Journal of Cleaner Production 274 (2020) 123026

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Assessment of climate change impacts on energy capacity planning in Ontario, Canada using high-resolution regional climate model

Shuo Wang [a], Jinxin Zhu [f,*], Gordon Huang [b], Brian Baetz [c], Guanhui Cheng [b], Xueting Zeng [d], Xiuquan Wang [e]

[a] Department of Land Surveying and Geo-Informatics, the Hong Kong Polytechnic University, Hong Kong, China
[b] Faculty of Engineering and Applied Science, University of Regina, Regina, Saskatchewan, S4S0A2, Canada
[c] Department of Civil Engineering, McMaster University, Hamilton, ON, L8S 4L7, Canada
[d] Capital University of Economics and Business, Beijing, 100072, 266400, China
[e] School of Climate Change and Adaptation, University of Prince Edward Island, Charlottetown, PEI, C1A 4P3, Canada
[f] School of Geography and Planning, Sun Yat-Sen University, Guangzhou, China

ARTICLE INFO

Article history:
Received 9 March 2020
Received in revised form
18 June 2020
Accepted 20 June 2020
Available online 16 July 2020

Handling Editor: Zhifu Mi

Keywords:
Climate change
Energy capacity
Dynamical downscaling
RCPs scenarios
Energy security

ABSTRACT

Climate change may alter energy demand as well as energy supply, thus posing a threat to energy security. This study investigates the long-term energy security responses to climate change for Ontario from a planning perspective. A regional climate model (RCM) is employed to assess the climate-driven changes in energy sectors at a 25 km × 25 km resolution. Reliable projections of changes in climatic variables are provided to assess their impacts on cooling degree days, heating degree days, and energy availability. Quantified sensitivities of residential and commercial energy consumptions to degree days are incorporated with future projections to estimate energy demand changes. We then estimate the impact of climate change on the primary power sources, including nuclear power, hydropower, gas, wind energy, and solar energy from a capacity planning perspective. Results indicate that winter warms more rapidly than summer in Ontario. This leads to heating degree days decreasing 2 times faster than cooling degree days increasing. Changes in degree days result in an increase in summer electricity demand and a reduction in winter gas consumption. We also find that efficiencies of hydropower and wind energy could be reduced in different scales because of decreased resource availability. The efficiency of nuclear power is sensitive to the temperature rise, but relatively less reduced compared to other energy sources. Solar energy production can benefit from climate change for the perspective of a decrease in rainy and cloudy days. With the increased electricity demand and decreased availability of water and wind resources, more green energy capacities are expected to build to ensure the long-term energy security for Ontario.

© 2020 Elsevier Ltd. All rights reserved.

1. Introduction

Rising temperature is a major determinant to influence the residential and commercial energy demand in Ontario. Due to Ontario's high latitudes, the temperature-sensitive energy demand is directly determined by seasonal variability (Wang et al., 2014). Such energy demand, therefore, can be divided into winter heating demand and summer cooling demand. Canada is shifting toward higher temperatures in winter and summer according to the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (Hartmann et al., 2013). The warming trend may decrease winter heating fuel consumption and increase the summer cooling electricity demand. Of greater concern may be that a future of hotter summers will place further stress on the province's energy system. The rising temperatures will not only change the temperature-sensitive energy demand but also decrease the power generation because of the reduced efficiency of thermal conversion (Linnerud et al., 2011). The changing regional weather patterns are likely to affect the weather-driven renewables' availability that underpins renewable energy generation (e.g., a reduction in precipitation amount, might lead to water deficiency, which could result in an interruption in the stability of generating

* Corresponding author.
E-mail addresses: shuo.s.wang@polyu.edu.hk (S. Wang), zhujx29@mail.sysu.edu.cn (J. Zhu).

https://doi.org/10.1016/j.jclepro.2020.123026
0959-6526/© 2020 Elsevier Ltd. All rights reserved.

hydroelectricity). Ontario's power generation, therefore, can be adversely or positively impacted by changes in climatic variables. Consequently, it is critical for Ontario to incorporate the impacts of climate change into the assessment of the regional energy system's long-term plans concerning rising temperatures and changing weather patterns in the future.

Past studies have investigated the link between rising temperatures and energy demand under climate change (Moral-Carcedo and Vicens-Otero, 2005; Mirasgedis et al., 2007; Scapin et al., 2014; Liu et al., 2016) which is widely utilized in short- or mid-term energy consumption forecasting (Robinson, 1997; Pardo et al., 2002; Mirasgedis et al., 2006). However, only a few of these studies address the impacts of climate change on energy demand patterns in the long run. Furthermore, most of the studies focusing on long-term energy consumption use simulated future climate patterns based on historical climate statistics and projections of climate change from global climate models (GCMs). As for the link between changing weather patterns and renewable energy availability, some research has been carried out to investigate the impacts of a selected climatic variable on its potential energy generation. For instance, Vincuna et al. (2008) implemented a linear programming model for estimating the effects of changing weather patterns on hydropower generation in the State of California. Researchers adopted a similar approach incorporated with results from GCMs for the continental United States, and found notable changes concerning overall wind energy supply attributable to the availability of wind resources (Breslow et al., 2002). Plus, the specified climate variable is estimated at a national level with uniform changes based on the projections from GCMs.

GCMs are widely used to reproduce large-scale climates (Racherla et al., 2012; Flato et al., 2013; Cheng et al., 2017a,b) and projecting the climate response to future external forces with roughly 100 km $\times$ 200 km spatial resolution (Taylor et al., 2012). Consequently, a uniform change in the climate system may be applied over a vast continent (Wang et al., 2015a). But the key to a regional analysis lies in considering the differences in local energy systems, which include energy resources, supply, and conventional infrastructure, and characteristics of end-users (Amato et al., 2005). Downscaling approaches are adopted to deal with these issues including statistical and dynamical downscaling techniques (Wilby et al., 2004; Jones et al., 2004). Detailed advantages and disadvantages of two downscaling techniques are compared in the Supplementary Information Table S1. The statistical approach is not capable of taking multiple variables into account and, thus, cannot show how these relationships evolve in the future. Regional Climate Models (RCMs) are developed to dynamically downscale the resolution of GCMs to be fine enough (50 km $\times$ 50 km or 25 km $\times$ 25 km) to capture region-specific climate responses (Giorgi and Mearns, 1991; Giorgi, 2006; Christensen et al., 2007; Liang et al., 2008; Colette et al., 2012; Racherla et al., 2012; Hewitson et al., 2014; Wang et al., 2015b) with the initial and lateral boundary conditions provided by GCMs. Such region-specific climate information projected by RCMs needs to be incorporated to assess the long-term implications of climate change on energy demand and the entire spectrum of energy supply.

Most of the existing studies typically quantify the impacts of a single climatic variable on the isolated energy sector without considering multiple climatic variables. Plus, the specified climate variable is mostly estimated with uniform changes based on GCMs at a regional level. GCMs' resolutions are too coarse to represent fine-scale physical processes in the climate system. There were no studies to date examining the influence of multiple climatic variables (temperature, precipitation, cloud cover, and wind speed) on the entire energy production spectrum with employing the dynamical downscaling approach to include a large physically consistent set of climate variables at a fine resolution.

This study is the first attempt to employ a high-resolution RCM to assess the long-term energy security responses to climate change at a regional level by examining the influence of multiple climatic variables (temperature, precipitation, cloud cover, and wind speed) on the entire energy production spectrum. The objective of this study is to provide robust estimates of climate change impacts on energy demand and energy capacity in Ontario through the RCM. Firstly, the selected RCM's skill in reproducing the historical climate over Ontario will be gauged through validating the historical simulation against the observation dataset in terms of regional-specific climatic variables. Secondly, the future climate will be projected through the dynamical downscaling under different representative concentration pathways (RCP4.5 and RCP8.5). Thirdly, the validated and projected results of RCM will be used to calculate the cooling and heating degree days for residential and commercial buildings. Fourthly, sensitivities of energy consumption to climate drivers will be quantified and incorporated with the projections to estimate the future energy demand responses to changes in degree days. Fifthly, we then evaluate the impact of climate change on the main power sources, including nuclear power, hydropower, gas, wind energy, and solar energy from a capacity management perspective. Efficiencies of nuclear power and biofuel energy are estimated by considering the relationship between the water-cooling effect and the rising temperature. Hydropower, solar energy, and wind energy are investigated by examining the resources availabilities related to precipitation, cloud cover, and wind speed changes. Lastly, the changes in future energy capacity installation can be addressed based on the estimated results driven by the climate variables influencing the entire energy system spectrum. The long-term energy security for Ontario can then be assessed at a regional level within the context of climate change.

2. Model, data and methods

The Providing REgional Climate Impacts for Studies (PRECIS) model is selected to better simulate climatic variables and provide a solid foundation to study their impacts on the regional energy system. The selected PRECIS model is developed by Met Office Hadley Centre, UK (Jones et al., 2004; Wilson et al., 2015) and has two different horizontal resolutions, including 50 km for the simulation over a large continent (to save computing resources) and 25 km for the simulation over a relatively small domain (Jones et al., 2004; Wilson et al., 2011). For this study, the 25 km resolution was chosen for Ontario to depict its heterogeneous climate better and to capture the spatial and temporal variations in simulations. Based on an experimental design for PRECIS (Abebe, 2010), the domain was set between 40.46 °N to 56.81 °N and 261.88 °E to 285.88 °E. This covers the Great Lakes, Hudson Bay, the entire province of Ontario, and parts of Manitoba, Quebec, and US territory. The boundaries of the domain are placed over flat plains and oceans to avoid unrealistic results caused by sharp changes in altitude. Outside the boundaries, Hadley Centre Global Environment Model version 2-Earth Systems (HadGEM2-ES) was used to drive the RCM with the initial and lateral boundary conditions (Collins et al., 2008). For future greenhouse emission scenarios, two Representative Concentration Pathways (RCPs) scenarios were selected, namely a stabilization emission scenario with the total radiative forcing of 4.5W/m^2 until 2100 (RCP4.5) and a comparatively high emission scenario with stabilizing near 8.5W/m^2 (RCP8.5) (Moss et al., 2010; Van Vuuren et al., 2011). With these two RCP scenarios, a possible range of changes in the future climate can be obtained for investigating the impacts on the energy sector.

