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Future projections of temperature changes in Ottawa, Canada through stepwise clustered downscaling of multiple GCMs under RCPs

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Abstract
As the capital city of Canada, Ottawa has been experiencing significant impacts of global climate change. How to adapt to future climate change is one of the biggest concerns in the city's built and natural systems. It thus requires a comprehensive understanding of possible changes in the local climate of Ottawa, which can hardly be reflected in the coarse outputs of Global Climate Models (GCMs). Therefore, a stepwise clustered downscaling (SCD) model is employed in this study to help investigate the plausible changes in daily maximum, minimum, and mean temperatures in Ottawa. Outputs from multiple GCMs under the Representative Concentration Pathways (RCPs) are used as inputs to drive the SCD model in order to develop downscaled climate projections. The performance of SCD model is evaluated by comparing the model simulations to the observations ($R^2 > 0.87$) over the historical periods. Future temperature projections and their likely temporal trends throughout this century are analyzed in detail to explore the regional variations of global warming in Ottawa, thus to provide scientific basis for developing appropriate adaptation strategies at different management levels. The results suggest that the City of Ottawa is likely to expect significant increasing trends in temperatures (i.e., 0.18–0.38 °C per decade in maximum temperature, 0.16–0.31 °C per decade in minimum temperature, and 0.17–0.34 °C per decade in mean temperature under RCP4.5; 0.46–0.54 °C per decade in maximum temperature, 0.37–0.45 °C per decade in minimum temperature, and 0.42–0.50 °C per decade in mean temperature under RCP8.5) throughout this century.

Keywords Stepwise clustered downscaling · Temperature · Ottawa · Multiple GCMs · Climate change · Impact studies

1 Introduction

Climate change is a grave concern. With extensive mounted evidence over the past decades confirmed by the Intergovernmental Panel on Climate Change (IPCC), the associated impacts of climate change have also augmented, affecting numerous parts of the world with varied magnitude (IPCC 2014; OCCIAR 2012). Key sectors such as water resources, ecosystems, forestry, fisheries, agriculture, transportation, energy, mining, human health, tourism and recreation have already been adversely affected by climate change, leading to economic, social, cultural and environmental losses (Adger et al. 2013; Calzadilla et al. 2013; Cherry et al. 2017; Delworth and Zeng 2014; Grimm et al. 2016; Justice et al. 2017; Kløve et al. 2014; Li et al. 2009; OCCIAR 2012; Pecl et al. 2017; Rosenzweig et al. 2014; Santos et al. 2017; Wang et al. 2018; Wheeler and Von Braun 2013; Yang et al. 2017; Zhai et al. 2016). Moreover, previous studies conducted by researchers have proven that temperature is rising at different time scales over various parts of Canada (Briner et al. 2016; Jeong et al. 2016; Nalley et al. 2013; Razavi et al. 2016; Wang et al. 2013, 2015a; Way and Viau 2015; Zhang et al. 2000; Zhou et al. 2017a). Thus, investigating future climate change impacts is essential in improving our knowledge of climate change at a regional or site-specific scale. It can thus advance the understanding of the vulnerability of each sector to climate change in terms of the nature of climate change, the climatic sensitivity of the region being considered, and the capacity to adapt to the changes (Ayar et al.

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2016; Duhan and Pandey 2015; Lemmen and Warren 2004; OCCIAR 2012; Quintana-Segui et al. 2016).

Future changes in temperature have been projected by different Global Climate Models (GCMs), such as those archived in Phase 5 of the Coupled Model Intercomparison Project (CMIP5) (Sun et al. 2016; Wang et al. 2016b). However, due to their coarse spatial resolutions of hundreds of kilometres, the simulation results of GCMs under different greenhouse gas emission scenarios prescribed by the IPCC can hardly be directly adopted as inputs for impact models that require accurate estimates of climate information and projections for regional or local studies (Ayar et al. 2016; Duhan and Pandey 2015; Sachindra et al. 2014; Sun et al. 2016; Wang et al. 2015a, 2016b). By contrast, statistical downscaling methods are frequently adopted to handle such a mismatch for assessing the site-specific impacts of climate change on environmental features (Wang et al. 2016b; Zhou et al. 2018a). Empirical relationships between large-scale atmospheric variables (i.e., predictors) of GCMs and the climate variables (i.e., predictands) of interest at the regional scale are developed in order to estimate daily point-scale meteorological series. Moreover, statistical downscaling methods are widely used in the projection of local-scale climate due to their relatively low computational requirements and fast simulations; it can also provide site-specific estimations under a range of greenhouse gas emission scenarios so long as reliable observations of climate variable of interest are available (Duhan and Pandey 2015; Sun et al. 2016; Wang et al. 2015a, 2016b).

In recent years, several climate studies have been carried out on future climate change for the Province of Ontario by Wang et al. (2014, 2015a, 2015c, 2016a). The analysis from the studies have shown that Ontario will be experiencing significant warming trends and the annual mean temperature will vary between 1.6 and 7 °C . However, few studies have been done in the context of Ottawa. As the capital city of Canada, Ottawa has been experiencing significant impacts of global climate change, where increases in temperature have already had severe impacts on the city's built and natural systems (OCCIAR 2012). For example, Ottawa suffered a higher daily maximum temperature in July and August 2012, and such temperature was about 4 °C above those in 2004 and 2008. In addition, the average daily minimum temperatures in January 2008 and 2012 were about 8 and 6 °C warmer than that in 2004 (City of Ottawa 2014). The annual number of extreme heat days is also expected to increase in Ottawa in the future. For instance, the average number of days in a year when temperature exceeds 30 °C will be doubled by the end of the century. Moreover, the number of days in a year when the temperature during the night will be higher than 22 °C will increase from 4 per year to 18 per year by the end of the century. Furthermore, the average annual mean temperature in the City of Ottawa has increased over the last century by 1.7 °C (City of Ottawa 2014; Government of Canada 2015). In response to these changes and the increasing concerns for the environment, the City of Ottawa has prepared a number of plans in order to enhance its resiliency to climate change, and serious actions have been taken place to prepare for the future impacts of climate change (Government of Ontario 2016). The implementation of such actions/plans depends on reliable future projections of temperature for the City of Ottawa.

Therefore, the objective of this research is to develop a stepwise clustered downscaling (SCD) model to help investigate the plausible changes in daily maximum, minimum, and mean temperatures in Ottawa. The ability of the SCD model to statistically downscale three temperature variables of interest will be examined; how temperature variables would likely to change in the future for the City of Ottawa (as a typical northern city in North America) will be revealed as well. In detail, three GCMs simulated data (i.e., CanESM2, GFDL-ESM2M, and IPSL-CM5A-LR) under two Representative Concentration Pathways (i.e., RCP4.5 and RCP8.5) will be statistically downscaled through the SCD model. Three temperature variables including maximum, minimum, and mean temperatures (i.e., Tmax, Tmin, and Tmean) are used for this analysis. Future trends of the projected temperatures will be evaluated. The magnitudes of expected changes in the three temperature variables will be quantified. The results from this research can provide direct inputs for impacts assessment in the City of Ottawa, and consequently help explore the possible adaptation plans against the changing climate at local scales.

2 Study area and data

As shown in Fig. 1, the City of Ottawa is situated on the south shore of the Ottawa River, at confluence of the Gatineau River, the Rideau River and the Ottawa River (latitude 45°22′N and longitude 75°43′W) (Mohareb et al. 2008). Ottawa is covering an area of about 2760 km^2, with an estimated population of approximately 934,243 according to Statistics Canada (Statistics Canada 2017), and it is ranked the fourth-largest city in Canada (City of Ottawa 2017). Ottawa possesses a humid continental climate, with four distinct seasons. It is known for its temperatures extreme and harsh climate (Martin and Ballamingie 2016).

