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A coupled dynamical-copula downscaling approach for temperature projections over the Canadian Prairies

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Abstract
In this study, a coupled dynamical-copula downscaling approach was developed through integrating the Providing Regional Climates for Impacts Studies (PRECIS) modeling system and the copula method. This approach helps to reflect detailed features at local scales based on dynamical downscaling, while also effectively simulating the interactions between large-scale atmospheric variables (predictors) and local surface variables (predictands). The performance of the proposed approach in reproducing historical climatology of the Canadian Prairies was evaluated through comparison with observations. Future climate projections generated by the developed approach were analyzed over three time slices (i.e., the 2030s, 2050s, and 2080s) to help understand the plausible changes in temperature over the Canadian Prairies in response to global warming. The results showed that there would be an apparent increasing pattern over the Canadian Prairies. The projections of future temperature over three time slices can provide decision makers with valuable information for climate change impacts assessment over the Canadian Prairies.

Keywords Dynamical downscaling · Copula · Projected changes · Canadian Prairies

1 Introduction

Climate change is one of the most important and urgent environmental issues facing the globe. To investigate the potential impacts of climate change, climatic change projections are usually generated through global climate models (GCMs) under the representative concentration pathways (IPCC 2013; Van Vuuren et al. 2011). However, GCMs with a coarse resolution over 100 km are unable to reflect the mechanisms of climate at local scales. Future climate projections at a much higher resolution are a central prerequisite for conducting climate change impact studies (Jury et al. 2015; Notaro et al. 2015; Pérez et al. 2014). Therefore, to improve the representation of local climatology, downscaling techniques are required to tackle the spatial mismatch between GCMs and impacts assessment models (Hessami et al. 2008; Wang et al. 2013).

Previous studies have attempted to investigate the potential improvements through developing coupled dynamical-statistical or statistical-dynamical approaches for high-resolution climate projections (Bechler et al. 2015; Chavez-Arroyo et al. 2015; Gong et al. 2015; Hellström and Chen 2003; Kim et al. 2015; Li et al. 2016; Quintana-Seguí et al. 2016; Reyers et al. 2015; Sun et al. 2015; Tang et al. 2016; Walton et al. 2015; Wang et al. 2015a; Zollo et al. 2015). For example, Wang et al. (2013) developed a statistical downscaling tool (SCADS) to assist obtaining high-resolution climate change scenarios based on the stepwise cluster analysis method, which used a cluster tree to represent the complex relationship between large-scale atmospheric variables (predictors) and local surface variables (predictands). Wang et al. (2015a) integrated the PRECIS regional modeling system and the statistical method SCADS into a coupled dynamical-statistical downscaling framework, which helped generate very high resolution (i.e., 10 km × 10 km) climate projections for the Province of Ontario, Canada. Walton et al. (2015) developed a hybrid dynamical-statistical technique through integrating the computational savings of a statistical model to downscale multiple GCMs and the ability

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of dynamical downscaling to capture fine-scale dynamics, which demonstrated considerable improvement in capturing the spatial details. Moreover, the proposed hybrid dynamical-statistical technique was further applied to generate the end-of-century warming projections for predicting a new climate state in the Los Angeles Region (Sun et al. 2015).

Nevertheless, previous studies were unable to describe the dependence structure independently from the marginal distributions of both simulations and observations without any transformation (Genest and Favre 2007; Sraj et al. 2015). Meanwhile, there were few reports of coupled dynamical-statistical or statistical-dynamical downscaling approaches for generating high-resolution climate projections in the context of the Canadian Prairies. Previous studies have been mostly focused on the application of a single technique (either dynamical or statistical downscaling) for conducting climate change impact studies over the context of the Canadian Prairies Provinces (Asong et al. 2016; Chun et al. 2013; Gameda et al. 2007; PaiMazumder et al. 2013; Shepherd and McGinn 2003).

Therefore, the objective of this study is to downscale and analyze changes in temperature over the Canadian Prairies through a coupled dynamical-copula approach. It will incorporate the Providing Regional Climates for Impacts Studies (PRECIS) and a statistical downscaling method (i.e., copula) into a generalized framework to construct high-resolution climate projections for the Canadian Prairies. In detail, the PRECIS model will be employed to project the future climate over the Canadian Prairies at its highest spatial resolution of 25 km. The copula model will then be developed to obtain daily time series of mean, maximum, and minimum temperature in the study region. The performance of the coupled dynamical-copula downscaling approach in reproducing the relevant observations of the study region will be evaluated and presented. Moreover, the approach will be compared to the quantile mapping method (Boé et al. 2007; Piani et al. 2010) to further demonstrate its performance. Finally, future changes in the mean, minimum, and maximum temperature will be analyzed to help understand the regional and local effects of global warming in the context of the Canadian Prairies. It is expected that changes in the mean, maximum, and minimum temperature will be explored in the upcoming decades. The results in this study can provide valuable information to avoid severe impacts of climatic changes on economic, social, and environmental sectors at regional and local scales.

2 Model, study area, and data

As shown in Fig. 1, the Canadian Prairies comprise the Provinces of Manitoba, Saskatchewan, and Alberta, which are bordered by the Province of British Columbia to the west, and the Northwest Territories to the north, the Province of Ontario to the east, and the United States of America to the south. The total area of the Canadian Prairies is 1,960,681 km^2 and accounts for 19.6% of the total area in Canada (Statistics Canada 2015). The current population is 6.62 million, approximately 18.5% of Canada's population (Statistics Canada 2015).

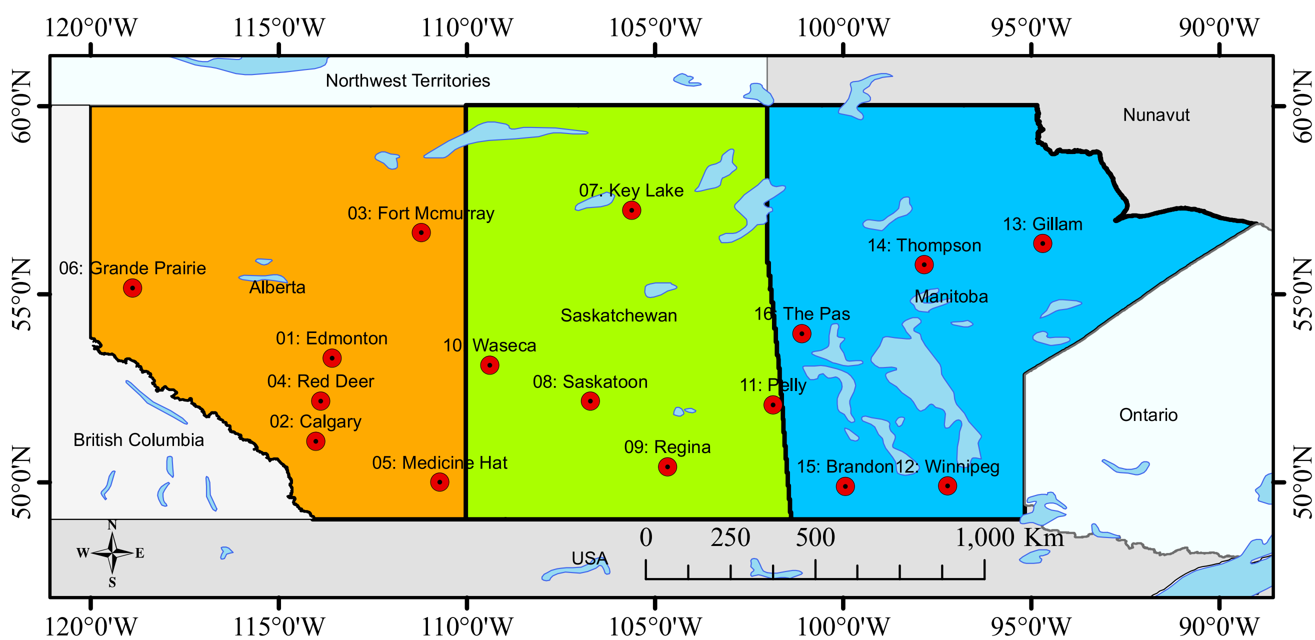

Fig. 1 The study area and 16 selected cities

In general, the climate of the Canadian Prairies is cold and subhumid due to its location in mid latitudes and the rain shadow of the Rocky Mountains (Natural Resources Canada 2015). During the period of 1986–2005, the averaged winter temperature is − 19.4 °C for 154 stations over the Canadian Prairies, whereas the averaged summer temperatures are 12 °C. The average increase in annual mean temperature since 1895 for climate stations across the Prairies is 1.6 °C (deJong et al. 2010; Natural Resources Canada 2015; Zhou et al. 2015). Moreover, the maximum and minimum temperature has increased by 1.7 and 1.1 °C during the period of 1950–1989, respectively (Skinner and Gullett 1993). During the period of 1920 –1995, the average amount of annual precipitation has increased 0.62 mm due to a warmer and earlier spring (Akinremi et al. 2001). The increase in annual mean temperature has contributed to both an enhanced greenhouse gas effect and land-cover changes (Skinner and Majorowicz 1999). In the Canadian Prairies, climatic change is expected to have significance consequences on agriculture, energy and other socio-economic sectors. However, understanding how the climate will change in both short and long terms is critical for developing adaptive strategies in the context of the Canadian Prairies. Therefore, it is desirable to downscale climate projections over the Canadian Prairies for improving mitigation and adaptation strategies against climate change.

