How the Environmental Lifting Condensation Level Affects the Sensitivity of Simulated Convective Storm Cold Pools to the Microphysics Parameterization

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ABSTRACT: Several studies have documented the sensitivity of convective storm simulations to the microphysics parameterization, but there is less research documenting how these sensitivities change with environmental conditions. In this study, the influence of the lifting condensation level (LCL) on the sensitivity of simulated ordinary convective storm cold pools to the microphysics parameterization is examined. To do this, seven perturbed-microphysics ensembles with nine members each are used, where each ensemble uses a different base state with a surface-based LCL between 500 and 2000 m. A comparison of ensemble standard deviations of cold-pool properties shows a clear trend of increasing sensitivity to the microphysics as the LCL is raised. In physical terms, this trend is the result of lower relative humidities in high-LCL environments that increase low-level rain evaporational cooling rates, which magnifies differences in evaporation already present among the members of a given ensemble owing to the microphysics variations. Omitting supersaturation from the calculation of rain evaporation so that only the raindrop size distribution influences evaporation leads to more evaporation in the low-LCL simulations (owing to more drops), as well as a slightly larger spread in evaporational cooling amounts between members in the low-LCL ensembles. Cold pools in the low-LCL environments are also found to develop earlier and are initially more sensitive to raindrop breakup owing to a larger warm-cloud depth. Altogether, these results suggest that convective storms may be more predictable in low-LCL environments, and forecasts of convection in high-LCL environments may benefit the most from microphysics perturbations within an ensemble forecasting system.

SIGNIFICANCE STATEMENT: Computer simulations of thunderstorms can have grid spacings ranging from tens to thousands of meters. Because individual precipitation particles form on scales smaller than these grid spacings, the bulk effects of precipitation processes in models must be approximated. Past studies have found that models are sensitive to these approximations. In this study, we test whether the sensitivity to these approximations changes with the relative humidity in the lowest 1–2 km of the atmosphere. We found that increasing the relative humidity decreases the sensitivity of simulations to the precipitation process approximations. These results can inform meteorologists about the uncertainties surrounding computer-generated thunderstorm forecasts and suggest environmental conditions where using several computer models with different precipitation process approximations may be beneficial.

KEYWORDS: Convective-scale processes; Cold pools; Cloud microphysics; Convective storms; Ensembles

1. Introduction

Over the last couple of decades, increases in computational power have given scientists the ability to simulate convective storms at increasingly higher resolutions in both operational forecast and research settings (e.g., Benjamin et al. 2016; Orf et al. 2017; Lawson et al. 2018). Although increasing the spatial resolution allows models to represent convection without a convection parameterization, some processes that are vital to deep, moist convection that occur on scales smaller than the model grid spacing, such as the microphysics, must still be parameterized. The microphysics parameterization1 can have a particularly large impact on the solution of a convection-allowing model at both relatively coarse (3 km) and fine (<0.25 km) grid spacings, largely owing to enthalpy changes associated with phase transitions and the impact of hydrometeor loading on buoyancy.

There are three broad classifications of microphysics parameterizations: bin, bulk, and Lagrangian particle-based. Bin and bulk schemes use an Eulerian framework that evolves particle size distributions (PSDs) for each of the hydrometeor types in each model grid cell, whereas Lagrangian particle-based schemes follow the evolution of “super particles” as they move through the model domain (Andrejczuk et al. 2008; Morrison et al. 2020). Bin schemes explicitly resolve the PSD using either mass or size bins, whereas bulk schemes use an analytic function to describe the PSDs for each hydrometeor type (Morrison et al. 2020). Bulk schemes are further distinguished by the number of PSD moments predicted by the parent dynamical model, with some commonly predicted moments including the third (related to mass mixing ratio), zeroth (number concentration), and sixth (radar reflectivity). These moments can be used to constrain the parameters that appear in the analytic PSD. Owing to their reduced computational cost, the majority of convection-allowing numerical models use bulk schemes. For this reason, our focus will be on bulk schemes.

1 “Parameterization” and “scheme” will be used interchangeably.

