Boundary Layer Parameterizations to Simulate Fog Over Atlantic Canada Waters

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Abstract In this study, a series of fog events that occurred near Halifax, Canada, during 20 June to 31 July 2016 are investigated using the Weather Research and Forecasting Model Version 3.8.1 (WRF), in comparison with in situ and satellite remotely sensed observations from the Moderate Resolution Imaging Spectroradiometer. We evaluate five planetary boundary layer (PBL) schemes available in WRF. Results show that these five PBL schemes lead to overestimates in liquid water content, especially the nonlocal schemes, and that they are biased early, in terms of the predicting the onset of fog, and late, in terms of fog dissipation, although their spatial patterns of fog are in good agreement with those suggested by Moderate Resolution Imaging Spectroradiometer imagery. The Kunkel equation is used to calculate visibility, based on WRF modeling of liquid water content. Comparisons with observed visibility show that this methodology sometimes fails to predict fog dissipation. We present a modification of this formulation for visibility that shows improved agreement with observations and more accurate fog dissipation. Continued improvements in the PBL scheme and visibility parameterization are needed for more accurate fog prediction.

1. Introduction

Fog is a visible aerosol consisting of minute water droplets or ice crystals suspended in the air or near the Earth’s surface, lowering the horizontal visibility to less than 1 km (Gultepe, 2008). Advection fog typically occurs when warm and moist air mass moves over cold sea surface temperatures (Lewis et al., 2004). Halifax, Nova Scotia (NS), tends to be foggy because of the pool of cold water from the Labrador Current that lingers off the NS coast collocated with southerly winds caused by the North Atlantic High (NAH). In terms of occurrence, the peak frequency for Halifax fog events occurs in summer (Gultepe et al., 2009) when the NAH is dominant in this area, bringing warm moist air from the southern North Atlantic over the cold surface of Nova Scotian coastal waters, leading to the formation of fog. Dense fog can affect marine transport, offshore oil and gas activities, fisheries and recreational activities, search and rescue, and other marine operations, emphasizing the need for accurate marine fog forecasts.

Numerous fog modeling studies have been performed in recent decades. Many of these efforts used single-column models to investigate fog physics. In one of the earliest numerical studies of fog and low stratus, Fisher and Caplan (1963) proved that single-column models can be used to predict the life cycle of radiation fog. Zdunkowski and Nielsen (1969) and Brown and Roach (1976) showed radiative cooling at the fog top can stabilize fog formation. Bergot and Guedalia (1994) stress that initial relative humidity (RH) is more important than the height of the mixed layer. They also showed that horizontal advection in the boundary layer is less significant for fog formation at the beginning of the fog event than during the fog development period, in a single-column model. However, Gultepe et al. (2007) pointed out that single-column models have trouble simulating clouds, atmospheric turbulence in strongly stable conditions, moisture, and heat fluxes sometimes.

Three-dimensional (3-D) mesoscale meteorological models have been mainly utilized in order to reliably predict fog. Pagowski et al. (2004) showed that generation and development of fog has a sensitive dependence on initial conditions and vertical resolution. Yang et al. (2010) used the Global Environment Multiscale configuration model, which is a high-resolution model running operationally at the Canadian

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Meteorological Centre, to simulate marine fog, to suggest that a delicate balance of different physical processes and dynamics is needed for successful fog forecasts. Van Der Velde et al. (2010) used a very high-resolution Numerical Weather Prediction model and confirmed that high vertical resolution is essential for modeling the formation of fog, and growth of the fog layer. Lin et al. (2017) simulated an advection fog event over Shanghai Pudong International Airport with WRF (Weather Research and Forecasting), and pointed out that the onset and dissipation of advection fog is sensitive to the initial time, microphysical parameterization, and longwave and shortwave schemes. Simulation of fog using WRF depends on the PBL (planetary boundary layer), which is the atmospheric layer at the Earth’s surface where small-scale turbulence is generated by wind shear or thermal convection (Deardorff, 1972). The PBL has an important role in fog formation and evolution, which depend on differing estimates for vertical mixing, heat flux, moisture, and momentum fluxes, which will impact the ability of the model to simulate fog (Chaouch et al., 2017).

Fog simulation is sensitive to the choice of the PBL parameterization scheme. PBL schemes are mainly distinguished by two components: the order of the turbulence closure and whether a local or nonlocal mixing approach is employed (Cohen et al., 2015). A local closure scheme estimates the turbulent fluxes from the mean atmospheric variables at each point of the model grid, or possibly their gradients. In nonlocal schemes, multiple vertical levels can be used to determine variables at a given point. In past studies, the sensitivity of fog simulations to three widely used parameterization schemes, denoted as YSU, MYJ, and ACM2 (defined in the following sections), has been investigated, showing that the two nonlocal schemes (YSU and ACM2) from this group can generate relatively accurate and long duration simulations of cloud water (Chaouch et al., 2017; Lin et al., 2017). However, only a few studies have examined the sensitivity of fog simulation to the differences of capabilities of these formulations to simulate fog, among local and nonlocal PBL schemes (Chaouch et al., 2017; Lin et al., 2017).

In spite of notable achievements in fog modeling, there are still challenges that may influence the simulation and forecast skill. First, satellite remote sensing of fog during daytime in the visible range has to consider diurnal changes in solar elevation, and the separation of fog from clouds. Čermak and Bendix (2008) introduced a technique allowing for a clear separation of fog/low stratus from other processes. However, it is still difficult to distinguish fog from low stratus with satellite observations, which limits our ability to validate model simulations. In addition, it is even more difficult to have ground truth satellite images based on vertical profiles, which, in turn, are based on the retrieval of atmospheric temperature profiles determined from microwave-sounding observations. Therefore, the application of satellite images in fog observations has limitations. Second, fog is a mesoscale phenomenon. Patches of fog can be transported to other locations easily, which can cause intermittency in observation records, and the duration for these events at a given location can be short. Third, the visibility estimated from the Kunkel (1984) equation depends on liquid water content (LWC), which also depends on differing types and varieties of fog. Moreover, the extinction coefficient calculation is influenced by the fog droplet size distribution. For example, Eldridge (1966) derived a relationship between the extinction coefficient and LWC for “stable and evolving conditions,” inferred from measurements of spectral transmission through fog with the aid of Mie scattering theory. Tomasi and Tampieri (1976) used modified gamma size distribution models for “wet and warm” fog and “dry and cold” fog.