In this study, the latest version of the PRECIS regional climate modeling system (PRECIS2.0) developed by the UK Hadley Centre is employed to develop fine-scale physically-based climate projections over the Canadian Prairies. It can be applied easily to any area of the globe to provide detailed regional climate change projections for conducting impacts studies (Jones and Hassell 2004; Wang et al. 2015b). The PRECIS model can be run at two different horizontal resolutions: $0.44° \times 0.44°$ and $0.22° \times 0.22°$, which respectively provides a minimum resolution of 50 km × 50 km and 25 km × 25 km at the equator of the rotated grid (Centella-Artola et al. 2015; Wang et al. 2014). The PRECIS model comprises 19 levels described by a hybrid vertical coordinate (a combination of σ-coordinate and pressure coordinate), which is a hydrostatic, primitive equation grid-point model (Wang et al. 2015b; Wilson et al. 2005). The convective scheme is the mass flux penetrative scheme with an explicit downdraught (Gregory and Rowntree 1990), while the Met Office Surface Exchange Scheme is employed as the land surface model component (Cox et al. 1999). The radiation scheme includes the seasonal and diurnal cycles of insolation, computing short wave and long wave fluxes (Jones et al. 2004). Jones et al. (2004) described the detailed model parameterization.

The PRECIS system can be driven by boundary data from the HadGEM2-ES historical experiment (1950–2005) and future experiments under Representative Concentration Pathways (RCPs) (2006–2099). The GHG concentration trajectories of RCPs (i.e., RCP2.6, RCP4.5, RCP6, and RCP8.5) are generally different than each other after 2050. More details are can be found in Moss et al. (2010). In this study, the PRECIS model first runs at its highest resolution (i.e., 25 km) driven by boundary data from the HadGEM2-ES historical experiment from 1950 to 2005 with the purpose of providing full simulations for present-day climate. The boundary data from HadGEM2-ES RCP4.5 and RCP8.5 scenario experiments (2006–2099) are then downscaled through the PRECIS model to generate projections for future climate. Outputs from the PRECIS ensemble simulations are extracted and split into four 20-year periods, including 1986–2005 (the baseline period), 2016–2035 (2030s), 2046–2065 (2050s), and 2076–2095 (2080s).

To conduct the below downscaling and validation analysis, the daily mean, maximum, and minimum temperature used in this study for the period of 1986 to 2005 is obtained from Environment and Climate Change Canada (Environment and Climate Change Canada 2015). In this study, 16 cities are selected, which are spatially distributed across the Canadian Prairies (Fig. 1). The data between 1986 and 2005 at these cities is extracted to represent the observations of historical climate in the context of the Canadian Prairies. The first 10-year data (i.e., 1986–1995) were used for development of coupled dynamical-copula downscaling model, and the remaining 10-year (i.e., 1996–2005) data are emplyed for the model validation.

3 Methodology

In general, copula functions can provide a functional link between two univariate marginal distributions (Nelsen 2007; Fan et al. 2017):

$$F_{XY}(x, y) = C\big(F_X(x),\ F_Y(y)\big) \tag{1}$$

where $F_{XY}(x,\ y)$is the joint cumulative distribution function of (X, Y); $F_X(x)$ and $F_Y(y)$ are marginal distributions of random vectors X and Y. The Copula function is able to derive joint distributions given the marginal distributions, and allows for modeling the dependence between two random variables (Nelsen 2007; Fan et al. 2016). A large number of different copula families mainly including the Archimedean, elliptical, extreme value copulas are widely used in practice. Among them, the Archimedean copula family is quite attractive due to the advantages: (1) it can be easily generated; (2) it is able to capture huge varieties of dependence structure with various stochastic copula models; and (3) it can be employed for both positively and negatively correlated random variables (Jeong et al. 2014). Moreover, It is indicated that the copula formulation can be also used without much statistical association between the two variables (Zhang 2005; Zhang and Singh 2006). For example, Zhang and Singh (2006) derived the bivariate distributions by using the copula method, while the lowest Kendall correlation coefficient is 0.15. In general, a bivariate Archimedean copula can be expressed as (Nelsen 2007):

$$C_\theta(u,\ v) = \phi^{-1}[\phi(u) + \phi[v]] \tag{2}$$

where u and v are a realisation of U and V, respectively; $U = F_X(x)$ and $V = F_Y(y)$; $F_X(x)$ and $F_Y(y)$ are cumulative distributions function (CDF) of random vector X and Y, respectively; the subscript θ is the parameter hidden in the generation function ϕ (Karmakar and Simonovic 2009). The unknown parameter (i.e., θ) in Archimedean copulas can be estimated from the Kendall correlation coefficient (Nelsen 2007). The Archimedean copulas are the most commonly used copulas for capturing dependence structure with several desirable properties. Therefore, in this study, four single-parameter bivariate Archimedean copulas (i.e., Clayton, Frank, Gumbel, and Joe copulas) are considered. Some basic properties for the four families of Archimedean copula are listed in Table 1.

Once the parameter for the joint distributions is estimated, the root-mean-square error (RMSE) and Akaike information criterion (AIC) are used to evaluate the goodness-of-fit of both the PRECIS simulations and sample datasets to the theoretical joint distribution (Karmakar and Simonovic 2009).The RMSE can be expressed as (Willmott and Matsuura 2005):

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N}\left(x_k^e - x_k^o\right)^2}{N}} \tag{3}$$

where N is the sample size; x_k^e are the theoretical values obtained from the fitted probability distribution; andx_k^o denote the empirical probabilities given by the Gringorten plotting position formula (Gringorten 1963):

$$P(K \leqslant k) = \frac{k - 0.44}{N + 0.12} \tag{4}$$

where k denotes the k^{th} smallest observation; and the observations is arranged in an increasing order. Based on RMSE, the AIC criteria can be obtained as follows (Karmakar and Simonovic 2009):

$$AIC = N * \log(MSE) + 2k \tag{5}$$

where k is the number of unknown parameters in the probability distribution, and MSE represents the mean square error (i.e., squared value of RMSE). The potential optimal copula is the one with the minimum value of RMSE, AIC or a combination of these criteria (Genest et al. 2009).

In order to evaluate the performance of copulas, the goodness-of-fit test based on Rosenblatt transformation would be employed based on the recommendation of Genest et al. (2009). They argued that test statistics based on the Cramér von Mises functional of a process tend to be more powerful than those based on the Kolmogorov–Smirnov distance taken on the same process (Genest et al. 2009). Consequently, Cramér von Mises statistic test was adopted to test the performance of the copulas with the corresponding p-values being approximated through Monte Carlo simulation. Detailed procedures for performing goodness-of-fit test for copulas based on Rosenblatt transformation are provided by Genest et al. (2009).

If an appropriate copula function is selected, the conditional joint distribution (i.e., $F_X(x)$, $F_Y(y)$, and $C_\theta(u,\ v)$) can thus be obtained. Conditional random samples can be generated through Monte Carlo simulations. Following Salvadori et al. (2007), the simulation is based on a conditional distribution of U given $V = v$ or V given $U = u$ which can be expressed as:

$$C_{U|V=v}(u) = C(U \leqslant u|V = v) = \frac{\partial}{\partial v}C(u, v)|V = v \tag{6}$$

$$C_{V|U=u}(v) = C(V \leqslant v|U = u) = \frac{\partial}{\partial u}C(u, v)|U = u \tag{7}$$

Detailed steps (Fig. 2) for coupled dynamical-copula downscaling approach can be summarized as follows:

Table 1 Properties of the selected bivariate Archimedean copulas

Copula family	Function $[C_\theta(u,\ v)]$	Range of θ	Generating functions $[\phi(t)]$	$\tau = 1 + 4\int_0^1 \frac{\phi(t)}{\phi'(t)}dt$
Clayton	$\left[u^{-\theta} + v^{-\theta} - 1\right]^{-1/\theta}$	$[-1,\ \infty)/\{0\}$	$t^\theta - 1$	$\frac{\theta}{\theta+2}$
Frank	$-\frac{1}{\theta}\ln\left\{1 + \frac{(e^{-\theta u}-1)(e^{-\theta v}-1)}{e^\theta - 1}\right\}$	$[-\infty,\ \infty)/\{0\}$	$\ln\left[\frac{e^{\theta t}-1}{e^\theta - 1}\right]$	$1 - \frac{4}{\theta}\left[\frac{1}{-\theta}\int_0^1 \frac{t}{e^t-1}dt - 1\right]$
Gumbel	$\exp\left\{-\left[(-\ln u)^\theta + (-\ln v)^\theta\right]^{1/\theta}\right\}$	$[1,\ \infty)$	$(-\ln t)^\theta$	$1 - \theta^{-1}$
Joe	$1 - \left[(1-u)^\theta + (1-v)^\theta - (1-u)^\theta(1-v)^\theta\right]^{1/\theta}$	$[1,\ \infty)$	$-\ln(1-(1-t)^\theta)$	$1 - 4\sum_{k=1}^{\infty}\frac{1}{k(\theta k+2)(\theta(k-1)+2)}$

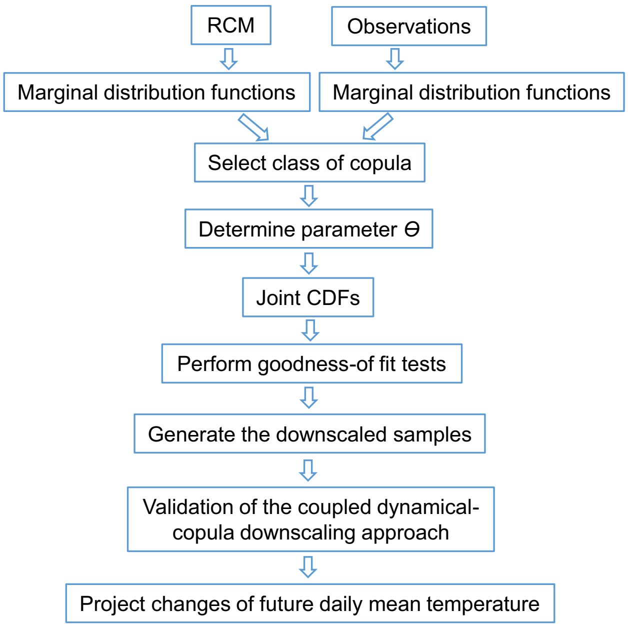

Fig. 2 Schematic diagram of the coupled dynamical-copula downscaling approach

Step 1 Estimate the marginal distribution $F_X(x)$ and $F_Y(y)$ for the PRECS simulation and observation data, respectively.