Faithful reproduction of historical climate conditions is the

premise for an RCM to project a plausible range of future climate conditions. The simulated results will be validated with the observation dataset in terms of regional-specific climatic variables, namely temperature, precipitation, and wind speed, to gauge the RCM's skill of reproduction. The observed data for temperature and precipitation is obtained from the Climate Research Unit (CRU) monthly gridded dataset. The CRU dataset is developed from interpretations of monthly meteorological data from observational stations across the world's land areas with a temporal range for over 50 years (Harris et al., 2014). The available data for wind speed (10m above ground) covers the period from 1961 to 2010. We used the dataset with 20-year (1985–2004) averaged to show differences between simulation and observation in the detailed spatial patterns. The study also adopts the wind speed observations from 12 meteorological stations in Ontario to validate the simulation (AHCCD, 2013). These twelve stations are spatially distributed across the landmass of Ontario. Twelve stations were selected for analysis after passing the temporal consistency test, namely Kenora (94.37 °W, 49.78 °N), Kingston (76.60 °W, 44.22 °N), London (81.15 °W, 43.03 °N), Ottawa (75.67 °W, 45.32 °N), Toronto (79.40°W, 43.63°N), Sudbury (80.80 °W, 46.62 °N), Timmins (81.38 °W, 48.57 °N), Thunder Bay (89.25 °W, 48.38 °N), Sault Ste. Marie (84.35 °W, 46.52 °N), Windsor (83.04 °W, 42.31 °N), Moosonee (80.64 °W, 51.27 °N) and Wiarton (81.14 °W, 44.74 °N). The temporal consistency test adopted here mainly checks if the values of time-resolved observations are implausible with comparison to meteorological time series (Shafer et al., 2000; Fiebrich and Crawford, 2001).

For the energy demand analysis, we used the degree-day methodology to estimate possible energy consumption responses to climate drivers. The degree-day methodology presumes a V-shaped temperature-energy consumption curve with a base temperature at the bottom. At the base temperature, energy consumption is at a minimum scale when outside climatic conditions equal to the desired indoor condition (Zhou et al., 2014). As outdoor conditions driving the indoor temperature deviate above the base temperature, energy consumption increases accordingly for cooling the indoor temperature. For each unit above the base temperature, it accounts for one cooling degree day (CDD). When indoor temperatures deviate below the base temperature, each unit below accounts for one heating degree day (HDD). For residential and commercial buildings in Canada, temperature-energy-consumption analyses commonly use a base temperature of 18.3 °C (calculated from local thermal capacity, the efficiency of heat loss, and infiltration) as the threshold to estimate the degree days (Hamlet et al., 2010; Data Catalogue, 2016). Each degree deviation from the base temperature is counted as one degree-day. CDD (HDD) is calculated by subtracting the base temperature (the mean daily temperature) from the mean daily temperature (the base temperature) and summing only the positive values over a certain period. For example, when the base temperature of 18.3 °C is chosen, and the day's average temperature is 29.3 °C, this would result in 11-unit CDD for that day. The relationship between electricity consumption and temperature is nonlinear. But HDDs and CDDs adopted in this study can replace the nonlinear relationship with a linear one (Meng et al., 2018). Functions for calculating HDDs and CDDs are shown as follows:

$$HDDs = \sum_{1}^{N} (1-\beta)(T_b - T_m) \tag{1}$$

$$CDDs = \sum_{1}^{N} (\beta)(T_m - T_b) \tag{2}$$

where β takes a value of 1 when the daily mean temperature is higher than the base temperature and takes a value of 0 otherwise; N represents the number of days; T_b represents the base temperature; T_m represents the daily mean temperature.

Under climate change, changes in hydropower resources can be estimated by a hydrological model with the ability to link simulated runoff scenarios to the Ontario hydro system (Cheng et al., 2017a,b; Wang et al., 2017, 2018). Watershed Analysis Risk Management Framework (WARMF) was chosen in this study to simulate the runoff impacts on the hydro system. It is a continuous simulation model that can provide a physical representation of the watershed in Ontario by using a GIS database with inherent reservoir capabilities and stream diversions (Chen et al., 2001). Daily time-series of RCM outputs such as precipitation, temperature, evaporation rate, and surface runoff rate are inputted into the WARMF simulation to estimate the changes in the hydropower resources in response to projected climate changes.

The energy density in each grid cell is calculated based on the wind speed projected by the PRECIS model to explore the potential impact of the wind speed change on the wind power generation. The average hub height of Ontario turbines is 115m. The 10m wind speed from the RCM needs to be transformed into the wind speed at the elevation of 115m:

$$\frac{v1}{v2} = \left(\frac{h1}{h2}\right)^{1/7} \tag{3}$$

where v (m/s) is the wind speed at the height of h (m). The power density can be calculated by:

$$\frac{P}{A} = \frac{1}{2}\rho v^3 \tag{4}$$

where P/A (W/m2) is the power density, ρ is the air density (kg/m3). This density function is adopted to calculate the mean power from a range of mean wind speeds over a selected area. This function is widely used to quantify the wind energy production due to its excellent fit with the observed long-term distribution of mean wind speed (Manwell et al., 2009).

Nuclear energy accounts for 38% of the total generation capacity of the Ontario electricity system (WNA, 2017). Currently, the province has three nuclear generation stations located at Darlington, Bruce, and Pickering. As reactors are designed with a lifetime of over sixty years, the new construction or decommission of reactors has direct impacts on the long-term energy security of Ontario. Compared to hydropower and wind power, a nuclear power plant has the least sensitivity to climate change. A warmer climate may lower thermal efficiency in nuclear power generation because of the temperature of cooling water increased (Chiotti and Lavender, 2008). Linnerud et al. (2011) introduced a dummy variable for the summer months' fixed effects in their model to account for the impact of a temperature change on a nuclear power plant. The equation was used to estimate the effect of the temperature change on monthly production. Equation Eqn 5 is used to derive the estimated effects on the nuclear output due to a change in temperature for the summer months:

$$\widehat{\Delta q/q} = \frac{-0.666*\Delta T - 0.023\left((T+\Delta T)^2 - T^2\right)}{92.44 - 0.666*T - 0.023*T^2} \tag{5}$$

where q is the thermal efficiency, T is the temperature of cooling water.

We synthesized daily climate data considering two future climate scenarios for the 20-year period of 2080–2099 as the outputs of the PRECIS model. The methodological framework is

depicted in Fig. 1 and comprises five steps for quantifying the impacts of climate change on regional energy system. First, the resolution of GCMs is dynamically downscaled by the PRECIS model to 25 km. RCM has the advantages of generating physically consistent datasets across different variables. Second, the climatic variables (temperature, precipitation and wind speed) from the RCM output are validated against the observation dataset. Third, two RCPs (RCP4.5 and RCP8.5) are used to estimate the future climatic conditions in terms of selected climatic variables. Fourth, the RCM is able to provide climate data used in energy sectors for our study. Finally, we calculate the changes in electricity consumption and the energy availabilities due to the changes in the projected climatic variables.

3. RCM validation

Three months of results, namely for June, July, and August (JJA) in summer, December, January, and February (DJF) in winter, are selected to calculate the seasonal mean temperatures for the period from 1985 to 2004. The validation results for the seasonal mean temperature over Ontario derived from PRECIS and CRU are shown in Fig. 2. The figure for CRU shows that summer mean temperature is relatively high over the southwest corner of the domain, and it is decreasing northeastward and then reaching the minimum in Hudson Bay. The winter mean temperature exhibits similar spatial distribution , but it is decreasing northward instead of northeastward. Compared to CRU, the PRECIS model can well simulate spatial patterns of seasonal temperatures. The PRECIS model captures the warm observational center located in the southwest corner in summer and the cold center in the north in winter. However, the simulated summer temperature is higher (up to 2 °C) than the observed values over the southwest corner. Over Ontario, the PRECIS model reproduces well the mean temperatures with differences to CRU dataset less than 1 °C for JJA. The RCM not only well captures the spatial patterns of mean temperatures for DJF, but also the magnitudes of winter temperatures. The difference between simulations and observations is only less than 0.5 °C over the entire province.

To validate temporal climate patterns, the annual cycles of temperature are estimated from based on outputs of the PRECIS model and the observed data for Ontario (as shown in Fig. S1). The curve for PRECIS matches well with the annual cycle of CRU concerning mean, maximum, and minimum temperatures. Although the PRECIS model captures the trends of the observed annual cycle, it overestimates the mean and maximum temperatures for DJF and holistically overestimates the minimum temperature by approximately 0.3 °C. The PRECIS model captures the trends of the observed temperatures for JJA and DJF. For each temperature pattern, the results of the PRECIS model remarkably match the curves of CRU for the mean and maximum temperatures and show little overestimations (about 0.8 °C) for the minimum temperature. The overestimations are all less than 1 °C, which is considered acceptable for climate modeling (Wang et al., 2014). Plus, the holistically overestimation can be removed through the constant bias

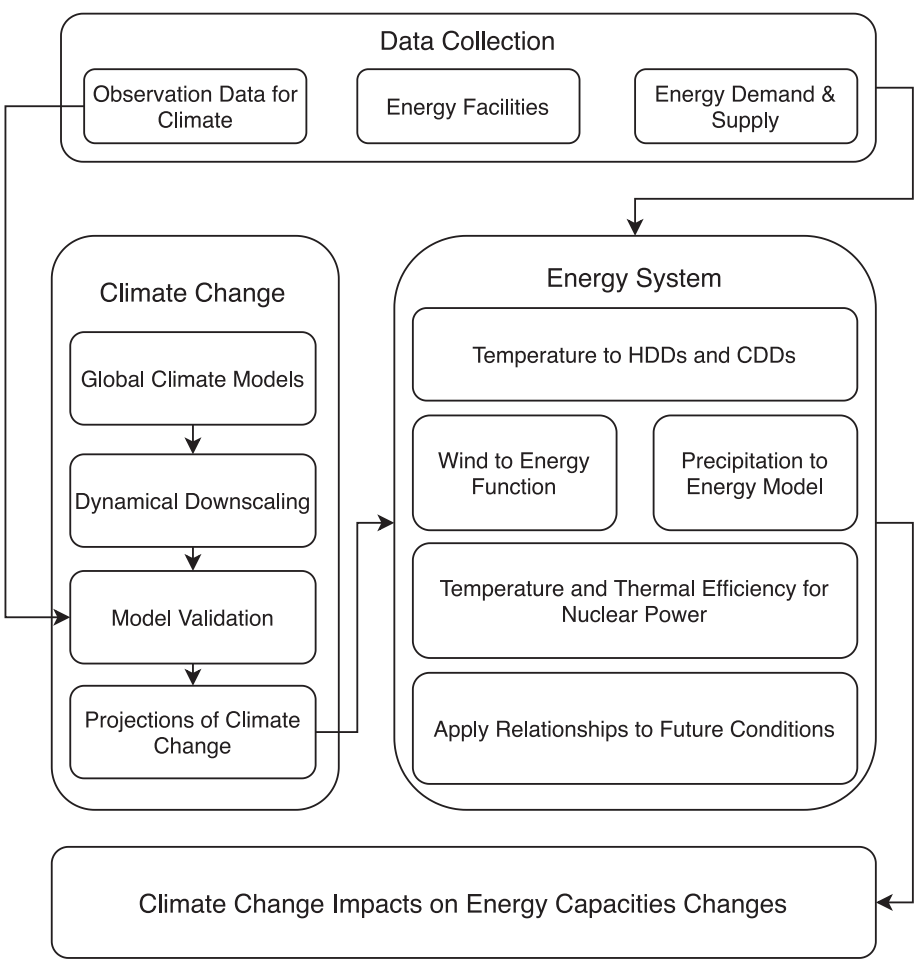

Fig. 1. Methodological process for estimating climate change impacts on the energy capacity planning.