The paper is organized as follows: Section 2 introduces the data and methods; section 3 shows model results, including comparisons of LWC model results and field observations, with respect to local and nonlocal PBL schemes. Section 4 presents a modification of the visibility equation and provides validation for its application. Section 5 gives discussion, and section 6 conclusions.
0.946, 0.931, and 0.915 to investigate the vertical structure of the fog. The physical parameterization schemes used in all model domains include the rapid radiative transfer model longwave radiation (Iacono et al., 2008), rapid radiative transfer model shortwave radiation (Iacono et al., 2008), the Thompson et al. (2008) scheme for microphysics, and the Noah land surface scheme (Chen & Dudhia, 2001). We note that the Thompson et al. (2008) scheme includes prognostic equations for cloud water, cloud ice, snow, rain, and graupel mass mixing ratio. In order to maintain computational efficiency while increasing the accuracy of the scheme, only cloud ice and rainwater species are represented by a double moment; all other species are represented by a single moment (Cintineo et al., 2014; Thompson et al., 2008), which leads not only computational efficiency but also accuracy. This approach has provided the best prediction of fog duration (Lin et al., 2017) and reasonable estimates for fog dispersal (Radi et al., 2008). The Thompson et al. (2008) scheme is also used to simulate the North Atlantic subtropical high (Li et al., 2015), which is important for the background circulation when simulating fog.

The PBL schemes and surface layer (SFC) formulations are different in each experiment. PBL schemes parameterize turbulent vertical fluxes of heat, momentum, and components like moisture in the PBL and also in the atmosphere. Because some PBL schemes are tightly coupled to particular surface layer schemes in WRF, it is not possible to have a common surface layer scheme for all experiments. In this study, we evaluate three local PBL schemes, MYJ (Janjic, 1994), MYNN2.5 (Nakanishi & Niino, 2006), and MYNN3.0 (Nakanishi & Niino, 2006), and two nonlocal PBL schemes, YSU (Hong et al., 2006) and ACM2 (Pleim, 2007). A description of the five PBL schemes is given in Table 1. Regarding the marine boundary layers, both MYNN schemes provide the least-biased thermodynamic structure (Cohen et al., 2015). MYNN schemes use closure constants in the stability functions and mixing length formulations that are based on large-eddy simulation results instead of observational data sets (Coniglio et al., 2013). MYNN 2.5 improves the PBL representation over nonlocal schemes for springtime PBLs, and MYNN3.0 is reasonably good at the simulation of radiation fog development (Cohen et al., 2015). The YSU scheme enhances mixing in the stable boundary layer (Hong & Kim, 2008) by increasing the critical bulk Richardson number from 0 to 0.25 over land. The ACM2 scheme (Pleim, 2007) is modified to improve the shape of vertical profiles near the surface. Both nonlocal schemes

![Figure 1](image_url)

**Figure 1.** (a) Fog mask derived from Terra and Aqua MODIS data between 14:30 and 14:35 on 22 June AST; white means missing data. Stratus is the cloud top height between 500 and 900 m, and cloud is defined when the cloud top height is higher than 1,000 m. (b) The average LWP (g/m²) of three simulations with local PBL schemes (MYJ, MYNN2.5, and MYNN3.0) based on the lowest ten prognostic WRF model levels at 16:00 June AST. (c) The same as (b) but for two nonlocal schemes (ACM2 and YSU).

| Table 1 A Comparison of PBL Schemes |
|------------------------------------|
| PBL scheme | Closure type | Short description |
|------------|--------------|--------------------|
| MYJ        | 1.5 local    | An improved scheme based on Mellor-Yamada 1.5 order local scheme for a complete description of turbulence model, which is suitable for stable flows but MYJ may underestimate vertical mixing. |
| MYNN2.5    | 1.5 local    | Updated scheme in order to overcome the inadequate growth of convective boundary layer by improving the mixing length scale based on large-eddy simulation data. |
| MYNN3.0    | 2.0 local    | Similar to MYNN2.5 and may have some capability to simulate radiation fog because of more accurate boundary layer representation. |
| YSU        | 1.0 nonlocal | Closely reproduces vertical PBL profiles using large-eddy simulations of idealized experiments, particularly in the afternoons, but may have too deep PBL in the evenings. |
| ACM2       | 1.0 nonlocal | Enhanced mixing for the stable boundary layers, but may over deepen the PBL for springtime deep convective environments. |
may lead to strong vertical mixing, sometimes resulting in drier and warmer daytime PBLs. Detailed differences among all PBL schemes can be found in the study by Cohen et al. (2015).

Initial conditions and boundary conditions for WRF are provided by ERA5 data from the European Center for Medium-Range Weather Forecasts on 0.3° × 0.3° grids, every 6 hr. ERA5 is the fifth generation atmospheric reanalysis produced by the Copernicus Climate Change Service operated by European Center for Medium-Range Weather Forecasts. Thus far, ERA5 data have been released for the years of 1979 to present, with details described by Weger (2015) and Malardel et al. (2015). ERA5 has been validated and shown to give good agreement with radiosonde profiles (Bindu et al., 2018). In additional tests, ERA5 showed improved simulation of near-surface winds at a site near Yerevan, Armenia, with significantly reduced root-mean-square error (RMSE) relative to those forced by the Global Forecast System fields when using ERA5 initial and boundary conditions (Gevorgyan, 2018). Motivated by these good results, we used ERA5 as initial and boundary conditions to simulate fog, because in our tests, fog was sensitive to the near surface southern wind, which brings warm moist air masses over cold water. However, there has not been any known simulation of fog using ERA5 as initial data, for the Northwest Atlantic. Thus, a secondary goal of this paper is to evaluate the ability of ERA5 as initial conditions in model simulations of fog. The data are available online (https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5).

