Bayesian model averaging of the RegCM temperature projections: a Canadian case study

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ABSTRACT

The choices of physical schemes coupled in the regional climate model (RegCM), the input general circulation model (GCM) results, and the emission scenarios may cause considerable uncertainties in future temperature projections. Therefore, the ensemble approach, which can be used to reflect these uncertainties, is highly desired. In this study, the probabilistic projections for future temperature are generated at 88 Canadian climate stations based on the developed RegCM ensemble and obtained Bayesian model averaging (BMA) weights. The BMA weights indicate that the RegCM coupled with the holtslag PBL scheme driven by the HadGEM can provide relatively reliable temperature projections at most climate stations. It is also suggested that the BMA approach is effective in simulating temperature over middle and eastern Canada through taking the advantage of each ensemble member. However, the effectiveness of the BMA method is limited when all the models in the ensemble cannot simulate the temperature robustly. The projected results demonstrate that the temperature will increase continuously in the future, while the temperature increase under RCP8.5 will be significantly larger than that under RCP4.5.

Key words: BMA, Canada, ensemble projections, RegCM, temperature

HIGHLIGHTS

• The RegCM simulations coupled with different PBL schemes driven by multiple GCMs have been conducted.
• The probabilistic projections for future temperature are generated at climate stations over Canada through the Bayesian model averaging method.
• The temperature will increase continuously in the future, and the temperature increase under RCP8.5 scenario would be significantly larger than that under RCP4.5 scenario.

1. INTRODUCTION

With the increasing level of greenhouse gas emissions all over the world, considerable temperature changes will be observed in the future, leading to a series of severe consequences (IPCC 2014; Karimi et al. 2020; Li et al. 2020; Shrestha & Wang 2020). For example, the increased ocean temperature may cause the glacier retreat and sea-level rise to some extent (Slangen et al. 2014). Assessing the potential influences caused by temperature changes is thus important for the policy-making of adaptation actions (Yu et al. 2020; Zhou & Li 2020). However, since the temperature simulations are affected by the local detailed geographical features (e.g., landcover) significantly, reliable temperature projections at a regional scale are highly desired.

Regional climate models (RCMs) are widely used to generate regional-scale climate projections (Giorgi 2019). There are three commonly used RCMs: Regional Climate Model (RegCM), Providing Regional Climates for Impacts Studies (PRECIS) model, and Weather Research and Forecasting (WRF) model. Since the effectiveness of RegCM has been validated...
through a number of previous studies (Kim et al. 2017; Lu et al. 2019), and the choices of physical schemes coupled in RegCM have been investigated thoroughly (Song et al. 2020), it has been selected in this study.

It is well known that there exist multiple uncertainties from varied sources in the RegCM modeling system, which includes the outputs of general circulation models (GCMs), physical schemes coupled within the RegCM, and emission scenarios. In order to reflect these uncertainties, the ensemble projections of future temperature are more encouraged. In recent years, the Bayesian model averaging (BMA) algorithm has been extensively applied in hydroclimate ensemble projections (Raftery et al. 2005). For example, Alinezhad et al. (2021) introduced the BMA method for weighting the hydrologic results and the GCMs based on their capabilities of simulating the historical period; Strazzo et al. (2019) applied the BMA approach to yield optimal forecasts of temperature and precipitation on the basis of pre-developed bridging and calibration models; Ma et al. (2018) proposed a framework for integrating multiple satellite precipitation data through the dynamic BMA method.

To date, most of previous BMA applications over Canada only considered the uncertainties from individual aspects (e.g., input datasets), and few of them took the interactive uncertainties from input GCMs, physical schemes coupled in the RegCM, and emission scenarios into consideration.