A record of observed daily temperature related variables from the Ottawa International Airport Weather Station (latitude 45°19′N and longitude 75°40′W) are procured from the Environment and Natural Resources (Government of Canada 2015). The observed temperature data are downloaded for the period of 1940–2011. These variables include daily maximum temperature (i.e., Tmax), daily minimum temperature (i.e., Tmin), and daily mean temperature (i.e.,

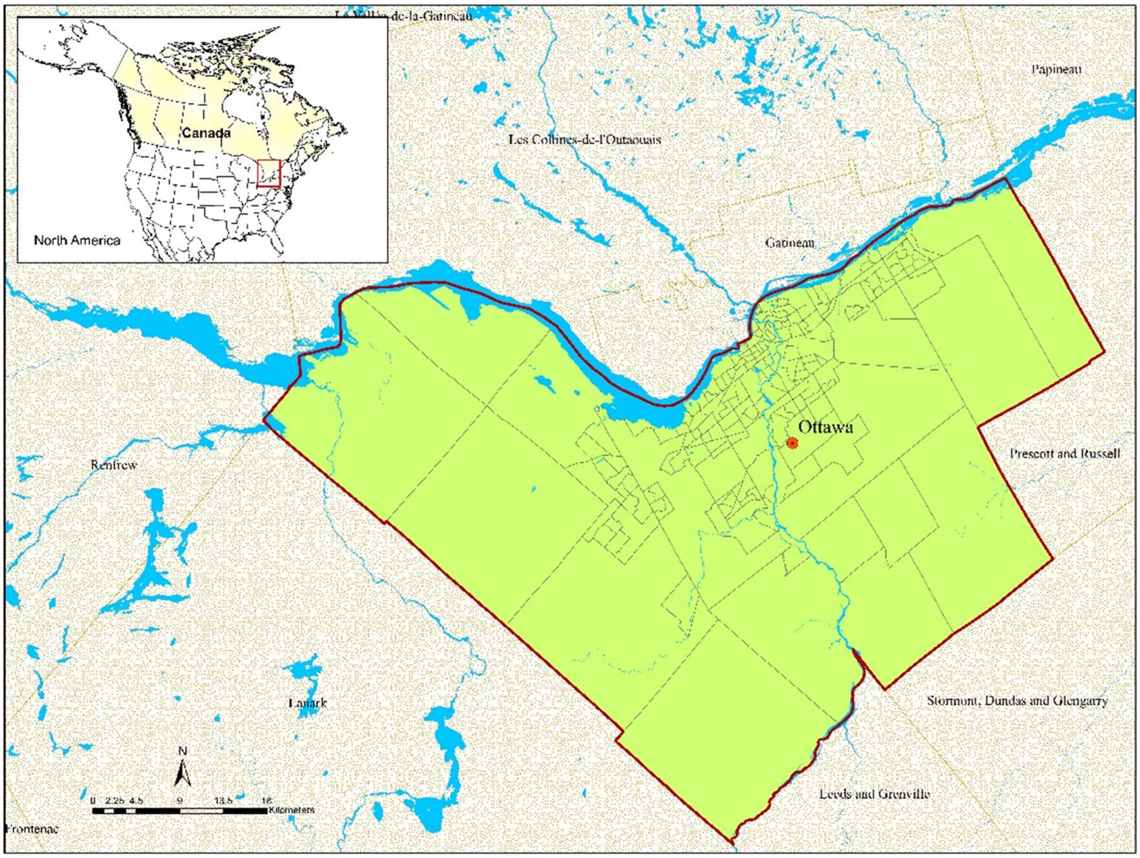

Fig. 1 Study area

Tmean). Quality of the data was checked prior to conduct the analysis, such as missing data detection. For example, missing data was detected and interpolation was performed to fill in the gaps of the missing data. In order to provide inputs into the SCD model, as well as to construct the relationship between GCM outputs with the observed data, daily mean atmospheric variables at different levels (e.g., pressure level, near-surface level, and mean sea level) are downloaded from the North American Regional Reanalysis (NARR) dataset produced by the National Centers for Environment and Prediction (NCEP) (NCEP 2016). The data has a resolution of 32 km and are extracted for the period of 1979–2015.

Daily outputs from three GCMs (i.e., CanESM2, GFDL-ESM2M, and IPSL-CM5A-LR) are downloaded from CMIP5 dataset archive (Table 1). The data comprise present-day (i.e., historical) and future simulations forced by four emission scenarios, namely RCP2.6, RCP4.5, RCP6.0, and RCP8.5. Among them, RCP4.5 is a scenario in which the radiative forcing is stabilized in the year of 2100 (Thomson et al. 2011), whereas RCP8.5 is a scenario which assumes high population and slow income growth, moderate rates of technology development, high energy demand and greenhouse gas emissions in absence of climate change policies (Riahi et al. 2011). Therefore, in this study, the daily gridded data simulated by the three GCMs under historical, RCP4.5 and RCP8.5 scenarios are extracted for the periods of 1979–2004 and 2006–2099 for the City of Ottawa. The NARR data are then re-gridded to the coarsest GCM (i.e., IPSL-CM5R-LR) resolution using bilinear interpolation method in order to develop (e.g., calibrate and validate) the

Table 1 Global climate models considered in this study

GCM model	Institute	Resolution (deg)
CanESM2	Canadian Centre for Climate Modelling and Analysis, Canada	2.79 × 2.81
GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory, USA	2.02 × 2.5
IPSL-CM5A-LR	Institut Pierre-Simon Laplace, France	1.89 × 3.75

stepwise clustered downscaling (SCD) model. The extracted data from the three GCMs are then treated as inputs into the developed SCD model.

3 Stepwise clustered downscaling model

The stepwise clustered downscaling (SCD) model was developed based on the stepwise cluster analysis (SCA) method introduced by Huang (1992). The SCA method has been widely used in a number of studies on climatic change, hydrology, and environmental pollutions (Fan et al. 2015, 2016; Huang et al. 2006; Li et al. 2015; Qin et al. 2007; Wang et al. 2013, 2015a, b; Zhuang et al. 2016). The SCA method is a multivariate statistical technology designed for capturing discrete and nonlinear relationship between local-scale predictors and large-scale predictands; it also has the ability to consider complex interactions between predictors and predictands as a cluster tree, without requiring assumptions of functional relationship (Fan et al. 2015, 2016; Li et al. 2015; Qin et al. 2007; Sun et al. 2009; Wang et al. 2012, 2013). Furthermore, the significance levels of different branches can be clearly delineated through SCA and has been proven to be an effective forecasting method for various resources and environmental systems (Fan et al. 2015, 2016; Li et al. 2015; Qin et al. 2007; Sun et al. 2009; Wang et al. 2012, 2013). A flowchart of the SCA method is presented in Fig. 2.

The essence of the SCA method is to form a classification tree based on a series of cutting or mergence processes according to given statistical criteria (Sun et al. 2009). Such a classification tree can be adopted to specify the inherent complex relationship between predictors and predictands. Thus, new values of predictands can be predicted for any new input of the predictors. In this study, the input and output data for the the developed SCD system should be identified first. Let $x=x_1, x_2,..., x_i$ represent a group of large-scale atmospheric variables and $y=y_1, y_2,..., y_j$ represent a group of observed temperature variables. There are N samples for the SCD model; therefore, n series of large-scale atmospheric variables and local-scale surface variables can be obtained, which can be formed as matrices $X = (x)_{n\times i}$, $Y = (y)_{n\times j}$. As for temperature prediction of a specific site in this study, the predictands are maximum, minimum, and mean temperatures (i.e., Tmax, Tmin, Tmean), and the predictors include large-scale atmospheric variables such as temperature, specific humidity, and geopotential height at pressure level. Once the training set is formed, a cluster tree can be obtained through a series of cutting and mergence actions according to the F test based Wilk's likelihood-ratio criterion (Huang et al. 2006; Li et al. 2015; Rao 1952; Wang et al. 2013; Wilks 1962). Based on such criterion, the sample set of dependent variables is first cut into two subsets and then grouped the sample sets into one for the sample classification. Such a cutting and mergence action is performed sequentially until no cluster can be cut and merged. Therefore, the training procedure is completed and prediction can be performed. Huang et al. (2006) has provided more detailed descriptions on the SCA method.