2.2. Observational Data and Measurement Methodology

Fog is defined as occurring when visibility is less than 1 km based on aviation operations (Gultepe et al., 2009). Two observation periods are used in model simulation tests and efforts to improve the Kunkel (1984) visibility equation in this paper. The first data set includes temperature, RH, dew point temperature, visibility, droplet number concentration, and LWC during 10 June to 22 July 2016. Within this time period, fog events were observed over a period of 117 hr with individual fog events varying from 1 to 14 hr. The second data set only includes temperature, droplet number concentration and LWC, which were measured by a subset of the instruments from 24 July to 31 July 2016, when six continuous fog events were captured. Fog events observed in this study were mainly influenced by cyclonic systems and the NAH over Atlantic waters. In order to evaluate the ability of WRF to simulate both fog types, four cases were selected for study. However, we found that WRF had trouble simulating fog events that were influenced by strong NAH conditions, which seems to have been caused by too much vapor transport. In this study, we will only investigate fog events influenced by cyclonic systems; a future study will investigate why simulations of fog dominated by the NAH compared poorly with the observations. A more detailed discussion of the NAH-dominated fog events can be found in section 5.

All the instruments were set up at Sambro (44.5°N, −63.6°W), a rural fishing community located outside Halifax, NS, in Canada. The fog monitor FM-120 from Droplet Measurement Technologies was used to measure droplet sizes with a diameter of 2–50 μm using a laser beam and a pair of photodetectors. One cubic meter per minute was sampled and a droplet size distribution was generated every 20 s, which was averaged over 5 min to match the sampling frequencies of other instruments. The fog monitor was installed at a fixed position near the edge of the cove at Sambro with the sampling inlet facing south, which was the most frequent direction of the incoming wind during fog events. The setup of the instruments and environs of the experiment are shown in Figure 2. Visibility data were collected by a Belfort Model 6500 visibility sensor. Visibility was determined by the extinction coefficient, which was calculated from the amount of infrared radiation that was detected. Temperature, dew point, and RH were collected by Met One Instruments model AIO 2 all-in-one weather sensor (https://metone.com/). Further details about the observations can be found in an upcoming publication.

2.3. MODIS

In addition to the in situ observations at Sambro, satellite data from the MODIS (Moderate Resolution Imaging Spectroradiometer) sensor onboard the EOS Terra and Aqua (Platnick et al., 2017), the Level 2
MODIS cloud products were used to validate the fog spatial patterns and extent. In this methodology, fog is detected when the cloud top pressure is greater than 950 hPa (roughly 500 m); the vertical extent of dense fog is covered within this height (Leipper, 1994). Cloud optical thickness is between 0.1 and 30 and cloud effective radius is between 3 and 15 μm. Here, 20 μm is used as the maximum optical thickness for coastal fog (Čermak & Bendix, 2008). Obviously, fog can be obscured by higher altitude clouds, which makes fog difficult to detect by MODIS satellite observations. The MODIS data are available online (https://ladsweb.modaps.eosdis.nasa.gov/).

2.4. Method

In an earlier study (Kunkel, 1984), the relationship between computed extinction coefficients (β) and measured LWC was derived as follows:

\[
\beta = 144.7 \times W^{0.88},
\]

where β is the extinction coefficient and W is the LWC, and visibility can be calculated as follows:

\[
Vis = \frac{-\ln(0.05)}{\beta}
\]

There are two challenges with the application of this equation as an indicator of the presence of fog. On the one hand, the calculated visibility decreases sharply with slowly increasing values of LWC near 0.012 g/m³, which is the commonly used threshold value, when visibility is less than 1 km. Thus, a tiny positive bias in modeling the LWC will influence whether fog is formed or dissipated in the simulation, resulting in underestimates for visibility. On the other hand, the experiment conducted by Kunkel (1984) for the relationship between measured LWC and visibility was based on data collected at a test facility at Otis Air National Guard Base on Cape Cod. Although this formulation may be adequate for the experimental field data that were available, it may need modification in order to be applied to observations collected at coastal locations of NS, because the latter are exposed to different PBL surface regimes.

Our main objective is to evaluate the LWC sensitivity to different PBL schemes in WRF, especially the difference between local and nonlocal schemes. LWC is one of the most critical forecast factors for fog. We are aware that \(N_d\) (number concentration) is also a function of visibility and that estimates of visibility without variability in \(N_d\) can cause 50% uncertainty (Gultepe et al., 2006). However, \(N_d\) is not an output of the WRF model, and the Thompson et al. (2008) microphysics scheme assumes that \(N_d\) is a constant, which therefore cannot simulate the variability of LWC caused by changes in \(N_d\). Furthermore, observations of droplets start from 1.5 μm diameters, which means that the smaller droplets are missing. This can cause a large bias when we calculate visibility, because small droplets cause lower visibility (Gultepe & Isaac, 1999).

Above all, our focus is on fog intensity, onset and dissipation time, improvements in the overall ability of WRF to simulate fog, and optimization of the Kunkel (1984) formulation with respect to our two data sets. The first data set is used to revise the Kunkel (1984) formulation, and the second is used to validate the revised formulation.

