The Impact of Incorporating the Air-Lake Interaction on Quantitative Precipitation Forecasts over Southern Ontario, Canada

Zuohao Cao\textsuperscript{1}, Stéphane Bélair\textsuperscript{2}, and Da-Lin Zhang\textsuperscript{3}

\textsuperscript{1}Meteorological Research Division, Environment and Climate Change Canada, Toronto, Ontario, Canada
\textsuperscript{2}Meteorological Research Division, Environment and Climate Change Canada, Dorval, Quebec, Canada
\textsuperscript{3}Department of Atmospheric and Oceanic Science, University of Maryland, College Park, Maryland, USA

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Corresponding author: Dr. Zuohao Cao
Meteorological Research Division
Environment and Climate Change Canada
4905 Dufferin Street, Toronto
Ontario, Canada M3H 5T4
E-mail: zuohao.cao@ec.gc.ca
Tel: 416-739-4551

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Abstract

A short-range regional, two-way coupled atmosphere-ocean-ice model has been recently developed in an attempt to improve, among other things, quantitative precipitation forecasts (QPFs) over southern Ontario, Canada by incorporating air-lake interaction over the Great Lakes region. Here, we attempt to (1) assess the impact of the air-lake coupling on daily QPFs, as verified against the Canadian Precipitation Analysis and independent observations, over southern Ontario during the period of June 2016–May 2017; (2) diagnose major physical processes governing the QPF differences between the coupled and uncoupled models by relating precipitation to those processes at the air-water interface and above. Results indicate that the coupled model tends to reduce the area- and monthly-averaged daily QPF biases and standard deviations in 5 months of October, November, and December 2016, and April and May 2017, but increase and deteriorate precipitation biases during the summer months. Most of the deteriorations occur during the daytime, while improvements are observed during the nighttime (in 7 of 12 months). During the daytime, slight improvements appear in 2 months. A further diagnosis indicates that the daily QPF differences between the two models are highly correlated with the differences of their sensible and latent heat fluxes. The maximum (minimum) difference of sensible (latent) heat flux in August 2016 (December 2016) is in phase with the maximum (minimum) difference of the two-model daily QPFs. The daily QPF differences in the other months are also controlled by the differences of vertically integrated water vapor flux convergence, and surface temperature.
1. Introduction

The importance of developing a coupled atmosphere-ocean-ice system for seasonal and longer time scale weather forecasts has been recognized for many years. However, the progress in the short- to medium-range coupled prediction of precipitation is relatively new (e.g., Brassington et al. 2015; Pullen et al. 2017), especially on the regional scale. Considerable effort for performing coupled modeling has focused on the present climate and future climate projections in the context of temperature and precipitation changes (e.g., Ren and Qian 2005; Wang et al. 2015; Larsen et al. 2016; Dong et al. 2017; Su et al. 2020; Minallah and Steiner 2021). Recently, more attention has been paid to the conduct of case studies using the short- to medium-range coupled prediction models (e.g., Brassington et al. 2015; Gu et al. 2016; Umek and Gohm 2016; Fujisaki-Manome et al. 2017).

Despite some incremental improvements in QPFs during the past decades (e.g., Gallus et al. 2008; Lombardo and Colle 2010; Jessup and Colucci 2012; Sukovich et al. 2014), it still remains very challenging to accurately predict precipitation in terms of its amount, location, and timing (e.g., Olson et al. 1995; Applequist et al. 2002; Fritsch and Carbone 2004; Cao and Zhang 2016; Cao et al. 2019; Xia and Zhang 2019; Wang et al. 2021) owing to complicated multi-scale dynamic and thermodynamic processes involved in precipitation production. Applications of coupled models to daily QPF have shown some promising results in several operational numerical weather prediction (NWP) centers, such as the Bureau of Meteorology of Australia, the UK Met Office, the National Centers for Environment Prediction of the United States, the European Centre for Medium-Range Weather Forecasts, the Naval Research Laboratory of the United States, Environment and Climate Change Canada of Canada (ECCC), and Mercator-Océan/Meteo-France of France (Brassington et al. 2015).

A coupled atmosphere-ocean-ice model system has been recently developed by ECCC (Brassington et al. 2015) in an attempt to improve guidance from NWP models, such as QPFs. In this study, we systematically assess benefits and challenges in promoting the improvement of and using this coupled model for daily QPFs over Southern Ontario during a one-year period of June 2016 to May 2017.
The objectives of this study are to (i) evaluate the daily QPF performance over southern Ontario using ECCC’s coupled and uncoupled operational models through verification against the Canadian Precipitation Analysis (CaPA) and two independent observational precipitation datasets; (ii) develop a systematic method to diagnose physical processes at the air-water interface and above to inform on the differences between the coupled and uncoupled models for daily QPFs in order to help understand the impact of the two-way coupling system with respect to QPFs.

The next section describes the data and methodology used in this study. Section 3 presents model verifications and analyzes differences of physical processes resulting in daily QPF differences in the two models. A summary and concluding remarks are given in section 4.

2. Data and methodology

Five datasets are employed in this work to evaluate the performance of the coupled atmosphere-ocean-ice (GEM-NEMO-CICE) system and uncoupled GEM model in QPFs over southern Ontario region for a one-year period of June 2016 to May 2017. Here GEM refers to the Global Environmental Multiscale atmospheric model (Cote et al. 1998), NEMO to the Nucleus for European Modelling of the Ocean (Madec et al. 1998; Madec 2016), and CICE to the Community Ice CodE (e.g., http://www.cesm.ucar.edu/models/cesm1.0/cice_ice_usrdoc.pdf; Roy et al. 2015; Durnford et al. 2017; Smith et al. 2016 and 2018). For the sake of convenience, like Smith et al. (2018), here the term “coupled” means the GEM model coupling with the NEMO-CICE model, even though the operational GEM model is also coupled with a land surface model (Bélair et al. 2003). In the uncoupled GEM, surface temperatures over lakes and oceans do not evolve in time, although their initial conditions are provided from real-time analyses (Mailhot et al. 1998). Both the coupled and the uncoupled model QPF data are obtained from the Canadian Centre for Meteorological and Environmental Prediction Centre (CCMEP). The GEM forecasts have a horizontal grid spacing of 10 km, while the NEMO-CICE forecasts have a horizontal grid spacing of 2 km.

The computational spatial domain is the same for comparisons of two models, that is, over the southern Ontario domain (see Fig. 1b), even though the integration domains are...
different for the two models. The three datasets, i.e., QPFs from the coupled and uncoupled models and the CaPA data, are interpolated onto the same grids with the same horizontal resolution of 10 km.