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Numerous studies have demonstrated that characteristics of simulated deep, moist convection, such as updraft strength, surface precipitation, and cold-pool strength, are sensitive to how the microphysics are parameterized. A few examples are noted here. Early studies found that including ice in the microphysics parameterization increased storm updraft speeds and surface precipitation area owing to the added buoyancy from the enthalpy of fusion and the slower fall speeds of ice particles, respectively (Johnson et al. 1993; Gilmore et al. 2004a). Cold pools and precipitation amounts are sensitive to the fall-speed parameters used for the rimed ice species (RIS), with faster-falling, hail-like RIS resulting in stronger cold pools and more precipitation early in the simulation owing to a greater flux of water mass into the melting layer, which is then converted to rain (Morrison and Milbrandt 2011; Bryan and Morrison 2012; Van Weverberg et al. 2012; Van Weverberg 2013). Cold-pool strength has also been found to increase when using a more aggressive raindrop breakup parameterization (Morrison and Milbrandt 2011; Morrison et al. 2012) or PSD parameters that favor smaller raindrops or smaller RIS particles (van den Heever and Cotton 2004; Cohen and McCaul 2006; Snook and Xue 2008; Freeman et al. 2019). The presence of smaller hydrometeors results in increased cooling via evaporation and melting owing to a larger hydrometeor surface area-to-volume ratio. Other studies have also documented sensitivity of convective storm characteristics to the number of moments predicted by the bulk scheme (e.g., Morrison et al. 2009; Dawson et al. 2010; Van Weverberg et al. 2012; Bryan and Morrison 2012) and the melting parameterization (Kakan and Lebo 2019). This list is not exhaustive, and sensitivities of convective storms to some of the other aspects of bulk microphysics schemes have yet to be tested. Further, convective storms are also sensitive to quantities closely related to the microphysics scheme, such as the number of aerosols available to be cloud condensation nuclei (e.g., Lebo and Morrison 2014). In this case, the microphysics can also impact the distribution of aerosols through processes like the regeneration of aerosols during evaporation (Engström et al. 2008), which represents another way that the microphysics can impact the storm system. Based on this discussion, it is clear that more research needs to be done to better constrain microphysics parameterizations to better simulate convective storms.

Unlike the aforementioned studies, our primary goal is not to document additional sensitivities of convective storms to the microphysics parameterization. Instead, we seek to examine how the sensitivity to the microphysics parameterization changes in different environments. Given that the microphysics are a source of uncertainty in convective storms, storms should be more predictable in environments where the sensitivity to the microphysics is reduced (or less predictable in environments where microphysics sensitivity is enhanced), all else being equal. This knowledge will improve our understanding of the uncertainty in convective storm forecasts and could perhaps be used to identify conditions where accounting for microphysical uncertainty in an ensemble forecasting system using either a mixed-microphysics ensemble (e.g., Duda et al. 2014; Loken et al. 2019) or stochastically perturbed parameters within the microphysics scheme (e.g., Stanford et al. 2019; Thompson et al. 2021) would be beneficial.

Some studies have examined how the sensitivity of convective storms to the microphysics parameterization changes when systematically varying a single aspect of the environment. Gilmore et al. (2004a) found that the sensitivity of supercell longevity to the inclusion of ice in the microphysics scheme changed with the environmental shear, with storms in environments closer to the “tipping point” (e.g., Lawson 2019) between supercellular and multicellular storms being more sensitive to the microphysics scheme. Using a similar model, Gilmore et al. (2004b) show that the sensitivity of surface precipitation amounts to the RIS intercept parameter and bulk density increase with vertical wind shear. Simulated squall lines studied by Morrison et al. (2012) exhibited different sensitivities to the raindrop breakup parameterization depending on the environmental 0–2.5-km vertical wind shear. Van Weverberg (2013) and Morrison et al. (2015) both simulated convective storms that became increasingly sensitive to the choice of RIS in the microphysics scheme as the environmental convective available potential energy (CAPE) increased. Cohen and McCaul (2006) showed that the collection of cloud droplets by rain and RIS in a supercell simulation were more sensitive to the shape parameter and total number concentration of cloud droplets as the environmental precipitable water decreased. Collectively, these studies demonstrate that the sensitivity of convective storms to the microphysics is dependent on the environment.