The LWP (liquid water path) is the integral of a column of LWC. In this study, we use the lowest 10 prognostic model levels, corresponding to geopotential heights up to roughly 500 m and covering the vertical extent of the densest fog bank (Leipper, 1994). Jiang and Cotton (2000) used cloud LWP to estimate the depth of the cloud layer. LWP is calculated as follows:

\[
LWP = \int_{Z_2}^{Z_1} LWC \cdot dz
\]

where \(dz\) is the geopotential height difference between two model levels. We use LWP to compare model results with fog estimates derived from MODIS, rather than use a single layer of LWC. This approach is taken because LWP can represent both fog extent and fog depth and is therefore a more reliable measure of the characteristics and development of a fog layer, whereas a single layer of LWC may miss fog at upper layers.
3. Results

3.1. Weather Conditions and Fog Observations

Since we only expect the model to work for really obvious fog events, we define criteria for the fog events that are long-lived and well established. Our criteria are (a) visibility less than 1 km and (b) fog that lasts more than 4 hr. Four events met these criteria in the first data set. However, we only focus on two which were primarily influenced by cyclones. Case 1 was influenced mainly by a weak cyclone in Phase 1 and the NAH in Phase 2. The cyclone in Case 1 was weaker, lasting for only 12 hr as it moved directly from south to north and merged into a stronger cyclone located over NFLD. In Case 1 (Figure 3a), fog started at 03:00 on 21 June as the northeastern part of the initial cyclone reached our measurement site at Sambro. With the lower nighttime temperatures, the fog lasted for 4 hr until 7 am, after sunrise, although a remnant of fog continued until 10 am. The latter may have been caused by wind transport, whereby a small patch of fog moved near Sambro and was captured by the fog droplet monitor. A secondary phase started later at 22:00 on 21 June, consisting of typical coastal advection fog. During this phase, the weather conditions were dominated by the NAH and Sambro experienced warm, moist southwesterly winds, which provided favorable conditions for the formation of fog in conjunction with the cool ocean surface. The fog in the secondary phase lasted longer and was stronger than fog in Phase 1. In Case 2 (Figure 3b), the cyclone moved from Boston to an area south of NS, with predominantly southwesterly winds over Sambro. Fog formed from 18:00 July 5 to 5:00 July 6 due to the longwave radiation cooling that occurred after sunset; the timing and wind field was similar to Phase 2 of Case 1, with southwesterly winds. RH reached 100% about 3 hr before fog formation, and the temperature decreased 4.4 °C from 16:00 5 July to 03:00 6 July. The other two fog events were dominated by strong NAH conditions that lasted for several days, which brought strong southerlies instead of southwesterly winds. Moreover, we found that WRF had difficulty in simulating this kind of fog. Additional details regarding these two fog events can be found in section 5.

3.2. Comparison of WRF LWP With MODIS

We show only a few figures of MODIS in this section, because Aqua and Terra only scan this area four times a day and therefore relatively few satellite images are available. Moreover, high cloud can cover the (lower tropospheric) fog identified by our algorithm, so that the fog patches under the cloud are undetected. Although we may miss detection of some fog patches, we show that our methodology is able to simulate fog occurrences that are consistent with MODIS data. For example, the estimated fog mask for Case 1 is presented in Figure 1a, for the MODIS image showing a ribbon of fog along the west coast of NFLD, and a large fog patch covering the waters to the east of NFLD. As indicated in Figure 1a, it is unfortunate that because of higher-level cloud caused by the NAH over much of NS and NFLD, the satellite could not provide information about the fog occurrence beneath the cloud cover. However, the averaged LWP of the three local PBL schemes in Figure 1b provides a reasonable spatial pattern in comparison with the MODIS data. Thus, Figure 1b suggests the same fog ribbon on the west coast of NFLD as shown in Figure 1a, and a large fog patch to the east of NFLD. The averaged LWP of the two nonlocal schemes in Figure 1c shows higher
LWP and wider fog extent than the local schemes, covering almost all the Grand Banks; but the spatial pattern of the ribbon-like fog on the west coast of NFNL is consistent with MODIS observations. The LWP estimates of Figure 1 also suggest a fog patch along the south coast of NS, but that area is covered by upper level cloud and therefore not evident in the MODIS imagery. Overall, our simulation successfully shows some ability to capture fog patches, thereby indicating that WRF has some capability to simulate fog over the North Atlantic waters.

3.3. Model Results

In this section, we evaluate the ability of different PBL schemes to simulate fog using WRF estimates of LWC. The objective is to determine which PBL scheme is able to simulate fog successfully and to motivate improvements in its formulation. As motivation for this section, we focus on differences between local and nonlocal schemes because these are much more significant than differences among local schemes, or differences among nonlocal schemes, separately per se.

Here, we present the first three layers of WRF model results in comparison with observations. As shown in Figure 3, we find that almost all the numerical experiments suggest values for LWC that are nearly two times higher than the observations. For both cases, different PBL schemes have differing abilities to simulate the correct onset and dissipation times of fog, especially between local and nonlocal schemes. As is shown in Figure 3a for Case 1, the first phase of observed fog events starts at 03:00 on 21 June. However, all the PBL schemes indicate an earlier onset, with the two nonlocal schemes (YSU and ACM2) showing times that are an hour or more earlier than the local schemes, and 5 hr earlier than observations. Results for the other phase are similar, with onset times that are 3 hr earlier than the observations, on average. The local schemes, MYJ, MYNN2.5, and MYNN3.0, generate more accurate results, especially MYNN2.5 and MYNN3.0, which appear to both simulate almost the exact times for onset and dissipation. Moreover, these latter two, MYNN2.5 and MYNN3.0, generate almost the same fog periods for Phase 2 of Case 1 and for Case 2, as were observed (Figure 3b), whereas both nonlocal schemes show the earliest onset (on average 5 hr earlier than the local schemes) and longer durations than the observations. As for MYJ, it misses the fog in Case 2, suggesting an onset that is 4 hr later than the observation. We also examined the first model layer of cloud LWC in ERA5, which can represent fog, and found that it missed the fog in both cases.

3.4. Basic Meteorological Variables

We conduct further comparisons for temperature, dew point temperature, and RH. Figure 4 shows the temperature and dew point depression time series. The temperature time series for Case 1 does not show an obvious diurnal cycle and was approximately constant during the entire period of the fog event. Even after fog events formed, no significant decline in temperature is evident in Figure 4. Five PBL schemes show very similar temperatures, although ACM2 showed slightly higher temperatures in Case 1 Phase 2. Moreover, all experiments exhibit warmer temperatures than those that are shown in observations, except for a small period from 20 June at 18:00 to 21 June at 06:00 indicated in Figure 4a. In the latter situation, sudden cooling occurred before sunset on 20 June. Figure 5 shows the modeled and observed values of RH, which
Phase 1 of Case 1 (Figure 5a) had similar results, although the nonlocal schemes simulated values for RH that are consistent with observations, whereas local schemes showed lower RH before the formation of fog. We found that WRF underestimates RH when there is no fog, in both cases. For example, in Case 2 during 06:00 to 18:00 on 5 July (Figure 5b), the mean modeled RH is about 6.7% lower than observations. Moreover, after fog has dissipated, modeled RH values are different from observations during 08:00 to 20:00 on 6 July. MYJ exhibits the highest RH (88.7%) compared to ACM2, which exhibits the lowest RH (69.5%). MYJ showed similar RH time series as other schemes, but it still missed the fog event in Case 2, which indicates that MYJ had some additional problems in simulating this fog event. Detailed discussion can be found in section 3.5.