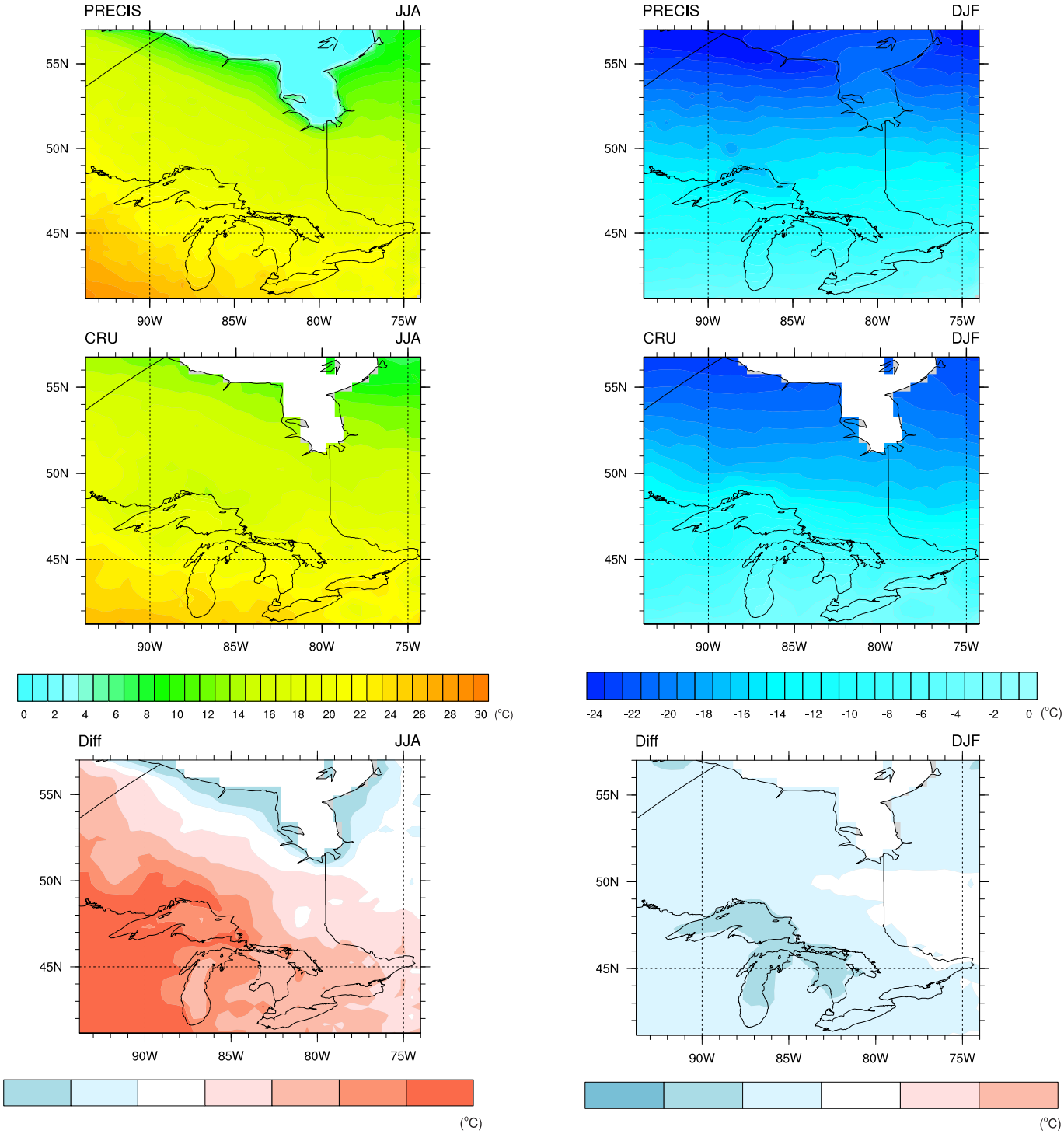

Fig. 2. Spatial distributions of summer mean (JJA) and winter mean (DJF) temperatures (unit: °C) over Ontario for PRECIS and CRU for 1985–2004.

approach by subtracting the values for the control period (1985–2004) from future projections.

The spatial distribution of annual mean precipitation over Ontario from the PRECIS is validated against the CRU dataset from 1985 to 2004 (as shown in Fig. S2). CRU shows that mean precipitation amounts are relatively low over the northern area surrounding Hudson Bay, and they are increasing southward and then reaching the maximum at the bottom of the domain. The precipitation simulated by the PRECIS model exhibits geographical features similar to the observed values. Furthermore, the PRECIS captures the observed maximum precipitation area located at the southeast corner of the domain. There is a slight difference in the amounts of precipitation. The simulated amounts of precipitation are lower than the observed ones over the region below the Great Lakes. For Ontario and the Great Lakes, the RCM reproduces the right precipitation amount and related spatial patterns. In comparison to CRU, the PRECIS model captures the fine-scale variations in the precipitation caused by the complex land surfaces. The

differences between simulated results and observational data are less than 1 mm/day for the reference period. As for the temporal patterns, the annual cycles of precipitation from the RCM and the observations are demonstrated in Fig. S3 for Ontario. The curve of the PRECIS generally matches the curve of CRU. The PRECIS model overestimates the precipitation from February to April and underestimates the precipitation from October to December. It is noteworthy that the PRECIS model simulates the exact peak value in July and reproduces observed values in June and August. Overall, the RCM shows high skill in reproducing the temporal pattern of the mean precipitation.

In Fig. 3, the PRECIS results show good agreement with the CRU dataset in terms of the spatial patterns of wind speed for the baseline period. The overall magnitude of wind speed in the Great Lakes simulated by the RCM is higher than in CRU. But the PRECIS model captures the maximum wind speed centered in the Great Lakes. The PRECIS model simulates the right wind patterns and values along the shorelines of the Great Lakes and Hudson Bay. As for the RCM versus the observation dataset for the control period from 1985 to 2004, the two sets of wind speed are compared at twelve weather stations across the landmass of Ontario. The patterns shown in Fig. 4 are in accordance with Fig. 3 that the PRECIS simulations of wind speeds generally follow the observational trends of weather stations with proximity to Great Lakes. But the RCM simulate wind speed lower than the observed values for the inland stations. And there is no bias larger than 2 km/h between the PRECIS simulation and stational data for the reference period. In comparison to CRU, the PRECIS model shows a reliable representation of the spatial and temporal patterns of wind speed (for further details, please refer to Fig. S4).

4. High-Resolution Projections of climate change

Once the simulation for the baseline period is validated against the observed values, it is reasonable to assume that the RCM can project the meteorological processes with high plausibility for the future periods. Therefore, the possible changes in the future climate can be investigated by subtracting the historical simulation from the projected simulation under various scenarios. In Figs. 5 and 6, the projected changes in summer and winter mean temperatures are shown under RCP4.5 and RCP8.5 scenarios for the period 2041–2060 (the 2050s) and the period 2081–2100 (the 2080s) relative to the baseline period. Under both scenarios, PRECIS projects general increases in the mean temperature all over Ontario in both summer and winter for two future periods. But winter warms more rapidly than summer, and up to 4 °C higher under RCP8.5 for the 2080s. Compared to RCP4.5, Ontario will experience more substantial increases (approximate 2.2 °C for JJA and 4 °C for DJF) in the seasonal mean temperature under RCP8.5 for the 2080s.

Fig. 7 shows the projected precipitation changes relative to the baseline period under two RCPs for the 2050s and 2080s. Under both scenarios, the RCM projects a general decrease in the annual precipitation over Ontario for each period. Under RCP4.5, the PRECIS model projects a −5% change over the southern Ontario (below 50°N where all river basins and hydropower plants are located, as shown in Fig. S5) for the 2050s. For the 2080s, the RCM projects −11% changes over southern Ontario. Under RCP8.5, the magnitude of negative changes in the summer precipitation becomes larger than under RCP4.5. For the 2050s, the PRECIS model projects a −15% change over southern Ontario. For the 2080s, the projected change in precipitation over the region is −12%. Therefore, southern Ontario will experience a large decrease in annual precipitation and thus water resources reduction in watersheds under climate change.

The variations in wind speed are derived from subtracting the

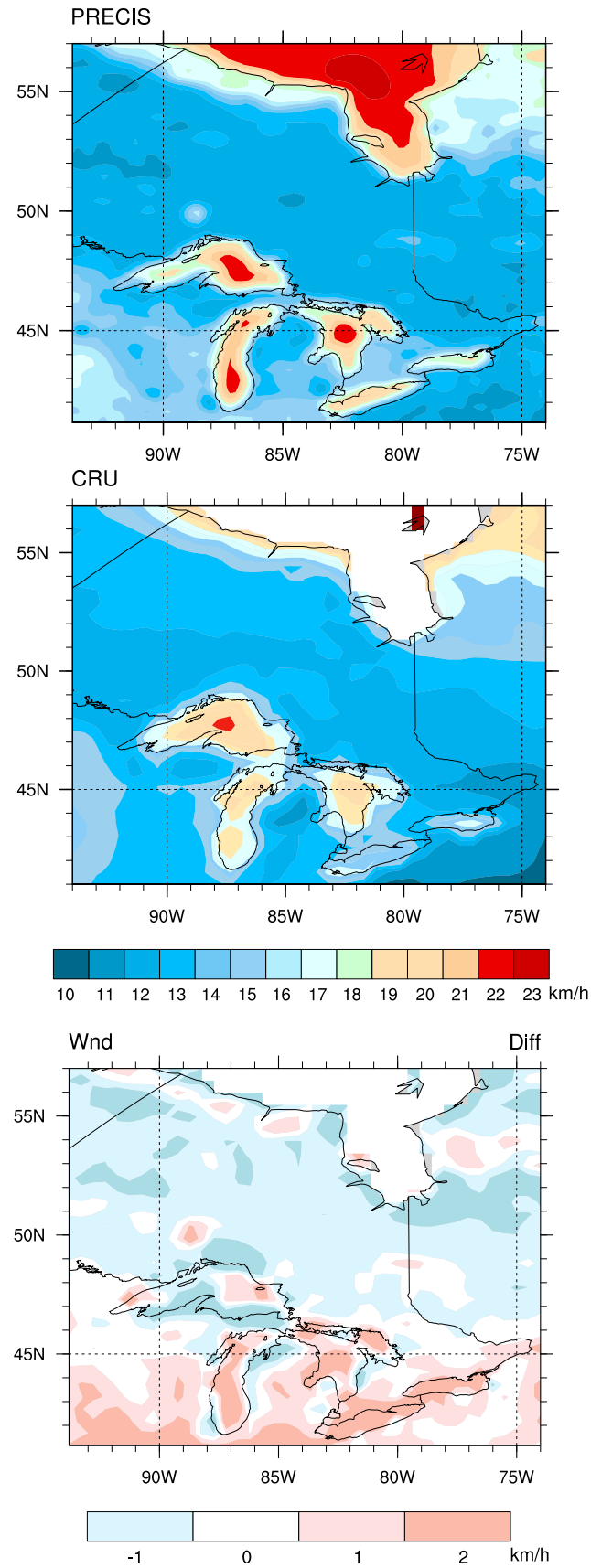

Fig. 3. Spatial distribution of annual mean wind speed (unit: km/h) over Ontario for PRECIS and CRU.