Therefore, the objective of this study is to generate the BMA probabilistic projections of future temperature over Canada based on the developed RCM ensemble. In detail, the RCM ensemble will be developed on the basis of four RegCM simulations with different GCMs and physical schemes during one historical period (i.e., 1996–2005) and three future periods (i.e., 2030–2039, 2060–2069, 2090–2099) under two emission scenarios (i.e., RCP4.5 and RCP8.5). Then the BMA weights, which measure the relative importance of each ensemble member, will be obtained through the BMA algorithm according to the simulation results and observation data in the historical period. On this basis, the probabilistic projections of future temperature will be generated at 88 climate stations over Canada.

2. DATA AND METHOD

Multiple uncertainties from a variety of sources (e.g., initial and boundary conditions, model selection, and configuration) coexist in the climate system. In this study, the BMA method is applied to generate the probabilistic projections of future temperature to reflect these uncertainties. The general framework of this study is shown in Figure 1.

2.1. Development of the RCM ensemble

Regional climate models (RCMs) are considered effective in projecting future climate change with detailed regional information (Wang et al. 2014). In this study, the Regional Climate Model version 4.6 (RegCM 4.6) developed by the International Center for Theoretical Physics (ICTP), which is one of the most commonly used RCMs, is employed to generate future temperature projections over Canada (Giorgi et al. 2012). The RegCM simulations are conducted at 18 vertical sigma layers through the hydrostatic core with a 50-km horizontal resolution. As indicated by previous studies, the temperature projections are influenced by the planetary boundary layer (PBL) scheme significantly (Song et al. 2020). In addition, different choices of GCMs may cause considerable uncertainties in future temperature projections (Christensen & Kjellström 2020). Therefore, a $2 \times 2$ RCM ensemble with two different PBLs (i.e., University of Washington PBL (UW PBL) and Holtslag PBL)
and two different GCMs (i.e., Hadley Centre climate model (HadGEM) and Geophysical Fluid Dynamics Laboratory Climate Model (GFDL)) will be developed in this study (Holtslag et al. 1990; Bretherton et al. 2004; Collins et al. 2011; Delworth et al. 2012). The selected GCMs are commonly used as the inputs of RegCM, while their applicability has been validated through a series of previous studies (Lu et al. 2019; Sawadogo et al. 2020). Other physical schemes used in this study include: Community Land Model version 4.5, Explicit moisture (SUBEX) scheme, Coare bulk flux algorithm, and Kain–Fritsch scheme (Pal et al. 2000; Fairall et al. 2003; Kain & Kain 2004; Lawrence et al. 2011).

The RegCM simulations are conducted during one historical period (i.e., 1996–2005) and three future periods (i.e., 2030–2039, 2060–2069, and 2090–2099). Due to the limitation of simulation time, the projections of 2030–2039, 2060–2069, and 2090–2099 are used to represent the early-, mid-, and far-future climate, respectively. The observation data used in this study are downloaded from Environment and Natural Resources Canada (https://climate.weather.gc.ca/historical_data/search_historic_data_e.html). Eighty-eight climate stations with comparatively few missing data (less than 5%) are selected, while their locations are presented in Figure 2. The moving median method is applied to fill the missing values. In order to match the simulation results with the observation data, the simulated outputs are downscaled to 88 climate stations based on the geophysical distance.

2.2. BMA method

The BMA method is an effective ensemble approach, which has been extensively used in generating probabilistic projections of future climate for reflecting the uncertainties that existed in the climate system (Raftery et al. 2005; Duan et al. 2007). The BMA approach can be expressed as follows briefly.

There exist $n$ members in the RCM ensemble, and the simulation results of $i$th ensemble member can be described as $S_i = [s_{i1}, s_{i2}, ..., s_{ij}]$, where $j$ denotes the number of climate stations. Correspondingly, the observed data can be expressed as $Obs = [o_1, o_2, ..., o_j]$. Consider that $Y = [y_1, y_2, ..., y_j]$ is the predicted climate variable at station $j$. Based on the total