3.5. Profile Differences Between Local and Nonlocal Schemes

The temperature and the LWC profile are evaluated in this section. We find that the differences between individual local and nonlocal schemes are not obvious. These schemes share similar patterns of bias (colder when fog formed) compared to ERA5 data (see Figure S1 in the supporting information) in local and nonlocal schemes. However, differences between local and nonlocal PBL schemes are significant. Therefore, we present the mean profiles for temperature and we focus on these differences.

Figure 6 shows the mean temperature profiles and the differences in temperature and LWC for each case. In general, all the profiles show an intense, persistent inversion layer during the fog events. The top of the inversion layer is defined where the lapse rate is less than 0. For Case 1 this is about 700 m, while it is 450 m for Case 2. The fog layer is immediately below the top of the inversion layer, so simulation of the appropriate vertical temperature structure is important in order to provide turbulent mixing (below) and stable weather conditions (above), which is the typical vertical structure for the marine atmosphere boundary layer during fog events, in agreement with the results reported by Zhang et al. (2009). Figure 6 also shows the difference between the average of the local schemes minus the average of the nonlocal schemes. For Case 1 (Figure 6c), a cold bias is found in the nonlocal schemes at 18:00 on 21 June, at about 300 m in Phase 2. Moreover, the LWC in this area is higher, which causes the fog to form earlier. The same also occurs in Case 2, when an obvious cold bias occurred at 18:00 on 5 July, at about 100 m. The fog started to form at this level, then started to lift as stratus began to develop. Even though Phase 2 in Case 1 and Case 2 are affected by different systems, both cases have similar patterns. The onset of fog develops after sunset, which may be caused by excessive vertical mixing as simulated in the nonlocal schemes (Hu et al., 2010), and excessive water vapor. Thus, heat is transported into the upper layers, reducing the surface temperature, and warming the upper levels. Due to the strong mixing as simulated by the nonlocal schemes, the atmosphere near the surface is more stable, which tends to favor the necessary vertical conditions for fog formation. Furthermore, the vertical transport from the ground may cause the transport of more water into the air,
which may be one of the reasons that LWC, as simulated by nonlocal schemes, is larger than that resulting from the local schemes.

As discussed in section 2, the MYJ simulation in Case 2 completely missed the fog event. Thus, we try to explore the cause for this result. Figure 7 shows the profile of static stability. The stable layer shown by the MYJ simulation starts to descend at 12:00 on 5 July. The bottom of the stable layer reaches the surface at 00:00 on 6 July. After sunrise, the static stability continues to rise, which means that the base of the inversion layer reaches the ground. However, this kind of vertical structure is not favorable for the formation of fog, because the stable layer near the surface vertical structure cannot provide enough turbulent mixing. After sunrise, an inversion layer forms at about 440 m. Fog starts to develop at this height and reaches the ground almost immediately. We suggest that the weak vertical mixing of MYJ (Coniglio et al., 2013; Hu et al., 2010) might be the main reason that this scheme misses the fog event; we note that MYJ usually simulates lower PBL height than other local PBL schemes. In this situation, vertical mixing that is too weak cannot transport sufficient heat and moisture into the PBL, which may make the inversion layer descend as time progresses.

Figure 6. Vertical profiles (time in AST) from surface to 1,000 m for two cases; (a) shaded is temperature of the mean of local schemes, contour lines are LWC; (b) the same as (a), but for nonlocal schemes; (c) shaded is the temperature difference of the local minus the nonlocal schemes; orange solid contour line is the positive LWC, while green dashed contour line is the negative LWC; black solid line is 0.

Figure 7. (a) Shading represents vertical profile of atmospheric static stability; contour lines are LWC of PBL MYJ; (b) the same as (a), but for the mean of MYNN 2.5 and MYNN 3.0. The date is in AST.
MYNN2.5 is the updated version of MYJ and was developed to overcome the weak vertical transport in MYJ (Nakanishi & Niino, 2004, 2009), allowing the stable layer to stay at about 100 m until 6:00 on 6 July. Fog starts to form at about midnight on 6 July. After sunrise, sunlight starts to heat the atmosphere and the ground, and the increasing temperature of the ground provides strong turbulent mixing, moving dry, warm air from the surface to the upper layers, causing the inversion layer to start to be uplifted and to weaken. With the uplifting of the inversion layer, the fog layer also starts to be uplifted as stratus, as fog is dissipated in the surface layer and at the ground. Comparison of the modeled LWC with observations suggests that in MYNN2.5 and MYNN3.0, the updated PBL schemes formulated to solve the weak mixing problem of MYJ perform more reasonably in terms of the vertical structure of fog. In summary, in this case, MYJ fails to simulate the processes related to lifting of the fog as stratus.