Step 2 Determine the copula parameter θ for the bivariate empirical copula (bivariate probability density plot) (Fig. 3) and perform goodness-of fit tests to identify the best copula function $C_\theta(u, v)$.

Step 3 Calculate the copula distribution of V given $U=u$ representing the PRECIS simulation time series.

Step 4 Generate the downscaled samples for the observations v at each time step through the conditional copula distribution.

Step 5 Transform the downscaled samples to the corresponding values through the probability integral transformation $y = F_y^{-1}(v)$.

Step 6 Evaluate the copula downscaling approach through comparing the model results with the observed data series.

Step 7 Project the changes of future mean, maximum, and minimum temperature relative to the baseline period base on the validated copula model.

4 Results and discussion

4.1 Implementation of the proposed approach

To determine the parameters in the joint distributions, the coupled dynamical-copula downscaling approach requires the fitting of suitable marginal distributions for both the PRECIS simulations and observed data at each city. In the present study, non-parametric fitting for the two datasets through kernel estimation method is employed. After parameter estimation for the marginal distribution, the Kolmogorov–Smirnov (K–S) statistic test is thus used to evaluate the performance of the marginal distributions (Argüeso et al. 2014).

The non-parametric dependence measure (i.e., Kendall's tau) is employed to evaluate the dependence between the PRECIS simulations and observed data at each station. Figure 4d presents the values of Kendall's tau correlation coefficients for the 16 selected cities. The values of Kendall's tau for all the cities are higher than 0.58, which indicates that the PRECIS simulations and observed data are highly correlated with each other. The unknown parameters in the four Archimedean copulas at each city are determined through inversion of empirical Kendall's tau. Once the copula parameters are determined, the joint cumulative distribution functions for all 16 selected cities can be obtained.

To identify the most appropriate copulas for downscaling the daily mean temperature, the differences among the four chosen copulas are further investigated. Figure 4a presents RMSE and AIC for joint distributions obtained through different copula functions at each city. It is indicated that the differences among the four copulas are relatively small for quantifying the joint cumulative probabilities between two datasets at each city. For example, the RMSE value for the Clayton, Gumbel, Frank, and Joe copula functions to downscale the daily mean temperature in Regina is 0.0431, 0.0215, 0.0115, and 0.0342 respectively. Based on the minimum RMSE (Fig. 4a) and AIC (Fig. 4b) values, it can be concluded that the Frank copula would be the most appropriate copula to downscale the daily mean temperature. Figure 4c provides the parameters for the Frank copula for all 16 cities.

In the meantime, the Rosenblatt transformation with Cramér von Mises statistic is employed to evaluate performance in modelling joint distributions of two datasets based on the selected most appropriate copula (i.e., Frank copula). A parametric bootstrap procedure detailed by Genest et al. (2009) is employed to compute p-values in this studies. The results of statistic test results for the goodness of fit of the joint distributions of two datasets at the 16 selected cities are also provided in Fig. 4d. It can be seen that the selected Frank copula can be applicable for further downscaling the daily mean temperature with the p-values larger than 0.05.

4.2 Performance in hindcasting current climate

To evaluate the performance of coupled dynamical-copula downscaling model in hindcasting recent climate, the values of daily mean, maximum, and minimum temperature during the period of 1996–2005 are reproduced through the developed model. The reproduced daily mean, maximum, and minimum temperature is then compared with the observed

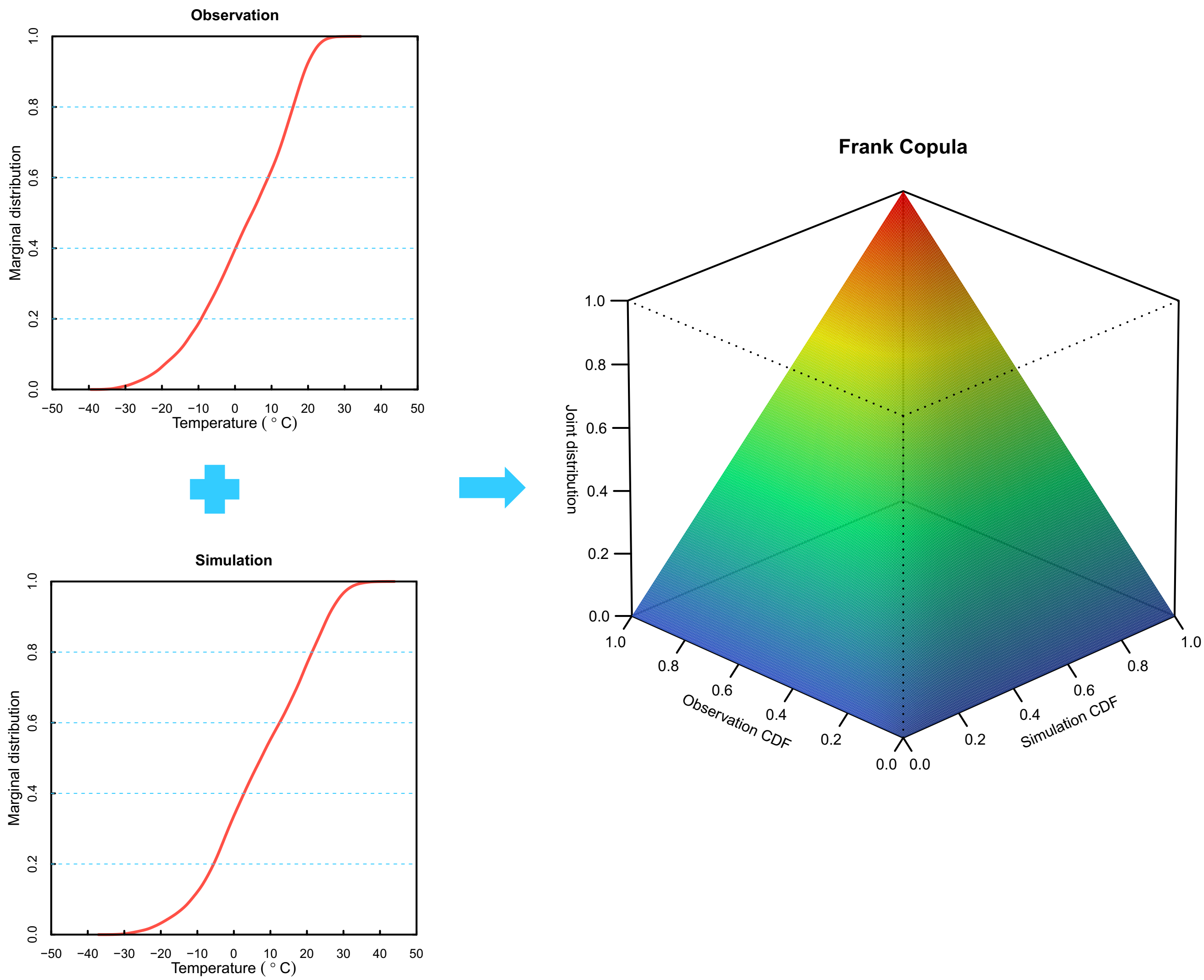

Fig. 3 Parameter estimation for the bivariate empirical copula from marginal distributions

data at the 16 selected cities retrieved from Environment and Climate Change Canada. Moreover, the coupled dynamical-copula downscaling model is compared to the quantile mapping (QMAP), which is an efficient statistical downscaling and bias correction method. The detailed information of QMAP can be found in previous work (Boé et al. 2007; Piani et al. 2010). In this study, the values of the R-squared coefficient (i.e., coefficient of determination) are calculated to evaluate the capability of the developed model in reproducing the observations.

Figure 5 provides the evaluation results of R-squared values from two models (i.e., the coupled dynamical-copula downscaling model and the QMAP method) for observed and reproduced monthly mean temperature at each city during the evaluation period of 1996–2005. It can be seen that the R-squared values for the 10-year period at the 16 selected cities in the Canadian Prairies are higher than 0.86. Moreover, compared to the QMAP method, higher coefficients of determination consistently demonstrate outstanding performance of the coupled dynamical-copula downscaling model in terms of reproducing monthly mean temperature.

To further investigate the performance of the developed model, the daily mean temperature for monthly variations is compared between the observed data and the outputs (Fig. 6). The results indicate that simulated estimates and spatial patterns of observed monthly mean temperature are well captured by the developed model. Figure 6 also compares the results from the coupled dynamical-copula downscaling model and the QMAP method. As shown in Fig. 6, there are only small differences in the mean temperature for monthly time-scales, which further verifies its good capability to reproduce the current observed temperature for monthly time-scales at the 16 selected cities. Moreover, the comparison results of monthly maximum and minimum