In this study we examine an aspect of the environment not considered by the studies mentioned above: the lifting condensation level (LCL), which is a proxy for low-level relative humidity. We are focused on the LCL because there is a direct, physical link between the LCL and evaporational cooling, which is one way that changes in the microphysics parameterization impact storm dynamics. In particular, evaporational cooling is an important driver of convective cold pools (James and Markowski 2010; Mallinson and Lasher-Trapp 2019), which can influence the likelihood of tornadogenesis (e.g., Markowski et al. 2002; Grzych et al. 2007; Markowski and Richardson 2014; Brown and Nowotarski 2019), bow echo development (e.g., James et al. 2006), the triggering of new cells (e.g., Morrison et al. 2015), and squall line maintenance and evolution (e.g., Rotunno et al. 1988; Morrison et al. 2012; Lombardo and Kading 2018). The physical link between LCLs and evaporational cooling can be seen in the Maxwellian mass tendency for a single raindrop undergoing condensation or evaporation:

\[
dm_d/dt = 4\pi r_d^2 \rho_l G(s - s_K)F, \tag{1}
\]

where \(m_d\) and \(r_d\) are the drop mass and radius, respectively; \(\rho_l\) is the density of liquid water; \(G\) is a slowly varying function of environmental conditions that acts as a diffusivity; \(s\) is the
supersaturation; \( s_K \) is the Köhler supersaturation; and \( F \) is a ventilation factor, which increases with increasing drop fall speeds (Lamb and Verlinde 2011). Assuming a drop is evaporating \((s < s_K)\), increasing the LCL will increase the evaporation rate because \( s - s_K \) will be more negative and the depth over which \( s - s_K < 0 \) will be deeper owing to the higher cloud bases. Thus, more evaporational cooling would be expected as the LCL increases. This process where a drier environment results in more evaporation will be referred to as the “environmental control” on evaporation. Note that this physical connection between rain evaporation and LCL via the environmental control relies on the LCL being a good proxy for low-level relative humidity. This is the case for environments with well-mixed boundary layers, such as those used in this study, but it may not always be the case.

In addition to directly influencing the evaporation of rain near the surface through the environmental control, changing the LCL may also impact near-surface rain PSDs, which also influence the near-surface evaporation rate (hereinafter the “microphysical control”). In particular, a smaller distance between the LCL and freezing layer (the “warm-cloud depth”) in a high-LCL environment may reduce warm-rain processes and increase cold-rain processes, resulting in more ice aloft. This likely results in more cooling from ice melting and sublimation aloft. Although this cooling is unlikely to directly influence the near-surface cold pool because of the compensating effects of compressional warming and entrainment as these parcels descend (e.g., as speculated by Mallinson and Lasher-Trapp 2019), such processes can influence near-surface rain PSDs, which also influence rain evaporation [note in Eq. (1) how rain evaporation depends on raindrop size]. Further, higher LCLs are also associated with deeper subcloud layers, which result in more evaporation before raindrops reach the surface. This process can also influence near-surface rain PSDs, likely by reducing the number of raindrops as the LCL is raised, which would reduce evaporational cooling. Therefore, even though higher LCLs are considered favorable for increased rain evaporation near the surface owing to the environmental control, this trend is likely modulated by the impact of the LCL on near-surface rain PSDs, which influences evaporation through the microphysical control. The impact of the LCL on near-surface rain PSDs is another avenue through which changing the LCL can influence the sensitivity of cold pools to the microphysics.

Based on this discussion, we hypothesize that the cold pools of convective storms in environments with high LCLs will be more sensitive to microphysical processes than the cold pools of storms in low-LCL environments. Our rationale is that the additional evaporation expected in the high-LCL convective storms (owing to the environmental control) will magnify differences in the evaporation rates that arise from simulating storms in the same environment with different parameter choices within the microphysics scheme. This leads to the research questions posed by this study:

1) Are the cold pools of simulated ordinary convective storms (i.e., storms in environments with no vertical wind shear) more sensitive to various choices made in the microphysics parameterization when the environmental LCL is raised?