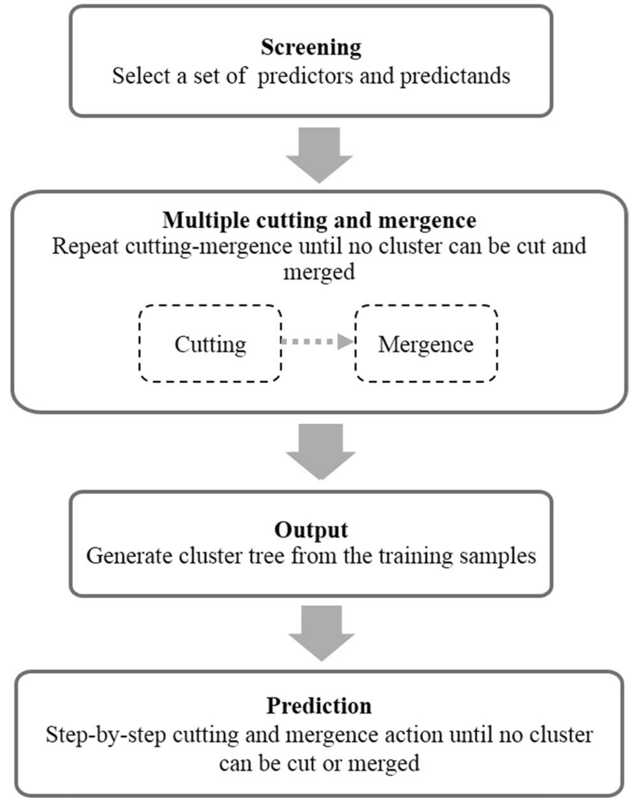

Fig. 2 Flowchart of stepwise cluster analysis

A critical aspect related to the application of statistical downscaling model is the selection of predictors (i.e., input variables). According to previous studies, a number of large-scale predictor variables from the NARR reanalysis dataset for predicting local-scale daily temperature variables of interest (i.e., Tmax, Tmin, and Tmean) are screened out based on correlation analysis between the predictors and the predictands (Ayar et al. 2016; Fan et al. 2013; Mtongori et al. 2016; Onyutha et al. 2016; Pierce et al. 2013; Su et al. 2016; Teutschbein et al. 2011; Trzaska and Schnarr 2014; Wang et al. 2013, 2015a, 2016b; Wilby et al. 2004; Wilby and Wigley 1997; Zhou et al. 2017b). To provide a better mutual comparability of results, same number of predictors are selected from the three GCMs and are then used to build the SCD model. The 21 potential predictors selected for this study include: specific humidity at 850, 700, and 500 hPa pressure levels; air temperature at 850, 700, 500, 250, 10 hPa pressure levels; eastward wind at 100, 50, and 10 hPa; geopotential height at 800, 700, 500, 250, 100, 50, and 10 hPa;

Table 2 Potential NARR predictors selected for Tmax, Tmin, and Tmean

NARR variable selected	Unit	Pressure level (hPa)
Specific humidity	kg/kg	850
		700
		500
Air temperature	K	850
		700
		500
		250
		10
Eastward wind	m/s	100
		50
		10
Geopotential height	m	850
		700
		500
		250
		100
		50
		10
Surface temperature	K	Surface
Near-surface air temperature	K	2 m
Near-surface specific humidity	kg/kg	2 m

surface temperature, near-surface air temperature at 2 m, and near-surface specific humidity at 2 m (Table 2). Once the screening process is done, training of the suitable SCD model can be taken place.

For the development of the SCD model, the observed data for Tmax, Tmin, and Tmean for the City of Ottawa, as well as the selected NARR reanalysis data are split into two sets. The first set, containing potential selected NARR predictors and observed temperature variables' data from 1979 to 1989, is allocated to the calibration of the SCD model. The remaining data from 1990 to 2004 is used for the validation of the model. The performance of the SCD model is evaluated quantitatively through R^2 (i.e., coefficient of determination).

Daily gridded data simulated by the three GCMs are then used as inputs into the validated SCD model. Specifically, the data for the selected predictors shown in Table 2 from CanESM2, GFDL-ESM2M, and IPSL-CM5R-LR are extracted to drive the SCD model. Due to varied timespan of all the datasets, including NARR reanalysis, CanESM2, GFDL-ESM2M, and IPSL-CM5R-LR, their overlap period is extracted (i.e., 1979–2004). Projections of Tmax, Tmin and Tmean are produced by feeding the outputs of the three GCMs individually into the developed SCD model. In detail, historical data (1979–2004) are input into the SCD model to generate the simulated values of station-based Tmax, Tmin, and Tmean during the present day; results are then compared to the observed data for validation purposes. Once the reproduced results are consistent with the observed data, projections of the three temperature variables by the three GCMs under RCP4.5 and RCP8.5 are fed into the SCD model to project future climate for the City of Ottawa.

The performance of the SCD model in the validation periods are assessed numerically and graphically. The numerical assessment of the model is performed by comparing the statistics (i.e., R^2) of the three temperature variables reproduced by the SCD model with the observation. Scatter plots and time-series plots are used to assist in visual representation of the comparison between model predictions and observations.

4 Results and discussions

4.1 Model calibration and validation

The downscaling results are calibrated and validated with the NARR dataset according to the correspondence of their time series to the observations. The validation results infer that the SCD model is well developed. Figure 3 shows the validation results of the downscaling model. A 15-year monthly average scatter plots are presented for the observed temperature variables (i.e., Tmax, Tmin and Tmean) and those reproduced by the downscaling model using NARR data as inputs during 1990–2004. During the validation phase, it is evident that the NARR trained SCD model shows outstanding ability ($R^2 > 0.8209$) in reproducing observed Tmax, Tmin, and Tmean.

In order to validate the reproduced results, the statistical value of R^2 for the monthly observed data (i.e., Tmax, Tmin, Tmean) and those reproduced from the SCD model for the City of Ottawa is calculated for the period of 1981–2000 (Fig. 4). It can be concluded that the SCD model presents outstanding performance in reproducing the 20-year monthly Tmax, Tmin and Tmean for the City of Ottawa. The maximum R^2 of 0.8818 is associated with the reproduced Tmin from CanESM2; the minimum R^2 of 0.8731 is with the reproduced Tmax from IPSL-CM5R-LR. The performance of the SCD model in reproducing the present-day climate from the three GCMs is further examined by comparing monthly mean of the model outputs to the observed Tmax, Tmin and Tmean downloaded from Environment and Natural Resources (Government of Canada 2015). Figure 5 shows the 20-year (1981–2000) monthly mean time series plot for the observed and downscaled present-day Tmax, Tmin and Tmean. Although results from the SCD model possess similar trends and captures the seasonal variation of temperatures very well, it is obvious that the ability of them in capturing present-day temperature variables varies. In detail, Tmax, Tmin and Tmean are well captured by the downscaled results from IPSL-CM5R-LR (from August to December