Boundary conditions of the coupled and uncoupled models have little impact on QPFs over the southern Ontario domain, since the southern Ontario domain is small and is located in the middle of the integration domains of the two models. The integration domain of the uncoupled model covers North America that is larger than the integration domain of the coupled model. The boundaries of the coupled-model integration domain are about 2000–3000 km away from the southern Ontario domain. Besides, there are mature techniques to deal with the boundaries such as sponge boundary conditions in the models.

Coupling GEM with the NEMO-CICE models is achieved through a coupler called the Globally Organized System for Simulation Information Passing (GOSSIP) (see Fig. 1a). This coupler allows a bidirectional transfer of fluxes (Smith et al. 2018). First of all, state variables predicted by the atmospheric model GEM are transferred to the ocean-ice model NEMO-CICE through the coupler where the NEMO-CICE regrids GEM’s atmospheric fields. Then, fluxes are calculated on the computational grid with higher resolution, i.e., from NEMO-CICE, using GEM’s flux formulation library. Finally, the fluxes calculated by the NEMO-CICE model are regridded prior to being used in GEM. These flux exchanges between two models are carried out at every time step using the GOSSIP coupler.
Figure 1 (a) Schematic diagram of coupling GEM model with NEMO-CICE model, and (b) southern Ontario domain covered by both the coupled GEM-NEMO-CICE model and uncoupled GEM model forecasts.

The main differences between the coupled and the uncoupled models is the incorporation of the surface fluxes from NEMO-CICE at the air-water interface, such as the one over the Great Lakes (Cao et al. 2018; Smith et al. 2018). Therefore, more emphasis in this study is given on these fluxes and their association with QPFs (particularly daily QPFs) predicted by the two models.

To verify the two models’ QPFs, the Canadian Precipitation Analysis (CaPA) data (Mahfouf et al. 2007; Lespinas et al. 2015) are used. The CaPA data used in this study are a combination of Canadian and U. S. radar data, rain gauge data, and a first guess provided by the uncoupled GEM regional model with 10-km horizontal grid spacing (Fortin et al. 2015; Lespinas et al. 2015). CaPA generates precipitation accumulations at intervals of 24 h and 6 h. The quality of CaPA data not only depends on these observations but also relies on the first guess, which is taken from the uncoupled GEM regional model short-range forecasts in this case. In areas with sparse observations the first guess makes an important contribution to the precipitation analysis, which could be an advantage of the uncoupled model when comparing its QPF performance to that of the coupled model. Because of this, any model performance evaluation based on a comparison...
against precipitation analyses may have some uncertainty. However, in summer months over a region such as Southern Ontario with a relatively dense surface network and a good radar coverage, the role of the first guess is less important.

In winter, this uncertainty in precipitation is greater, since CaPA does not assimilate surface observations for solid precipitation (determined from near-surface air temperature) when near-surface winds are greater than a certain threshold, due to an undercatch problem. Moreover, radar retrievals are currently not used in winter months because there are not enough surface observations at the surface to calibrate or unbias the radar retrievals. Without this unbiasing, the inclusion of radar retrievals leads to deterioration of CaPA data. As shown later in section 3, on the other hand, the differences between the two models’ QPFs in winter are actually small and limited impact results.

Hydrometeorological fields (e.g., 24-h precipitation accumulation) extracted from the coupled and the uncoupled models are based on their 1200 UTC runs since the CaPA data are assimilated daily at 1200 UTC. Spatial and temporal verifications of the QPFs are mainly performed over the southern Ontario domain, which is approximately defined as an area of 84-75°W and 41-47°N (Fig. 1b), where dense precipitation observations are available (e.g., Cao et al. 2004), whereas Southern Ontario is the Canadian portion of what is shown in Fig. 1b.

We will further employ additional independent observations to assess the verification results against the CaPA data, whenever and wherever the independent observations are available. In this study, we will use two independent observation datasets to further evaluate the two models’ performance for daily QPFs. The first independent dataset is the AmeriFlux (https://ameriflux.lbl.gov/data/) measured half-hourly surface precipitation. Although it is available only at observational stations (while CaPA data are available over certain areal extent), the AmeriFlux observed precipitation fully meets our requirement of its independence of both coupled and uncoupled models. Over Southern Ontario, there are three AmeriFlux stations (CA-TP3, CA-TP4, and CA-TPD) having precipitation observations (Arain 2018; Table A1). Since their locations are very close (located near the north shore of Lake Erie) with the same precipitation measurements, we only present evaluations of QPFs of the two models against one station observations at CA-TP4. We
have also looked for other AmeriFlux stations in New York, Pennsylvania, Ohio, and Michigan. It turns out that there is no station in New York, one station in Pennsylvania with lots of missing data, stations in Ohio without observations in 2017, and only two stations in Michigan with precipitation observations but one with lots of missing data and the other outside of Southern Ontario.

To perform QPF evaluations over areas of interest, we employ another independent precipitation observations of the North American Great Lakes hydrometeorological database, which is developed in National Oceanic and Atmospheric Administration’s Great Lakes Environmental Research Laboratory (NOAA GLERL) (https://www.glerl.noaa.gov/ahps/mnth-hydro.html; Hunter et al. 2015). These GLERL Great Lakes monthly- and lake-averaged precipitation data were derived from quality-controlled data collected from the United States and Canada federal agencies’ surface observations near and over lakes (about 700-800 stations over the Great Lakes basin, see Figs. 2 and 3 of Hunter et al. 2015). The original data can be interpolated using the Thiessen polygon method and averaged over areas of interest (Hunter et al. 2015). These data are periodically updated to reflect additional data and to extend the period of record.

To quantify the accuracy of the daily QPFs from the two different models, we calculate the bias, defined as an average of differences between the model predicted and analyzed precipitation:

\[
\text{Bias} = \frac{1}{N} \sum_{i=1}^{N} (F_{ip} - F_{ia}),
\]

where \(F_{ip}\) and \(F_{ia}\) are \(i\)th \((i=1,\ldots,N)\) model predicted and analyzed precipitation amounts, and \(N\) is the number of the total time level of measurements.

While the bias measures an average direction of model-prediction errors, the standard deviation (SD) measures the variation of model-predicted errors, defined as

\[
\text{SD} = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (F_{ip} - F_{ia})^2}.
\]

The standard deviation equation (2) is very similar to the root mean squared error (RMSE). The former is divided by \(N-1\) whereas the latter is divided by \(N\). In other words,
 RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (F_{ip} - F_{ia})^2}. \quad (3)

To evaluate the model skill in predicting daily precipitation, we can calculate the bias score (BS):

\[ BS = \frac{F}{O}, \quad (4) \]

where F is the number of point (area) forecast to receive a threshold amount of precipitation, and O is the number of points (areas) where the threshold amount is observed. Therefore, BS is the ratio of the forecast area to the observed area of precipitation amounts over any given threshold. It indicates if the models’ forecasts are systematic overprediction (bias > 1) or underprediction (bias < 1), when a representative sample of observations is available in both space and time. In this study, we have chosen a threshold value of daily QPF 2 mm d^{-1} since monthly averaged daily precipitation is mostly equal to or greater than this amount.