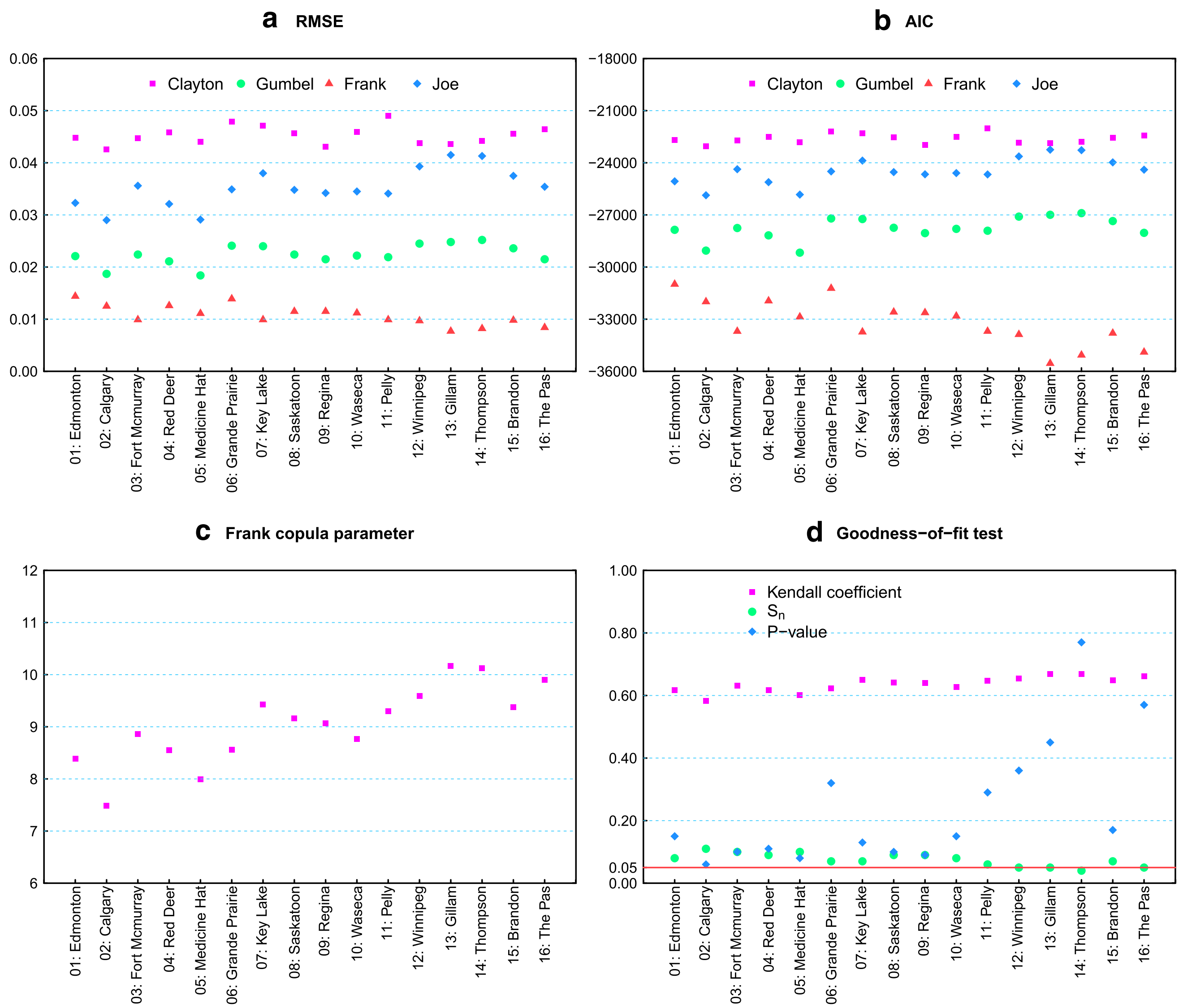

Fig. 4 Copula family comparison through RMSE and AIC, as well as the parameters and goodness-of-fit test for the Frank copula at all cities

temperature are further provided in Figs. 7 and 8. In general, the coupled dynamical-copula downscaling model has relatively higher coefficients of determination, which further demonstrates its performance in simulating both monthly maximum and minimum temperature over the Canadian Prairies. Therefore, the coupled dynamical-copula downscaling model can be an effective tool to downscale the daily mean, maximum, and minimum temperature for the selected cities in the Canadian Prairies.

4.3 Projections of future temperature changes

To better understand future temperature changes in the 16 selected cities across the Canadian Prairies, the future projections for the three 20-year periods (i.e., the 2030s, 2050s, and 2080s) under two RCP scenarios (i.e., RCP4.5 and RCP8.5) are developed through the coupled dynamical-copula downscaling model. The mean climate is then computed for the three 20-year periods under the two RCP scenarios and compared with the historical climate. The projections of changes in daily mean temperature under the two RCP scenarios at the 16 selected cities will thus be analyzed for providing a better understanding of possible future features. Moreover, the developed model will be further employed to 154 stations, which have less missing data during the period of 1986–2005.

Figure 9 presents projected changes in annual mean temperature at the 16 selected cities for the 2030s, 2050s, and 2080s relative to the historical climate under RCP4.5. The results indicate that the annual mean temperature is

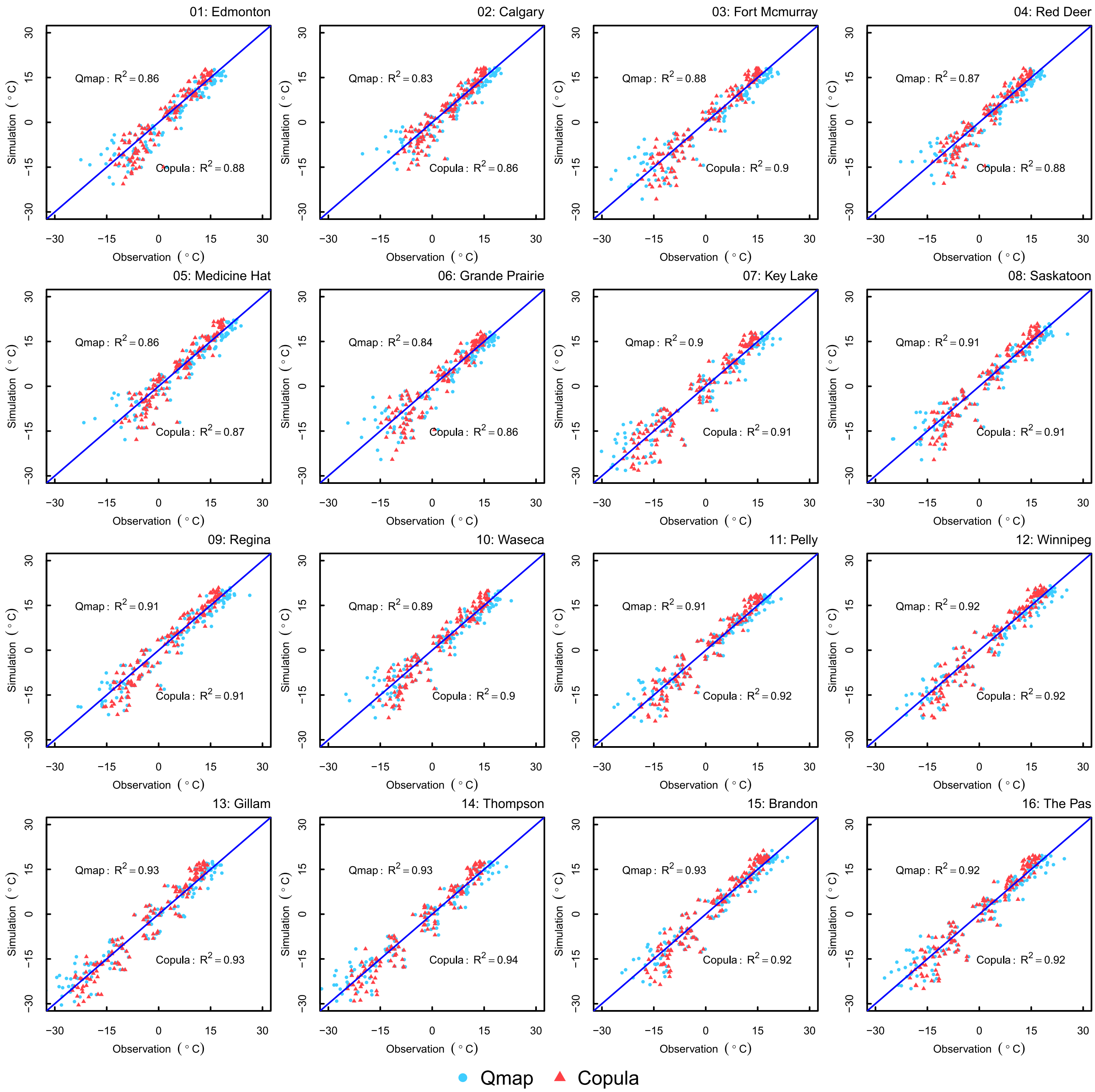

Fig. 5 Evaluation results for monthly mean temperature at the 16 selected cities

projected to increase over the 16 selected cities for the two RCPs considered from the 2030s to the end of this century (i.e., the 2080s). For instance, the changes in the annual mean temperature for the City of Calgary will be 2.6 °C in the 2030s, 3.5 °C in the 2050s, and 4.7 °C to the end of this century for the RCP4.5 scenario, while the projected change values for the City of Calgary under the RCP8.5 scenario will be 2.6 °C in the 2030s, 4.9 °C in the 2050s, and 7.2 °C in the 2080s. However, the developed model tends to project larger changes in annual mean temperature in the City of Regina, where the annual mean temperature is projected to be 8.9 °C for the 2030s, 9.9 °C for the 2050s, and 11.1 °C for 2080s. This result is consistent with a previous study (Zhou et al. 2017), which projected that the annul mean temperature in City of Regina under the Special Report on Emissions Scenarios is most likely to be 8.3 °C in the 2030s, 10.5 °C in the 2050s, and 12.5 °C in the 2080s. Moreover, the gradually increased pattern in annual mean temperature from the 2030s to the end of this century is also agreed with the findings in the previous study (Zhou et al. 2017).