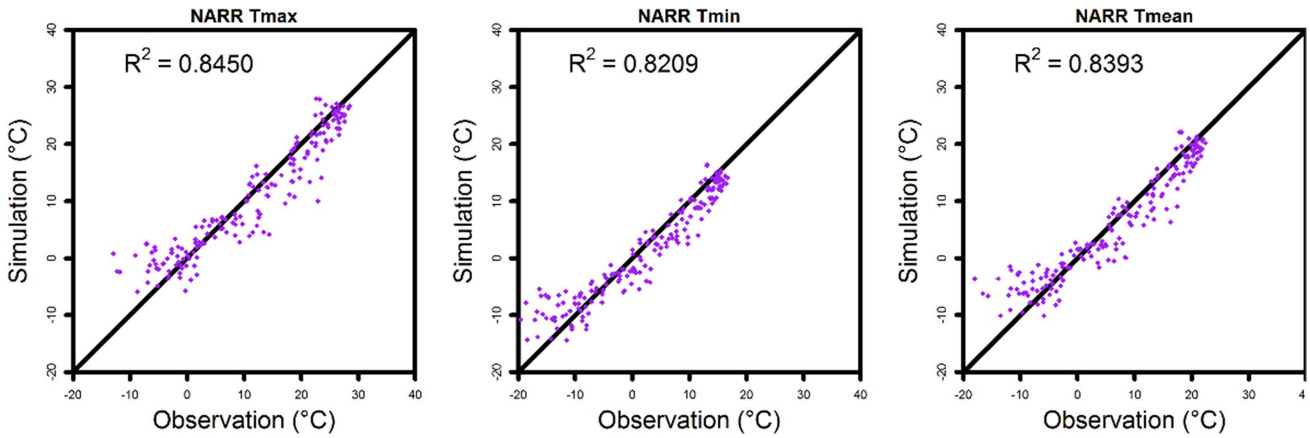

Fig. 3 Comparison between observed and NARR reproduced Tmax, Tmin, and Tmean, 1990–2004

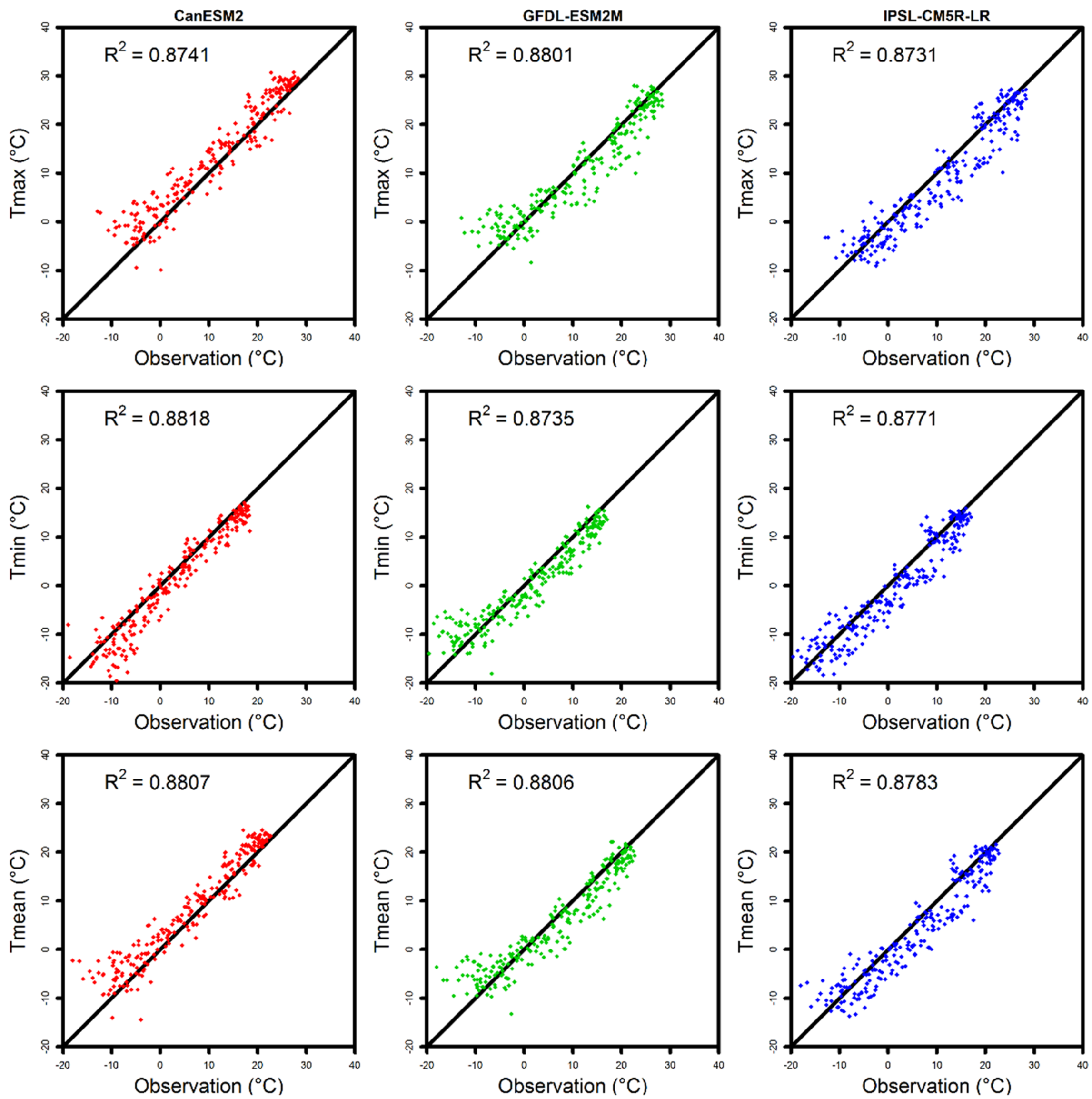

Fig. 4 Validation results for multi-year monthly mean of Tmax, Tmin, and Tmean for the City of Ottawa

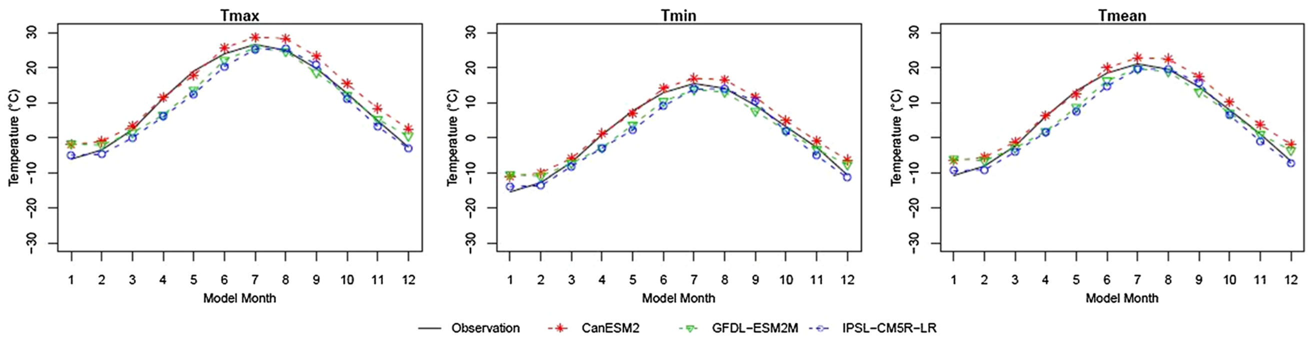

Fig. 5 Monthly mean for the observed and downscaled present-day Tmax, Tmin and Tmean from CanESM2, GFDL-ESM2M, and IPSL-CM5R-LR, 1981–2000

and from January to February) and GFDL-ESM2M (from July to November and from February to March). As oppose to IPSL-CM5R-LR and GFDL-ESM2M, Tmax, Tmin and Tmean are well captured by downscaling CanESM2 outputs from March to May. As a result, it can be concluded that the under- and over-estimations from the downscaled outputs are mainly due to model uncertainties because models are constructed based on physical and numerical formulations, and different parameterization used in the climate models wil respond differently to climate change.