![Figure 2](https://example.com/figure2.png)
probability law, the BMA probabilistic projections of \( Y \) can be formulated as:

\[ p(Y|\text{Obs}) = \sum_{i=1}^{n} p(S_i|\text{Obs}) \cdot p(Y|\text{Obs}, S_i) \tag{1} \]

\[ \sum_{i=1}^{n} p(S_i|\text{Obs}) = 1 \tag{2} \]

where \( w_i = p(S_i | \text{Obs}) \) denotes the BMA weight of ensemble member \( i \), which measures the similarity of the simulation results and observation datasets; the \( p_i(Y | \text{Obs}, S_i) \) means the posterior distribution of \( Y \) when the simulation results \( S_i \) and observation dataset \( \text{Obs} \) are known. Then, the expected value and variance of BMA probabilistic projection can be summarized as:

\[ E(Y|\text{Obs}) = \sum_{i=1}^{n} p(S_i|\text{Obs}) \cdot E(Y|\text{Obs}, S_i) = \sum_{i=1}^{n} w_i S_i \tag{3} \]

\[ \text{Var}(Y|\text{Obs}) = \sum_{i=1}^{n} w_i \left( S_i - \sum_{j=1}^{n} w_j S_j \right)^2 + \sum_{i=1}^{n} w_i \sigma_i^2 \tag{4} \]

where \( \sigma_i^2 \) is the variance of the result simulated by model \( i \) with respect to the observation dataset; \( \sum_{i=1}^{n} w_i \left( S_i - \sum_{j=1}^{n} w_j S_j \right)^2 \) denotes the variance among different ensemble members, while the \( \sum_{i=1}^{n} w_i \sigma_i^2 \) represents the variance within a single ensemble member.

The conditional distribution \( p_i(Y | \text{Obs}, S_i) \) is assumed to be Gaussian in BMA algorithm. However, the simulation results are not subject to Gaussian distribution on some occasions. Therefore, the Box–Cox transformation approach is employed in this study (Sakia 1992). The core algorithm of the Box–Cox approach is summarized in the following equation:

\[ d_k^i = \begin{cases} \frac{(d_k + \lambda_2 \epsilon)^{\lambda_1} - 1}{\lambda_1} & \lambda_1 \neq 0 \\ \ln (d_k + \lambda_2) & \lambda_1 = 0 \end{cases} \tag{5} \]

where \(-\lambda_2 \epsilon \) is the minimum value of the dataset \((d_k)\), and the \( \epsilon \) is the infinitely small positive number; \( \lambda_1 \) is the coefficient of Box–Cox transformation approach. Through this transformation, the transformed data are close to the Gaussian distribution.

Since it is quite difficult to obtain the analytical solution of parameter set \( \theta = \{ w_i, \sigma_i, i = 1, 2, \ldots, n \} \), which can maximize the log-likelihood function (Equation (6)), the Expectation–Maximization (EM) method is applied.

\[ l(\theta) = \log \left( \sum_{i=1}^{n} w_i \cdot p_i(Y|\text{Obs}, S_i) \right) \tag{6} \]

The detailed procedure of EM algorithm can be described as follows:

**Step 1**: Initialization. Let \( t = 0 \), \( w_i(t) = 1/n, \sigma_i^2(t) = 1/J \sum_{j=1}^{J} \left( \sum_{i=1}^{n} (\text{Obs}_j - S_i)^2 \right) / J \), where \( J \) is the number of climate stations.

Then calculate \( \dot{\theta}(t) = \log \left( \sum_{i=1}^{n} w_i \cdot \sum_{j=1}^{J} g(\text{Obs}_j | S_i, \sigma_i(t) ) \right) \), where \( g(x) \) represents the normal distribution. It is worth mentioning that the prior probability of each ensemble member is assumed to be equal.

**Step 2**: Expectation step. Let \( t = t + 1 \), for \( i = 1, 2, \ldots, n \), and \( j = 1, 2, \ldots, J \), the \( z_i(t) = g(Y_j | S_i, \sigma(t-1)) / \sum_{i=1}^{n} g(\text{Obs}_j | S_i, \sigma(t-1)) \).