2) Physically, why does the sensitivity of the cold pool to the microphysics change (or not change) with LCL? If sensitivity increases with LCL, is this because higher LCLs magnify differences in evaporation rates that already exist owing to perturbations in the microphysics? Are these changes in evaporation with LCL primarily a result of the environmental or microphysical control?

3) Do these results depend on the microphysics scheme, convection initiation method, model grid spacing, environmental level of free convection (LFC), or weak vertical wind shear?

The rationale behind examining ordinary convection (instead of, e.g., supercells) is to remove some of the complexity that arises from the strong dynamic vertical perturbation pressure gradient accelerations that are present in convective storms that occur in environments with strong vertical wind shear (e.g., Weisman and Klemp 1984) and because of the simple morphology of ordinary convection.

2. Method

To address these research questions, a series of ordinary convective storms is simulated using environments with different LCLs and different alterations to a single microphysics parameterization. The approach taken here is to construct seven different perturbed-microphysics ensembles, each using a horizontally homogeneous thermodynamic base state with a different LCL between 500 and 2000 m. Each ensemble will include nine members with different variations of the Morrison two-moment microphysics scheme (Morrison et al. 2005, 2009). For consistency, the same nine variations will be used in each ensemble. To assess the sensitivity of the simulated convective cold pools to the microphysics scheme, the ensemble standard deviation of three different cold-pool properties will be computed and then compared across the seven ensembles. The cold pool is defined as the area 50 m AGL with a potential temperature perturbation \( \theta' < -0.5 \) K, and the three cold-pool properties are (i) minimum \( \theta' \) at 50 m AGL, (ii) mean cold-pool \( \theta' \), and (iii) fractional cold-pool area (fraction of all grid points at 50 m AGL that are in the cold pool). A schematic of the perturbed-microphysics ensembles is presented in Fig. 1.

a. Model configuration

Each ensemble member is an idealized numerical simulation of ordinary convection performed using Cloud Model version 1, release 19.8 (CM1; Bryan and Fritsch 2002; Bryan and Morrison 2012). CM1 is configured with a spatial domain of 120 km \( \times \) 120 km \( \times \) 20 km. The horizontal grid spacing is 500 m; the vertical grid spacing is 100 m in the lowest 4 km, stretches to 500 m at 16 km AGL, and is constant at 500 m above 16 km. The increased vertical resolution in the lowest 4 km is desirable to better resolve the cold pool. Each simulation is run for 2 h with a large time step initially set to 2.5 s and then modified during run time using the adaptive time-stepping algorithm included in CM1. CM1 is set up using the large-eddy simulation (LES) option, and a turbulent kinetic energy scheme is used to parameterize subgrid-scale turbulence. Pseudorandom \( \theta' \) values between \(-0.05 \) and \(+0.05 \) K drawn from a uniform
distribution are added to the initial state in each simulation to disrupt the unphysical symmetry of the simulated convective storms. To maintain uniformity, the same perturbations are added to each simulation. Other aspects of the CM1 configuration are listed in Table 1. Time series using cold-pool properties presented later in this article use the CM1 statistical output instead of being computed from the 3D output, which has lower temporal resolution.

Convection is initiated in each simulation using a 2-K warm bubble located 1.5 km AGL with a horizontal radius of 10 km, vertical radius of 1.5 km, and a relative humidity profile that matches the thermodynamic base state. A relative humidity-conserving warm bubble is used in order to keep the LCL for parcels originating within the warm bubble the same as for parcels at the same altitude that originate from outside the warm bubble. For this study, we are interested in the initial convective cell, which is sensitive to the initiation method used (e.g., Morrison et al. 2015; Murdzek et al. 2021). To demonstrate the robustness of our results, sensitivity tests using four other initiation methods are presented in section 4c.