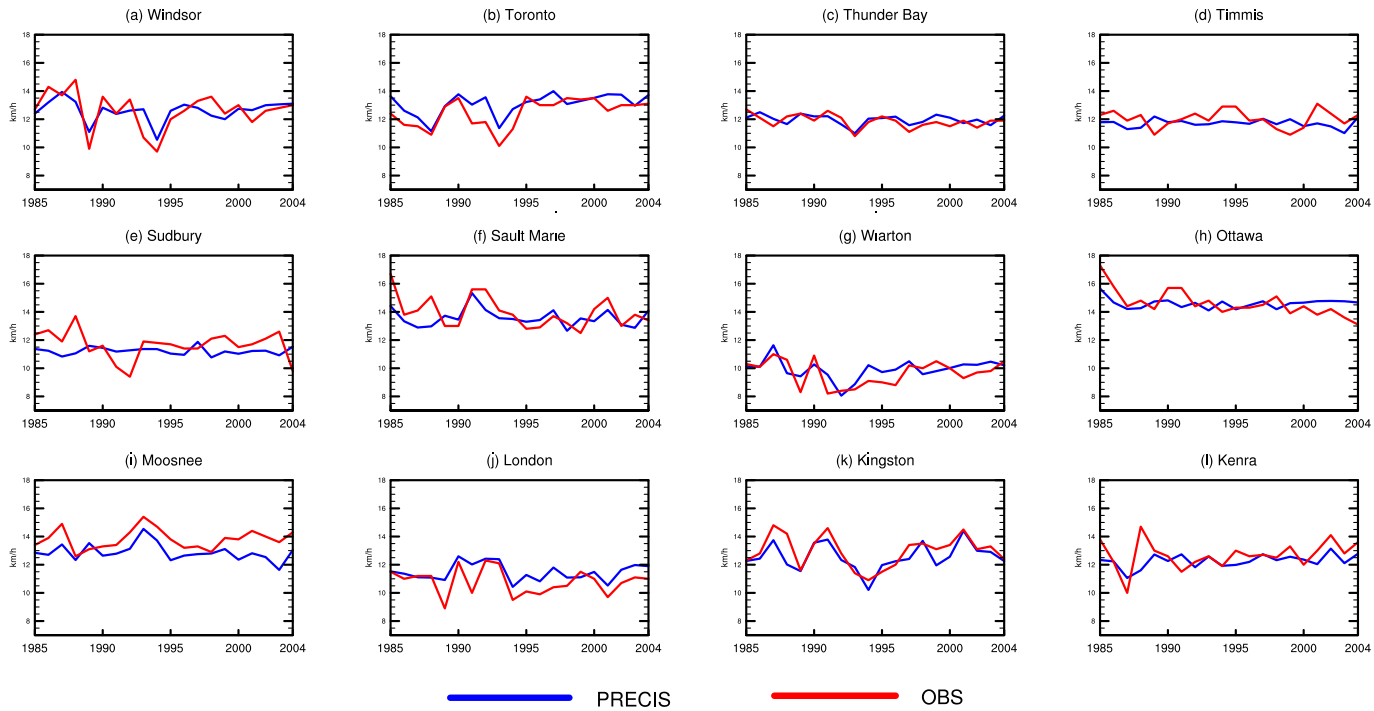

Fig. 4. Wind speed data from PRECIS and Observations compared at 12 weather stations.

wind speed in the baseline period from the 2050s and 2080s under two RCPs to investigate how wind speeds will change. As shown in Fig. 8, there is an insignificant increasing trend (0.013 km/h/year for the 2050s and 0.016 km/h/year for the 2080s) over Hudson Bay and its surrounding area. On the one hand, A relatively stable decreasing trend (−0.077 km/h/year for the 2050s and −0.115 km/h/year for the 2080s) is found in the Great Lakes and their surrounding area. This decreasing trend can be further enhanced under RCP8.5 than under RCP4.5. The most substantial decrease is approximate −7 km/h over the Great Lakes under RCP8.5 for the 2080s. Moreover, changes in wind speed with −4 km/h and over can be located at Lake Ontario, Lake Erie, and Lake Huron. The wind speed variations on the shorelines of Ontario range from −3 km/h to −1 km/h. Although the wind speed decrease from the onshore to the offshore areas, the absolute value of wind speed over the Great Lakes is still larger than the value over their adjacent areas. On the other hand, Hudson Bay preserves the most abundant wind power resource from the control period to the 2080s.

5. Energy demand and supply under climate change

Fig. 9 and Fig. 10 show the projected changes in CDD for JJA and changes in HDD for DJF under RCP4.5 and RCP8.5 for two future periods. Under both scenarios, PRECIS projects a general increases in CDD and a decrease in HDD over the entirety of Ontario for the 2050s and 2080s. It can be found that the magnitude of CDD changes is larger for the 2050s than for the 2080s under each RCP. The same patterns with respect to changing magnitude can be found in HDD under both RCPs. With the radiative forcing increase, Ontario will experience larger increases in the mean CDD and larger decreases in the mean HDD under RCP8.5 than RCP4.5 for the selected period. Under RCP4.5, the RCM projects that CDD will increase 112-unit for the 2050s relative to the control period. Under RCP8.5, CDD can increase 260-unit for the 2080s over Ontario. The RCM projects a 440-unit decrease under RCP4.5 for the 2050s and an approximate 615-unit reduction over Ontario under RCP8.5 for the 2080s. Many studies have demonstrated that a one-unit increase in daily CDD (HDD) is associated with an increase (a decrease) in electricity consumption to some extent (Chen et al., 2001; Chiotti and Lavender, 2008; Linnerud et al., 2011). Therefore, the percentage of changes in CDD/HDD relative to the reference period is directly linked to the rate of energy consumption change. From an energy capacity installation perspective, it is convenient for us to use the percentage change in energy consumption to estimate how much energy capacity needs to be built in the future. It can be noted that the reduction in heating degree days is about 2 times of increment in cooling degree days under the most aggressive emission scenario at the end of this century. When transferring the absolute change in degree days to percentage changes for better analysis (as shown in Figs. S6 and S7), there is an increase of 297% in CDD (nearly 3 times of historical values) and only a decrease of 24% in HDD (i.e., under RCP8.5 for the 2080s) relative to their historical values. Without considering the socio-economic conditions, the future climate condition can lead to the increase in the electricity demand for cooling 10 times of the decrease in the energy consumption for heating. As natural gas energy is solely used for space heating for residential and commercial buildings, less gas energy capacity needs to be installed in the future. More electricity-type energy capacities are expected to be built to cope with the possible energy crisis triggered by climate warming.

Daily time-series of RCM outputs such as precipitation, temperature, evaporation rate, and surface runoff rate are used as inputs of the WARMF simulation to estimate the changes in the hydropower resources in response to projected climate change. The RCM projects plausible ranges of changes in these factors under future climate scenarios for two periods. Under these statistics, the seasonal mean streamflow response to climate change is quantified by the WARMF model. Hydropower resources can be estimated by simulating the reservoir storage, hydraulic head, and rate of fluid flow under different climate scenarios. Under RCP4.5, there are sharp reductions in hydropower production near −11% for the

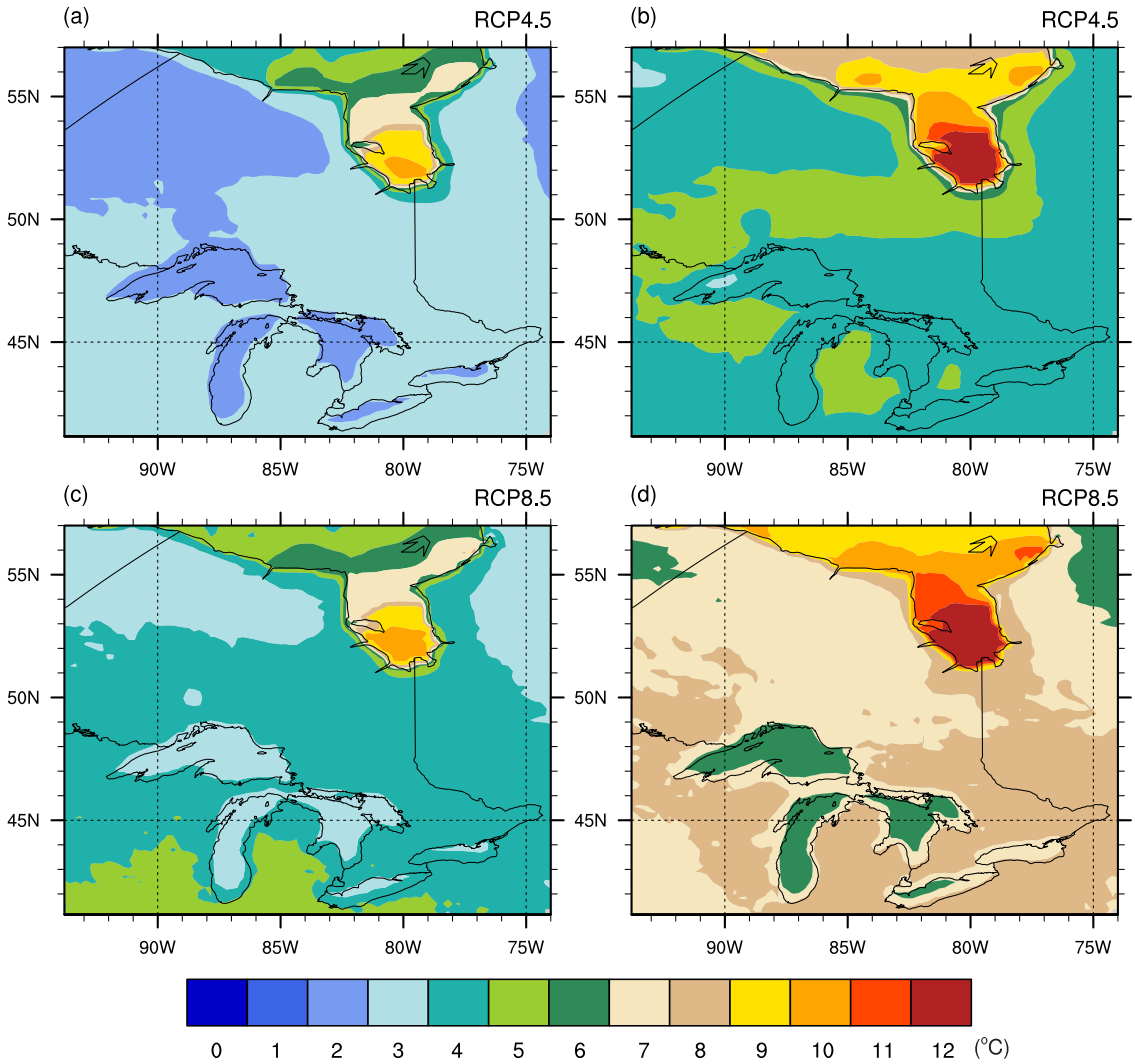

Fig. 5. Projected changes in summer mean temperature (unit: °C) under RCP4.5 and RCP8.5 scenarios for the 2050s and the 2080s relative to the baseline period.