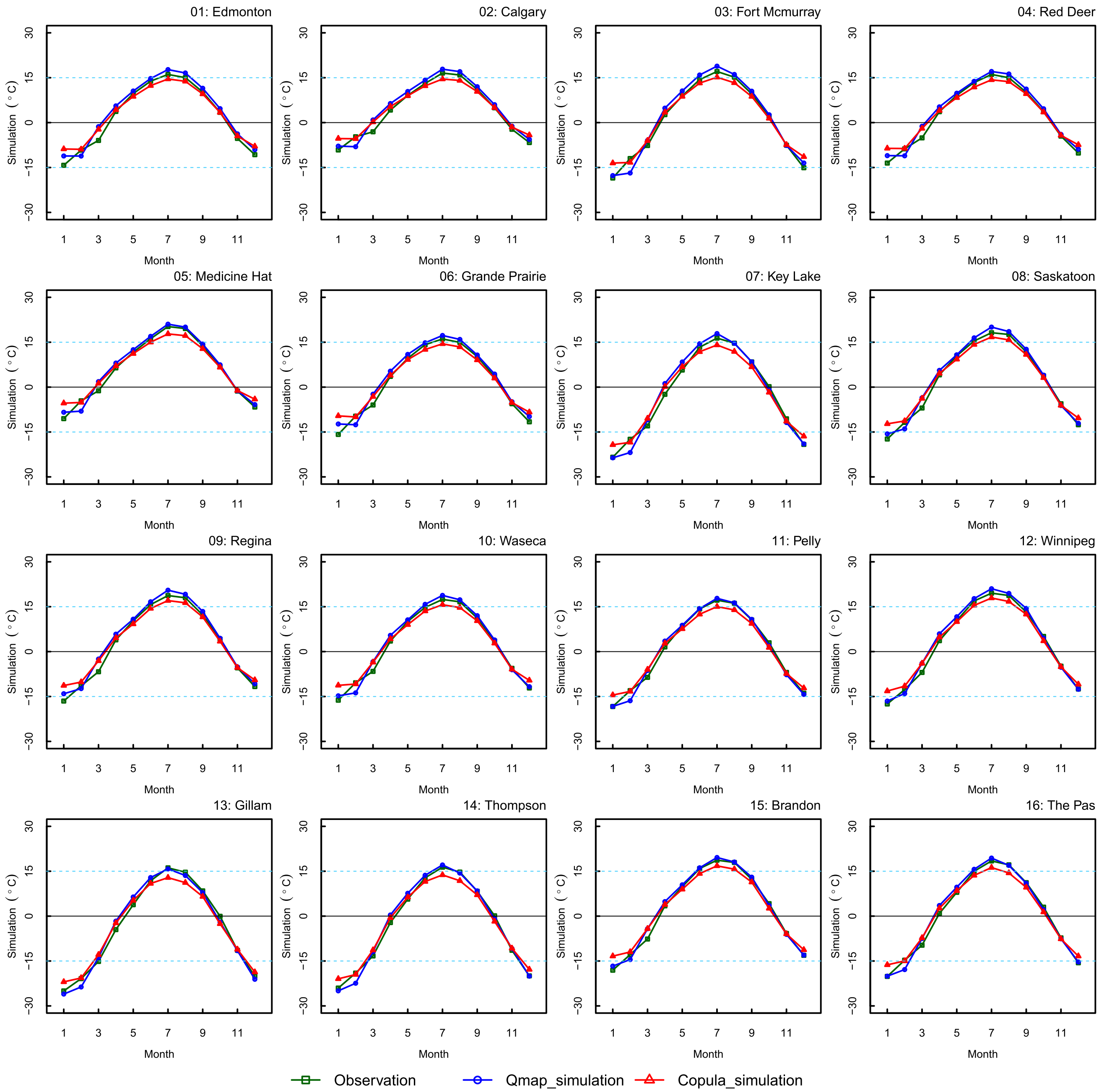

Fig. 6 Comparisons of monthly variations of daily mean temperature at the 16 selected cities

Moreover, Fig. 9 depicts projected changes in annual mean temperature for the 2030s, 2050s, and 2080s relative to the historical climate under RCP8.5. In general, the projected changes in temperature at the 16 selected cities under RCP8.5 are basically similar to those under RCP4.5, but the magnitude of changes are different. Specifically, it is observed that the projected temperature changes are much higher under the high emissions scenario (RCP8.5) than that under the RCP4.5 scenario. This is mainly because the sensitivity of future projections is increased with the GHG concentration in the atmosphere. The results also indicate that there is a larger associated variability of projected changes under RCP8.5. Moreover, the results indicate that there is a gradual increase in the annual mean temperature from the 2030s, to the 2050s, and the 2080s for the 16 selected cities.

In order to understand projected dynamics of temperature changes over the study area temporally, changes in monthly mean temperature are computed for the future periods. Figure 10 shows changes in monthly mean

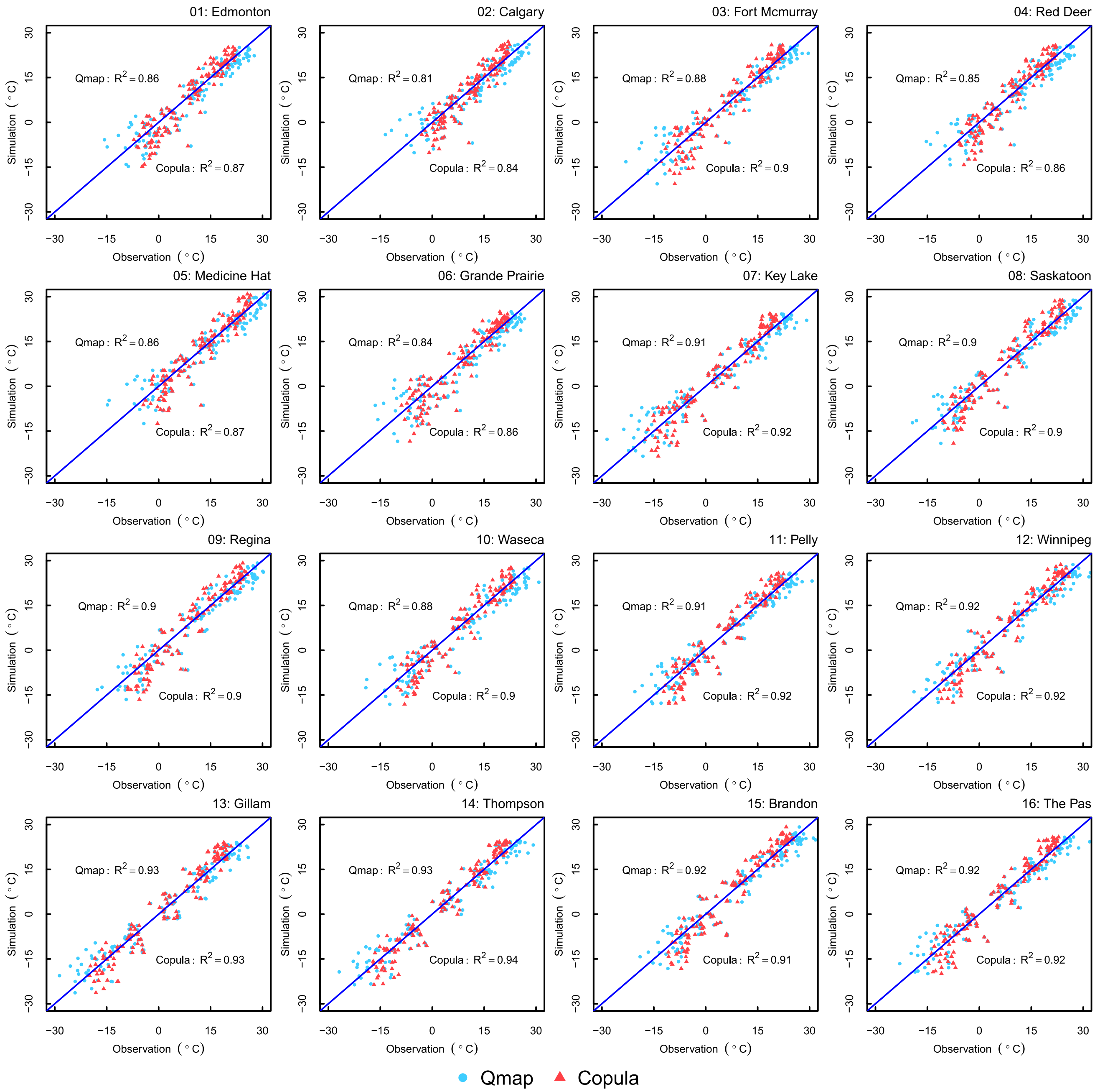

Fig. 7 Evaluation results for monthly maximum temperature at the 16 selected cities

temperature at the 16 selected cities during the period of 2076–2095 under the RCP4.5 scenario relative to the mean temperature in the baseline period. It is indicated that there is a consistent increase of mean temperature in all months for the selected 16 cities under RCP4.5, except for a small decrease (by less than 0.3 °C) in the mean values in January in the City of Calgary. In Fig. 10, the greatest warming in the mean temperature for the 2080s under RCP4.5 occurs in the City of Regina, exceeding 14.4 °C relative to the historical climate.

The results also show that the average changes of all months for the 16 selected cities are greater than 4.7 °C. In particular, changes of the mean temperature in summer are larger than those in winter for all 16 selected cities. For example, in the City of Winnipeg, there is an apparent warming phenomenon in June, July, and August with the change as high as 10.7–12.6 °C, while the winter months show relatively low increases (by less than 4.4 °C). Similarly, there is a gradually increased trend in the mean values under RCP8.5, which is a higher emissions scenario