4. The Extinction Coefficient and Visibility

Fog prediction and modeling need accurate estimates of LWC. To be of practical use, the extinction coefficient $\beta$ should be derived from LWC (Kunkel, 1984). There are many studies (Eldridge, 1966, 1971; Pinnick et al., 1978; Tomasi & Tampieri, 1976) that focus on the relationship between the extinction coefficient and visibility using LWC, which result in various relationships depending on the field location and the type of fog. All of these contribute to improvements in our ability to predict fog. Here, we present a reexamination of the relationship between LWC and visibility, motivated primarily by the fact that the WRF model has shown a moist bias in recent studies (Banks et al., 2016; García-Díez et al., 2013; Ghonima et al., 2017). This previously observed overestimate in water may cause the higher liquid water and water vapor in our simulations, which would explain the negative bias in the visibility predicted by the Kunkel equation. Moreover, the location of various field observations is often different, which can change the relationship between LWC and visibility. However, we do not expect that the topography and fog formation mechanisms of our site to differ greatly from Kunkel’s original study. Due to WRF’s moist bias, it may be inappropriate to apply equation (1) directly, using the WRF model output. The black line in Figure 8 shows the Kunkel extinction relationship, with the visibility decreasing rapidly when LWC is near 0.012 g/m$^3$. Visibility will be less than 1 km when LWC is greater than 0.012 g/m$^3$, which is a commonly used threshold for the formation of fog. However, due to the moist bias in the WRF model, it is therefore likely to underestimate visibility.

Here, a power law curve is fitted to the observed visibility, hourly averaged data is calculated from 5 min intervals, using hourly modeled LWC. As we previously discussed, we find that MYJ misses the fog event in Case 2. In order to reduce the bias in the model results, we remove the MYJ time series in Case 2 in the LWC comparison when we perform an optimization of these fog simulation schemes. Combining these two cases, the exponent is 1.353 within 95% significance confidence, and the significance confidence is 1.299 to 1.408. A mean relationship is derived, as shown in Figure 8:

$$\beta = 144.7 \times W^{1.353}$$  \hspace{1cm} (4)

Using this relation, the threshold for fog (visibility <1 km) is about 0.0569 g/m$^3$ where the new exponent (1.353) is about 47% higher than the old exponent (0.88), given in equation (1).

It is interesting to note that our new equation does not work well when visibility is greater than 1 km. When visibility is defined as less than 1 km, the steep slope in Figure 8 is due to the fact that the observed droplet spectra do not change significantly with LWC, especially when LWC is larger than 0.2 g/m$^3$ (Kunkel, 1984). The new exponent is calculated based on the fact that WRF (Version 3.8.1) has a moist bias; newer versions with altered water processes will require a new parameterization, and a reexamination of the exponent. In this formulation, modeled LWC is almost 2.5 times greater than observed LWC. However, the fog onset and dissipation times are consistent with observations (Figure 3), which indicate that WRF has some ability to...
simulate LWC well when visibility is not considered; this also motivates the need to change the parameterization to better determine visibility. The linear regressions were calculated with observed visibility, using the new exponent (1.353) and the original exponent (0.88). Results show that the new exponent has higher slope (0.89) than the original exponent (0.19), which implies that the new exponent can more precisely estimate the visibility, compared to the original exponent.

4.1. Comparison of MODIS With LWP for the Second Data Set

The weather during the second time period, 24 to 31 July, was similar to that of the first time period 10 June to 22 July. Fog events developed on 26, 27, and 30 July, influenced by a cyclone that passed by from Québec. Southerlies were generated by the southeastern part of the cyclone. Fog events that developed on 28 and 29 July were influenced by the NAH, which dominated the area over NS as the cyclone weakened.

We use the same method as in section 3.2 to validate the WRF simulation. Due to the influence of higher-level clouds, it is not possible to see the complete fog spatial pattern that might otherwise be observed by MODIS. In addition, from historical data, we know that in the North Atlantic, fog frequently occurs over the Gulf of St. Lawrence, Grand Banks, and the coastal area south of NS and north of the Gulf Stream. Therefore, as mentioned previously, the spatial patterns of fog over these regions are comparable to the modeled area for LWP, shown in Figure 9. However, because high cloud obscures many of the MODIS images, we show only three images out of an archive of 73.

The difference between local and nonlocal schemes is given in Figure 9, showing similar spatial patterns. However, nonlocal schemes usually show higher LWP and wider fog extents than local schemes. Thus, we show the results simulated by local schemes only. On 27 July 16:45, fog was detected over the Gulf of St. Lawrence, coastal areas south of NS, and along the southern coast of NFLD. Results from WRF showed good agreement with the observed scattered fog patches over the Gulf of St. Lawrence and the large fog patch over the area south of NS but underestimated the small fog patch over the southern coast of NFLD. On 27 July, 14:05, an extended wide area of fog was detected over the Grand Banks. However, high-level cloud covered the fog area extending to the east of NFLD and Labrador. In this example, the fog mask in the MODIS

Figure 9. Comparison among MODIS, ERA5 and WRF; the date is in AST. The first column is the fog mask derived from MODIS; white means missing data. The second column is the LWP integrated cloud water mixing ratio from ERA5. The third column is the mean LWP integrated by LWC from WRF for the three local PBL schemes (MYJ, MYNN2.5, and MYNN3.0) experiments. The last column is the mean LWP integrated by LWC from WRF for the two nonlocal PBL schemes (ACM2 and YSU).
data appears to be scattered around the cloud patch, which suggests that fog is present under the cloudy area. Therefore, we suggest that WRF provides a reasonable spatial pattern for fog compared to MODIS imagery over the Grand Banks, but may underestimate the fog over the eastern coast of NFLD. This appears to be the situation because there is a small fog mask scattered over this region, whereas WRF shows only some minor fog patches. On 29 July 14:50, a ribbon-like fog area extended over the Gulf of St. Lawrence in the MODIS imagery, in good agreement with WRF results. MODIS also detected fog over the Grand Banks, but high-level cloud covered a large part of this area, so that we cannot complete the comparison with the WRF simulation. Regarding ERA5, there is poor agreement with MODIS, and failure to compare with almost any of the fog areas except a small patch to the south of NS on 27 July; this reflects the capability of the ERA5 boundary layer parameterizations used to simulate the near surface processes.