2050s and −20% for the 2080s. The resultant changes under RCP8.5 are −35% for the 2050s and −31% for the 2080s. It is unequivocal that the projected warming and reductions in precipitation have adverse effects on hydropower resources. In opposite, decreased precipitation together with cloud cover changes imply that there will be less rainy days and cloudy days over Ontario under climate change. The development of solar energy can possibly benefit from climate change due to the reduced number of rainy days and cloudy days. Most of the province's solar installations are small systems connected to local distribution networks, but solar to electricity generation over Ontario can be increased by 41% for the 2050s under RCP4.5, 52% for the 2080s under RCP4.5, 67% for the 2050s under RCP8.5, and 70% for the 2080s under RCP8.5.

The dominant wind farms in Ontario (installed capacity > 10 MW) were built on the shorelines along the lakes (Canwea, 2017). The projected results indicate that the wind speed over this area will decrease under both RCPs for the two future periods. According to the projected results, the average wind speed will reduce by 16% and 7% under RCP4.5 and RCP8.5 scenarios respectively for the 2050s, and 21% and 13% for the 2080s. The power density function (Function 3 & 4) is fitted to the 115m high equivalent wind speed to investigate the detailed impact on the actual power production of the wind farms (Manwell et al., 2009). The results show that the wind energy density will drop down dramatically as its value is proportional to the cube of wind speed. The changes in the power density are −41% and −20% under RCP4.5 and RCP8.5 for the 2050s, and −51% and −34% for the 2080s. Despite the decreasing trend, there are still enormous untapped wind resources across Ontario that are available to be deployed at a certain scale to match the load growth. It is noticeable that future wind resources are relatively abundant in the Great Lakes, Hudson Bay, and its surrounding area. Moreover, Ontario needs to continue to prioritize the emission-free generation to meet its aggressive greenhouse gas emission reduction target of 80% by 2050. As the lifespan of a wind turbine is 20–30 years, all the operating wind turbines will be decommissioned by 2050. Ontario needs to deploy wind turbines with more than the current installed capacity to maintain the wind power generation and to achieve the emissions-free generation goal. From 2050 to 2080, new wind turbines will be built to replace the decommissioned ones again. Thus, there are

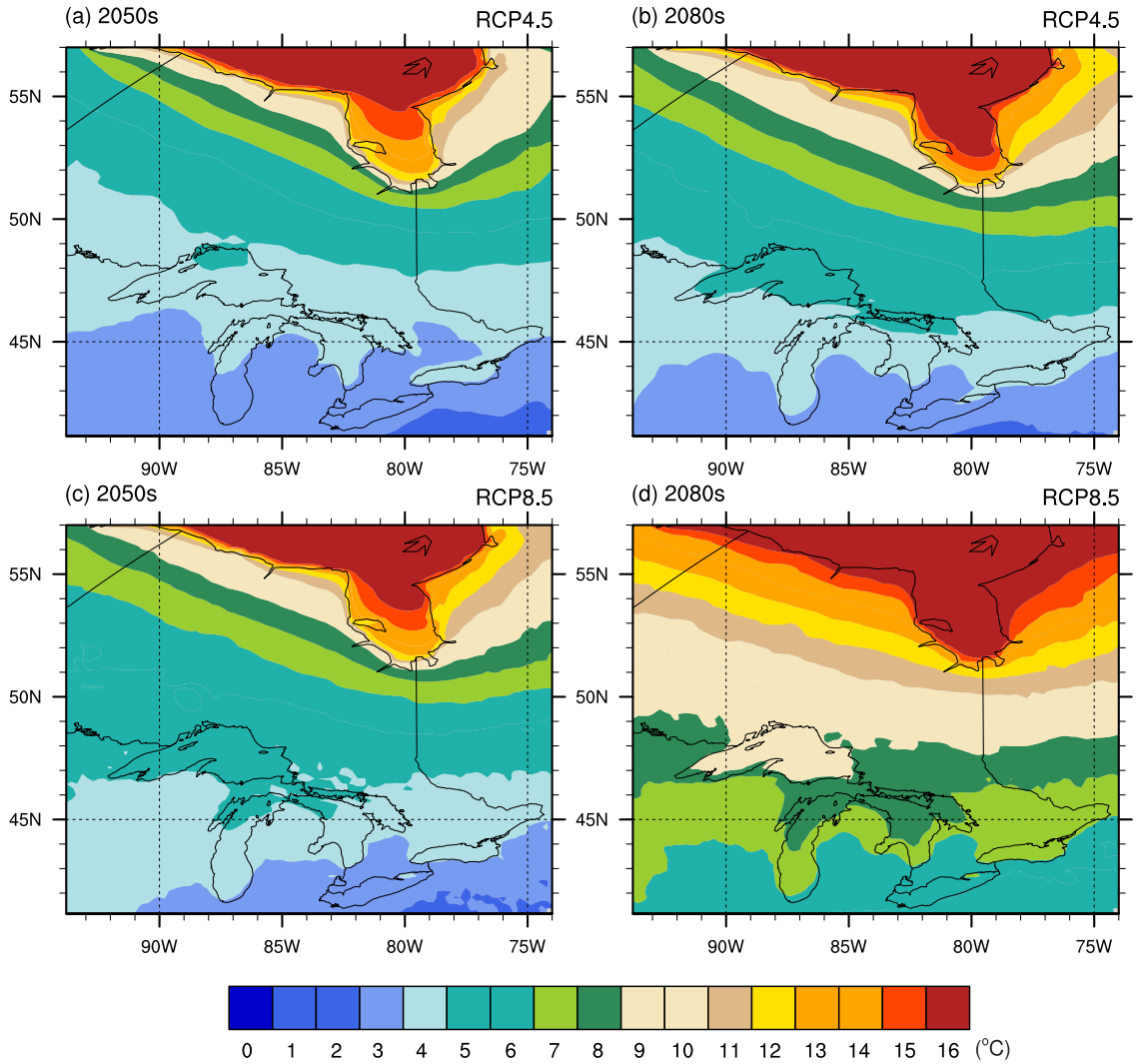

Fig. 6. Projected changes in winter mean temperature (unit: °C) under RCP4.5 and RCP8.5 scenarios for the 2050s and the 2080s relative to the baseline period.

two opportunities for the provincial government to determine where to deploy the wind farms best to maximize the wind power generation that is economically competitive.

The availability of wind resources could be significantly influenced by the geographical factor (onshore or offshore). Considering the distance to transmission lines and the locations of load centers, Georgian Bay (to the east of Lake Huron, referred to offshore of the Great Lakes), James Bay (to the south of Hudson Bay, referred to offshore of Hudson Bay) and the James Bay shoreline (the northernmost area that transmission lines can reach, referred to onshore of Hudson Bay) are determined from the beforementioned three areas with abundant wind resources to represent the potential area for deploying wind turbines (Yao et al., 2012). The mean wind speed over the area with commissioned wind farms (referred to onshore of the Great Lakes) for the reference period is used as the control group for comparison with the wind speed over the potential deployed areas under both RCPs for the 2050s and 2080s. The percentage of changes in wind density can be calculated in terms of spatial and temporal variation. As shown in Table 1, there will be a decrease in the wind power density at the shorelines of Great Lakes for both periods. The offshore wind power production will increase between 19% and 95% for the 2050s and change between −6% and 9% for the 2080s. At Hudson Bay, both onshore and offshore wind power densities are estimated to increase. In comparison, the growth potential of offshore wind power production is much larger than onshore production for both periods. It is thus reasonable to consider James Bay and its shoreline as a potential hotspot for wind energy in the context of climate change.

To compute the climate change impacts on electricity generation from nuclear power plants, we derived the average monthly temperatures for the reference and scenario periods. According to Equation 5 in the section 2, a 1 °C increase in water temperature reduces 0.5% nuclear power generation due to its effect on thermal efficiency (Linnerud et al., 2011). With projected increased temperatures, there will be 1.5% and 2.5% reductions under RCP4.5 and RCP8.5 in nuclear power production for the 2050s and 2.5% and 4.0% reductions respectively for the 2080s.

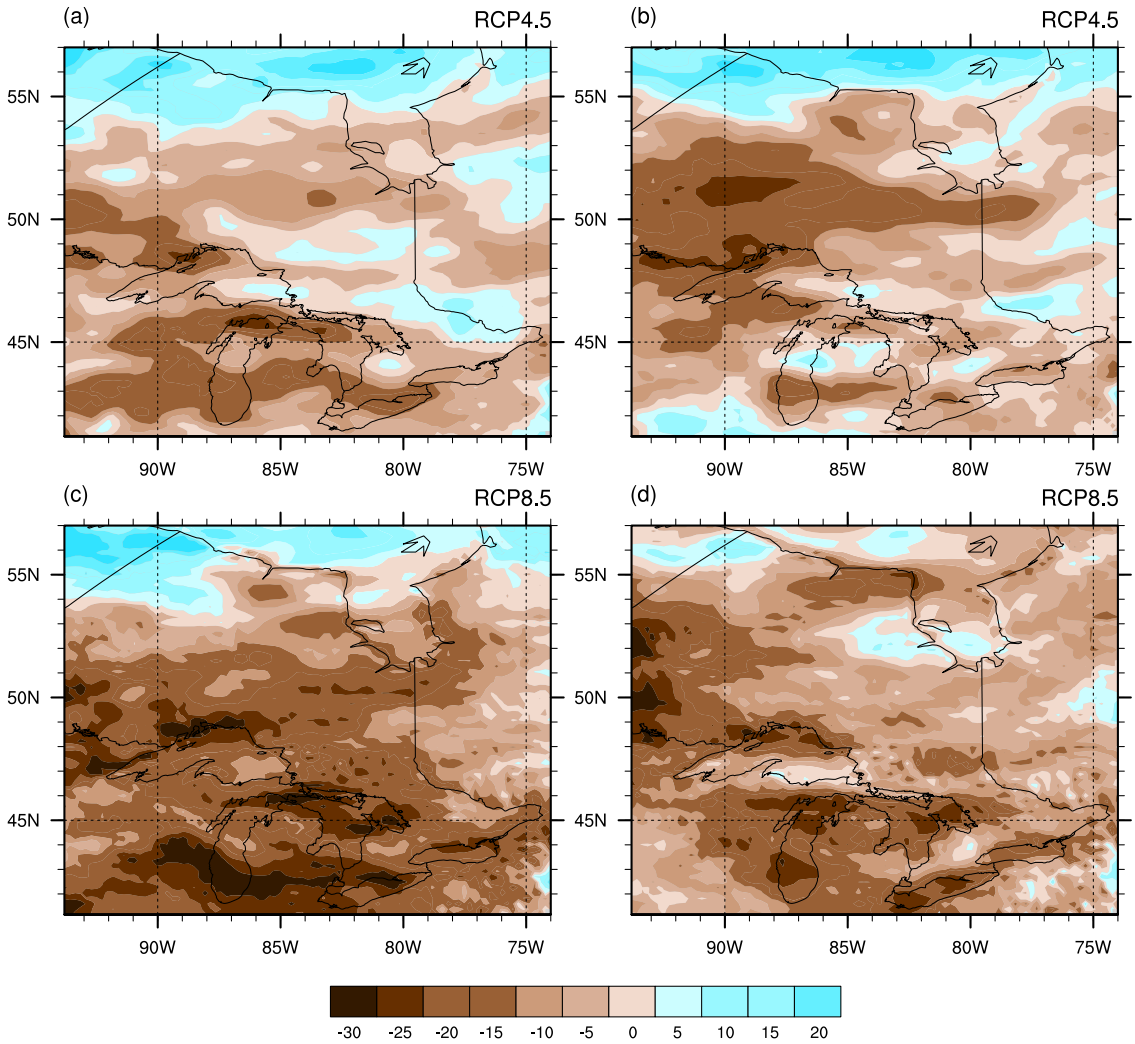

Fig. 7. Projected changes in annual mean precipitation (unit: %) under RCP4.5 and RCP8.5 for the 2050s and the 2080s relative to the baseline period.

