS ensemble validation

To validate the capability of PRECIS ensemble experiments in reproducing the temperature means of current climate in the context of Ontario, we extract the simulations of three temperature variables (i.e.,  $T_{\text{mean}}$ ,  $T_{\text{max}}$  and  $T_{\text{min}}$ ) for the baseline period from each model run. By combining the simulations from five PRECIS runs, we obtain a range of projected temperature for the baseline period which are bounded by the maximum and minimum of the ensemble runs. Thus, we can validate the performance of PRECIS ensemble simulations by checking if observations of current temperature are within the predicted range. We first analyze the performance in simulating the observed temperature means at 17 major cities (including some Indian reserves) which are spatially distributed across the landmass of Ontario (see Table 1). Then, we extend the similar analysis to cover all 25-km grid cells over the entire Province, by generating the maps of difference between the ensemble simulations (including the minimum, mean, and maximum of the ensemble) and the observations for the three temperature variables.

Figure 2 shows the validation results at the major cities for three temperature variables. The observed means for  $T_{\text{mean}}$  and  $T_{\text{max}}$  at the major cities are well captured by the ensemble simulations, except for small warm bias (by less than 0.3 °C) for the observation of  $T_{\text{mean}}$  in the city of Marathon. By contrast, the ensemble simulations demonstrate poor performance in reproducing the observed means for  $T_{\text{min}}$  at most of the major cities. In particular, only the observations for  $T_{\text{min}}$  at those cities in southern Ontario (i.e., Toronto, Ottawa, London, Windsor, Kingston, and Owen Sound) and at the most north city (i.e., Fort Severn) are well covered by the ranges of the ensemble simulations; otherwise, the simulations for the remaining cities show slight warm bias to the observed  $T_{\text{min}}$  by 0.2–1.5 °C.

Figure 3 shows the maps of difference between the ensemble simulations and observations for all 25-km grid cells over the entire Province of Ontario. For each temperature variable, we calculate the minimum, mean, and maximum of the PRECIS ensemble simulations and map their differences from the observations at grid point scales. The results indicate that the differences for  $T_{\text{mean}}$  mainly range between –3 °C (in the Min maps) and 3 °C (in the Max

**Fig. 2** Validation results at the major cities. The observed temperature means are displayed as *round points*, and the range bounded by the maximum and minimum of the ensemble simulations is indicated by the *linear bar*