### Table 1. CM1 configuration.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domain size</td>
<td>120 km × 120 km × 20 km</td>
</tr>
<tr>
<td>Horizontal grid spacing</td>
<td>500 m</td>
</tr>
<tr>
<td>Vertical grid spacing</td>
<td>100 m below 4 km; 500 m above 16 km</td>
</tr>
<tr>
<td>Initial large time step</td>
<td>2.5 s</td>
</tr>
<tr>
<td>Lateral boundary conditions</td>
<td>Open radiative</td>
</tr>
<tr>
<td>Top and bottom boundary conditions</td>
<td>Free slip</td>
</tr>
<tr>
<td>Initiation method</td>
<td>2-K relative humidity–conserving warm bubble</td>
</tr>
<tr>
<td>Microphysics</td>
<td>Morrison two moment (with variations)</td>
</tr>
<tr>
<td>Radiation</td>
<td>None</td>
</tr>
<tr>
<td>Surface fluxes</td>
<td>None</td>
</tr>
<tr>
<td>Coriolis acceleration</td>
<td>None</td>
</tr>
<tr>
<td>3D output frequency</td>
<td>300 s</td>
</tr>
<tr>
<td>Statistical output frequency</td>
<td>60 s</td>
</tr>
</tbody>
</table>

**FIG. 1.** Schematic representation of the seven perturbed-microphysics ensembles. Each box on the left represents a nine-member ensemble with a different LCL. A sample ensemble is shown on the right, with the raindrop breakup threshold diameter $D_b$ and rimed ice species (RIS) labeled for each ensemble member.

#### b. Thermodynamic base states

The thermodynamic base states follow the analytic approach of McCaul and Weisman (2001) and McCaul and Cohen (2002) and include the four thermodynamic base states used in Murdzek et al. (2021). These base states are particularly appealing because the user can control several aspects of the base-state environment, such as the CAPE, LCL, LFC, and buoyancy distribution. The thermodynamic profile consists of three vertical layers: (i) the sub-LFC layer [hereinafter the planetary boundary layer (PBL)], (ii) the free troposphere, and (iii) the stratosphere.

The PBL is constructed using a surface temperature, surface pressure, PBL pseudoequivalent potential temperature $\theta_{ep}$, PBL lapse rate, and PBL depth. The hydrostatic balance equation is integrated upward from the surface pressure and temperature while following the PBL lapse rate and holding $\theta_{ep}$ constant at 335 K. Once the LCL of the surface-based parcel is reached, the PBL lapse rate is changed to be 0.1 K km$^{-1}$ less than the moist adiabatic lapse rate (following a pseudoadiabatic ascent). Integration of the hydrostatic balance equation continues upward from this point through the rest of the PBL depth (2300 m). The end result is a constant-$\theta_{ep}$ layer that is nearly well-mixed below the LCL and slightly stable to moist parcel displacements above the LCL.

The free troposphere thermodynamic profile is determined using the analytic buoyancy profile of McCaul and Weisman (2001). This buoyancy profile is

$$b(z') = E \frac{m^2}{H^2} z' \exp\left(-\frac{m}{H} z'\right),$$

where $b$ is the buoyancy, $z'$ is the height above the PBL top, $E$ is the CAPE, $m$ is the profile compression parameter (alters the vertical distribution of buoyancy), and $H$ is the vertical scale (McCaul and Weisman 2001). We set $E = 2000$ J kg$^{-1}$, $m = 2.2$, and $H = 12.5$ km. The environmental virtual temperature is determined at each vertical level by finding the virtual temperature of a surface-based parcel following pseudoadiabatic ascent, computing $b$ using Eq. (2), and then solving for
Table 2. Thermodynamic base-state parameters. Here, \( p_{sfc} \) and \( T_{sfc} \) refer to the surface pressure and temperature, respectively. LCL, LFC, EL (equilibrium level), CAPE, and CIN are computed for a surface-based parcel following pseudoadiabatic ascent using the base states interpolated to the CM1 grid (computations are performed using the getcape subroutine in CM1, which includes the virtual temperature correction). The \( \delta_0 \) and PBL \( \Gamma \) refer to the absolute supersaturation \( (q_a - q_{sfc}) \) at the lowest model level and the PBL lapse rate, respectively. In the text, all LCLs are rounded to the nearest 50 m.