The correlation coefficient \( r_{xy} \) is often used to measure of the strength and the signs of a linear relationship between two variables x and y, defined as

\[ r_{xy} = \frac{\frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})^2} \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (y_i - \bar{y})^2}}. \quad (5) \]

It is important to note that statistical uncertainty may be associated with the objective evaluation of the above metrics due mainly to a sampling size. In this work, all spatial averages are calculated with 6700 grid points over the southern Ontario domain, and monthly averages are performed using daily values with sampling at least four forecasts (at 6 hours apart) a day.

The equations derived for understanding physical processes and/or variables associated with sensible and latent heat fluxes at the interfaces, their energy partition (i.e., Bowen ratio), temperature at the interface, and vertically integrated water vapor flux convergence that cause differences in QPFs between the two models are presented in the next section.

3. Results
a. Verification of daily QPFs by the coupled and uncoupled models

For the first 24-h lead time of QPFs (i.e., forecasts between 0 and 24 hours), the domain and monthly averaged bias in daily QPFs is positive for both the coupled and the uncoupled models, implying that both models over-predict the daily precipitation compared to CaPA’s daily accumulation (Fig. 2a, and Table 1). Results also show a seasonal signal, with larger biases of daily QPFs in summer than in winter (Fig. 2a). Similarly, the standard deviation exhibits a seasonal cycle, with larger values mainly in the warm season (Fig. 2b).

During the months of November and December of 2016, as well as April of 2017, the coupled model predicted daily QPFs (bias, SD) (mm day$^{-1}$) are, respectively, (0.3, 0.42), (0.37, 0.60), and (0.89, 1.15) whereas the uncoupled model predicted daily QPFs (bias, SD) (mm day$^{-1}$) are, correspondingly, (0.32, 0.44), (0.45, 0.65), and (0.96, 1.20) (Table 1). This indicates that the coupled model is better than the uncoupled one in reducing the bias and SD of daily precipitation in these three months (Fig. 2, and Table 1).
Figure 2 Time series of domain- and monthly-averaged daily QPF (a) bias with the standard errors at the top of bars, and (b) standard deviation (SD) against 24 h precipitation analyses for coupled GEM-NEMO-CICE and uncoupled operational GEM forecasts between 0 and 24 hours, as well as (c) and (d) same as (a) and (b) respectively but for forecasts between 24 and 48 hours.
Figure 2 (c) and (d) same as Fig. 2 (a) and (b) respectively but for forecasts between 24 and 48 hours.
Table 1. Statistic for domain- and monthly-averaged daily QPF (mm d\(^{-1}\)) of coupled and uncoupled models (bold typefaces denote values of the coupled model less than those of the uncoupled model).

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<td>Means</td>
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<td>Bias</td>
<td>0.57, 0.56</td>
<td>1.08, 0.92</td>
<td>1.10, 0.81</td>
<td>0.68, 0.42</td>
<td>0.56, 0.26</td>
<td>0.30, 0.32</td>
<td>0.37, 0.45</td>
<td>0.36, 0.35</td>
<td>0.44, 0.31</td>
<td>0.36, 0.34</td>
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<td>SD</td>
<td>0.98, 0.99</td>
<td>1.66, 1.48</td>
<td>1.71, 1.51</td>
<td>1.13, 1.01</td>
<td>0.95, 0.93</td>
<td>0.42, 0.44</td>
<td>0.60, 0.65</td>
<td>0.56, 0.54</td>
<td>0.64, 0.54</td>
<td>0.57, 0.55</td>
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During the months of July - October 2016, February and May 2017, however, the coupled model is worse than the uncoupled (Fig. 2, and Table 1). As shown in Fig. 2 and Table 1, in July - October 2016 the coupled model predicted daily QPFs (bias, SD) (mm day\(^{-1}\)) are (1.08, 1.66), (1.10, 1.71), (0.68, 1.13), and (0.56, 0.95) whereas the uncoupled model predicted daily QPFs (bias, SD) (mm day\(^{-1}\)) are, respectively, (0.92, 1.48), (0.81, 1.51), (0.42, 1.01), and (0.26, 0.93). In February and May 2017, the daily QPFs (bias, SD) (mm day\(^{-1}\)) are (0.44, 0.64) and (1.01, 1.33) for the coupled model versus (0.31, 0.54) and (0.94, 1.27) for the uncoupled model, respectively.

For the second 24-h lead time of QPFs (i.e., forecasts between 24 and 48 h), the domain and monthly averaged bias and SD in daily QPFs are similar to those at the first 24-h lead time of QPFs, i.e., both models over-predicting the daily precipitation with respect to CaPA’s daily accumulation, plus a slight phase shift (Fig. 2). In other words, the performance of the coupled model is better than the uncoupled model in reducing the bias and SD of daily QPFs over the months of October and November of 2016, as well as May of 2017 while the coupled model is worse than the uncoupled during the other months (Fig. 2). The comparisons indicate that in October and November 2016, and May 2017, the coupled model predicted daily QPFs (bias, SD) (mm day\(^{-1}\)) are, respectively, (0.56,
1.09), (0.58, 0.71), and (1.45, 1.76) whereas the uncoupled model predicted daily QPFs (bias, SD) (mm day$^{-1}$) are, respectively, (0.88, 1.41), (0.63, 0.76), and (1.50, 1.83) (Fig. 2).

In the rest of the paper, we will focus on the first 24-h lead time of QPFs.

Over most of months of the one-year period, the uncoupled model performance appears better than the coupled model in the domain- and monthly-averaged daily QPF over the first and second 24-h lead time, particularly in July-August 2016. Given the identical model physics and data assimilation system, as well as identical initial and boundary conditions, the model forecast accuracy is mainly determined by the type of weather system needed to predict and the forecast lead time.

During the winter, weather systems are usually dominated by large scale systems while in the summer they are dominated by small scale systems. The larger scale weather systems are more predictable at longer lead times than small-scale and quickly developing weather systems, because the former usually lasts longer and causes slower changes in meteorological variables that can be more easily anticipated ahead of time.

Typically, after initial spin up, weather forecast models’ prediction accuracy increases for hours and then gradually decreases (e.g., Haupt 2018) because effects of initial data assimilation fades with time. Comparisons between Figs. 2a and 2c show that forecasts with lead time of 0-24 h are more accurate than those with lead time of 24-48 h over the period of June 2016 to May 2017 except January 2017.