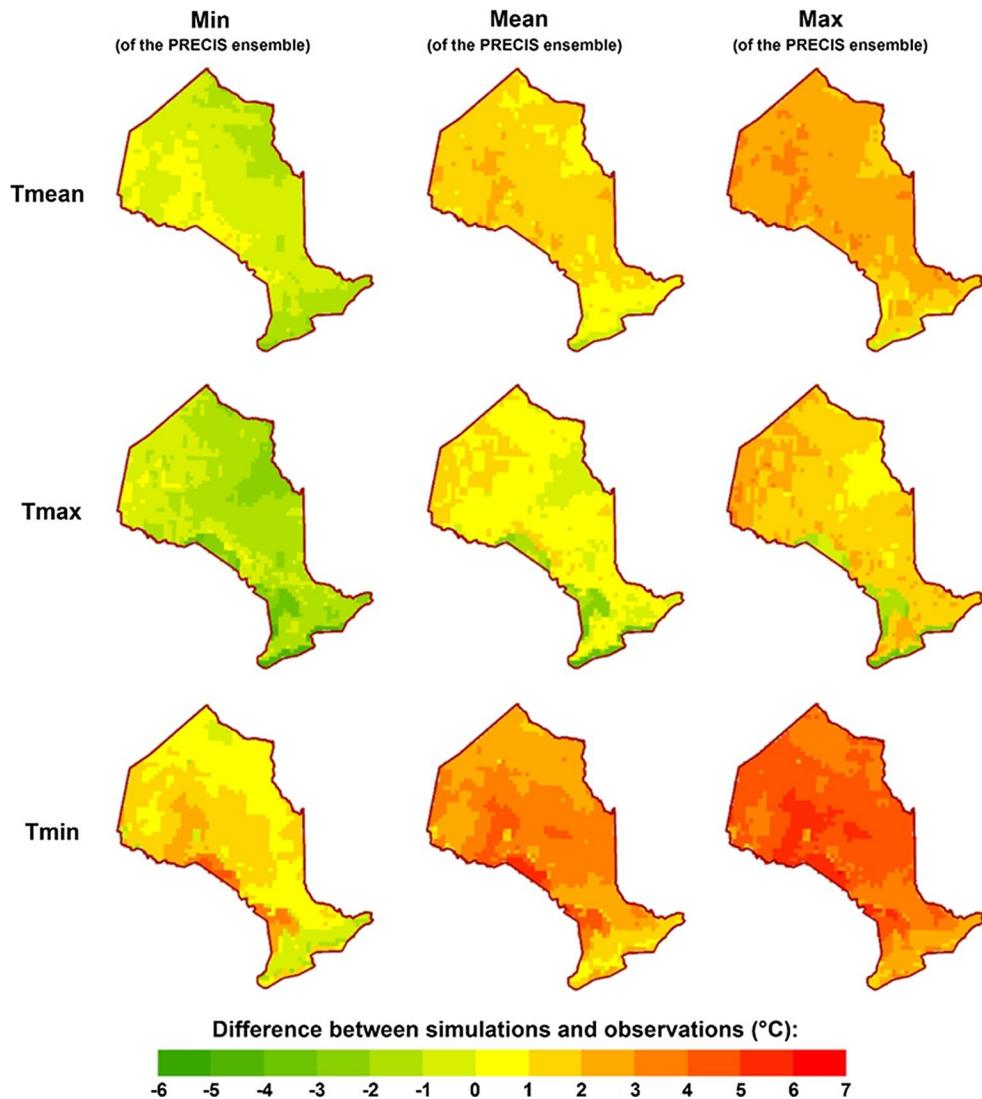
maps), which means that the observed  $T_{\text{mean}}$  at most of grid cells is included within the range bounded by the minimum and maximum of the ensemble simulations. Similarly, it can be found that the maps also demonstrate the good performance of the PRECIS ensemble in terms of simulating the observed  $T_{\text{max}}$ , except for slight cold bias by  $-1$  to  $-3$   $^{\circ}\text{C}$  at those grid cells over the Great Lakes (i.e., Lake Superior, Lake Huron, Lake Erie, and Lake Ontario). As for the maps of  $T_{\text{min}}$ , the calculated differences are mainly varying between  $0$   $^{\circ}\text{C}$  (in the Min map) and  $6$   $^{\circ}\text{C}$  (in the Max map), implying that the PRECIS ensemble tends to slightly overestimate the observed  $T_{\text{min}}$  at most of the grid cells.

### 3.2 Future temperature projections

The projections for future temperature in the context of Ontario are developed by adding the probabilistic changes in temperature to the observed temperature for current

climate. Here we divide the projections for this century into three 30-year periods: 2020–2049 (or 2030s), 2040–2069 (or 2050s), and 2070–2099 (or 2080s). The annual averages of three temperature variables (i.e.,  $T_{\text{mean}}$ ,  $T_{\text{max}}$ , and  $T_{\text{min}}$ ) are calculated for each 30-yr period to represent the plausible climatology corresponding to the period. For each variable, the threshold values at three probabilities (i.e., 10, 50, and 90 %) are calculated to provide a better understanding of possible future outcomes of the three temperature variables. Specifically, we regard the threshold value at 50 % probability as the most likely value of the future outcome; the interval bounded by the threshold values at 10 and 90 % probabilities is used to represent the mostly likely range within which the future outcome will fall. We first analyze the projections of three temperature variables at the major cities, and then present the maps of projected future temperature covering all 25-km grid cells over the Province of Ontario.

**Fig. 3** Validation results at all 25-km grid cells over Ontario. The Min maps (placed in the *1st column*) show the difference between the minimum of the PRECIS ensemble simulations and the observations for each temperature variables. Similarly, the Mean and Max maps (placed in the *2nd and 3rd columns*) show the differences of the mean and maximum of the ensemble from the observed values, respectively