**Step 3**: Maximization step. Update the weight: \( w_i(t) = 1/J \sum_{j=1}^{J} z_i(t) \); update the variance: \( \sigma_i^2(t) = \sum_{j=1}^{J} z_i(t) \cdot (\text{Obs}_j - S_i)^2 / \sum_{j=1}^{J} z_i(t) \); then update the likelihood.

**Step 4**: Convergence check. If \( l(\theta(t)) - l(\theta(t - 1)) < \delta \), stop; else go back to step 1, where \( \delta \) is the pre-defined tolerance level.

The advantages of the proposed framework can be summarized as: (1) it can reflect the various uncertainties in the climate system through generating probabilistic projections of future climate rather than deterministic predicted values; (2) compared with GCM ensembles, it is based on a RCM ensemble, which can provide more detailed information of local climate; (3) the statistical downscaling technique makes it possible to match the grid-scale simulation results with station-scale observation data.
3. RESULTS ANALYSIS

3.1. Uncertainties in future temperature projections

Based on the results of the $2 \times 2$ RCM ensemble (specified in Section 2), the simulated differences for three temperature variables (i.e., mean temperature, maximum temperature, and minimum temperature) at 88 climate stations (presented in Figure 2) are calculated through the following equation:

\[ S_{\text{diff}} = S_{\text{max}} - S_{\text{min}} \]  

(7)

where $S_{\text{max}}$ and $S_{\text{min}}$ represent the maximum and minimum values of the simulation results within the RCM ensemble, respectively.

The simulated differences of annual and seasonal mean temperature are presented in Figure 3. (The corresponding results of maximum temperature and minimum temperature are shown in Supplementary Figure S1 and Figure S2, respectively.) The results suggest that there exist significant modeling uncertainties in future temperature projections. For example, the spatial average simulated difference of spring mean temperature at the end of 21 century under RCP8.5 is 6.63 °C. Moreover, the uncertainties of future temperature projections will increase over time. In detail, the spatial average simulated differences of annual mean temperature under RCP8.5 are 4.82, 6.03, and 6.31 °C in 2030–2039, 2060–2069, and 2090–2099, respectively.

In addition, the spatial variations of the simulated differences for mean temperature, maximum temperature, and minimum temperature are also non-negligible (Figure 4, the corresponding results of maximum temperature and minimum temperature are presented in Supplementary Figure S3 and Figure S4, respectively). Specifically, the simulated differences in the middle region of the study area are the largest, reaching approximately 10 °C in 2090–2099 under RCP4.5.

In summary, since there exist considerable modeling uncertainties in future temperature projections, generating probabilistic projections based on the RCM ensemble is highly important. In the following sections, the validation results of the BMA algorithm and the projected changes of future temperature will be discussed in detail.

Figure 3 | Simulated differences in the annual and seasonal mean temperatures. (Note that the simulated differences are calculated through Equation (7). The corresponding results of maximum and minimum temperatures are presented in the Supplementary Material).
3.2. Validation of the BMA probabilistic projections

The conditional distribution $p_i(Y | \text{Obs}, S_i)$ is assumed to be Gaussian in this study, which requires that the probability distribution of temperature errors is approximately subject to Gaussian distribution. However, this condition is hard to be satisfied on most occasions. In order to address the above challenges, the Box–Cox transformation algorithm (Equation (5)) is employed in this study at all climate stations. It is worth mentioning that the parameters $\lambda_1$ and $\lambda_2$ in Equation (5) are the common optimal estimates based on both simulation results and observation data (Duan et al. 2007). The normal probability plots for one climate station (located at 45.68°N, 63.23°W) are presented in Figure 5 (selected randomly as an example), which indicate that the transformed data of both simulation results and observation data are close to normal distribution. The results for the other 87 climate stations can be obtained and interpreted similarly.