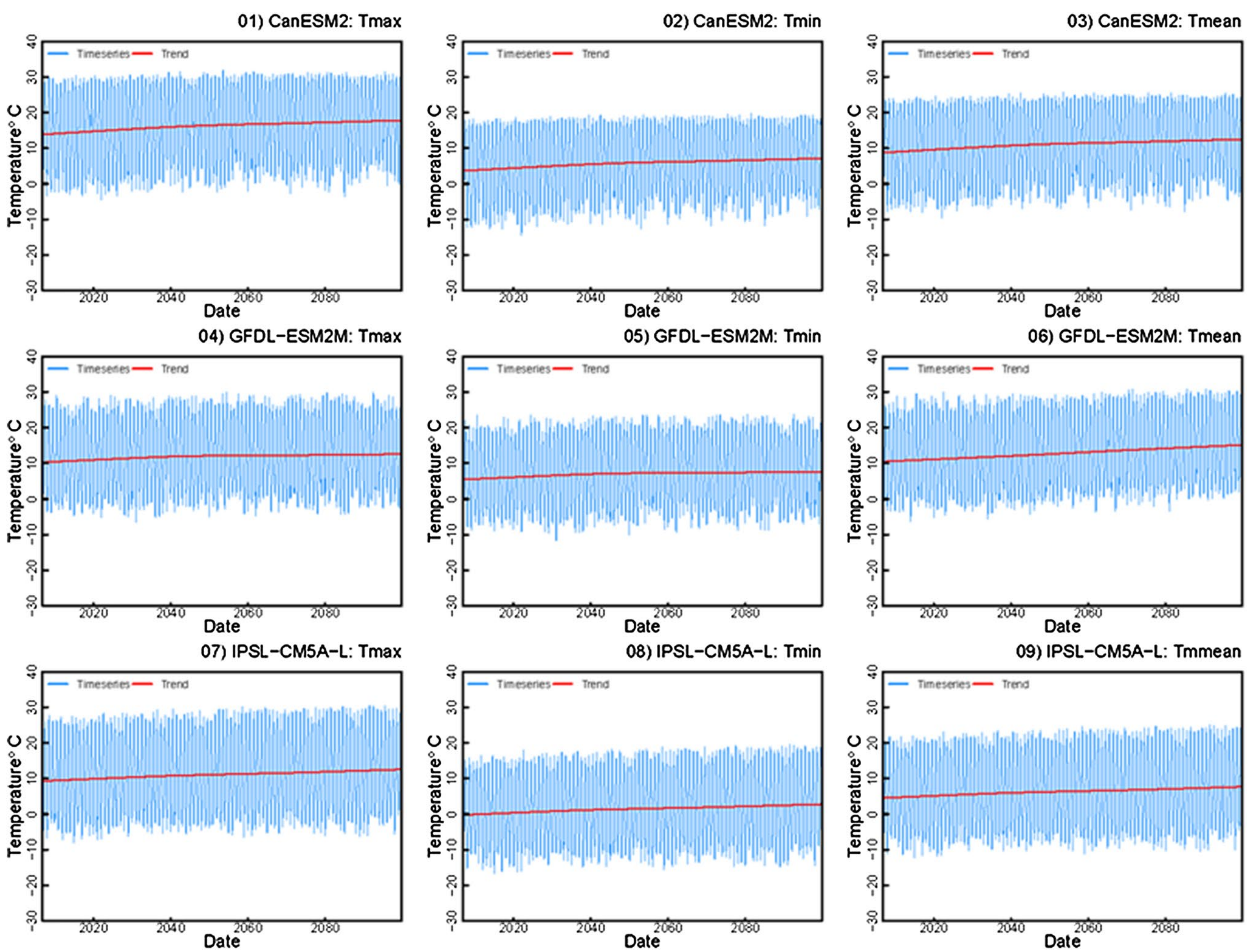

Fig. 6 Projected monthly temperature (Tmax, Tmin, and Tmean) for the City of Ottawa from 2007 to 2099 under RCP4.5

According to Figs. 3, 4 and 5, it is obvious that the reproduced data from the SCD model with NARR reanalysis data as input is much more consistent with the observations compared to those downscaled from the three GCMs. This is mainly due to the fact that the quality of NARR reanalysis data is much higher than that of the GCMs outputs. Since the NARR reanalysis data are quality controlled and corrected against observations, they are inherently more accurate than any GCM output (Kalnay et al. 1996; Sachindra et al. 2014). As oppose to the NARR reanalysis dataset, the GCMs outputs are often associated with higher degree of uncertainty. In other words, the high resolution model used by NARR dataset along with the associated assimilation system have led the NARR data set to be more accurate than that of the GCMs'; and the model uncertainty of the climate models are often associated with different parameterization used to present the real-world climate system. Therefore, it is essential to present how the SCD model would reproduce the present-day temperature variables with multiple GCMs outputs since their outputs pertaining to future climate would be used for the projections of local-scale temperature variables into the future.

4.2 Future temperature projections

Projections from CanESM2, GFDL-ESM2M, and IPSL-CM5R-LR under RCP4.5 and RCP8.5 are resulted from the SCD model. The projected maximum, minimum and mean temperatures, as well as their changes for the City of Ottawa are shown in Figs. 6, 7, 8, 9, 10 and 11. Figures 6 and 7 present the projected monthly mean Tmax, Tmin, and Tmean for the City of Ottawa. A smoothed red bold line shows how maximum, minimum, and mean temperatures would likely to change under RCP4.5 and RCP8.5; such a trend line for the monthly time series are fitted using the *lowess* method. It is obvious that the increasing trends are consistent, indicating that Ottawa will be experiencing a warmer climate in the future. For instance, CanESM2 presents the highest