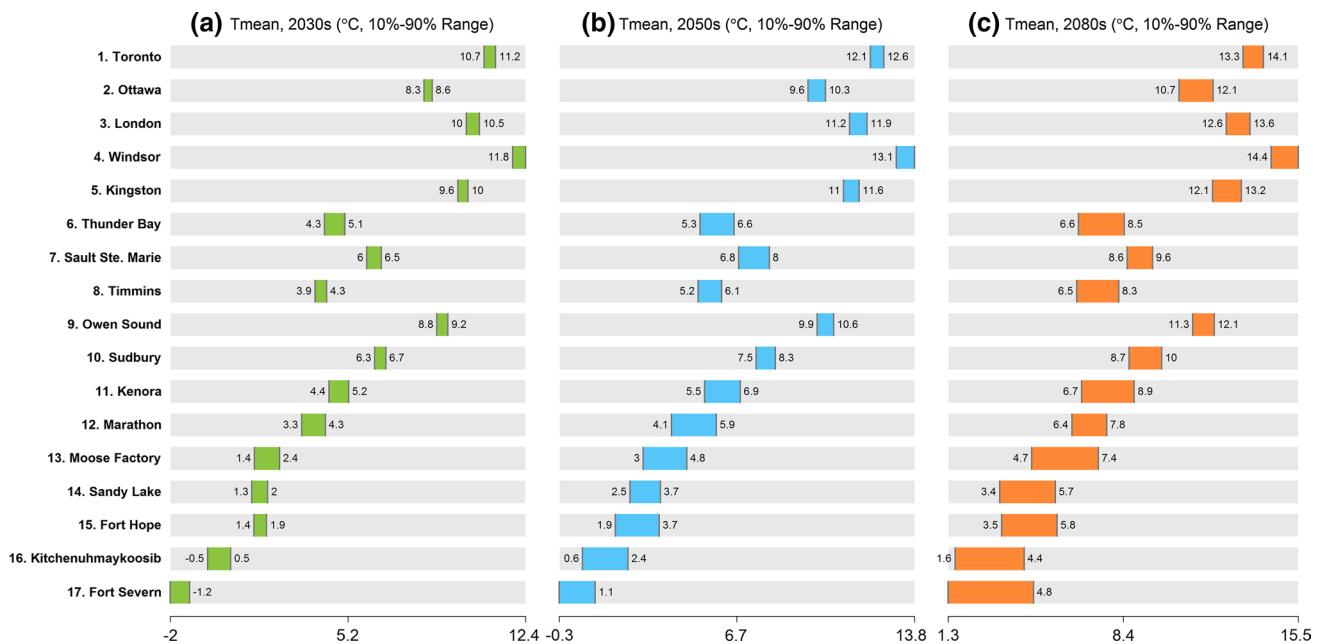
The projected  $T_{\text{mean}}$ ,  $T_{\text{max}}$ , and  $T_{\text{min}}$  for the major cities at 50 % probability are presented in Table 2. There is a consistent increasing trend in all three temperature variables throughout the 17 major cities. For example, the average daily mean temperature (i.e.,  $T_{\text{mean}}$ ) in the City of Toronto is most likely to be 10.9 °C in 2030s and 12.3 °C in 2050s, and it is likely to jump to as high as 13.7 °C to the end of this century (i.e., in 2080s); by contrast, the average  $T_{\text{mean}}$  in the most north city (i.e., Fort Severn) is projected to be less than 0 °C (most likely to be  $-1.6$  °C) in 2030s, while the value for 2050s is projected to exceed 0 °C (most likely to be 0.4 °C) and the mean temperature to the end of this century would be as high as 3.0 °C. The similar increasing trends for  $T_{\text{max}}$  and  $T_{\text{min}}$  are also reported by the PRECIS ensemble simulations.

Figures 4, 5 and 6 show the most likely ranges (expressed as 10–90 % probability range) of the possible future outcomes of  $T_{\text{mean}}$ ,  $T_{\text{max}}$ , and  $T_{\text{min}}$  at all major cities.

It is reported that the spread of the ranges at all major cities for all three temperature variables shows a consistent widening trend with time periods. For example, the most likely range of the  $T_{\text{mean}}$  in the City of Ottawa would be [8.3, 8.6] °C (with a spread of 0.3 °C) in 2030s, while the projected ranges in 2050s and 2080s would expand to [9.6, 10.3] °C (with a spread of 0.7 °C) and [10.7, 12.1] °C (with a spread of 1.4 °C), respectively; by comparison, the width of the projected ranges of  $T_{\text{mean}}$  in Fort Severn is likely to increase significantly from 0.8 °C in 2030s, to 1.4 °C in 2050s, and to as wide as 3.5 °C to the end of this century. Similar expanding patterns in terms of the spread of the most likely ranges of  $T_{\text{max}}$  and  $T_{\text{min}}$  are also revealed at all major cities. Such a consistent expanding trend in the width of the most likely ranges of future temperature outcomes from 2030s to 2080s suggests that the long-term climate change is more difficult to forecast than the near-term change, as many more uncertain or unknown factors