We have directly compared the coupled model performance with the uncoupled model in daily QPFs by calculating RMSE differences of daily QPFs between the coupled and uncoupled models. If the difference is negative, the coupled model is better than the uncoupled model. Otherwise, an opposite is true. Figure 3 shows that the coupled model is better than the uncoupled model for the months of November and December of 2016, and April of 2017, which is consistent with Fig. 2. Figure 3 also shows that the coupled model is slightly better than the uncoupled model in June 2016, which is again consistent with the SD calculation in Fig. 2b. However, the coupled model is worse than the uncoupled model in the other months, especially in July - September 2016, February and May 2017 (Fig. 3). This is consistent with Fig. 2 that larger deterioration of the coupled model occurs mainly during the warm season.
Figure 3 The domain- and monthly-averaged RMSE difference of daily QPF (mm day\(^{-1}\)) during the period of 0 to 24 hours between coupled and uncoupled models. The standard errors are shown at the top of bars.

Figure 4 shows the domain- and monthly-averaged BS in daily QPFs with a threshold of ≥ 2 mm d\(^{-1}\) for both the coupled and the uncoupled models. Over the period of June 2016 to May 2017, both models have BS > 1, suggesting that the coupled and uncoupled models over-predict daily precipitation, which is consistent with the above analyses in bias and SD. In general, the differences between the two models are small even though the coupled model slightly improves over the uncoupled model in some months such as July and November 2016, and March 2017. As compared with the bias and SD scores, the BS accounts for a range of precipitation amount above a given threshold, rather than an exact difference between the predicted and observed (or analyzed) precipitation.
Figure 4 The domain- and monthly-averaged daily QPF bias score (BS) with a threshold of 2 mm d$^{-1}$ against 24 h precipitation analyses for coupled GEM-NEMO-CICE and uncoupled GEM forecasts. The standard errors are shown at the top of bars.

To gain insight into the diurnal variations of QPFs in the two models, we further plot their daytime (defined as 12 UTC – 00 UTC) and nighttime (defined as 00 UTC – 12 UTC next day) QPFs, as verified against the sum of two 6-h CaPA data. As shown in Fig. 5, during daytime both models have a positive bias for the whole year except for November and December 2016 with a negative bias (Fig. 5a). During night time both models have a positive bias for the whole year except August 2016, February and May 2017 with a negative bias (Fig. 5b).
During daytime, the slight improvements from the coupled model over the uncoupled system occur in November and December 2016 (Fig. 5a). It is observed from Fig. 5a that the deterioration of the coupled model in daytime precipitation mainly occurs over the warm season. During nighttime, the slight improvements of the coupled model over the

Figure 5 Time series of domain- and monthly-averaged QPF bias (mm 12h$^{-1}$) against sum of two 6 h precipitation analyses for coupled GEM-NEMO-CICE and uncoupled GEM forecasts during (a) daytime (12 UTC-00 UTC) and (b) nighttime (00 UTC-12UTC).

During daytime, the slight improvements from the coupled model over the uncoupled system occur in November and December 2016 (Fig. 5a). It is observed from Fig. 5a that the deterioration of the coupled model in daytime precipitation mainly occurs over the warm season. During nighttime, the slight improvements of the coupled model over the
uncoupled model happen in June, August, November, and December 2016, as well as in January to April 2017 while an opposite is true for the rest of the months. In particular, in June, August, November, and December 2016, and February to April 2017, the coupled model-predicted 12-h QPF biases (mm 12 h$^{-1}$) are, respectively, 0.24, -0.20, 0.33, 0.83, -0.23, 0.28, and 0.23 whereas the uncoupled model-predicted 12-h QPF biases (mm 12 h$^{-1}$) are, correspondingly, 0.31, -0.27, 0.36, 0.91, -0.34, 0.31, and 0.36. These indicate that the improvements of the coupled model over the uncoupled model in QPFs occurring mostly during the nighttime rather than the daytime.

To understand where in southern Ontario the coupled model improves over the uncoupled model, we compute absolute bias differences in daily QPF between the coupled and the uncoupled models. If the differences are less than zero, the coupled model overforecast in daily QPF is smaller than the uncoupled model. Otherwise, the difference greater than zero indicates that the opposite is true.

Figure 6 shows the spatial distributions of monthly-averaged daily precipitation over the southern Ontario domain for the CaPA data, the coupled model, and the uncoupled model forecasts. The overall coupled and uncoupled model daily QPFs (the 2$^{nd}$ and 3$^{rd}$ columns of Fig. 6) are greater than the CaPA (the 1$^{st}$ column of Fig. 6) especially in the summer, consistent with their overpredicted QPFs mentioned earlier. The entire-year maximum daily QPF is about 5-6 mm day$^{-1}$, which is consistent with the magnitude mentioned in Cao and Ma (2009).
Figure 6 The 1st, 2nd, and 3rd columns are, respectively, monthly averaged daily precipitation accumulation of CaPA, coupled model, and uncoupled model forecast (at an interval of 1 mm d$^{-1}$). The 1st, 2nd, 3rd, and 4th rows are for July, October 2016, January, and April 2017, respectively.
Figure 7 Monthly averaged daily QPF of bias difference between the coupled and the uncoupled models (at an interval of 0.5 mm d⁻¹) at (a) June, (b) July, (c) August, (d) September, (e) October, (f) November, (g) December 2016, (h) January, (i) February, (j) March, (k) April, and (l) May 2017. The shading areas represent the bias of the coupled model less than the uncoupled model.

The bias differences between the two models varied considerably in both space and time (Fig. 7). The negative values (denoted by shaded areas with blue colors) in Fig. 7 represent the coupled model bias less than the uncoupled model bias and hence the
improvement of the former over the latter. In June 2016, the coupled model showed improvements over the uncoupled model mainly located at lee sides of Georgian Bay and Lake Huron, over Lake Erie and part of Lake Ontario, as well as over eastern Pennsylvania (Fig. 7a). In July 2016, the improvement of the coupled model over the uncoupled model was strengthened to the east of Georgian Bay and Lake Huron, over the leeside of Lake Ontario and majority of Lake Ontario itself, and slight improvement to the south of Lake Erie (Fig. 7b). Deteriorations of the coupled model were, on the other hand, mainly observed over Lake Erie and a portion of Lake Huron. Deteriorations occurred in August and September 2016 over most land and Lake Huron and Erie while improvements appeared over Lake Ontario and to its south and part of Georgian Bay, as well as at areas near the interaction of Lake Huron and Erie (Figs. 7c and 7d). In October 2016, regions of improvements were mainly switched to south portion of southern Ontario, covering areas of Lakes Erie and Ontario as well as their vicinity (Fig. 7e). In November, the improvement areas were extended to include the northern portion of the domain (Fig. 7f). The regions of improvement were further expanded in December to include almost entire domain of southern Ontario where the coupled model bias is less than the uncoupled one (Fig. 7g). In January 2017, the areas of improvements still occupied the majority of southern Ontario especially Lake Erie and Ontario, and leeside of Lake Huron and Georgian Bay (Fig. 7h). However, the areas of improvements were substantially shrunk in February, replaced by the areas of deteriorations (Fig. 7i). A sea saw occurred since March 2017 when improvement areas were increased particularly in Georgian Bay, Lake Huron and Ontario, and their leeside (Fig. 7j). Improvement areas were rapidly expanded in April and May, covering almost all water surfaces in southern Ontario, with the areal orientations in zonal and northeast-southwest directions, respectively (Figs. 7k and 7l).