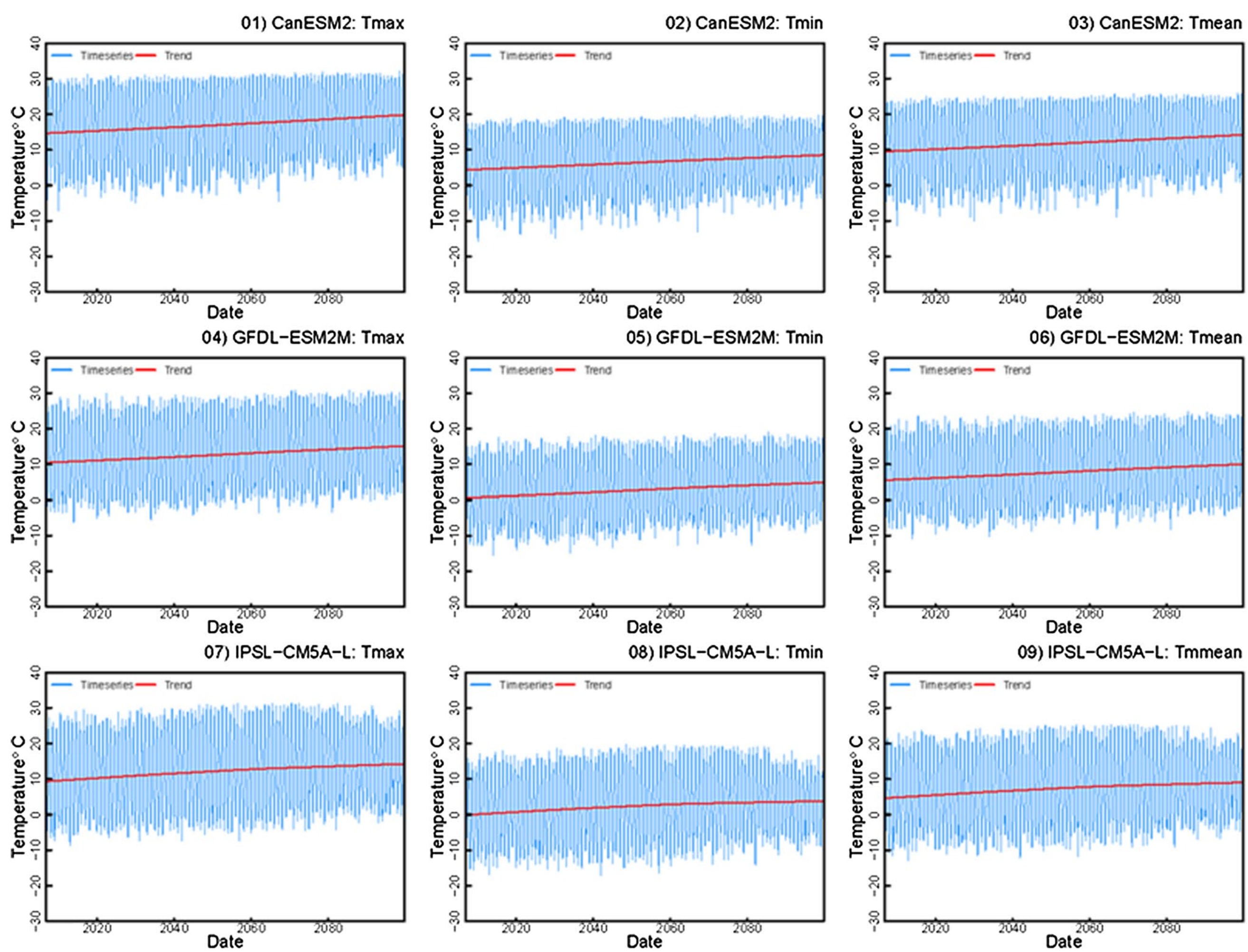

Fig. 7 Projected monthly temperature (Tmax, Tmin, and Tmean) for the City of Ottawa from 2007 to 2099 under RCP8.5

Table 3 Monthly and decadal trends in temperature for the City of Ottawa in the twenty-first century (2007–2099)

GCMs	Temperature	RCP4.5				RCP8.5			
		Monthly		Decadal		Monthly		Decadal	
		MK *p* value	Sen's slope (°C/month)	MK *p* value	Sen's slope (°C/decade)	MK *p* value	Sen's slope (°C/month)	MK *p* value	Sen's slope (°C/decade)
CanESM2	Tmax	< 0.001	0.0028	< 0.002	0.376	< 0.001	0.0039	< 0.001	0.540
	Tmin	< 0.001	0.0026	< 0.002	0.306	< 0.001	0.0034	< 0.001	0.451
	Tmean	< 0.001	0.0027	< 0.002	0.339	< 0.001	0.0036	< 0.001	0.504
GFDL-ESM2M	Tmax	< 0.050	0.0016	< 0.050	0.178	< 0.001	0.0043	< 0.001	0.488
	Tmin	< 0.050	0.0016	< 0.050	0.160	< 0.001	0.0039	< 0.001	0.449
	Tmean	< 0.050	0.0016	< 0.050	0.168	< 0.001	0.0041	< 0.001	0.466
IPSL-CM5R-LR	Tmax	< 0.001	0.0027	< 0.002	0.307	< 0.001	0.0043	< 0.005	0.460
	Tmin	< 0.002	0.0025	< 0.001	0.270	< 0.001	0.0036	< 0.005	0.365
	Tmean	< 0.001	0.0026	< 0.001	0.289	< 0.001	0.0039	< 0.005	0.419

increasing trends of the maximum, minimum and mean temperatures for the City of Ottawa. Furthermore, the trend of monthly and decadal means of Tmax, Tmin and Tmean are investigated through Mann Kendall test and Sen's slope estimator test (Table 3), which have been widely used in the studies of climatological time series (Duhan and Pandey 2015; Kendall 1970; Mann 1945; Sen 1968; Vikhamar-Schuler et al. 2016). It is quite obvious that most monthly and decadal trends are significant with p values less than 0.001. During the twenty-first century, the magnitude of Tmax, Tmin and Tmean varies. For instance, the magnitude of the projected Tmax for CanESM2, GFDL-ESM2M, and IPSL-CM5R-LR are 0.38 °C, 0.18 °C, and 0.31 °C per decade under RCP4.5, whereas these values have increased to 0.54 °C, 0.49 °C, and 0.46 °C per decade under RCP8.5.

The plotted time series of annual and seasonal mean of the three temperature variables for the City of Ottawa are adopted to further describe their near- and long-term trends (Figs. 8 and 9). As shown in Fig. 8, it is suggested that the Tmax, Tmin, and Tmean are continuing to increase, which is consistent with the previous results that Ottawa will be experiencing a warmer climate in the future. Projection results from CanESM2 always hold the largest values among the three GCMs. However, it is found that during summer under RCP4.5, results from GFDL-ESM2M show a slight decrease in the trends of the projected temperatures at the end of the century, while such a decrease is also found with the projected temperatures from IPSL-CM5R-LR during autumn. Similar increasing trend is further discovered for most of the seasons under RCP8.5 (Fig. 9), and CanESM2 shows the highest increasing trend. The magnitude of such an increase is more noticeable compared to those under RCP4.5 (Fig. 8). However, the projected values of the three temperature variables from IPSL-CM5R-LR reveal a more noticeable decreasing trend during summer after the year of 2080 (Fig. 9).

Moreover, results have shown that variability exists in the future projections of the three temperature variables; such variability in the temperature trends is different among models and the variability is expected to be more significant in winter. The resulted variability can be explained by uncertainty in climate projections due to the following three aspects: 1) uncertainty in emissions scenario, 2) uncertainty in model, and 3) natural variability (Deser et al. 2012a). Emission scenario uncertainty is often related to the level of our knowledge of the external factors that influences the climate system; the model uncertainty is due to the fact that different responses from different models can be resulted because of different physical and numerical formulations adopted by the climate models; uncertainty from natural variability is associated with the internal variability to the climate system, which poses limits to climate predictability because the inherent natural force of the climate fluctuations beyond years or even decades are hard to predict (Deser et al. 2012a, b; Hawkins and Sutton 2009, 2011; Zhou et al. 2018b).

The projections for maximum, minimum, and mean temperatures are then sliced into three 20-year periods (2015–2034, 2035–2054, 2075–2094) under RCP4.5 and RCP8.5 (Figs. 10, 11, and 12); thus, near- and long-term monthly projected temperature changes for the City of Ottawa relative to the historical observation (1981–2000) can be understood. The annual mean of maximum, minimum, and mean temperatures under the two RCP scenarios are computed for 2015–2034, 2035–2054, 2075–2094 (i.e., 2030s, 2050s, and 2080s); their projected changes relative to the historical period (1981–2000) are presented in Figs. 10, 11, and 12. Results show that the projected Tmax, Tmin and Tmean are increasing to the end of the century under RCP4.5 and RCP8.5. For instance, projected annual changes (Fig. 10) of Tmax from CanESM2 will result in an increase of 3.96 °C, 5.31 °C, and 6.07 °C during