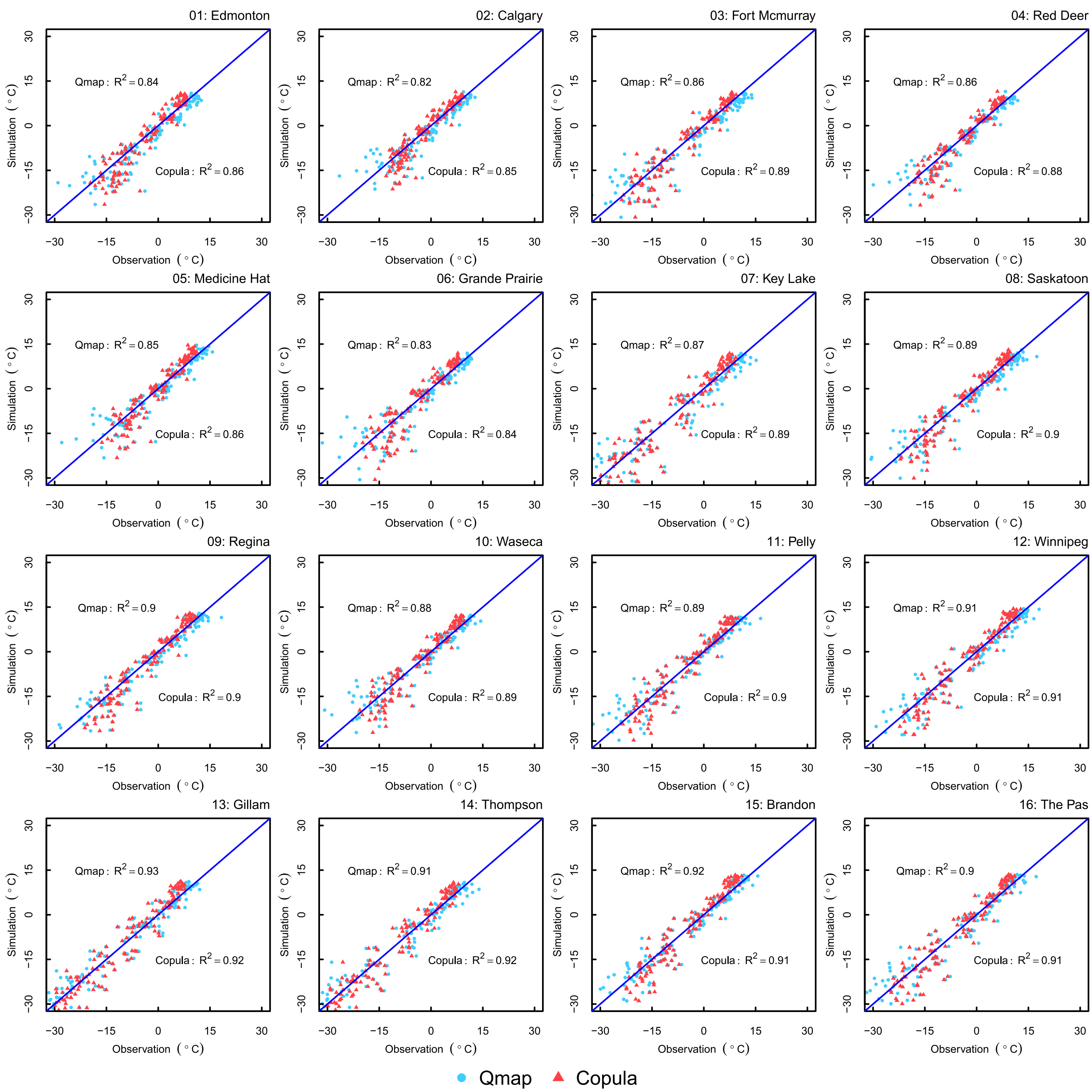

Fig. 8 Evaluation results for monthly minimum temperature at the 16 selected cities

(Fig. 11). In addition, it can be seen that the increases in the mean temperature during the period of the 2080s are more significant under RCP8.5. It thus can be concluded that a higher emission scenario will result in a higher change in the mean temperature values. Overall, the projected temperature to the end of this century for the 16 selected cities across the Canadian Prairies will be consistently increased under both RCP scenarios.

To further analyze the temperature changes across the study area spatially, the developed model is applied to extensive weather stations, which have been screened out from all the stations across the Canadian Prairies for the quality and record length of data. In total, observed temperature data from 154 weather stations are used in this study. Figure 12 provides the spatial distribution of projected changes in annual mean, maximum, and minimum temperature in three future periods (i.e., 2030s, 2050s, and 2080s) under both RCP scenarios for 154 weather stations over the Canadian Prairie Province. It can found that there is a consistent increasing trend in annual mean temperature

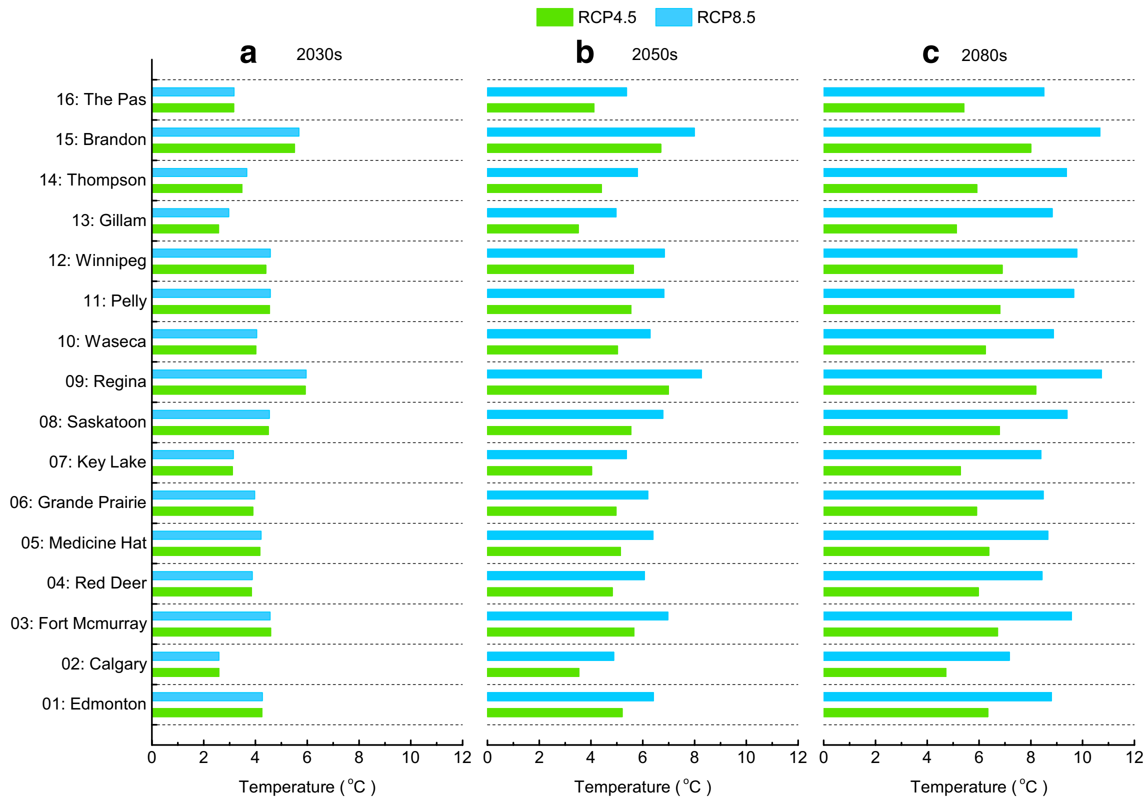

Fig. 9 Projected changes in annual mean temperature at the selected cities

values from the 2030s to the end of this century under the RCP4.5 and RCP8.5 scenarios. In addition, results in the projected maps reflect the spatial variability of the temperature changes under both RCP scenarios. The stations with highest changes of annual mean temperature are mostly distributed in the southeast regions, while the stations with lowest changes of mean temperature values are projected in the northwest regions. This implies that there is a larger variability and change in high elevation regions since the elevation is increased from the northeast to the southwest. Likewise, there are apparent increasing patterns for the projected changes in annual maximum (Fig. 12g–l) and minimum (Fig. 12m–r) from the coupled dynamical-copula downscaling model. However, the developed model projects larger increases in the annual minimum temperature than in the annual maximum temperature under RCPs for three future periods.

Figures 13 and 14 present projected changes in the mean, maximum, and minimum temperature for both winter and summer in the period of 2030s, 2050s, and 2080s under two RCPs. It can be observed that there is a substantial intermodel variability among seasons. For example, the coupled dynamical-copula downscaling model projects larger increases of mean temperature in summer than in winter for the 2030s, 2050s, and 2080s. For the mean temperature in winter in the period of 2050s under RCP4.5, the largest increase over the Canadian Prairies is expected to be 7.2 °C. However, the mean temperature is projected to be a maximum increase of 13.4 °C in summer in the 2050s under RCP4.5. More importantly, the results presented in Figs. 13 and 14 indicate that the spatial patterns of changes in annual mean, maximum, and minimum temperature for both winter and summer in the period of 2050s and 2080s under RCP8.5 are in a similar manner to those under RCP4.5. Nevertheless, the magnitude of changes is significantly different from the results under RCP4.5, implying that the projected changes in annual mean, maximum, and minimum temperature would be intensified under RCP8.5 due to greater GHG concentrations.

5 Conclusions

In this study, a coupled dynamical-copula downscaling approach has been developed to downscale climate change projections through integrating the PRECIS regional modeling system and the copula method into a general framework. It can not only reflect detailed features at local scales based on dynamically downscaling, but also can effectively simulate the dependence structure independently from the