Despite the substantial variation of bias differences between the two models in space and time, QPF improvement associated with the coupling mainly occurs at the lee sides of the water body, and sometimes over the lakes. On the other hand, the deteriorations of the coupled model mostly happen over the land where coupling effect is fading, especially in August, September, and February 2017.

As mentioned in section 2, the AmeriFlux (https://ameriflux.lbl.gov/data/) measured half-hourly surface precipitation data are used to assess both coupled and uncoupled
model performance in daily QPFs in order to avoid the CaPA data dependence on the uncoupled model.

Figure 8a shows the monthly-averaged daily QPF bias of the two models against 24 h precipitation observations at the CA-TP4 station (located at the north shore of Lake Erie, see Fig. 8b). The two model QPFs are taken as an average of QPFs at 11 grid points enclosing the station location. The same average is applied to sensible and latent heat fluxes later on. During the period of June 2016 to May 2017, the coupled model performance in daily QPF is better than the uncoupled model for 11 months except for July 2016. This is consistent with the result shown in Fig. 7 (near the north shore of Lake Erie), indicating that near water body, the coupled model improves over the uncoupled model in daily QPFs at least for this station.

Note that at the north shore of Lake Erie, the verifications of coupled model QPFs against the CaPA deteriorate in September 2016 (Fig. 7) whereas at the same location, the verifications of coupled model QPFs against the AmeriFlux observation improve over the uncoupled model QPFs (Fig. 8a). This is because precipitation observations at the AmeriFlux network are not only independent of the two model QPF but also independent of our ECCC observational network.
Figure 8 (a) The monthly-averaged daily QPF bias against 24 h precipitation observations at CA-TP4 station of the AmeriFlux network for coupled GEM-NEMO-CICE and uncoupled GEM forecasts. (b) Location of the CA-TP4 and US-UMB stations are, respectively, denoted by a red star and a red cross.

At the same location of the CA-TP4 station, the monthly-averaged sensible and latent heat fluxes in the coupled model are better than those in the uncoupled model over 10 months and 9 months, respectively (Figs. 9a, b). The improved latent heat flux in the coupled model over that in the uncoupled model occurs in 9 months, including June to
July 2016, November 2016 to May 2017 (Fig. 9b). Of the remaining 3 months, the sensible heat flux in the coupled model during August and September 2016 is better than that in the uncoupled model (Fig. 9a), while both sensible and latent fluxes in the uncoupled model during October 2016 are better than those in the coupled model (Figs. 9a, b). It turns out that the two model differences of sensible and latent heat fluxes in October 2016 could not be a key factor leading to the differences in daily QPFs between the coupled and uncoupled models, which is actually related to large-scale differences of vertically integrated water vapor flux convergence between the two models as shown later in Table 3.
Figure 9 The monthly-averaged (a) sensible and (b) latent heat flux bias against observations at CA-TP4 station of the AmeriFlux network for coupled GEM-NEMO-CICE and uncoupled GEM forecasts.

Furthermore, we performed two model QPF evaluations over Lake Erie using the quality-controlled independent precipitation observations of the North American Great Lakes hydrometeorological database developed by NOAA GLERL (https://www.glerl.noaa.gov/ahps/mnth-hydro.html; Hunter et al. 2015). As shown in Fig. 10, the coupled model performance in daily QPF is better than the uncoupled model for
the 7 months of June, October, November, and December 2016, as well as January, April, and May 2017. This is consistent with the results presented in Fig. 7.

![Bar chart showing the lake Erie area-averaged monthly-averaged daily QPF bias against 24 h precipitation observations of the North American Great Lakes hydrometeorological database for coupled GEM-NEMO-CICE and uncoupled GEM forecasts.](image)

Figure 10 Lake Erie area-averaged and monthly-averaged daily QPF bias against 24 h precipitation observations of the North American Great Lakes hydrometeorological database for coupled GEM-NEMO-CICE and uncoupled GEM forecasts.

Unlike situations near and over the water body (i.e., Lake Erie), Fig. 11 shows the monthly-averaged daily QPF bias of the two models against 24 h precipitation observations at the US-UMB station of the AmeriFlux network (located in Michigan near western boundary of the southern Ontario domain, see Fig. 8b and Table A1). The coupled model performance in daily QPF is better than the uncoupled model for the 6 months of July, September, November, and December 2016, as well as January and April 2017, whereas the former is worse than the latter for the remaining half year. This implies that away from the water body, the coupled model performance deteriorates (cf. Figs. 8a and 11).
Figure 11 The monthly-averaged daily QPF bias against 24 h precipitation observations at the US-UMB station of the AmeriFlux network for coupled GEM-NEMO-CICE and uncoupled GEM forecasts.

In the next section, we will discuss the physical processes that account for the differences in daily QPFs between the two models and try to understand why the coupled model performs better/worse in daily QPFs than the uncoupled model. Before proceeding to the next section, we examine whether or not the differences in QPFs of the two models are statistically significant using \( t \) tests (e.g., Cao 2008; Cao et al. 2021). As shown in Table 2, the monthly-averaged daily QPF differences between the two models are statistically significant at the >99.9% level over the eight months of June to October 2016 and March to May 2017 (Table 2). In February 2017, the difference is statistically significant at the 95% level (Table 2). Little statistically significant differences of two models’ QPFs only occur in December 2016 and January 2017, with a statistically-significant difference at a 70% level appearing in November 2016 (Table 2).
b. The physical processes associated with the different daily QPFs

We employ the following water balance equation to help understand the physical processes associated with precipitation (P) reaching the ground:

\[ P = E - \frac{\partial w}{\partial t} - \nabla \cdot \vec{Q}, \tag{6} \]

where \( E \) denotes surface evaporation, \( \nabla \cdot \vec{Q} \) is the vertically integrated water vapor flux convergence, and \( \frac{\partial w}{\partial t} \) is the local precipitable water tendency. In general, \( \frac{\partial w}{\partial t} \) is a small term contributing to \( P \) (e.g., Cao et al. 2002). The transport of water in liquid or solid form can normally be ignored on a mean monthly basis (e.g., Rasmusson 1968).