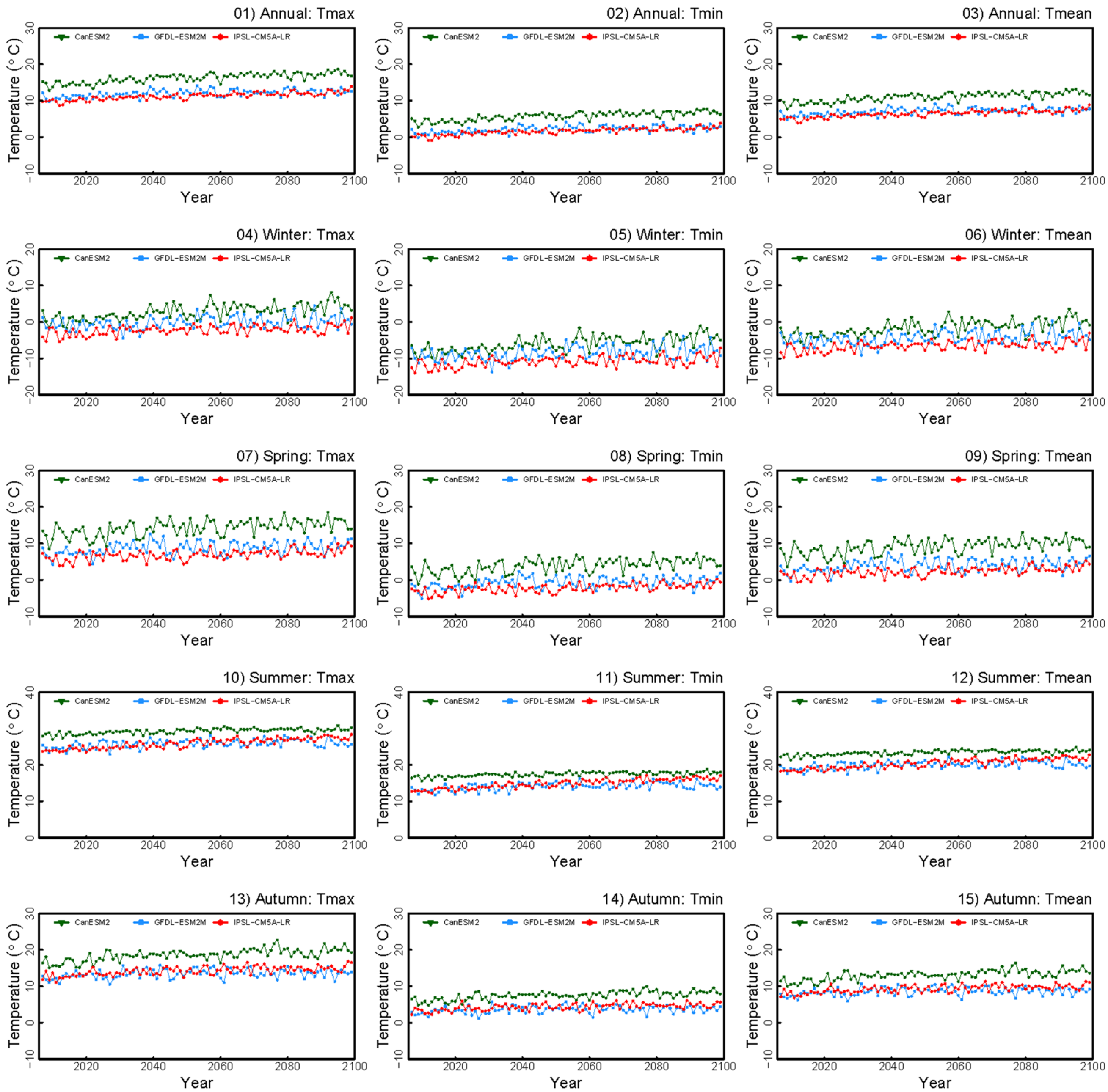

Fig. 8 Projected temperature (Tmax, Tmin, and Tmean) for annual and seasonal time series of the City of Ottawa under RCP4.5

2030s, 2050s, and 2080s under RCP4.5, whereas these numbers will augment to 4.43 °C, 5.82 °C, and 7.56 °C under RCP8.5. Unlike CanESM2 and GFDL-ESM2M, projected changes from IPSL-CM5R-LR show a slight decrease during the 2030s under both RCPs. Moreover, Fig. 11 shows the projected monthly maximum, minimum and mean temperature changes under RCP4.5 for the 2080s (2075–2094), relative to the historical period (1981–2000) for the City of Ottawa. Consistent increases in maximum, minimum and mean temperatures are found for CanESM2, while other two GCMs (i.e., GFDL-ESM2M and IPSL-CM5R-LR) present some decreases during the months from March to June. In January, CanESM2 has the largest increases in the projected changes in Tmax (8.72 °C), Tmin (9.54 °C) and Tmean (9.15 °C), respectively. However, it is interesting to reveal a phenomenon that the projected increase in temperatures during winter (December, January, and February) for the City of Ottawa is more prominent compared to the projected increase in the values for other seasons (i.e., Spring, Summer, and Autumn). Similar projected increasing trends

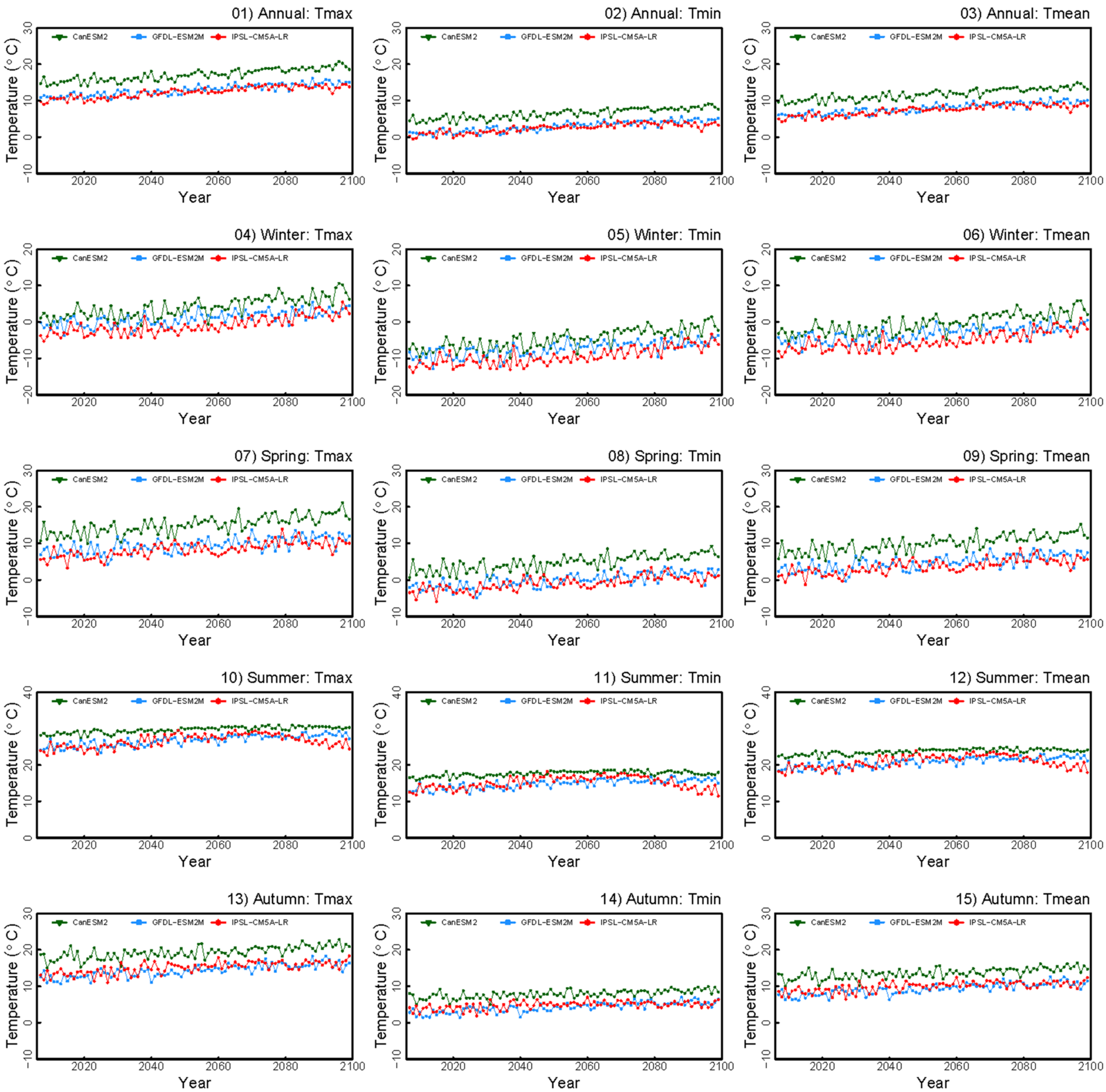

Fig. 9 Projected temperature (Tmax, Tmin, and Tmean) for annual and seasonal time series of the City of Ottawa under RCP8.5

are also revealed for the monthly mean of maximum, minimum and mean temperatures at the end of the century under RCP8.5 (Fig. 12), where the projected increased values are more significant compared to those under RCP4.5. Although the largest projected increases in maximum, minimum and mean temperatures under RCP8.5 is found in January for CanESM2, slight decreases in the projected maximum, minimum and mean temperature are found only from March to May for GFDL-ESM2M and IPSL-CM5R-LR. Moreover, it has also been noticeable that monthly mean of the minimum temperature will increase at a slightly higher rate than that of the maximum temperature, and this is true for the projected results from all the three GCMs under RCP4.5 and RCP8.5. Therefore, it can be concluded that although GCMs show different projections due to their inherent system complexities, one cannot ignore the fact that significant warming trends are very likely to be expected in the City of Ottawa throughout this century.