4.2. Validation of the Fog Parameterization

Figure 10 shows the LWC and visibility time series for six fog events that occurred over 8 days in July 2016. The two fog events that started on 24 and 26 July only lasted for several hours. WRF has differing ability to simulate these two fog events. While all the PBL schemes failed to predict the fog dissipation, the onset of fog on 26 July was predicted reasonably well by the MYJ and MYNN2.5 schemes. There were four long lasting fog events from 27 to 30 July. For these cases, the three local schemes performed well in simulating the fog. As before, the nonlocal schemes simulate too much LWC, although they can predict reasonable trends for LWC. However, WRF simulated two fog events on 25 and 31 July that were not observed; all PBL schemes showed about three hours’ duration for these fog events. On one hand, these simulation results may be due to the relatively coarse spatial resolution of the models. Fog is a small-scale weather phenomenon and it is difficult to predict the fog details. On the other hand, the occurrence of fog may be caused by the horizontal

Figure 10. (a) The time series of LWC (the date is in AST); (b) the time series of visibility; the solid lines are the visibility calculated with the new exponent (1.353); the dashed lines are the visibility calculated with the original exponent (0.88).
transport, advected by wind. Because the fog monitor at Sambro could only collect data from a single point, it is possible that the observations were unable to detect the fog formation.

When we apply the newly estimated exponent (1.353) in comparison with the original (0.88) exponent to the second case (24–31 July) in equation (1) to calculate the visibility, Figure 10b shows improvement compared to previous estimates. Problems regarding early bias in the onset of fog, and late bias in fog dissipation, are partly resolved, especially from 28 to 30 July. Three fog events simulated with MYNN2.5 and MYNN3.0 were detected more clearly with the new exponent (1.353), with fog dissipation on 28 and 29 July. However, the simulated visibility time series with the old exponent (0.88) showed continued fog from July 28 to 30. By comparison, the new estimate for the exponent in the visibility equation (4) applied to the nonlocal schemes still cannot simulate visibility well. Thus, visibility simulated by YSU and ACM2 suggest that continuous fog lasted from 25 to 29 July, which is unreasonable.

In order to determine an optimal PBL scheme to simulate fog, we calculate the correlation coefficient ($R$) and RMSE of LWC and visibility (Tables 2 and 3) and require that all the correlation coefficients are within 99% significance confidence. For the first data set, which is from 10 June to 22 July (Table 2), local schemes show higher correlations than nonlocal schemes, except for Case 2 simulated by MYJ; but nonlocal schemes show higher RMSE than all local schemes, caused by the higher LWC than simulated in the local schemes. ERA5 has the lowest values for $R$ and RMSE because it misses every fog event, suggesting that ERA5 may not be able to reliably simulate fog patterns near the surface compared to MODIS. For the second data set, which is from 24 July to 31 July (Table 3), MYJ performs with the highest $R$ (0.4117) and relatively good RMSE (0.1623), whereas MYNN2.5 obtains the second highest $R$ (0.3908) and least RMSE (0.1372). Both nonlocal schemes performed with greater RMSE and lower $R$ values compared to the local schemes. The new exponent (1.353) improves the model performance for predicting visibility, with the exception of MYJ, when compared to the original exponent (0.88); MYJ exhibits a slight increase in RMSE (from 4.2814 to 4.2818) and smaller $R$ (from 0.6673 to 0.6308). After applying the new exponent, MYNN2.5 is able to simulate visibility well. Although MYNN2.5 has smaller $R$ and greater RMSE compared to MYJ, we suggest that MYNN2.5 provides the best PBL for fog simulation over the Northwest Atlantic, as a result of this study. There are three reasons: (a) MYNN2.5 exhibits better performance than MYJ (Table 2) in the first data set and catches every fog event during 20 June to 31 July 2016, whereas MYJ fails to predict the fog event on July 5; (b) MYJ is a rather old PBL scheme, with weak vertical mixing which may result in larger bias in simulations of the vertical fog structure. (c) MYNN2.5 appears to be nearly unbiased in PBL depth, moisture and potential temperature, relative to North American Mesoscale Model forecasts (Coniglio et al., 2013).

We also compared our new equation with other visibility algorithms (Lin et al., 2017). As shown in Figure S2, all the visibility time series are calculated with MYNN2.5, which we recommend as the best PBL scheme for fog simulation. All algorithms show fog events on 25 and 31 July while the observations show none, which means that algorithms can avoid bias caused by the model. Except for those two days, there are no significant differences among the algorithms. However, the fog case on 29 July does result in different performances among the algorithms; our new equation shows the most consistent dispersal time compared to the observations, whereas other algorithms suggest longer fog duration. The statistics also

| Table 2 | Correlation Coefficients and RMSE Values With LWC for Data Set 1 |
|---------|---------------------------------------------------------------|
| $R$     | MYJ   | MYNN2.5 | MYNN3.0 | ACM2 | YSU  | ERA5 |
| Case 1  | 0.7616 | 0.8515 | 0.8333 | 0.3803 | 0.6569 | 0.2392 |
| Case 2  | −0.1858 | 0.8794 | 0.8708 | 0.9040 | 0.8918 | 0.2037 |
| RMSE    | Case 1 | 0.1224 | 0.1366 | 0.1381 | 0.1791 | 0.2273 | 0.0455 |
|         | Case 2 | 0.1183 | 0.0808 | 0.0761 | 0.1231 | 0.1498 | 0.0499 |

| Table 3 | Correlation Coefficients and RMSEs With LWC for Data Set 2 |
|---------|----------------------------------------------------------|
| $R_{LWC}$ | MYJ   | MYNN2.5 | MYNN3.0 | ACM2 | YSU  | ERA5 |
|          | 0.42  | 0.39   | 0.28    | 0.31  | 0.37  | 0.44  |
|          | 0.66(0.69) | 0.52(0.60) | 0.52(0.54) | 0.46(0.50) | 0.42(0.44) | 0.44(0.48) |
| RMSE$_{LWC}$ | 0.16  | 0.14   | 0.15    | 0.20  | 0.21  | 0.08  |
|          | 3.12(2.85) | 3.74(3.25) | 3.61(3.40) | 3.95(3.73) | 4.17(3.95) | 4.04(3.69) |

Note. The subscripts LWC and Vis represent the correlation coefficient or RMSE with respect to LWC and visibility, respectively. Values in parentheses present the correlation coefficient or RMSE calculated by the new visibility equation.
suggest that our new equation with 1.353 provides the best results, with the lowest RMSE (4.9145) and highest correlation (0.5088) compared to the observations.