Based on the transformed data, the EM algorithm is applied to obtain the BMA weight corresponding to each ensemble member at all climate stations. The BMA weight measures the relative importance of each ensemble member and yields the above-mentioned climate station as an example (Table 1). It is suggested that the BMA weights of four ensemble members (i.e., HadGEM-UW, GFDL-UW, HadGEM-holtslag, and GFDL-holtslag) for mean temperature are 0.20, 0.15, 0.39, and 0.26, respectively. The results for maximum temperature and minimum temperature can be acquired similarly.

Table 1 only summarizes the BMA weights for one climate station, while the information for the other 87 climate stations can be calculated in the same way. The Boxplots of BMA weights for four RCM ensemble members (i.e., HadGEM-UW, GFDL-UW, HadGEM-holtslag, and GFDL-holtslag) are presented in Figure 6. In general, the mean values of BMA weights corresponding to the aforementioned four ensemble members for mean temperature are 0.20, 0.15, 0.39, and 0.26, respectively. The results for maximum temperature and minimum temperature can be acquired similarly. It is suggested that the simulated errors (i.e., simulation results – observation data) of the RegCM coupled with the holtslag PBL scheme driven by HadGEM are the smallest among the RCM ensemble. Moreover, there exists no significant difference among the BMA weights for mean temperature, maximum temperature, and minimum temperature. In addition, the BMA weights of the above-mentioned ensemble members exhibit considerable spatial variations, which are presented in Figure 7. For example, the BMA weight of HadGEM-holtslag is relatively high in southwestern regions, indicating that the RegCM coupled with the holtslag PBL scheme driven by HadGEM performs well in these regions.
Figure 5 | Normal probability plots of the transformed mean temperature data: (a) HadGEM-UW; (b) GFDL-UW; (c) HadGEM-Holtslag; (d) GFDL-Holtslag; (e) observation. (Note that this climate station is located at 45.68°N, 63.23°W, which is selected randomly as an example. The results of other climate stations can be obtained and interpreted similarly).

Table 1 | The weights obtained from the BMA algorithm for mean temperature, maximum temperature, and minimum temperature

|                | HadGEM-UW | GFDL-UW | HadGEM-holtslag | GFDL-holtslag |
|----------------|-----------|---------|-----------------|---------------|
| Mean temperature | 0.20      | 0.15    | 0.39            | 0.26          |
| Maximum temperature | 0.20      | 0.16    | 0.38            | 0.26          |
| Minimum temperature | 0.24      | 0.18    | 0.32            | 0.26          |

Note that this climate station is located at 45.68°N, 63.23°W, which is selected randomly as an example. The results of other climate stations can be obtained and interpreted similarly.

Figure 6 | BMA weights for (a) mean temperature, (b) maximum temperature, and (c) minimum temperature. (Note that the RCM1, RCM2, RCM3, and RCM4 represent HadGEM-UW, GFDL-UW, HadGEM-holtslag, and GFDL-holtslag, respectively).
According to the obtained weights, the probabilistic projections based on BMA algorithm can be generated. In order to evaluate the accuracy of the generated probabilistic projections, the $R^2$ values and simulated errors are employed in this study. In detail, the values of $R^2$ can be calculated through the following equations:

$$O = \frac{1}{T} \sum_{t=1}^{T} O_t$$

$$SS_{total} = \sum_{t=1}^{T} (O_t - \bar{O})^2$$

$$SS_{residual} = \sum_{t=1}^{T} (O_t - S_t)^2$$

$$R^2 = 1 - \frac{SS_{residual}}{SS_{total}}$$

(8)