**Table 2** Projected  $T_{\text{mean}}$ ,  $T_{\text{max}}$ , and  $T_{\text{min}}$  for the major cities at 50 % probability

| No. | City name          | $T_{\text{mean}}$ ( $^{\circ}\text{C}$ , 50 %) |       |       | $T_{\text{max}}$ ( $^{\circ}\text{C}$ , 50 %) |       |       | $T_{\text{min}}$ ( $^{\circ}\text{C}$ , 50 %) |       |       |
|-----|--------------------|--|-------|-------|---|-------|-------|---|-------|-------|
|     |                    | 2030s  | 2050s | 2080s | 2030s   | 2050s | 2080s | 2030s   | 2050s | 2080s |
| 1   | Toronto            | 10.9   | 12.3  | 13.7  | 15.3  | 16.8  | 18.2  | 6.6   | 7.9   | 9.2   |
| 2   | Ottawa             | 8.4  | 9.9   | 11.4  | 13.8  | 15.4  | 16.8  | 3.2   | 4.6   | 6.2   |
| 3   | London             | 10.2   | 11.6  | 13.1  | 15.1  | 16.6  | 18.2  | 5.4   | 6.6   | 8.0   |
| 4   | Windsor            | 12.1   | 13.5  | 15.0  | 16.6  | 18.0  | 19.6  | 7.6   | 8.9   | 10.3  |
| 5   | Kingston           | 9.8  | 11.3  | 12.6  | 14.3  | 15.9  | 17.2  | 5.3   | 6.7   | 8.2   |
| 6   | Thunder Bay        | 4.7  | 5.9   | 7.6   | 10.5  | 11.9  | 13.7  | -0.9  | 0.5   | 1.9   |
| 7   | Sault Ste. Marie   | 6.2  | 7.4   | 9.1   | 11.6  | 13.0  | 14.5  | 0.9   | 1.9   | 3.9   |
| 8   | Timmins            | 4.1  | 5.7   | 7.4   | 10.4  | 11.9  | 13.6  | -2.1  | -0.6  | 1.3   |
| 9   | Owen Sound         | 9.0  | 10.3  | 11.7  | 13.7  | 15.2  | 16.8  | 4.3   | 5.4   | 6.6   |
| 10  | Sudbury            | 6.5  | 7.9   | 9.3   | 12.1  | 13.5  | 15.0  | 0.9   | 2.3   | 4.0   |
| 11  | Kenora             | 4.8  | 6.2   | 7.8   | 10.5  | 11.8  | 13.7  | -0.8  | 0.6   | 2.0   |
| 12  | Marathon           | 3.8  | 5.0   | 7.1   | 9.1   | 10.5  | 12.1  | -1.0  | 0.3   | 2.4   |
| 13  | Moose Factory      | 2.0  | 3.8   | 6.1   | 8.0   | 9.8   | 12.1  | -4.0  | -2.2  | 0.0   |
| 14  | Sandy Lake         | 1.6  | 3.1   | 4.6   | 7.0   | 8.5   | 10.1  | -3.7  | -2.3  | -1.0  |
| 15  | Fort Hope          | 1.6  | 2.8   | 4.6   | 7.6   | 9.0   | 10.6  | -4.3  | -2.8  | -0.8  |
| 16  | Kitchenuhmaykoosib | 0.0  | 1.5   | 3.0   | 5.3   | 6.8   | 8.3   | -5.7  | -3.7  | -1.8  |
| 17  | Fort Severn        | -1.6   | 0.4   | 3.0   | 5.2   | 7.7   | -6.5  | -4.8  | -2.4  |       |