5. Discussion

There remain many problems in simulating fog with nonlocal PBL schemes over the Northwest Atlantic. We found that our parameterization has trouble in simulating fog that is dominated by strong NAH conditions. For example, Case 3 (from 28 to 30 June) and Case 4 (from 17 to 19 July) were dominated by strong NAH conditions located at 42°N (Case 3) and 36°N (Case 4), with pressure centers for both cases that are higher than 1,030 hPa. Thus, both cases were dominated by warm, moist southerlies allowing the fog to form easily. By comparison, fog events in Cases 1 and 2 are affected by southwesterlies more frequently. The fog in Phase 2 of Case 1 is also dominated by a strong NAH; however, a strong cyclone located over NFLD changed the wind direction generating the westerly component. Southerlies can provide stronger moist, warm advection than southwesterly winds, thereby generating the formation of fog more easily. Fog periods in Cases 3 and 4 (Figure 11) were more complicated than those of Cases 1 and 2; fog occurred four times in Case 3, and three times in Case 4, in 2 days. In each case, the time interval between each fog event was not long. However, the model simulation suggested much higher LWC than was observed, even though the fog had dissipated in each case; this makes an unreasonable fog simulation last too long, by several days. Moreover, the trends are not consistent with observations. Thus, we found that the parameterization schemes used in this study have problems simulating fog when dominated by a strong NAH. Further study will be performed to control the excessively moist simulations, caused by a strong NAH. Thus, fog modeling still contains challenging tasks, especially for efforts to develop realistic PBL schemes.

Another limitation of our work is that we did not consider the influence of $N_d$ to visibility due to limitations of the mesoscale model and the observational data. $N_d$ can exhibit large variability for given values of LWC (Gultepe, 2005), and small droplets can cause lower visibility than large droplets because of their slow gravitational settling under the saturated conditions (Gultepe & Isaac, 1999). It has been recognized that $N_d$ plays an important role in visibility prediction. In future studies we plan to use a 1-D column model, PAFOG (Bott & Trautmann, 2002), to consider the total number concentration of cloud droplets and total cloud water content. PAFOG has been coupled to WRF and has shown better agreement with observations than simulations of fog using only WRF over the Yellow Sea (Kim & Yum, 2012). Thus, we plan to study fog over Canadian waters using the WRF-PAFOG model system.

6. Conclusions

This study evaluated the fog simulation capability of WRF with five possible PBL schemes. Two cases were selected during 10 June to 20 July 2016 as typical advection fog caused by different weather systems. They were examined in comparison with satellite imagery, ERA5 reanalysis data and in situ surface observations. After comparing the modeled LWC values with observations, a modified visibility equation was developed.
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and validated by comparisons with another six fog cases that occurred during 24 to 31 July 2016. The new visibility equation is of the same form as the conventional Kunkel (1984) equation, except that the exponent is set to 1.353 as given in equation (4), which appears to perform well to simulate visibility using the modeled LWC, compared to observations collected at a coastal location in NS.

The sensitivity of PBL schemes to their ability to simulate LWC varies significantly between local and nonlocal schemes. However, among local schemes the differences are not obvious, per se, nor among nonlocal schemes. Local schemes are good at simulation of fog events that are influenced by weak cyclones, providing reasonably good estimates of the onset and dissipation of fog. Nonlocal schemes tend to show larger biases, such as higher values for LWC, and earlier onset and deferred dissipation of fog events. In any case, we found that all schemes appear to perform surprisingly well in capturing the basic variables well, compared to observations but are not able to agree in modeling LWC values.

A particular example of the limitations of PBL schemes seems to be warm moist southerlies associated with strong NAH conditions, when fog can form easily. In these cases, model simulations give excessive estimates of LWC values. Additional study of strong NAH conditions is needed in order to achieve better simulate moisture and LWC values.

The profiles of temperature and LWC were examined to investigate the difference between local and nonlocal schemes. We found that near surface temperatures in nonlocal schemes were lower than in local schemes, especially during the onset of fog. Compared to observed values of LWC, the temperatures in nonlocal schemes have a negative bias when LWC is overestimated. This result may be caused by a cold bias at near surface levels, which is typical of nonlocal schemes. This leads to a stronger inversion layer making the atmosphere more stable, and trapping more water at near surface levels, thereby providing favorable conditions for the onset of fog.

As discussed in section 4, the LWC bias cannot be neglected or resolved by changing a parameterization in the WRF model. Thus, we modified the exponent in the extinction coefficient (Kunkel) equation (1), in order to use the WRF model to simulate visibility directly. The new exponent performs well in local PBL schemes but still cannot reduce the bias in nonlocal schemes because LWC values are too high. As shown in Figure 8, we have investigated a new possible exponential value (1.353) for different weather systems, as observed off NS.

Finally, this study has shown that despite the LWC bias in the WRF model, the Kunkel equation (1) with a new exponent (1.353) can capture fog events reasonably well in the waters off NS, with the local PBL schemes. This approach may be regarded as a tuning of this formulation for Nova Scotian waters. Although MYJ showed better statistics than MYNN2.5, in comparisons with observations, we suggest that the updated PBL scheme, MYNN2.5, provides better simulations than MYJ. For example, in Case 2, MYJ completely misses the fog event. We examined the atmospheric static stability and found that the vertical structure is incorrect in MYJ, thereby implying difficulty in simulating the processes that lift fog to become stratus, namely weak vertical transport. Moreover, the lack of heat and moisture causes an unstable upper layer, which leads to unreasonable fog development. Clearly, an accurate PBL scheme plays an important role in fog simulation, which is not a surprise. In spite of missing Case 2, MYJ was able to reasonably simulate LWC in the second data set, which suggests that MYJ has the ability to simulate fog. Thus, additional study is needed to evaluate MYJ’s overall ability to simulate fog.
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