Figure 7 | Spatial distributions of BMA weights in simulating mean temperature, maximum temperature, and minimum temperature.
where \( S_t \) represents the expected value of BMA probabilistic projection at time point \( t \), while \( O_t \) denotes the corresponding observation data. The spatial distributions of the \( R^2 \) values for BMA algorithm in simulating mean temperature, maximum temperature, and minimum temperature over the validation period are presented in Figure 8. The results demonstrate that there exist significant spatial variations in BMA performances. Specifically, the BMA method can be used to simulate the mean temperature, maximum temperature, and minimum temperature effectively in middle and eastern Canada. However, the effectiveness of the BMA approach is considered limited in western regions. One potential reason to account for that is that all the ensemble members (i.e., HadGEM-UW, GFDL-UW, HadGEM-holtslag, and GFDL-holtslag) are hard to simulate the temperature accurately in these regions. There are two possible reasons to account for it: (1) the elevation of a climate station may be significantly different from the average elevation of the corresponding grid cell, and the elevation may affect the temperature considerably; (2) the capability of RegCM in simulating coastal climate is considered limited since it has not been coupled with ocean modules. As a result, the expected values of BMA probabilistic projections are different from the observed values considerably over these areas. Therefore, it is reasonable to speculate that the effectiveness of the BMA algorithm is limited when no model in the ensemble can provide reliable temperature simulations. In addition, the spatial distributions of simulated errors, which are defined as the differences between the simulated results and observed values, are summarized in Figure 9. The results indicate that the BMA method underestimates the mean temperature, maximum temperature, and minimum temperature at almost all climate stations, especially in western regions. The primary reason is that most of models in this RCM ensemble underestimate the temperature over Canada. Since the BMA method can be interpreted as an integration of all the ensemble members based on posterior probabilities, it is hard to correct the simulated errors when all the models have the negative bias. In addition to the errors caused by the RCMs, the downscaling procedure from grid-scale simulation results to station-scale data may also cause non-negligible errors, accounting for the simulated bias to some extent.

**Figure 8** | Spatial distributions of the \( R^2 \) values for BMA algorithm in simulating: (a) mean temperature, (b) maximum temperature, and (c) minimum temperature over the validation period.

**Figure 9** | Spatial distributions of the simulated errors obtained from the BMA algorithm for: (a) mean temperature, (b) maximum temperature, and (c) minimum temperature over the validation period. (Note that the simulated errors are calculated through: Expected value of BMA – observation data).
In addition to the accuracy of the BMA probabilistic projections, the reliability of the projections also deserves detailed investigation. In this study, the reliability is defined as the coverage rate (%), which represents the percentage of confidence intervals (i.e., 50, 75, 90, and 95%) that cover the observed values (i.e., lower bound of confidence interval < observed value < upper bound of confidence interval). The coverage rates (%) of 50, 75, 90, and 95% confidence intervals for BMA probabilistic projections in simulating mean temperature, maximum temperature, and minimum temperature for all climate stations are presented in Figure 10. The results indicate that the 90% confidence intervals are capable of covering almost all the observed values, while the 50% confidence intervals can only cover approximately half of the observed values. In terms of the spatial variations, the coverage rate of BMA probabilistic projections is higher in coastal regions than that in inland areas.

In summary, based on the validation results, the BMA algorithm can take the advantage of each ensemble member for generating probabilistic projections over Canada. It is considered effective in most climate stations over middle and eastern Canada. However, the effectiveness of the BMA algorithm is limited when all the models in the RCM ensemble can not simulate the

Figure 10 | Coverage rate (%) of 50, 75, 90, and 95% confidence intervals for BMA probabilistic projections in simulating mean temperature, maximum temperature, and minimum temperature.
local temperature robustly. Moreover, the 90% confidence intervals of BMA probabilistic projections can cover almost all the observed values, indicating that the obtained probabilistic projections can be considered reliable to some extent.

3.3. Generation of the BMA probabilistic projection

Based on the obtained BMA weights and variances, the probabilistic projections for future mean temperature, maximum temperature, and minimum temperature over the 88 climate stations are generated. Due to the expensive computational costs of the RegCM, only three 10-year periods (i.e., 2030–2039, 2060–2069, and 2090–2099) are considered in this study, which represent early-, mid-, and far-future, respectively. Moreover, in order to reflect the uncertainties caused by different levels of greenhouse gas emissions, two RCP scenarios (i.e., RCP4.5 and RCP8.5) are employed in this study. The projected changes are defined as the temperature differences between the future periods and the historical period (i.e., 1996–2005). The spatial average projected changes of annual and seasonal mean temperature, maximum temperature, and minimum temperature during 2030–2039, 2060–2069, and 2090–2099 under RCP4.5 and RCP8.5 scenarios are presented in Figure 11. The results demonstrate that the mean temperature, maximum temperature, and minimum temperature will increase continuously in the future. For example, the annual temperature will grow 1.60, 3.49, and 5.61 °C during three future periods under RCP8.5 scenario, respectively. In addition, the temperature increase under RCP8.5 scenario is significantly larger than that under RCP4.5 scenario, especially at the end of the century. It is also worth mentioning that there exist no considerable differences among the four seasons with respect to temperature changes.