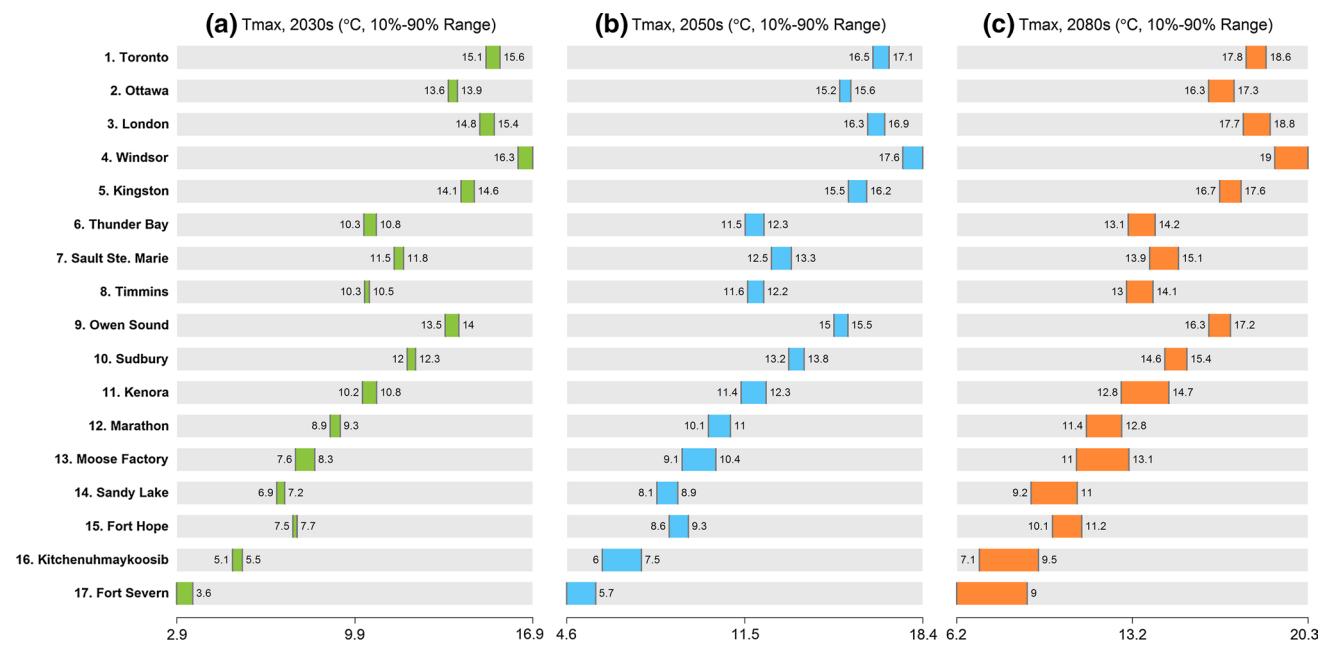
**Fig. 4** Projected ranges of  $T_{\text{mean}}$  at the major cities

affecting the long-term climate change might emerge as time goes and thus challenge our current understanding of the climate system as well as the complexity of climate change mechanisms (Claussen et al. 2002; Held 2005).

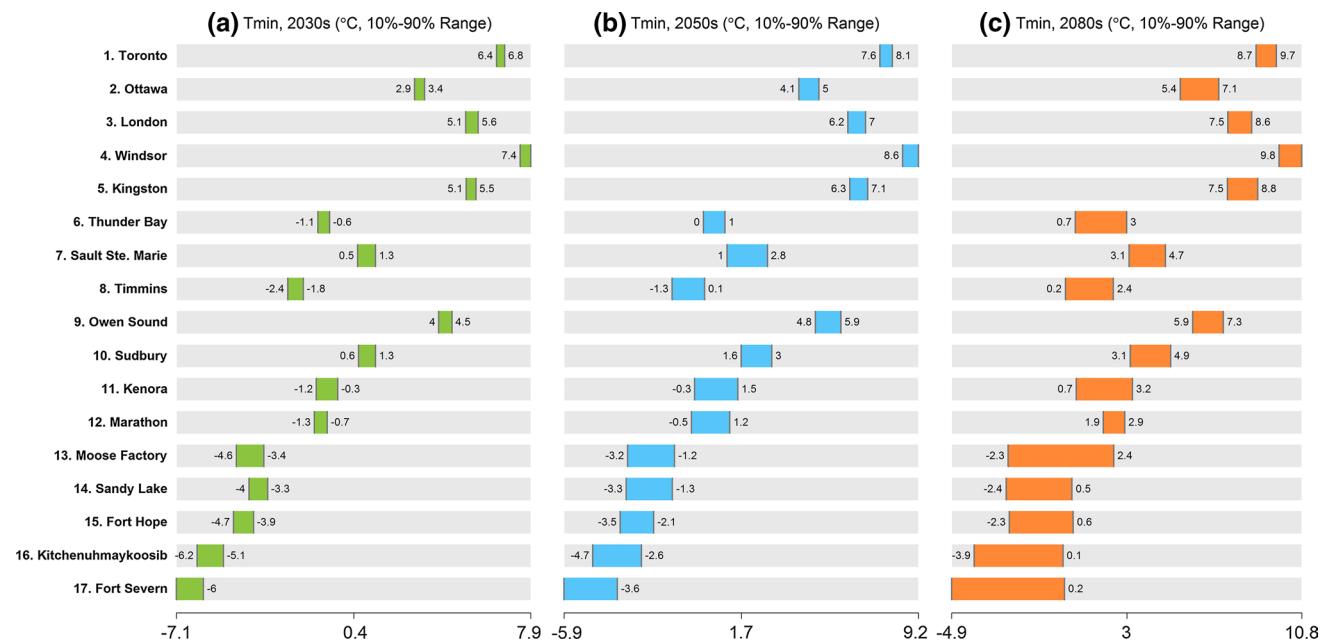
Figure 7 presents the maps of projected  $T_{\text{mean}}$ ,  $T_{\text{max}}$ , and  $T_{\text{min}}$  for three periods (i.e., 2030s, 2050s, and 2080s) at 50 % probability for all 25-km grid cells over the Province