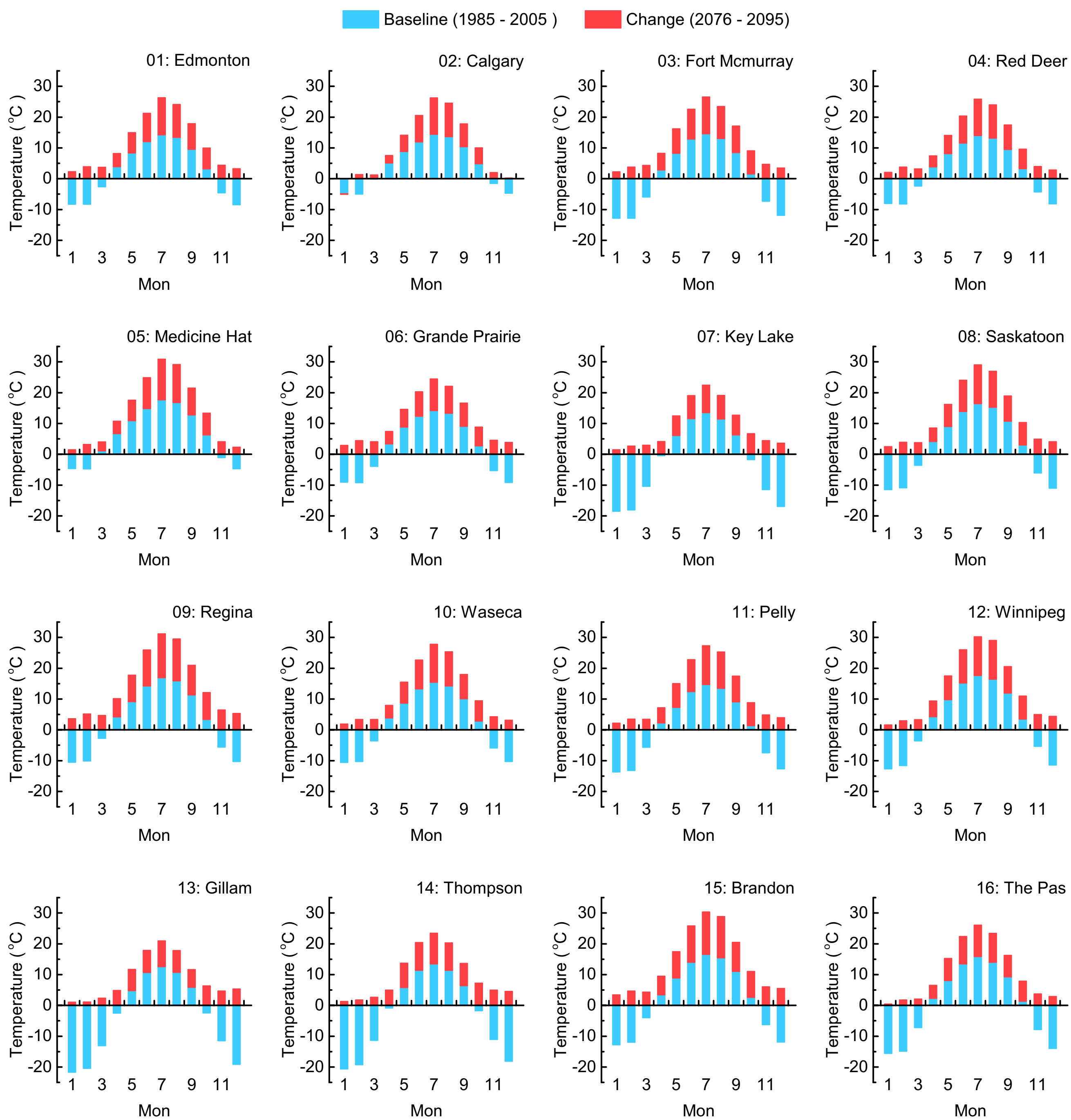

Fig. 10 Projected changes in monthly mean temperature at the selected cities between 2076–2095 and 1986–2005 under RCP4.5

marginal distributions between the large-scale atmospheric variable (predictors) and the local surface variable without any transformation. By evaluating the goodness-of-fit of the joint distributions, the Frank copula was the most appropriate copula to downscale the daily mean temperature for all 16 cities based on the tests. The performance of the coupled dynamical-copula downscaling approach in hindcasting recent climate was also evaluated through comparing model simulations with observed data at 16 selected cities across the Canadian Prairies. The evaluation results indicate that the developed model can capture the current climatology over the Canadian Prairies very well.

The coupled dynamical-copula downscaling approach was then employed for generating temperature projections over the Canadian Prairies under the two RCP scenarios. The future climatic changes in the contest of the Canadian

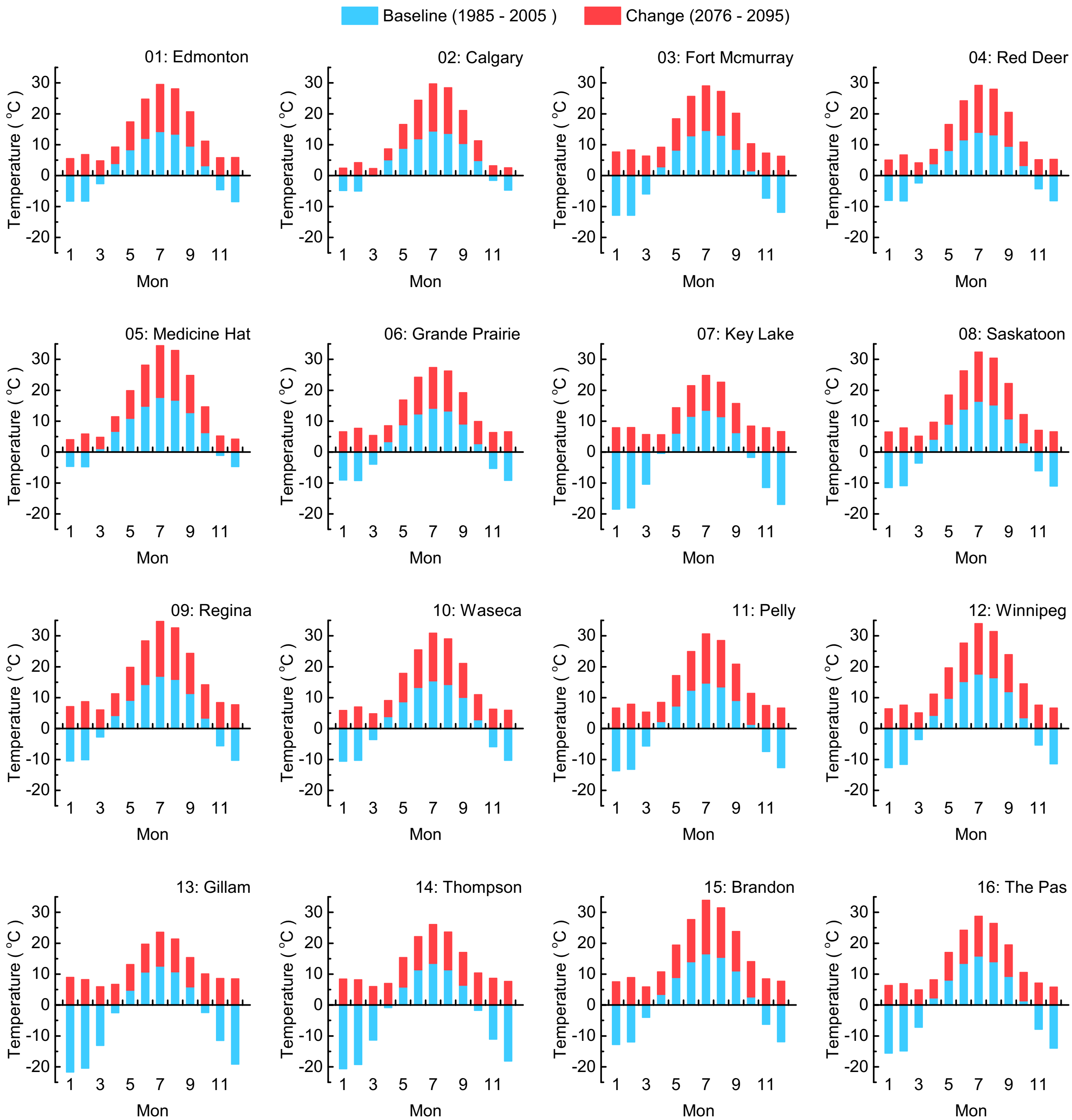

Fig. 11 Projected changes in monthly mean temperature at the selected cities between 2076–2095 and 1986–2005 under RCP8.5

Prairies over three time slices (i.e., the 2030s, 2050s, and 2080s) were analyzed. The analysis of climatic changes indicated that the daily mean temperature is projected to be consistently increased over the 16 selected cities across the Canadian Prairies for the two RCPs considered from the 2030s to the end of this century (i.e., the 2080s). The developed model was applied to an extensive array of weather stations to further analyze the temperature changes across the study area spatially. It is indicated that there is a consistent increasing trend in annual mean, maximum, and minimum temperature values from the 2030s to the end of this century over the 154 weather stations under the RCP4.5 and RCP8.5 scenarios. The results also reflected apparent spatial variability in the amount of the temperature changes over the Canadian Prairies under both RCP scenarios.