6. Discussions

As the electricity consumption in summer is projected to increase and gas demand in winter is projected to decrease, we examine how much capacity expansion of major electricity supply sources, namely nuclear, hydro, solar and wind power, is needed in response to the increasing energy demand induced by climate change. We realize that each sector's proportion to the total energy supply is 34%, 22%, 6%, and 12%, respectively (Canada Energy Regulator, 2017). Our results indicate that climate change has negative impacts on the hydro, wind, and nuclear energy sectors by decreasing their supply efficiencies to different extents. Within the optimal temperature range of the solar panel for energy transformation, the solar energy sector can be a beneficiary from climate warming with reduced cloudy and rainy days. Hydropower is the most affected, nuclear power is the least, and wind energy is in between (only if the future wind energy capacity is installed at offshore). The change of installed capacity can be calculated by subtracting the change in energy demand from the change in supply for each energy sector under two RCPs scenarios for each period. Except for solar energy, capacity expansions are already needed for each industry to maintain its proportion to the total energy capacity in 2017. As shown in Table 2, solar energy is the only sector with negative capacity installation to meet the electricity demand increase while remaining 1% of total energy supply. It implies that climate change could increase the solar to energy generation and hence decrease its cost per kWh for the installed solar capacity. To meet the energy supply gap caused by climate change and maintain their respective proportions to the total energy generation, the nuclear power sector will need the relatively less capacity expansion than the hydropower sector and the wind power sector. Due to the availability reduction, the cost per kWh for hydropower and offshore wind power will increase with different magnitude in Ontario under climate change. The cost per kWh for nuclear power will also increase due to the thermal efficiency reduced by the increased cooling water temperature. Considering the drop in gas energy for space heating, Ontario will have more green energy capacity and less gas energy capacity built without

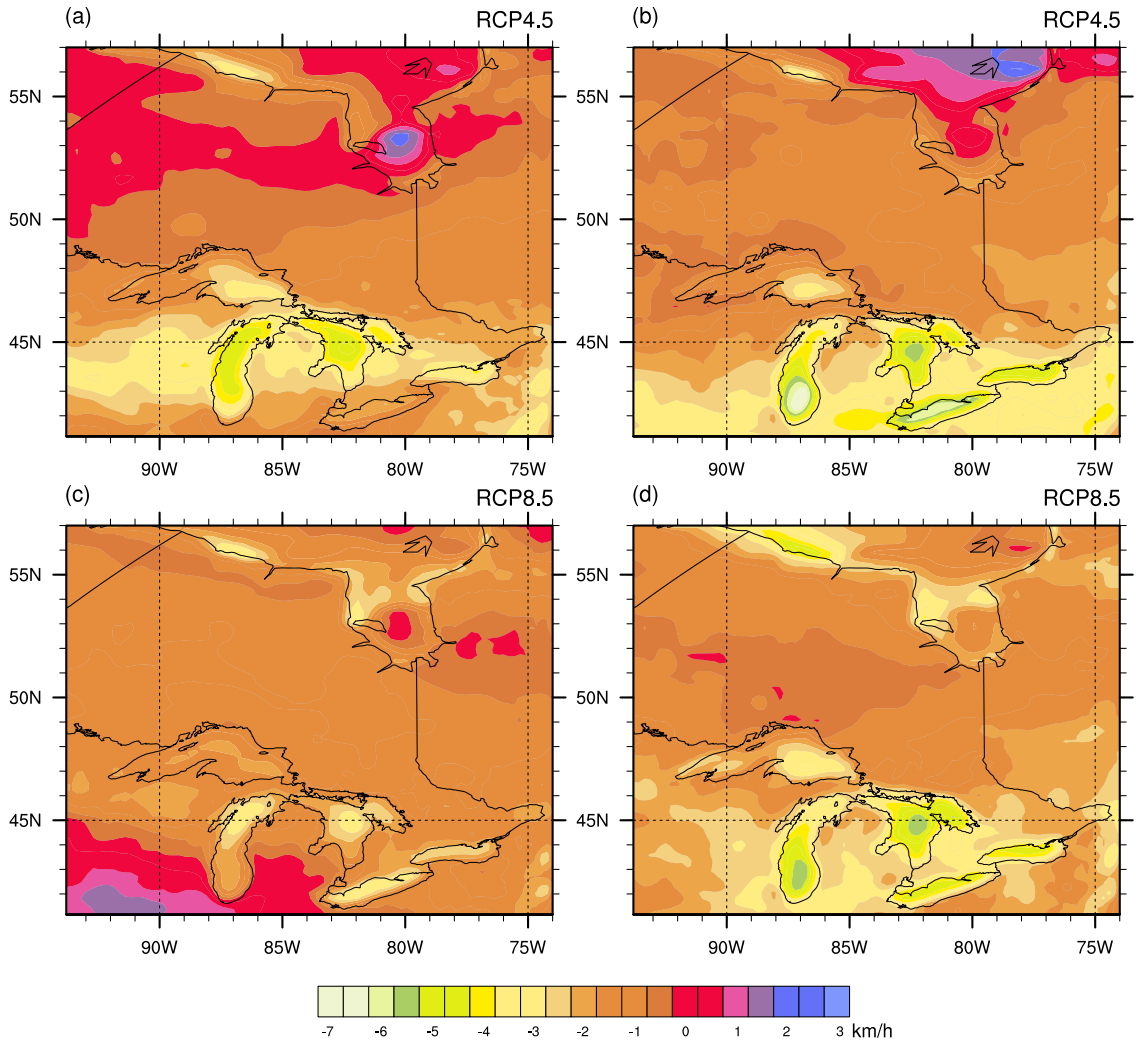

Fig. 8. Projected changes in annual mean wind speed (unit: km/h) under RCP4.5 and RCP8.5 for the 2050s and the 2080s relative to the baseline period.

any policy-driven incentives. Climate warming will alter the energy consumption patterns of residential and commercial end-users and, therefore, make energy providers install more electricity-type energy capacity and cut down the gas energy supply. Considering that Ontario's future electricity supply will be limited to nuclear, hydro, wind, and solar energy sectors, climate change could promote the development of green energy capacity (especially for solar power and offshore wind energy in terms of their increased sources) in Ontario. Combined with the large reduction in gas consumption caused by rapidly warming winter, the proportion of green energy to total energy capacity is expecting to be higher in the future than before.

7. Conclusions

This study is the first attempt to employ an RCM to assess the long-term climate change impacts on the energy capacity planning over Ontario with consideration of all concerning climatic variables. With a plausible range of future climates generated under two RCPs to capture region-specific energy responses to climate change at a fine spatial resolution, the changes in cooling and heating degree days are calculated for residential and commercial buildings. Results indicate that winter warms more rapidly than summer in Ontario. This leads to heating degree days decreasing 2 times faster than cooling degree days increasing. By converting the absolute change in degree days into the percentage change, we find that there are a 297% increase in CDD and only a 24% decrease in HDD under RCP8.5 for the 2080s relative to their corresponding historical values. Changes in degree days result in an increase in summer electricity demand and a reduction in winter gas consumption. Because that winter space heating solely relies on the gas energy, Ontario will expect a reduction in natural gas capacity installation without policy-driven incentives. The efficiency of nuclear power is sensitive to the temperature rise, but relatively less reduced compared to hydro and wind energy. Nuclear energy will be capable of providing the uninterrupted energy supply without