In this case, it may be safe to assume that the major differences in precipitation between the coupled and uncoupled models are related to surface evaporation, i.e., moisture fluxes at the underlying surfaces, and the vertically integrated water vapor flux convergence. Since surface sensible heat fluxes are linked to surface evaporation through a Bowen ratio, the differences in sensible heat fluxes also contribute to the differences of daily QPFs in the two models. Although the two processes differ, changes in both sensible and latent heat fluxes influence precipitation production through their impact on the lower tropospheric stability. Thus, our attention will be first paid to how and to what extent the

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Table 2. \( t \) test for monthly-averaged daily QPF differences between the coupled and the uncoupled models with degrees of freedom of \( n - 2 = 6700 - 2 = 6698 \) (statistical significance denoted by a bold typeface).
daily sensible and moisture flux differences in the two models cause different daily QPFs. To this end, we calculate the domain (84-75°W and 41-47°N, see Fig. 1) averaged and monthly averaged differences between the two models in daily sensible heat and moisture fluxes over Southern Ontario surfaces (including land and water surfaces) during the period from June 2016 to May 2017, and then examine these differences in relation to the daily QPF differences of the two models.

It is evident from Figs. 12a, b that the differences in the models’ daily QPFs are positively correlated with the differences in the surface sensible heat and moisture fluxes, with correlation coefficients of 0.89 and 0.75, respectively. It is interesting to note that the surface sensible heat flux has 0.14 higher correlation coefficient with precipitation than the surface evaporation. In other words, the relationship between the evaporation flux difference and the QPF difference has more spread from a linear relationship than the one between the sensible heat flux and QPF differences.
Figure 12 Scatterplots of domain- and monthly-averaged daily QPF bias (mm) difference between the coupled and the uncoupled models vs. (a) daily accumulated sensible heat flux (W m$^{-2}$) difference between the coupled and the uncoupled models and (b) daily accumulated evaporation (mm) difference between the coupled and the uncoupled models over the period of June 2016 to May 2017.

To help further understand the differences between the coupled and the uncoupled model in the context of the surface sensible heat and evaporation fluxes, we plot a time
series of their differences during the period of June 2016 to May 2017. As shown in Fig. 13a, the differences of domain- and monthly-averaged daily sensible heat flux reach a maximum in August 2016 and a minimum in November 2016. The differences in the daily evaporation fluxes follow a similar pattern with a slight phase shifts with a maximum and a minimum appearing in July 2016 and December 2016, respectively.

Figure 13 Domain- and monthly-averaged (a) daily accumulated sensible heat flux (W m$^{-2}$, left vertical axis) and evaporation (mm, right vertical axis) differences, and (b) daily QPF bias (mm) differences between the coupled model and the uncoupled model during the period of June 2016 to May 2017.
Meanwhile, the differences of domain- and monthly-averaged daily QPFs between the coupled and the uncoupled models show a maximum in August 2016 and a minimum in December 2016 (Fig. 13b). The former is consistent in time with the maximum difference of the daily sensible heat flux in August 2016 while the latter is consistent in time with the minimum difference of the daily evaporation in December 2016. This suggests that in the summer improvements of sensible heat flux may be even more critical than evaporation fluxes in reducing the maximum daily QPF difference between the two models. It is interesting to note that the largest differences of sensible heat and evaporation fluxes occur in summer (Fig. 13a) when the coupled system does not perform as well as the uncoupled model (Fig. 13b). In winter, the small differences in evaporation and sensible heat fluxes between the two models (Fig. 13a) could explain the small differences found for daily QPFs between the two models (Fig. 13b).

To gain further insights into seasonal variations of the difference of the daily QPF between two models, we examine the surface energy balance equation. The surface sensible and latent heat fluxes depend on the surface energy balance and associated energy partition:

\[ R = H + \lambda E + G, \quad (7) \]

in which latent heat flux \( \lambda E \) can be expressed as

\[ \lambda E = \frac{R - G}{1 + B}, \quad (8) \]

where \( R, H \) and \( G \) are, respectively, net radiation, sensible heat flux, and downward/upward heat flux into/from the ground. \( B = H / \lambda E \) is known as the Bowen ratio, defined as a ratio of sensible heat flux to latent heat flux (i.e., an energy partition between these two fluxes), which are representative of the major differences between the coupled and uncoupled models as well.

Substituting Eq. (8) into Eq. (6), we have

\[ P = \frac{(R - G)}{\lambda(1 + B)} \frac{\partial \omega}{\partial t} - \nabla \cdot \vec{Q}. \quad (9) \]
To synthesize the roles played by the surface sensible and latent heat fluxes in daily QPFs, we will examine the Bowen ratio differences of the two models and their effects on the daily QPF differences in the two models.

The surface Bowen ratio can be further expressed as a function of the surface (ground) temperature. Based on the PT (Priestley and Taylor 1972) formula, we have

\[ \lambda E = \frac{\alpha \Delta}{\Delta + \gamma} (R - G), \]  

(10)

where \( \alpha \) is the PT coefficient that is a function of underlying surfaces, \( \gamma \) is the psychometric constant that is proportional to the ratio of specific heat of moist air at constant pressure to latent heat of vaporization of water, and \( \Delta \) is the slope of saturated vapor pressure-temperature curve (i.e., \( \frac{d e_s}{dT} \)). Based on a widely-used saturation vapor pressure formula (Bolton 1980), \( \Delta \) can be expressed as

\[ \Delta = \frac{d e_s}{dT} = \frac{d}{dT} \left[ 6.112 \exp \left( \frac{17.67T}{T+243.5} \right) \right] = \frac{4302.645}{(T+243.5)^2} \times 6.112 \exp \left( \frac{17.67T}{T+243.5} \right) = \frac{4302.645}{(T+243.5)^2} e_s, \]

(11)

where surface temperature \( T \) and saturation vapor pressure \( e_s \) are in °C and hPa, respectively. Eq. (11) is similar to the Clausius-Clapeyron equation.