<table>
<thead>
<tr>
<th>LCL (m)</th>
<th>LFC (m)</th>
<th>EL (m)</th>
<th>CAPE (J kg(^{-1}))</th>
<th>CIN (J kg(^{-1}))</th>
<th>( p_{sfc} ) (hPa)</th>
<th>( T_{sfc} ) (K)</th>
<th>PBL ( \Gamma ) (K km(^{-1}))</th>
<th>( \delta_0 ) (g kg(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>500</td>
<td>2372</td>
<td>12466</td>
<td>1957</td>
<td>11.9</td>
<td>1000</td>
<td>295.7</td>
<td>9.12</td>
<td>-3.62</td>
</tr>
<tr>
<td>750</td>
<td>2368</td>
<td>12472</td>
<td>1955</td>
<td>12.4</td>
<td>1000</td>
<td>297.08</td>
<td>9.26</td>
<td>-5.67</td>
</tr>
<tr>
<td>1000</td>
<td>2362</td>
<td>12472</td>
<td>1955</td>
<td>12.3</td>
<td>1000</td>
<td>298.4</td>
<td>9.33</td>
<td>-7.82</td>
</tr>
<tr>
<td>1250</td>
<td>2360</td>
<td>12474</td>
<td>1955</td>
<td>13.6</td>
<td>1000</td>
<td>299.8</td>
<td>9.37</td>
<td>-10.09</td>
</tr>
<tr>
<td>1510</td>
<td>2361</td>
<td>12477</td>
<td>1955</td>
<td>14.6</td>
<td>1000</td>
<td>301.1</td>
<td>9.39</td>
<td>-12.48</td>
</tr>
<tr>
<td>1750</td>
<td>2364</td>
<td>12480</td>
<td>1955</td>
<td>17.2</td>
<td>1000</td>
<td>302.5</td>
<td>9.40</td>
<td>-15.01</td>
</tr>
<tr>
<td>2010</td>
<td>2376</td>
<td>12483</td>
<td>1955</td>
<td>20.7</td>
<td>1000</td>
<td>303.8</td>
<td>9.38</td>
<td>-17.64</td>
</tr>
</tbody>
</table>

The environmental virtual temperature. The environmental relative humidity in the free troposphere varies linearly from the PBL top to 10% at the tropopause (12 km), and above the tropopause, the temperature and relative humidity are constant (Warren et al. 2017).

A few additional notes about computing the base-state environments are detailed here. As in Warren et al. (2017) and Murdzek et al. (2021), the environmental thermodynamic profile above the PBL is computed iteratively until the computed CAPE (using a surface-based parcel following pseudoadiabatic ascent with the virtual temperature correction) is within 0.5 J kg\(^{-1}\) of 2000 J kg\(^{-1}\). Environmental profiles are initially computed on 50-m vertical grids and then interpolated to the CM1 grid, which results in slight differences between the sounding parameters computed on the two grids. The parameters presented in Table 2 are computed using the base states interpolated to the CM1 grid. When constructing these base states, the PBL lapse rates were subjectively selected to keep the vertical profile of convective inhibition (CIN) following pseudoadiabatic parcel ascent as similar as possible between the different base states (e.g., the LCL = 2000 m base state has more surface-based CIN than the LCL = 500 m base state, but a parcel originating at 1000 m AGL has more CIN in the LCL = 500 m base state). Vertical profiles of CIN for four of the thermodynamic base states used here are presented in Fig. 3b from Murdzek et al. (2021). Although the vertical profiles of pseudoadiabatic CIN are similar between the various base states, vertical profiles of reversible CIN differ substantially between the base states (e.g., Fig. 3d from Murdzek et al. 2021). As explained in section 4c, this does not appear to have a large impact on our results. Skew T-log pressure diagrams for four of the base states are presented in Fig. 2, with the corresponding base-state parameters listed in Table 2.