of Ontario. The results suggest that the most likely mean temperature in 2030s would be  $[-2, 2] ^{\circ}\text{C}$  in northern Ontario,  $[2, 6] ^{\circ}\text{C}$  in the middle, and  $[6, 12] ^{\circ}\text{C}$  in the south. The mean temperature in 2050s is projected to increase by  $2 ^{\circ}\text{C}$  throughout the Province and would be  $[0, 4] ^{\circ}\text{C}$  in the north,  $[4, 8] ^{\circ}\text{C}$  in the middle, and  $[8, 14] ^{\circ}\text{C}$  in the south, respectively. Likewise, the projected mean temperature in

## Projected increases in near-surface air temperature over Ontario, Canada



**Fig. 5** Projected ranges of  $T_{\max}$  at the major cities



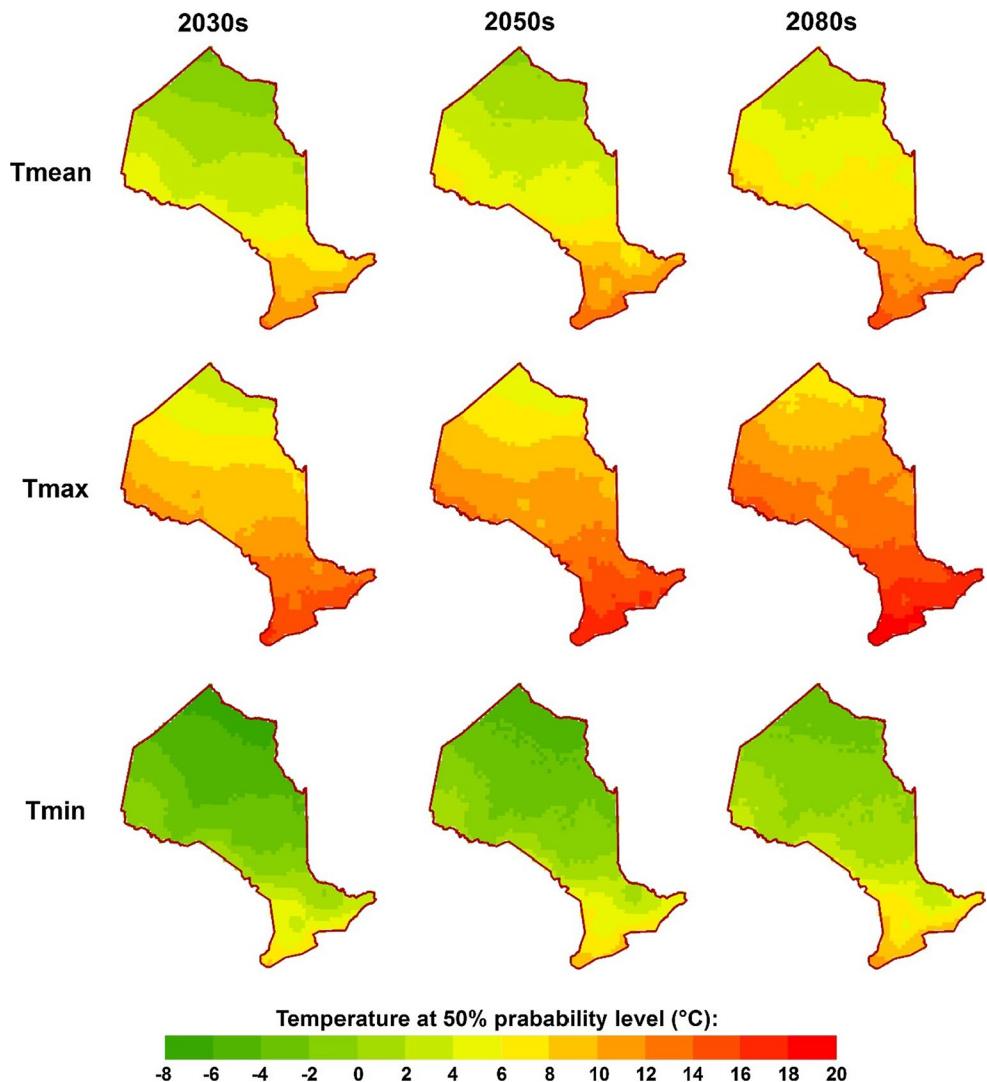
**Fig. 6** Projected ranges of  $T_{\min}$  at the major cities