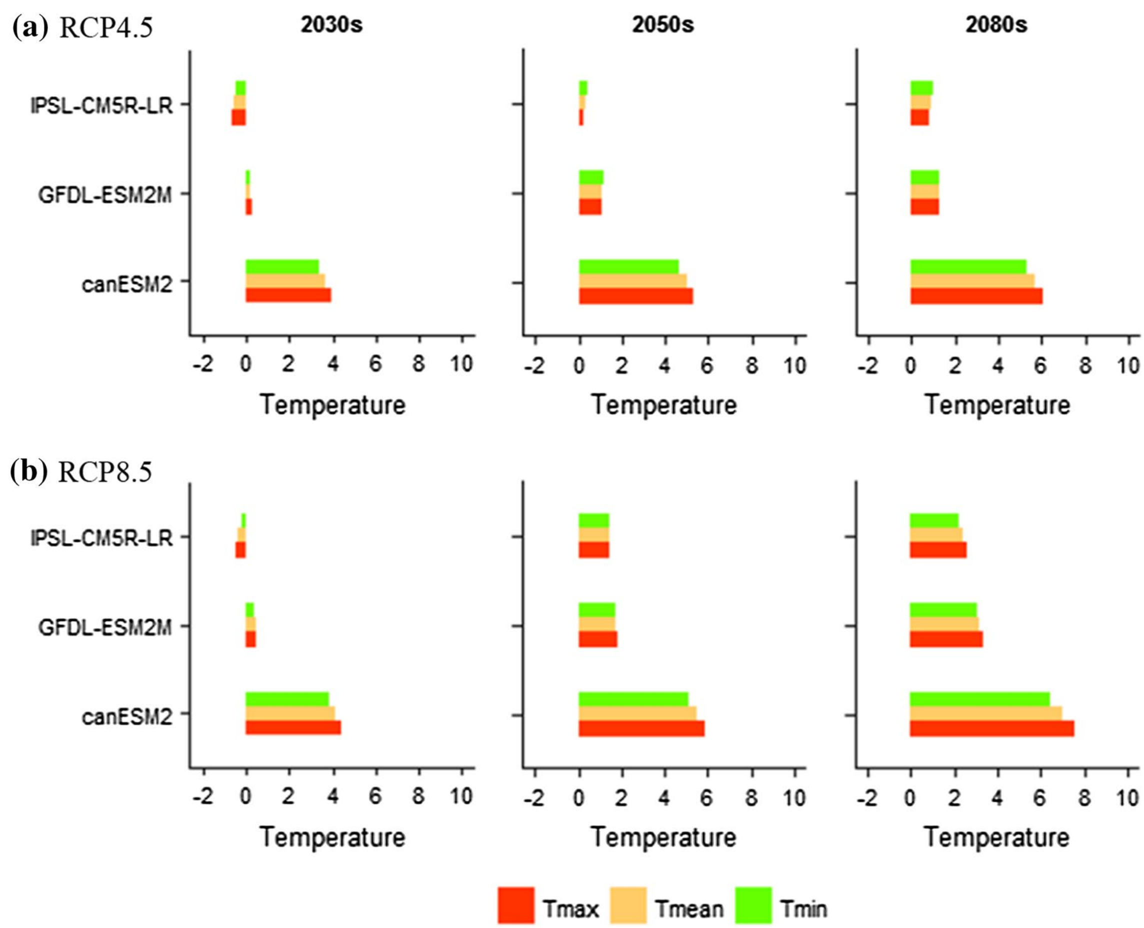

Fig. 10 Projected changes of annual mean Tmax, Tmin, and Tmean under RCP4.5 and RCP8.5 for the City of Ottawa

5 Conclusions

The common practice of developing a statistical downscaling model is to conduct calibration and validation with some historical reanalysis datasets of the climate; then, site-specific future projections can be produced by introducing outputs from GCMs, pertaining to future greenhouse gas emission scenarios (i.e., RCP4.5 and RCP8.5). In this study, a stepwise clustered downscaling (SCD) model was developed to downscale projected temperature changes in terms of daily maximum, minimum, and mean temperature variables from multiple GCMs (i.e., CanESM2, GFDL-ESM2M, and IPSL-CM5R-LR). The performance of the SCD model is then investigated in order to generate future temperature projections for a site-specific location (i.e., Ottawa).

By analyzing the overall trends of the projected three temperature variables (i.e., Tmax, Tmin, and Tmean), it is discovered that Ottawa will be experiencing a continuous increasing trend in the projected temperatures during this century. Moreover, the discovered variability in future projections of the temperature trend is different among models and such variability is expected to be more significant in winter time. The future climate change in terms of the projected changes in temperature in the City of Ottawa were analyzed under both RCPs (i.e., RCP4.5 and RCP8.5) and over three time slices (i.e., 2015-2034, 2035-2054, and 2075-2094). Under RCP4.5, trends of 0.38 °C, 0.18 °C, and 0.31 °C per decade in maximum temperature have been resulted from CanESM2, GFDL-ESM2M, and IPSL-CM5R-LR, respectively; while minimum temperature trends range from 0.16 °C to 0.31 °C per decade, and mean temperature trends range from 0.17 °C to 0.34 °C per decade. RCP8.5 even possesses higher trends compared to RCP4.5, with the trends of maximum temperature of the three GCMs ranging from 0.46 °C to 0.54 °C per decade, minimum temperature ranging from 0.37 °C to 0.45 °C per decade, and mean temperature ranging from 0.42 °C to 0.50 °C per decade during this century. In accordance to the previous findings, the highest trends have been resulted from CanESM2, which in turn brings out attention that results from only one individual climate model are inadequate to represent the climate system due to its inherent complexity. Therefore, an

Fig. 11 Projected monthly changes in Tmax, Tmin, and Tmean for the City of Ottawa during 2080s under RCP4.5

ensemble approach is often adopted as an effective way to study climate change in the future in order to provide reliable information towards climate adaptation and mitigation. The ensemble approach is widely accepted as an effective way to explore the range of projections from multiple GCMs and/or RCMs modeling results because results from one individual climate model are not adequate enough to describe the complexity in a climate system (Jeong et al. 2016; Tebaldi et al. 2005; Yang et al. 2012; Wang et al. 2016a). Therefore, through an ensemble approach, reliable climate change scenarios can be provided for the assessment of plausible effects of future climate change (Wang et al. 2015c).

Overall, this study presents an attempt in revealing an increasing trend along with the increased changes in temperatures for the City of Ottawa through the SCD model. Results suggests that such a downscaling model have demonstrated desired performance in the projections of maximum, minimum, and mean temperatures for the City of Ottawa. Moreover, comparisons of the projections among the three GCMs provide valuable information on how well the GCM models describe a long-term behavior of temperatures. Further improvements can be made on conducting an ensemble analysis and developing coupled dynamical–statistical downscaling method regarding projected future changes

Fig. 12 Projected monthly changes in Tmax, Tmin, and Tmean for the City of Ottawa during 2080s under RCP8.5

in temperature variables for the City of Ottawa. Moreover, projected changes in precipitation and their extremes will also be analyzed through an ensemble means at local scale to explore the role of natural variability in future climate in the City of Ottawa.

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