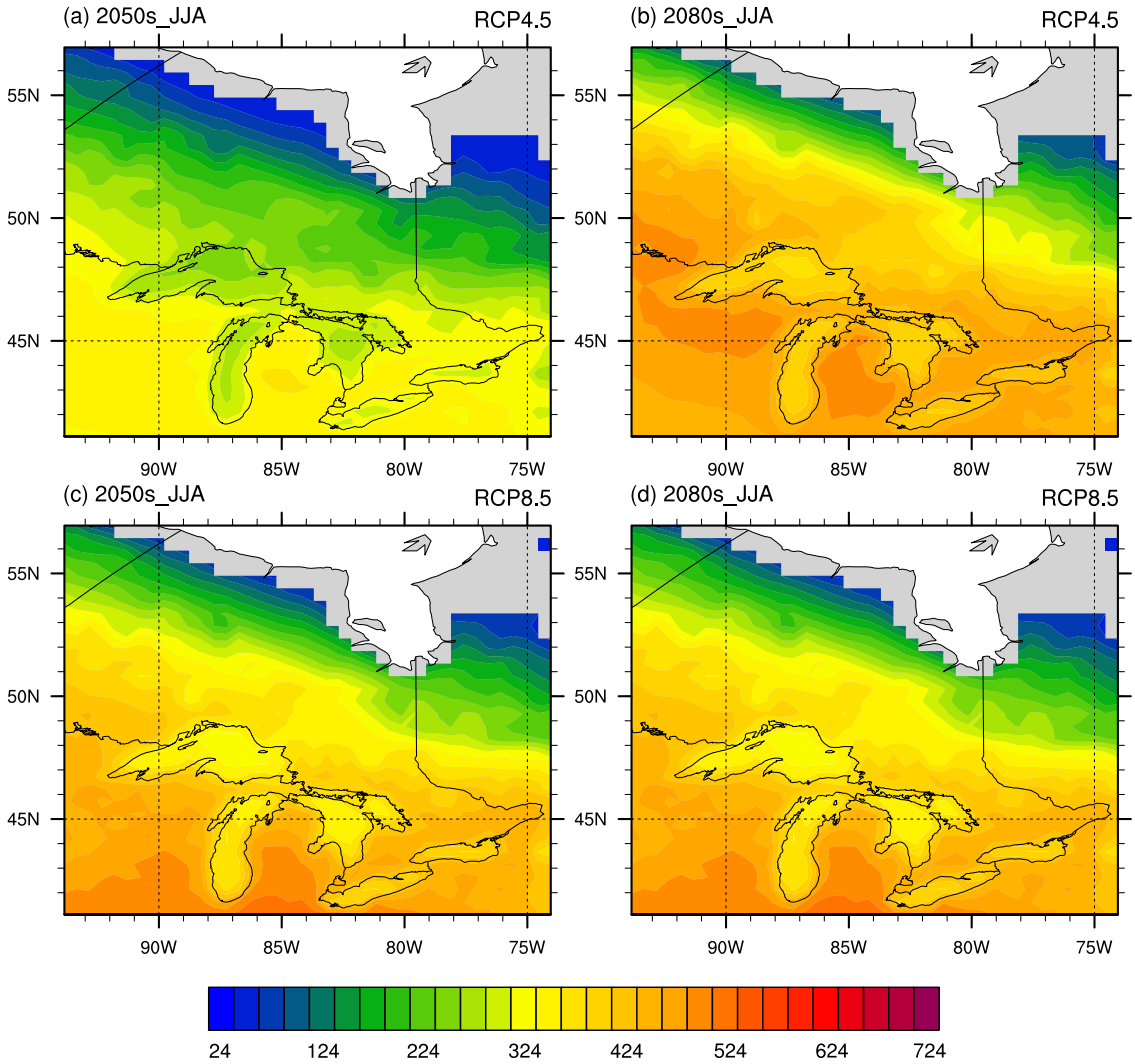

Fig. 9. Projected changes in summer mean CDD (unit: °C) under RCP4.5 and RCP8.5 for the 2050s and the 2080s relative to the baseline period.

capacity expansion, which can cause a little increase in energy investment. With more sensitivity to climate change than the nuclear power sector, the hydropower sector will experience lower generation because of a decline in the streamflows caused by reduced precipitation. The costs to maintain the proportional hydropower supply will be higher than the costs from the reference period with lower power generation. Wind energy generation at the shorelines of Great Lakes is estimated to decrease by more than 20%. We have concluded that more green energy capacity will be installed in Ontario to deal with dramatically increasing electricity demand triggered by climate warming trends. The proportion of green energy to total capacity will continue to grow with the reduction in gas consumption caused by rapidly warming winter.

In contrast, the growth potential of offshore wind energy availability is much larger than onshore production under two RCPs for both periods. It implies that the decreasing energy availability in the wind energy sector can be reversed to a certain extent by reasonably choosing the deployed locations of wind farms from onshore to offshore. In opposite, the solar energy production within an optimal temperature range may benefit from climate change for the decreased number of rainy and cloudy days. Hence, the costs per kWh for solar energy is expected to become less with the increased solar to electricity generation for current installed solar capacity. With the increased electricity demand, the decreased costs for solar energy, and the reduced availability of water and wind resources, more green energy capacities are expected to build to ensure the long-term energy security for Ontario. Combined with a considerable reduction in gas consumption caused by rapidly warming winter, the proportion of green energy to total energy capacity is expected to become higher in the future than before in Ontario. The results of this work also show that considerable investment will be required to provide adequate electricity generation capacity for Ontario under climate change conditions for the critical periods.

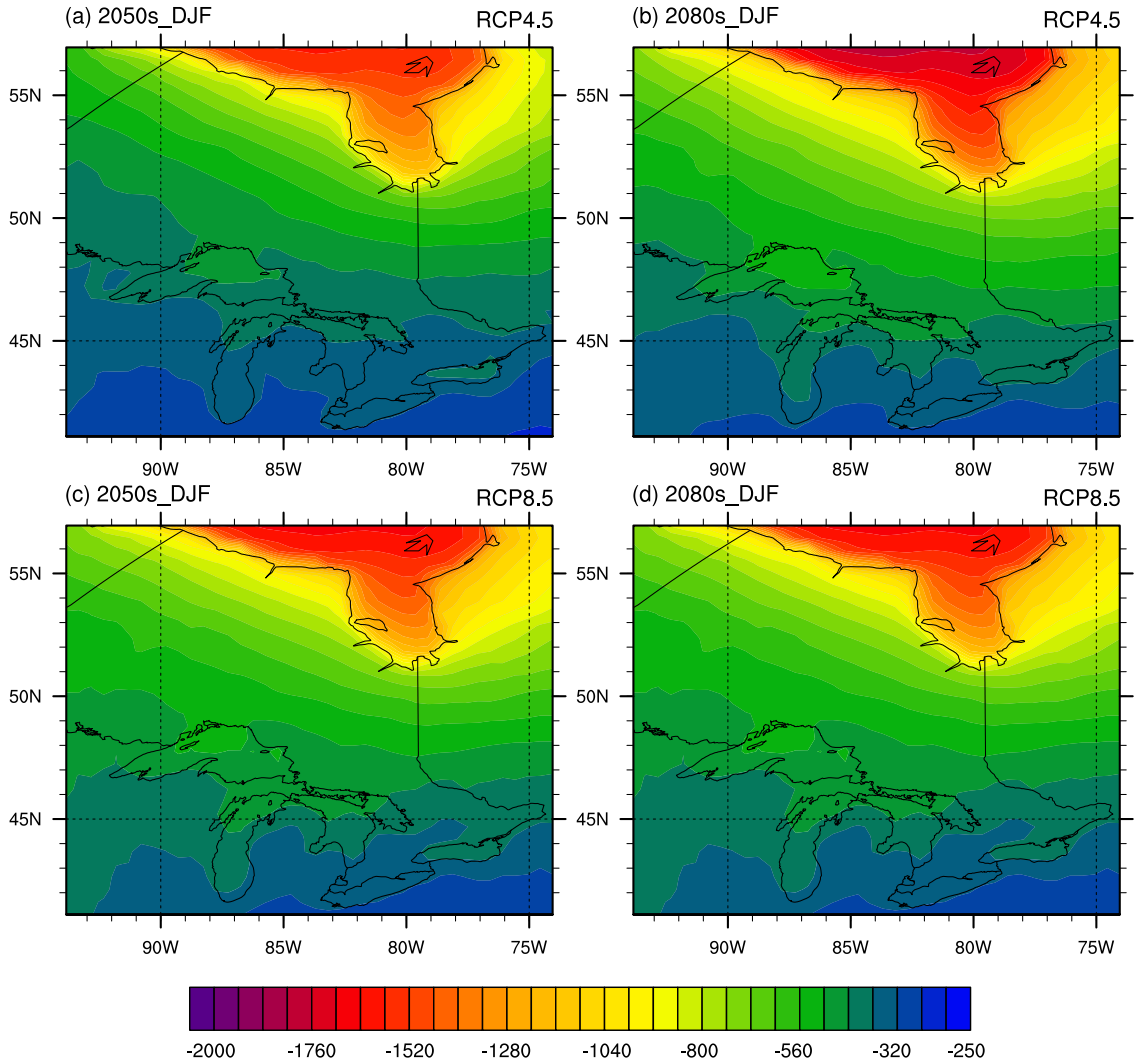

Fig. 10. Projected changes in winter mean HDD (unit: °C) under RCP4.5 and RCP8.5 for the 2050s and the 2080s relative to the baseline period.

Table 1
Predicted percentage changes in wind power over onshore and offshore under RCP4.5 and RCP8.5 for two periods.

Wind Resources Changes		2050s		2080s	
		RCP4.5	RCP8.5	RCP4.5	RCP8.5
Great Lakes	Onshore	−41%	−20%	−51%	−34%
	Offshore	19%	95%	−6%	9%
Hudson Bay	Onshore	82%	26%	44%	12%
	Offshore	218%	146%	180%	135%

Table 2
Predicted supply gaps and capacity expansion needs for energy sectors.

		Supply Gap	Capacity Expansion			
			Nuclear	Hydro	Wind (offshore)	Solar
2050s	RCP4.5	61%	47%	63%	89%	−11%
	RCP8.5	79%	60%	140%	135%	−28%
2080s	RCP4.5	192%	148%	203%	194%	−34%
	RCP8.5	331%	266%	409%	332%	−57%

CRediT authorship contribution statement

Shuo Wang: Formal analysis, Writing - original draft. **Jinxin Zhu:** Formal analysis, Writing - original draft. **Gordon Huang:** Writing - original draft. **Brian Baetz:** Writing - original draft. **Guanhui Cheng:** Writing - review & editing. **Xueting Zeng:** Writing - review & editing. **Xiuquan Wang:** Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We thank the anonymous reviewers and the editor for their valuable comments on this manuscript. This research was supported by the China Scholarship Council, the National Natural Science Foundation of China (Grant No. 51809223), the Hong Kong Polytechnic University Start-up Grant (Grant No. 1-ZE8S), and the Natural Science and Engineering Research Council of Canada. Readers can find the data that support or underlie the conclusions presented in the Climate Change Data Portal for Ontario (http://ontarioccdp.ca/). We have no conflicts of interest to disclose.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2020.123026.

References

Abebe, D., 2010. Future Climate of Ethiopia from PRECIS Regional Climate Model Experimental Design. Met Office Hadley Centre. http://www.metoffice.gov.uk/binaries/content/assets/mohippo/pdf/o/9/precis_experimental_design_dawit.pdf.

AHCCD, 2013. Adjusted and Homogenized Canadian Climate Data. Government of Canada. http://www.ec.gc.ca/dccha-ahccd/default.asp?lang=En&n=B1F8423A-1.

Amato, A., Ruth, M., Kirshen, P., 2005. Regional energy demand responses to climate change: methodology and application to the commonwealth of Massachusetts. Clim. Chg. 71, 175. https://doi.org/10.1007/s10584-005-5931-2.

Breslow, B., Sailor, D., 2002. Vulnerability of wind power resources to climate change in the continental United States. Renew. Energy 27 (4), 585–598. https://doi.org/10.1016/S0960-1481(01)00110-0.

Canada Energy Regulator, 2017. Canada's Renewable Power Landscape 2017 – Energy Market Analysis. https://www.cer-rec.gc.ca/nrg/sttstc/lctrct/rprt/2017cndrnwblpwr/prvnc/on-eng.html?=undefined&wbdisable=true.

Canwea, 2017. Building a Stronger, Cleaner and More Affordable Power System in Ontario. Canadian Wind Energy Association. http://canwea.ca/wind-energy/ontario/.

Chen, C.W., Herr, J., Weintraub, L., 2001. Watershed Analysis Risk Management Framework (WARMF): Update One – A Decision Support System for Watershed Analysis and Total Maximum Daily Load Calculation, Allocation and Implementation. Publication No. 1005181. Electric Power Research Institute, Palo Alto, CA.

Cheng, G.H., Huang, G., Dong, C., Zhou, X., Zhu, J.X., Xu, Y., 2017a. Climate classification through recursive multivariate statistical inferences: a case study of the athabasca river basin, Canada. Int. J. Climatol. https://doi.org/10.1002/joc.5052.