2080s is likely to keep rising following the similar pattern. Such a consistent warming trend throughout the Province would drive the lowest mean temperature up to 2 °C in the north and the highest mean temperature up to 16 °C in the south. Similar increasing patterns in the context of Ontario are also projected for the other two variables (i.e.,  $T_{\max}$  and  $T_{\min}$ ). The projected highest  $T_{\max}$  in the south is likely to

jump to as high as 20 °C in 2080s, while the lowest  $T_{\min}$  in the north is projected to be above -4 °C to the end of this century.

To future investigate the uncertainties involved in the probabilistic projections for future temperature obtained from the PRECIS ensemble simulations, we define the degree of uncertainty which is expressed as the width

**Fig. 7** Future temperature projections over Ontario at 50 % probability



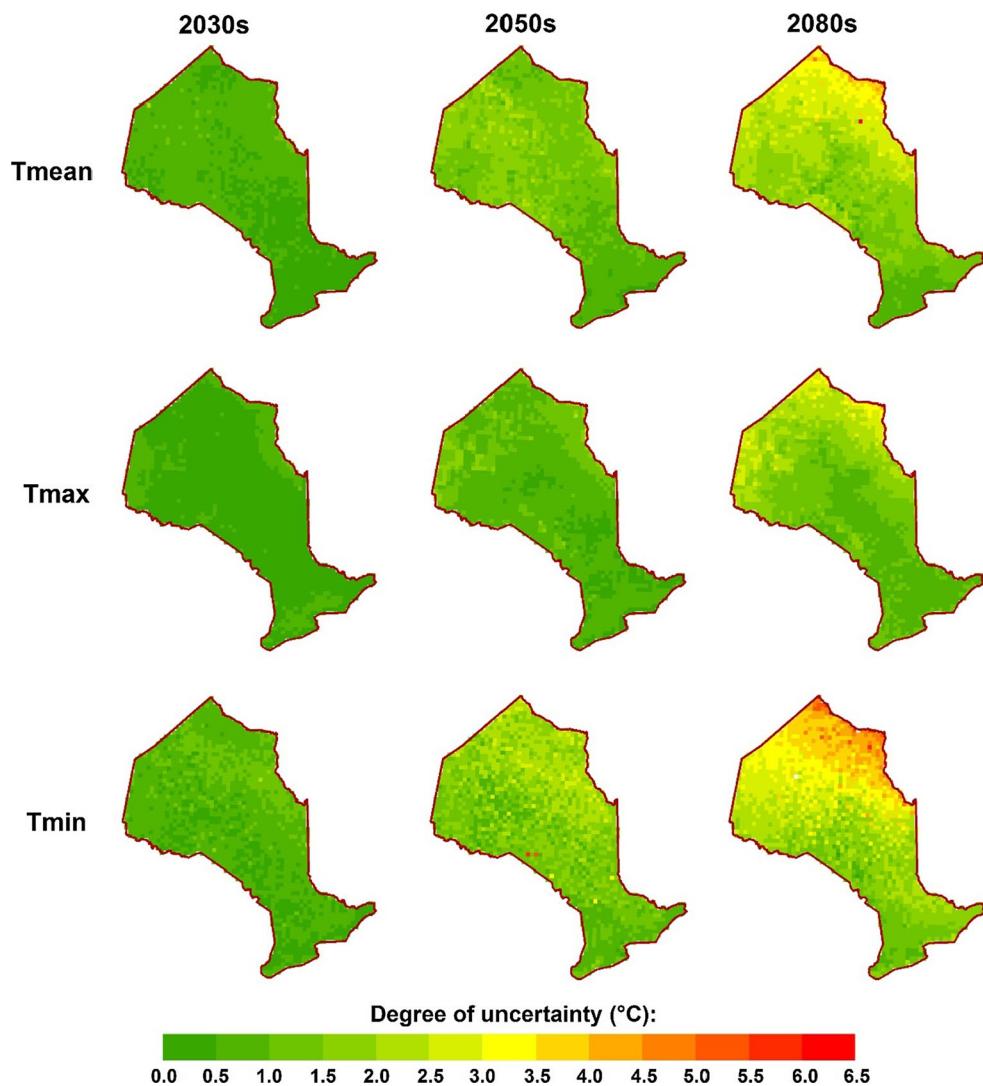
or spread of most likely range (i.e., 10–90 % probability range) because the wider the range is, the more uncertain or the less reliable the projection is. Figure 8 shows the maps of degree of uncertainty for future projections of  $T_{\text{mean}}$ ,  $T_{\text{max}}$ , and  $T_{\text{min}}$  in the periods of 2030s, 2050s, and 2080s. It can be found that there is an overall increasing trend in the degree of uncertainty for three temperature variables with time periods, which further confirms our findings based on the projections for the major cities—the long-term climate change tends to be more difficult to predict than the short-term does due to many emerging or unknown factors in the long-term climate simulation. The maps show that projections of  $T_{\text{max}}$  demonstrate the least degree of uncertainty, while  $T_{\text{mean}}$  reveals moderate degree of uncertainty and  $T_{\text{min}}$  comes with the highest degree of uncertainty. Moreover, the maps report an apparent decreasing trend in the degree of uncertainty for three temperature variables along with the latitude, especially for the projections in 2080s. In other words, the projections for northern areas display