In addition, the spatial distributions of projected annual and seasonal mean temperature changes during 2030–2039, 2060–2069, and 2090–2099 under RCP4.5 and RCP8.5 scenarios are presented in Figure 12. Negligible spatial variations can be found in terms of the projected temperature changes. One potential reason to explain it is that almost all the climate stations considered in this study are located in southern Canada due to the limitations of available observation data. Furthermore, in order to reflect the uncertainties in future temperature projections, the confidence intervals of them in three future periods under two emission scenarios are obtained. Figure 13 presents the upper and lower bounds of 90% confidence intervals for annual mean temperature, which is selected as an example. The results indicate that there exist significant uncertainties in future temperature projections. Moreover, the magnitude of uncertainties will also increase continuously in the future, which is measured by the width of confidence intervals.

Figure 11 | Projected changes of annual and seasonal mean temperature, maximum temperature, and minimum temperature during 2030–2039, 2060–2069, and 2090–2099 under RCP4.5 and RCP8.5 scenarios. (Note that the projected temperature changes are the spatial average expected values of the BMA probabilistic projections).
4. CONCLUSION

In this study, the BMA probabilistic projections for future temperature (i.e., mean temperature, maximum temperature, and minimum temperature) are generated at 88 Canadian climate stations based on the RCM ensemble. Specifically, four RegCM simulations with different GCMs and physical schemes in one historical period (i.e., 1996–2005) and three future periods (i.e., 2030–2039, 2060–2069, 2090–2099) under two emission scenarios (i.e., RCP4.5 and RCP8.5) are conducted. The BMA weights are obtained according to the simulation results and observation data in the historical period. Then the BMA probabilistic projections for three future periods are generated using the acquired BMA weights.

The results suggest that considerable modeling uncertainties exist in future temperature projections, enhancing the significance of conducting ensemble projections. Since the BMA weights can be used to measure the relative importance of each ensemble member, the results demonstrate that the RegCM coupled with the holtslag PBL scheme driven by the HadGEM has a relatively good performance at most climate stations. Moreover, the validation results suggest that the BMA algorithm can take the advantage of each ensemble member, and it is found to be effective at most climate stations over middle and eastern Canada. From another perspective, since the 90% confidence intervals of BMA probabilistic projections can cover almost all the observed values, it can be considered as a reliable method to some extent. However, when all the models in the ensemble cannot provide robust temperature projections, the effectiveness of the BMA algorithm is considered limited. Based on the obtained BMA weights, the probabilistic projections of temperature for three future periods under two emission scenarios are generated, which suggest that the temperature will increase continuously in the future. Moreover, the temperature increase under RCP8.5 scenario is significantly larger than that under RCP4.5 scenario, especially at the end of the century.
Due to the limitation of available observation data, all the climate stations considered in this study are located at southern Canada. With the development of climate observation datasets, more climate stations can be taken into consideration in the future. In addition, this study is focused on a RegCM ensemble, which does not include other RCMs (e.g., PRECIS and WRF). How to address the interactive uncertainties from GCM, RCM, model configuration, and emission scenarios would be an interesting topic for future studies. Furthermore, the Markov chain Monte Carlo method can be used to simulate complex probability distributions, which is a strategy to conduct the BMA without Gaussian approximation.

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DATA AVAILABILITY STATEMENT
All relevant data are included in the paper or its Supplementary Information.
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