Combining Eq. (10) with Eq. (8) gives

\[ B = \frac{1}{\alpha} + \frac{\gamma}{\alpha \Delta} - 1. \]  

(12)

After substituting Eq. (12) into Eq. (9), we have

\[ P = \frac{(R-G)}{\lambda (\frac{1}{\Delta} + \frac{1}{\Delta'})} - \frac{\partial w}{\partial t} - \nabla \cdot Q. \]

(13)

Equation (13) represents a series of physical processes involved in the QPFs due to the surface sensible and latent heat fluxes. Since sensible heat flux is inversely proportional to the boundary-layer stability (i.e., the more sensible heat fluxes, the more unstable) and latent heat flux is essentially evaporation, the Bowen ratio can be regarded as a measure of the ratio of low-level buoyancy to local moisture supply through evaporation. The Bowen ratio \( B \) is mainly controlled by surface temperature (Eq. 13) although the latter is closely associated with soil wetness (over land) and evaporation. Lower (higher) Bowen ratio is related to higher (lower) evaporation (Eq. 8) and higher (lower) precipitation (Eq. 9). On
the other hand, the way that surface temperature influences Bowen ratio as well as precipitation is nonlinear, depending on a surface temperature range [see Eqs. (11) and (12)]. Here, the surface temperature refers the temperature for any underlying surfaces, such as land, water, and many others.

In addition to linking the maximum and minimum differences of QPFs between the two models to the maximum and minimum differences of the sensible and latent heat fluxes in August and December 2016, respectively, it is desirable to explore the QPF differences associated with various physical variables over other months during the period of June 2016 to May 2017. To do so, we have calculated the correlation coefficient ($r$) between the monthly-averaged daily QPF differences of the two models and the monthly-averaged two model differences of daily variables such as vertically integrated water vapor flux convergence, sensible and latent heat fluxes, and surface temperature (Table 3). Over the southern Ontario domain (Fig. 1b), there are 6700 grid points where the monthly-averaged values of those physical variables and QPFs are obtained. To test statistical significance of the correlation coefficient $r$, we first obtain a critical correction value $r_{\alpha}$ (= 0.024), given $\alpha = 0.05$ and degrees of freedom of $n - 2$ (= 6700 – 2 = 6698). If $r > r_{\alpha}$, the linear relationship is statistically significant (at a level greater than 95%). Otherwise, an opposite is true when $r < r_{\alpha}$.

Table 3. Correlation coefficient $r$ between variable (listed in the table) and QPF differences of coupled and uncoupled models at a level of $\alpha = 0.05$ with degrees of freedom of $n - 2$ (= 6700 – 2 = 6698) (statistical significance denoted by a bold typeface, i.e., correlation coefficient $r$ greater than a critical $r_{\alpha} = 0.024$).

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As shown in Table 3, the monthly-averaged daily QPF differences between the coupled and the uncoupled models are of statistically significant relationship with the monthly-averaged two model differences of vertically integrated water vapor flux convergence and sensible heat flux in June and July 2016, respectively. In August 2016, those two factors contribute to daily QPF differences between the two models. In September 2016, the monthly-averaged daily QPF differences are not only significantly associated with the monthly-averaged two-model differences of sensible heat flux, but also latent heat flux and surface temperature. While in October 2016, the QPF differences are mainly linked to the monthly-averaged two-model differences of vertically integrated water vapor flux convergence. In addition to the vertically integrated water vapor flux convergence, in November 2016, and in January and February 2017, the linkages are extended to sensible and latent heat fluxes. Besides sensible and latent heat fluxes, in December 2016, surface temperature differences contribute to daily QPF differences of the two models. During spring 2017 (March, April, and May), the vertically integrated water vapor flux convergence remains a factor contributing to the QPF differences, with an additional factor of sensible heat flux in April 2017.

In short, the daily QPF differences in the two models are mainly determined by the differences of (1) the vertically integrated water vapor flux convergence in all seasons with relatively large $r$ values in winter (0.374 in January 2017), fall (0.264 in November 2016) and spring (0.186 in March 2017); (2) latent heat flux with a positive $r$ value in the winter (0.182 in December 2016); (3) sensible heat flux with a positive $r$ value in the winter (0.133 in December 2016); (4) surface temperature in the winter ($r = 0.099$ in December 2016) and the fall ($r = 0.090$ in September 2016).

The above-mentioned four factors contributed to precipitation can be classified into three categories and one feedback mechanism. The three components include (1) moisture availability (local and non-local sources), (2) low-level instability, and (3) lifting
conditions. It is well known that evaporation is a local moisture source for precipitation whereas a non-local moisture source associated with moisture advection contains in the vertically integrated water vapor flux convergence (VIWVFC) as illustrating through a mathematical decomposition as follows.

\[
\text{VIWVFC} = \nabla \cdot \left[ \frac{1}{g} \int_0^{p_0} q \, \mathbf{v} \, dp \right] = \frac{1}{g} \int_0^{p_0} \nabla \cdot (q \mathbf{v}) \, dp = \frac{1}{g} \int_0^{p_0} \mathbf{v} \cdot (\nabla q) \, dp + \frac{1}{g} \int_0^{p_0} q (\nabla \cdot \mathbf{v}) \, dp,
\]

(14)

where \(q\), \(\mathbf{v}\), \(g\), and \(p_0\) are, respectively, specific humidity, velocity, gravitational acceleration, and the surface pressure. On the right hand side of Eq. (14), the first term represents the vertically integrated horizontal moisture advection, and the second stands for the vertically integrated horizontal convergence. The moisture advection provides the non-local moisture source for precipitation likely through synoptic and mesoscale processes, in addition to local moisture source available through evaporation. The convergence offers favorable conditions for upward motion. Sensible heat flux, a function of the Monin–Obukhov length, is actually a measure of low-level stability because the more sensible heat fluxes, the more unstable.

In the coupled model, surface evaporation is different from the one in the uncoupled model, since the former includes latent heat flux from the Great Lakes through coupling processes while the latter does not. Because of this, horizontal moisture gradients in the coupled model will be different from the one in the uncoupled model, resulting in different moisture advection in two models. Furthermore, this can lead to differences of vertical moisture gradients in the two models especially in and near large water body such as the Great Lakes. Similarly, sensible heat fluxes and surface temperature in the coupled model are different from those in the uncoupled model, which may result in differences between the two models in thermally-induced local circulations and convergence. Therefore, surface temperature as well as sensible and latent heat fluxes, and their improvements can influence VIWVFC and its improvements. These physical processes and their interaction and feedback presented in equations derived in this study are general, while their magnitudes could be unique over the Great Lakes region due to the existence of large scale water bodies.

Since surface temperature increase leads to an increase of sensible and latent heat fluxes, respectively, through amplifying temperature and moisture contrast between the
underlying surface and the atmosphere above, this results in an increase of precipitation. On the other hand, precipitation often has a cooling effect on the surface it reaches, such as a lake, through lowering near-surface air temperature, the direct precipitation heat flux into the surface, mechanical and convective mixing the lake surface layer (e.g., Rooney et al. 2018). This negative feedback process is not included in the coupled model yet, but it may be important to reduce positive bias of surface temperature in the coupled model and precipitation thereby. It is therefore suggested to make additional efforts to quantify the cooling effect in order to incorporate it into the coupled model to improve weather and environment forecast, especially QPF.