c. Microphysics variations

The microphysics schemes of the various ensemble members vary in the treatment of raindrop breakup and RIS properties. These two aspects of the microphysics scheme are altered because previous studies have noted that they have a large impact on cold-pool strength (e.g., Morrison and Milbrandt 2011; Bryan and Morrison 2012; Morrison et al. 2012). Raindrop breakup in the Morrison two-moment scheme is handled following the approach of Verlinde and Cotton (1993), which reduces the raindrop self-collection efficiency once the number-weighted mean raindrop diameter exceeds some threshold value \( D_b \). The ensemble members use one of three values of \( D_b \): 105, 300 (default value), or 510 \( \mu m \). This parameter is fairly arbitrary given the difficulty in observing raindrop breakup in nature, so we chose the same values that were used in the squall line sensitivity study of Morrison et al. (2012). Using either a larger or smaller range of \( D_b \) values should not qualitatively impact the sensitivities to the microphysics examined in this article. The RIS properties altered between the different ensemble members include the bulk density and fall-speed parameters. Three different sets of parameters are used (Table 3): graupel-like from the Morrison two-moment scheme (graupel), hail-like from the Morrison two-moment scheme (hailMOR), and hail-like from the Milbrandt and Yau (2005a,b) microphysics scheme (hailMY). These three sets of RIS parameters were also used in the sensitivity tests of Morrison and Milbrandt (2011). As seen in Fig. 3, particles using the hailMY parameters generally have the largest fall speeds, whereas particles using the graupel parameters typically have the slowest fall speeds for particle diameters less than 10 mm. All possible combinations of the three \( D_b \) values and three RIS categories outlined above result in nine different microphysics scheme realizations, which are used by the nine members in each perturbed-microphysics ensemble (Fig. 1).

3 Vertical profiles of CIN are computed by determining the CIN of parcels originating from each vertical level. Note that this is different from the vertical profile of negative buoyancy for a surface-based parcel.
member and that our results are not skewed by the presence of strong secondary convection in a subset of our ensemble members.

a. Cold-pool strength and onset time

As the LCL increases, cold pools tend to be stronger, which agrees with past studies (e.g., McCaul and Cohen 2002; Brown and Nowotarski 2019). Horizontal cross sections of 50-m $u'$ show that the LCL = 500 m simulations tend to have weaker cold pools than the LCL = 2000 m simulations using the same microphysics scheme variation (Fig. 4). This observation is corroborated by ensemble-median time series of the three cold-pool properties, which generally show larger and colder cold pools as the LCL is raised (Fig. 5). As discussed more in section 4a, this increase in cold-pool strength with higher LCLs can be tied to increased rain evaporation.

TABLE 3. Parameters for the different rimed ice species used within the Morrison two-moment microphysics scheme; $V\cdot D$ refers to the velocity–diameter power-law relationship, with the coefficient denoted as $a$ and the exponent denoted as $b$.

<table>
<thead>
<tr>
<th>Name</th>
<th>Reference</th>
<th>Bulk density (kg m$^{-3}$)</th>
<th>$V\cdot D$ coef (m$^{1+b}$ s$^{-1}$)</th>
<th>$V\cdot D$ exponent (unitless)</th>
</tr>
</thead>
<tbody>
<tr>
<td>graupel</td>
<td>Locatelli and Hobbs (1974)</td>
<td>400</td>
<td>19.3</td>
<td>0.37</td>
</tr>
<tr>
<td>hailMOR</td>
<td>Matson and Huggins (1980)</td>
<td>900</td>
<td>114.5</td>
<td>0.5</td>
</tr>
<tr>
<td>hailMY</td>
<td>Böhm (1989)</td>
<td>900</td>
<td>206.89</td>
<td>0.6384</td>
</tr>
</tbody>
</table>

FIG. 2. Sample thermodynamic base states used for the CM1 simulations of ordinary convection: LCL = (a) 500, (b) 1000, (c) 1500, and (d) 2000 m. Solid red, orange, blue, and black lines show the temperature, virtual temperature, dewpoint, and surface-based parcel virtual temperature (following pseudoadiabatic ascent) profiles, respectively. The shaded red area is proportional to the surface-based CAPE.
These smaller RIS particles are found farther aloft because the smaller raindrops that freeze to form the RIS must reach colder temperatures, which are farther aloft, for heterogeneous freezing to occur, relative to larger raindrops (e.g., Bigg 1953). These smaller RIS particles that are located farther aloft in the high-LCL simulations take longer to reach the surface (e.g., see the difference in the LCL = 500 m and LCL = 2000 m hailMOR simulations in Fig. 10a). Thus, the presence of smaller raindrops in the higher-LCL simulations results in delayed precipitation onset from either warm-rain or cold-rain processes (Fig. 10b), which in turn delays cold-pool onset. Cold-pool onset may also be further delayed by the greater depth of sub-saturated air beneath the LCL in the high-LCL simulations, which may also reduce the amount of precipitation that can reach the lowest model levels owing to evaporation over a deeper layer.