higher degree of uncertainty than those for southern areas do. For example, the projections of  $T_{\text{mean}}$  in 2080s show less degree of uncertainty (ranging between 0 and 1 °C) in the south while degree of uncertainty can be as high as [2.5, 3.5] °C in the north, implying that the projections of  $T_{\text{mean}}$  in the south seems to be more reliable than those in the north. Similar findings on the spatial pattern of degree of uncertainty are also reported for  $T_{\text{max}}$  and  $T_{\text{min}}$ .

#### 4 Conclusions

In this study, high-resolution projections of near-surface air temperature outcomes including mean, maximum, and minimum daily temperature over the Province of Ontario are developed. The aim was to investigate how global warming can affect the local climatology of the major cities as well as the spatial patterns of air temperature over the entire Province. We first carried out five-member RCM

**Fig. 8** Maps of degree of uncertainty for future temperature projections



ensemble simulations using the PRECIS modeling system which was driven by the boundary conditions of a HadCM3-based perturbed-physics ensemble. The Bayesian hierarchical model proposed by Wang et al. (2014a, b) was then used to obtain probabilistic projections of future temperature outcomes with consideration of some uncertain parameters involved in the regional climate modeling process. Following that, the most likely estimates and uncertain ranges of future temperature outcomes at 17 major cities were calculated and analyzed in detail, and then the similar analyses were extended to cover all 25-km grid cells over the entire Province with the purpose of providing decision makers or policy makers with helpful information for assessing the potential effects of climate change in the context of Ontario.

The PRECIS ensemble simulations were validated in terms of their capability of reproducing the current climate, through comparison with the observed temperature means from the NLWIS dataset. The validation results showed

that the ensemble simulations performed very well in capturing the major features of the observed  $T_{\text{mean}}$  and  $T_{\text{max}}$  at most areas in Ontario, while the projected  $T_{\text{min}}$  for the current climate by the ensemble tended to slightly overestimate the observations at most of the grid cells. To minimize the influence of the bias of PRECIS ensemble simulations on future temperature projections, we only used the ensemble simulations to calculate the probabilities of possible changes in near-surface air temperatures and then added the probabilistic change scenarios to the observed ones for current climate to develop the probabilistic projections of future possible temperature outcomes. The probabilistic projections suggested that there would be a consistent increasing trend in three temperature variables (i.e.,  $T_{\text{mean}}$ ,  $T_{\text{max}}$ , and  $T_{\text{min}}$ ) with time periods from 2030s to 2080s. The most likely mean temperature in next few decades (i.e., 2030s) would be  $[-2, 2]^\circ\text{C}$  in northern Ontario,  $[2, 6]^\circ\text{C}$  in the middle, and  $[6, 12]^\circ\text{C}$  in the south, afterwards the mean temperature is likely to keep rising by  $\sim 2^\circ\text{C}$  per

30-year period. The continuous warming across the Province would drive the lowest mean temperature up to 2 °C in the north and the highest mean temperature up to 16 °C in the south. We also found that the spread of the most likely ranges of future temperature projections showed a consistent widening trend from 2030s to 2080s, implying that the long-term climate change is more difficult to predict than the near-term change because many more uncertain or unknown factors may continue to emerge as time goes and thus challenge our understanding and knowledge of the climate system and climate change mechanisms.

The high-resolution probabilistic projections developed in this study can provide direct inputs for climate impact researchers to study the possible impacts of global warming in the context of Ontario, meanwhile, the findings and implications of the study are potentially helpful for decision makers and development practitioners in terms of assessing the risks and costs associated with climatic change as well as planning the mitigation and adaptation strategies against the global warming at regional scales.

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