Cheng, G.H., Huang, G., Dong, C., Zhu, J.X., Zhou, X., Yao, Y., 2017b. High-resolution projections of 21st century climate over the Athabasca River Basin through an integrated evaluation-classification-downscaling-based climate projection framework. J. Geophys. Res. Atmos. 122 https://doi.org/10.1002/2016JD026158.

Chiotti, Q., Lavender, B., 2008. In: Lemmen, D.S., Warren, F.J., Lacroix, J., Bush, E. (Eds.), Ontario; in from Impacts to Adaptation: Canada in a Changing Climate 2007. Government of Canada, Ottawa, ON, pp. 227–274.

Christensen, J.H., et al., 2007. Regional climate projections. In: Solomon, S., et al. (Eds.), Climate Change 2007: the Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge Univ. Press, Cambridge, U. K., and New York, pp. 847–940.

Colette, A., Vautard, R., Vrac, M., 2012. Regional climate downscaling with prior statistical correction of the global climate forcing. Geophys. Res. Lett. 39, L13707. https://doi.org/10.1029/2012GL052258.

Collins, W., Bellouin, N., Doutriaux-Boucher, M., Gedney, N., Hinton, T., Jones, C., Liddicoat, S., Martin, G., O'Connor, F., Rae, J., Senior, C., Totterdell, I., Woodward, S., Reichler, T., Kim, J., 2008. Evaluation of the HadGEM2 Model. Met Office Hadley Centre Technical Note no. HCTN 74 available fromMet Office, FitzRoy Road, Exeter. http://www.metoffice.gov.uk/publications/HCTN/index.html.

Data Catalogue, 2016. The Ontario Energy Report Provides an Up-To-Date Snapshot of Ontario's Energy Sector. Energy Data Catalogue Fourth Quarter 2016. https://www.ontarioenergyreport.ca/data-catalogue.php.

Fiebrich, C.A., Crawford, K.C., 2001. The impact of unique meteorological phenomena detected by the Oklahoma mesonet and ARS micronet on automated quality control. Bull. Am. Meteorol. Soc. 82, 2173–2187.

Flato, G., et al., 2013. Evaluation of climate models. In: Stocker, T.F., et al. (Eds.), Climate Change 2013: the Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge Univ. Press, Cambridge, U. K., and New York, pp. 741–866.

Giorgi, F., 2006. Regional climate modeling: status and perspectives. J. Phys. IV 139, 101–118. https://doi.org/10.1051/jp4:2006139008.

Giorgi, F., Mearns, L.O., 1991. Approaches to the simulation of regional climate change: a review. Rev. Geophys. 29, 191–216. https://doi.org/10.1029/90RG02636.

Hamlet, A., Lee, S., Mickelson, K., Elsner, M., 2010. Effects of projected climate change on energy supply and demand in the Pacific Northwest and Washington State. Clim. Chg. 102, 103–128. https://doi.org/10.1007/s10584-010-9857-y.

Harris, I., Jones, P.D., Osborn, T.J., Lister, D.H., 2014. Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. Int. J. Climatol. 34, 623–642. https://doi.org/10.1002/joc.3711.

Hartmann, D.L., et al., 2013. Observations: atmosphere and surface. In: Stocker, T.F., et al. (Eds.), Climate Change 2013: the Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge Univ. Press, Cambridge, U. K., and New York, pp. 159–254.

Hewitson, B., Janetos, A.C., Carter, T.R., Giorgi, F., Jones, R.G., Kwon, W.-T., Mearns, L.O., Schipper, E.L.F., van Aalst, M., 2014. Regional context. In: Barros, V.R., et al. (Eds.), Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge Univ. Press, Cambridge, U. K., and New York, pp. 1133–1197.

Jones, R., Noguer, M., Hassell, D., Hudson, D., Wilson, S., Jenkins, G., Mitchell, J., 2004. Generating High Resolution Climate Change Scenarios Using PRECIS. Met Office Hadley Centre, Exeter, UK, p. 40. April 2004.

Liang, X.Z., Kunkel, K.E., Meehl, G.A., Jones, R.G., Wang, J.X., 2008. Regional climate models downscaling analysis of general circulation models present climate biases propagation into future change projections. Geophys. Res. Lett. 35, L08709. https://doi.org/10.1029/2007GL032849.

Linnerud, K., Mideksa, T., Eskeland, G., 2011. The impact of climate change on nuclear power supply. Energy J. 32 (1), 149–168.

Liu, Y., Cai, Y.P., Yang, Z.F., Tan, Q., Lin, X., 2016. Identification of optimal recourse strategies for power generation under a government-guided coal-pricing mechanism in north China. Int. J. Electr. Power Energy Syst. 79, 210–227. https://doi.org/10.1016/j.ijepes.2015.12.011.

Manwell, J., McGowan, J., Rogers, A., 2009. Wind turbine design and testing. In: Wind Energy Explained. John Wiley & Sons, Ltd, Hoboken, New Jersey, United States, pp. 311–357.

Mirasgedis, S., Sarafidis, Y., Georgopoulou, E., Lalas, D.P., Moschovits, M., Karagiannis, F., Papakonstantinou, D., 2006. Models for mid-term electricity demand forecasting incorporating weather influences. Energy 31, 208–227. https://doi.org/10.1016/j.energy.2005.02.016.

Meng, Q., Mourshed, M., Wei, S., 2018. Going Beyond the Mean: Distributional Degree-Day Base Temperatures for Building Energy Analytics Using Change Point Quantile Regression. IEEE Access 6, 39532–39540. https://doi.org/10.1109/ACCESS.2018.2852478.

Mirasgedis, S., Sarafidis, Y., Georgopoulou, E., Kotroni, V., Lagouvardos, K., Lalas, D.P., 2007. Modeling framework for estimating impacts of climate change on electricity demand at regional level: case of Greece. Energy Convers. Manag. 48 (5), 1737–1750. https://doi.org/10.1016/j.enconman.2006.10.022.

Moral-Carcedo, J., Vicens-Otero, J., 2005. Modeling the non-linear response of Spanish electricity demand to temperature variations. Energy Econ. 27, 477–494. https://doi.org/10.1016/j.eneco.2005.01.003.

Moss, R.H., et al., 2010. The next generation of scenarios for climate change research and assessment. Nature 463 (7282), 747–756. https://doi.org/10.1038/nature08823.

Pardo, A., Meneu, V., Valor, E., 2002. Temperature and seasonality influences on Spanish electricity load. Energy Econ. 24, 55–70. https://doi.org/10.1016/S0140-9883(01)00082-2.

Racherla, P.N., Shindell, D.T., Faluvegi, G.S., 2012. The added value to global model projections of climate change by dynamical downscaling: a case study over the continental U.S. using the GISS-ModelE2 and WRF models. J. Geophys. Res. 117, D20118. https://doi.org/10.1029/2012JD018091.

Robinson, P., 1997. Modeling utility load and temperature relationships for use with long-lead forecasts. J. Appl. Meteorol. 36, 591–598. https://doi.org/10.1175/1520-0450(1997)036<0591:MULATR>2.0.CO;2.

Scapin, S., Apadula, F., Brunetti, M., Maugeri, M., 2014. A preliminary approach to estimate the impact of climate change on electricity demand in Italy. In: Proceedings of the Second Annual Conference of the Italian Society for the Climate Sciences, Climate Change: Scenarios, Impact and Policy, Venice, ISBN 978-88-97666-04-2.
Shafer, M.A., Fiebrich, C.A., Arndt, D.S., Fredrickson, S.E., Hughes, T.W., 2000. Quality assurance procedures in the Oklahoma mesonetwork. J. Atmos. Ocean. Technol. 17, 474–494.
Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. Bull. Am. Meteorol. Soc. 93, 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1.
Vicuna, S., Leonardson, R., Hanemann, M.W., 2008. Climate change impacts on high elevation hydropower generation in California's Sierra Nevada: a case study in the Upper American River. Climatic Change 87, 123. https://doi.org/10.1007/s10584-007-9365-x.
Van Vuuren, D.P., et al., 2011. The representative concentration pathways: an overview. Climatic Change 109, 5–31. https://doi.org/10.1007/s10584-011-0148-z.
Wang, X., Huang, G., Liu, J., 2014. Projected increases in near-surface air temperature over Ontario, Canada: a regional climate modeling approach. Clim. Dynam. https://doi.org/10.1007/s00382-014-2387-y.
Wang, X., Huang, G., Lin, Q., Nie, X., Liu, J., 2015a. High-resolution temperature and precipitation projections over Ontario, Canada: a coupled dynamical-statistical approach. Q. J. R. Meteorol. Soc. 141, 1137–1146. https://doi.org/10.1002/qj.2421.
Wang, X., Huang, G., Liu, J., 2015b. Twenty-first century probabilistic projections of precipitation over Ontario, Canada through a regional climate model ensemble. Clim. Dynam. 46, 3979. https://doi.org/10.1007/s00382-015-2816-6.
Wang, B., Cai, Y.P., Yin, X., Tan, Q., Hao, Y., 2017. An integrated approach of system dynamics, orthogonal experimental design and inexact optimization for supporting water resources management under uncertainty. Water Resour. Manag. 31, 1665–1694. https://doi.org/10.1007/s11269-017-1608-7.
Wang, S., Ancell, B.C., Huang, G.H., Baetz, B.W., 2018. Improving robustness of hydrologic ensemble predictions through probabilistic pre- and post-processing in sequential data assimilation. Water Resour. Res. 54, 2129–2151.
Wilby, R., Charles, S., Zorita, E., Timbal, B., Whetton, P., Mearns, L., 2004. Guidelines for Use of Climate Scenarios Developed from Statistical Downscaling Methods.
Wilson, W., Hassell, D., Hein, D., Wang, C., Tucker, S., Jones, R., Taylor, R., 2015. Technical Manual for PRECIS: the Met Office Hadley Centre Regional Climate Modelling System, Version 2.0.0. www.metoffice.gov.uk/precis.
WNA, 2017. Nuclear Power in Canada. World Nuclear Association. http://www.world-nuclear.org/information-library/country-profiles/countries-a-f/canada-nuclear-power.aspx.
Yao, Y., Huang, G., Lin, Q., 2012. Climate change impacts on Ontario wind power resource. Env. Sys. Res. 1, 2. https://doi.org/10.1186/2193-2697-1-2.
Zhou, Y., et al., 2014. Modeling the effects of climate change on U.S. state-level buildings energy demands in an integrated assessment framework. Appl. Energy 113, 1077–1088. https://doi.org/10.1016/j.apenergy.2013.08.034.

Abbreviations List

GEA: Green Energy Act
GCMs: Global Climate Models
RCM: Regional Climate Model
RCPs: Representative Concentration Pathways
PRECIS: Providing REgional Climate Impacts for Studies
HadGEM2-ES: Hadley Centre Global Environment Model version 2-Earth Systems
CRU: Climate Research Unit
WARMF: Watershed Analysis Risk Management Framework
JJA: June, July, and August
DJF: December, January, and February
CDD: Cooling Degree Day
HDD: Heating Degree Day