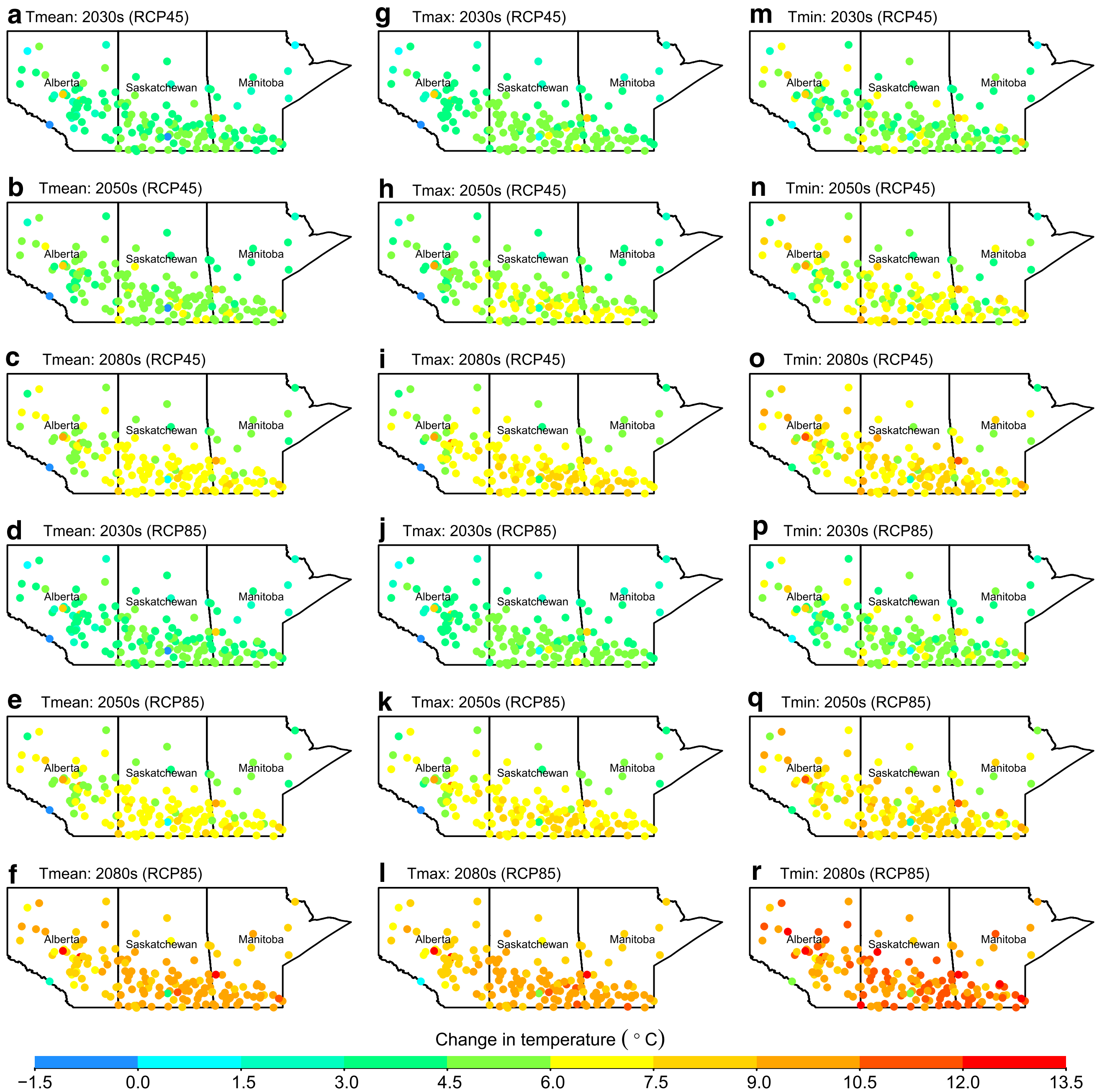

Fig. 12 Projected changes in annual mean (**a**–**f**), maximum (**g**–**l**), and minimum (**m**–**r**) temperature of 154 weather stations in the Canadian Prairie Province for the 2030s, 2050s, and 2080s under two RCP scenarios (color dots represent average change value in annual mean, maximum, and minimum temperature)

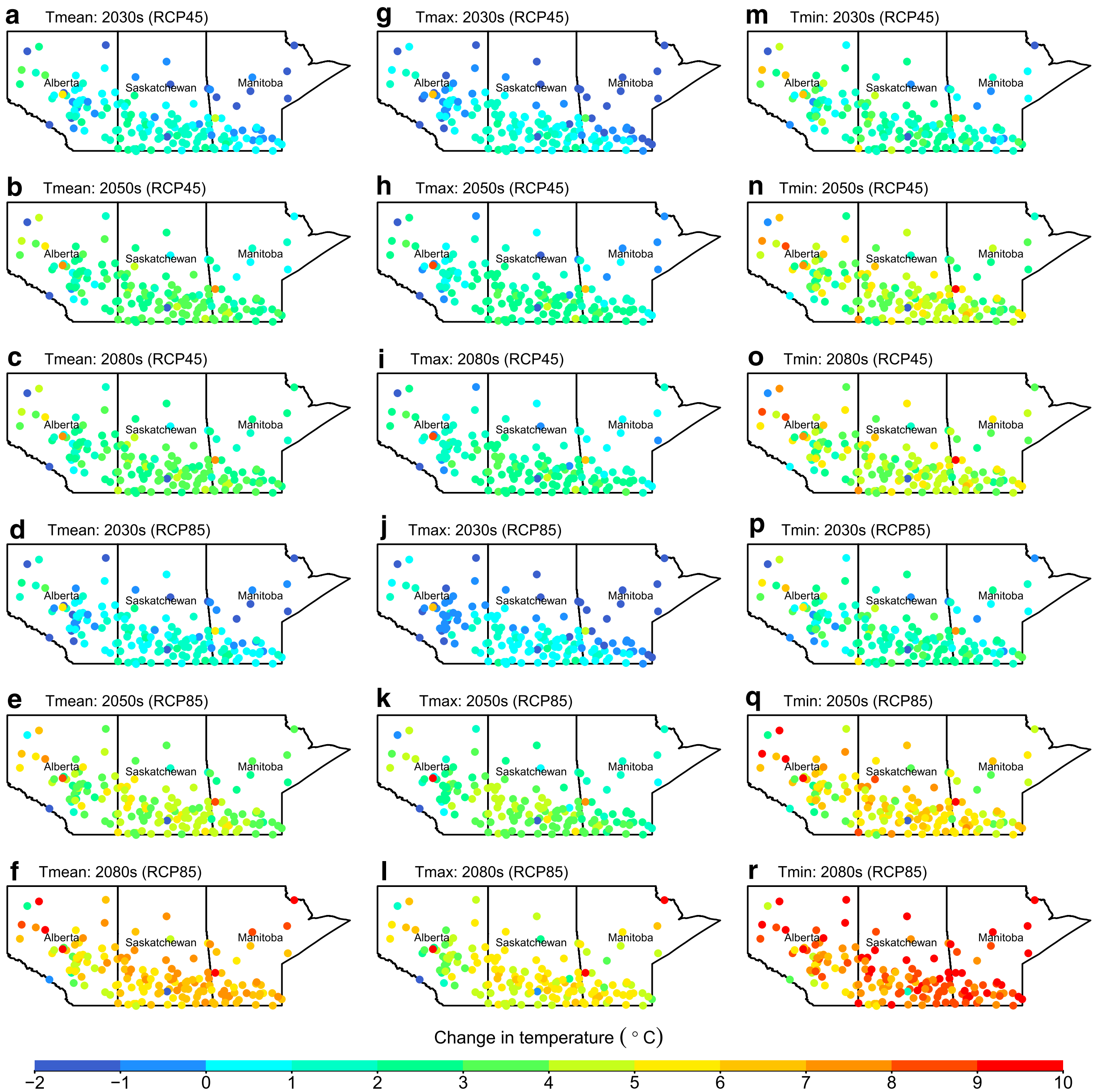

Fig. 13 The distribution and change in winter mean (**a**–**f**), maximum (**g**–**l**), and minimum (**m**–**r**) temperature of 154 weather stations in the Canadian Prairie Province for the 2030s, 2050s, and 2080s under two RCP scenarios (color dots represent average change value in winter mean, maximum, and minimum temperature)

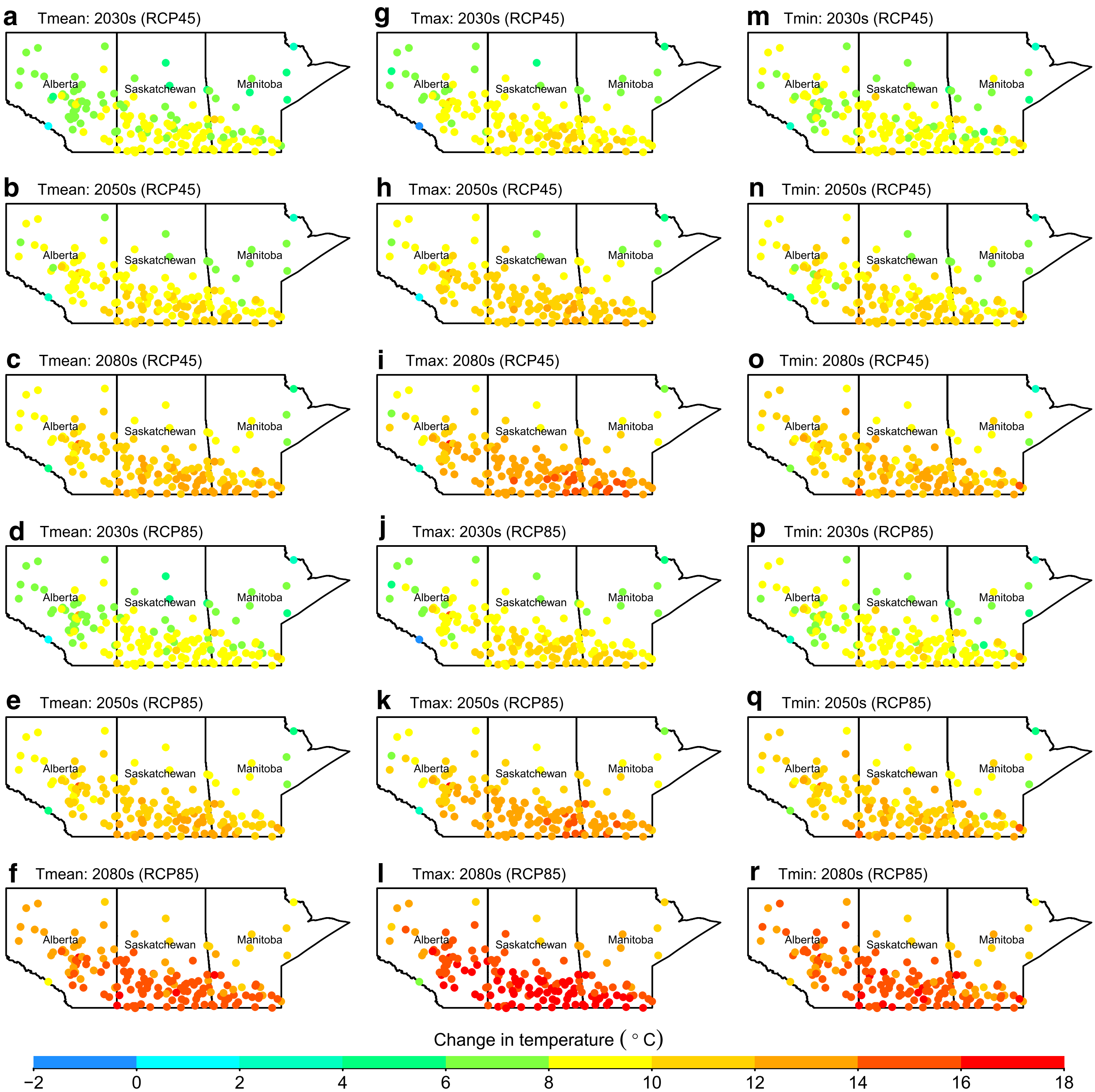

Fig. 14 The distribution and change of summer mean (**a**–**f**), maximum (**g**–**l**), and minimum (**m**–**r**) temperature of 154 weather stations in the Canadian Prairie Province for the 2030s, 2050s, and 2080s under two RCP scenarios (color dots represent average change value in summer mean, maximum, and minimum temperature)

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