4. Summary and conclusions

Based on the verification of the domain- and monthly-averaged daily QPF for both the coupled and uncoupled models against the CaPA product over a one-year period, we have shown that the coupled model has both positive and negative impacts on the daily QPF skill over the Great Lakes region. It is found that the negative (positive) impacts mainly occur in the summer (fall, winter, and spring) months. The improvements of the coupled model daily QPFs include reductions of domain- and monthly-averaged daily QPF (forecasts between 0 and 24 h) bias and SD in November and December 2016, and April 2017 while some errors occur in the other months especially during the summer. The improvements of the coupled model daily QPFs (forecasts between 24 and 48 h) over the uncoupled model are also observed in October and November 2016, and May 2017 whereas the deterioration of the coupled model occurs in the summer months.

From the diurnal variability viewpoint, the improvements of the coupled model over the uncoupled one in the domain- and monthly-averaged QPFs occur mainly during the nighttime instead of daytime. During nighttime, the improvements of the coupled model over the uncoupled one occur in June, August, November, and December 2016, and from February to April 2017. On the other hand, during the daytime the improvements of the coupled model over the uncoupled only happen in November and December 2016. Conversely, increased errors of the coupled model daytime QPFs occur in the other months particularly in the summer.
Using two independent observations at stations and over water areas of interest, we find that near and over Lake Erie, the coupled model performance in daily QPF is, respectively, better than the uncoupled model for 11 and 7 months out of the one year period. In the future, it will be interesting to compare the model QPFs with more precipitation observations once they become available over the southern Ontario domain. It will also be worthwhile to make an additional comparison with observed precipitation data such as Stage IV (https://data.eol.ucar.edu/dataset/21.093) over the U.S. portion of the Great Lakes region.

Based on the method developed herein for diagnosing QPF-related physical processes at air-water interface and above, the major differences in the domain- and monthly-averaged daily QPFs between the coupled and uncoupled models are mainly attributed to differences of sensible heat flux and evaporation, surface temperature, and vertically integrated water vapor flux convergence.

Since the coupled model incorporates the sensible heat flux and evaporation at the air-water interface through two-way interaction, whereas the uncoupled model does not perform this for the water surface, the differences in both sensible and latent heat fluxes between the two models have a realistic relationship with the QPF differences of the two models. Our results with the one-year data demonstrate that the sensible heat flux difference has higher correlation coefficients with the daily QPF difference than the evaporation difference. In the summer (winter), the maximum (minimum) difference of sensible heat flux (evaporation) between the two models is in phase with the maximum (minimum) daily QPF differences between the two models. The strong relationship between the surface flux differences and the daily QPF differences (see Figs. 12 and 13) provides confidence that the main causes are indeed related to the coupling between the atmospheric and ocean-lake models.

In this study, we have derived an analytic formulation of nonlinear effect of surface temperature on precipitation, which builds up a foundation not only for climate research on precipitation under warming conditions but also for weather research/forecast on precipitation through surface temperature influences. These influences are realized through physical processes of low-level buoyancy and local evaporation. Furthermore,
these impacts can only be fulfilled in two-way coupled models rather than uncoupled models because the latter specifies the surface temperature but does not predict it.

Our results indicate benefits to promote the future improvement of and challenges to use the coupled model for the daily QPFs. That is, while the coupled model adds more physical processes and complexity than the uncoupled model in the hope that forecast errors could be reduced, the former sometimes offers more possibilities to produce forecast errors than the latter, and those errors could propagate when weather systems evolve. Further improvements are needed, especially in the accurate representation of above-mentioned four elements of surface temperature, sensible heat flux and evaporation, and vertically integrated water vapor flux convergence. For example, surface temperature increase leads to increased precipitation via intensifying temperature and moisture contrast between the underlying surface and above. On the other hand, precipitation has cooling effect on surface it reaches such as a lake (e.g., Rooney et al. 2018). Including this negative feedback process (not in the coupled model yet) may be important to reduce positive bias of surface temperature in the coupled model and precipitation thereby. We suggest the cooling effect to be quantified by integrating it into the coupled model to improve weather and environment forecast, particularly QPF.

As shown in Eq. (14), the vertically integrated water vapor flux convergence is determined by spatial distribution of moisture, moisture advection, and convergence/divergence, which are essentially associated with dynamics and moisture. Improvement on these physical processes and/or factors especially at low levels of the troposphere will help advance QPFs in the coupled model.

The coupled model may act as to reduce or amplify the bias caused by the uncoupled model through coupling and nonlinear interactions between the surface and the atmosphere, which involves condensation processes. These condensation processes in the uncoupled model include a grid-resolved scheme, a convective parameterization scheme, and shallow convection. Examining those physical processes (e.g., Cao and Zhang 2016) is important but it is beyond the scope of the current study.

Future studies at ECCC will further examine the impact of the two-way coupling on QPFs and other aspects of short-range NWP, for example, evaluations over a longer
period with more recent versions of GEM. The projects are underway to substantially improve snowfall analyses in CaPA, with inclusion of more surface observations (through relaxation of rejection criteria related to near-surface winds and the use of transfer function to compensate for the undercatch problem) as well as radar and satellite products.

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Data Availability Statement.

The coupled and uncoupled operational regional model forecasts and Canadian Precipitation Analysis (CaPA) are obtained from the Canadian Meteorological Centre. AmeriFlux data are available at https://ameriflux.lbl.gov/data/how-to-uploaddownloaddata/. GLERL Great Lakes monthly hydrologic data are available at https://www.glerl.noaa.gov/pubs/tech_reports/glerl-083/UpdatedFiles/.

APPENDIX

Table A1 List of AmeriFlux stations used in the evaluation

<table>
<thead>
<tr>
<th>Site ID</th>
<th>Latitude (°)</th>
<th>Longitude (°)</th>
<th>Elevation (m)</th>
<th>DOI</th>
</tr>
</thead>
<tbody>
<tr>
<td>CA-TP3</td>
<td>42.7068</td>
<td>-80.3483</td>
<td>184</td>
<td>10.17190/AMF/1246011</td>
</tr>
<tr>
<td>CA-TP4</td>
<td>42.7102</td>
<td>-80.3574</td>
<td>184</td>
<td>10.17190/AMF/1246012</td>
</tr>
<tr>
<td>CA-TPD</td>
<td>42.6353</td>
<td>-80.5577</td>
<td>260</td>
<td>10.17190/AMF/1246152</td>
</tr>
<tr>
<td>US-UMB</td>
<td>45.5598</td>
<td>-84.7138</td>
<td>234</td>
<td>10.17190/AMF/1246107</td>
</tr>
</tbody>
</table>
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