Differences in cold-pool strength and onset time are also seen within a given ensemble as $D_b$ and RIS are varied. Generally, simulations using a more aggressive raindrop breakup parameterization (smaller $D_b$) have more intense cold pools (Fig. 4) that take longer to develop (Fig. 6). The former observation has been explained by other studies: more aggressive raindrop breakup results in more numerous, smaller drops that more readily evaporate (owing to a larger surface area-to-volume ratio) and are, therefore, more effective at cooling the air than a similar mass of larger raindrops (Morrison and Milbrandt 2011; Morrison et al. 2012). The increase in cold-pool onset time with more aggressive raindrop breakup can be explained by noting that raindrop fall speed increases monotonically with raindrop size. More aggressive raindrop breakup results in smaller raindrops that have slower fall speeds and take longer to reach the surface (Fig. 7), resulting in later cold-pool onset times.

For RIS, simulations employing hailMOR generally form intense cold pools quickly, whereas simulations employing graupel generally form weaker cold pools at later times (Figs. 4 and 6). The simulations using hailMY fall between these two extremes. These results agree with past studies using the Morrison two-moment scheme that show that cold pools tend to be stronger early in the simulation when using hail instead of graupel (Morrison and Milbrandt 2011), owing to the faster fall speeds and larger RIS fluxes into the melting layer when hailMOR is used instead of graupel (Fig. 10a). Larger fluxes of RIS into the melting layer result in more hydrometeor mass that can be evaporated near the surface, resulting in stronger cold pools. The faster fall speeds associated with hailMOR also cause hydrometeors to reach the surface at earlier times relative to simulations using hailMY or graupel, resulting in earlier cold-pool onset times.

### b. Cold-pool variability

Cold-pool variability is examined using both gridpoint-by-gridpoint ensemble standard deviations and ensemble standard deviation time series of the three cold-pool properties. Horizontal cross sections of gridpoint-by-gridpoint $\theta_e$ standard deviations 1800 s after cold-pool onset show larger spread, as well as a larger area with nonzero standard deviations, as the ensemble LCL is increased (Fig. 11). This suggests that the variability of
cold-pool $\theta'$ increases as the LCL is raised. Further, time series of the ensemble standard deviations of the three cold-pool properties generally show larger spread in the high-LCL ensembles, especially in the first 40 min after cold-pool onset (Fig. 12). To determine if the ratio of the ensemble standard deviations between the LCL = 2000 m and LCL = 500 m ensembles is greater than 1 and statistically significant (indicating that the LCL = 2000 m standard deviation is greater than the LCL = 500 m standard deviation), a one-sided hypothesis test is performed for each output time using a
bootstrap\(^5\) resampling technique with 1000 random samples from each of the two ensembles (Wilks 2011, chapter 5.3.5). The ratio between the standard deviations of the LCL = 2000 m and 500 m ensembles is found to be greater than 1 and statistically significant at the 0.05 level for almost every output time between 0 and 50 min for each of the three cold-pool properties (Fig. 12). From 50 to 70 min, the standard deviation ratios of the mean cold-pool \(u'\) and fractional cold-pool area are greater than 1 and statistically significant at every output time. Qualitatively similar results can be obtained using other measures of spread (median absolute deviation, interquartile range, and range were also examined) as well as from a subjective analysis of the raw distributions of the cold-pool properties from each ensemble. These results show that the sensitivity of the cold pools to the microphysics parameterization appears to increase as the environmental LCL increases.

\(^5\) A bootstrap is used to determine statistical significance because it makes no assumptions about the underlying distribution shapes. An examination of the ensemble cold-pool properties show that these distributions generally do not have any obvious outliers or clusters, with the exception of the fractional cold-pool area for the high-LCL ensembles, which are more multimodal.

To determine whether the differences in spread between the seven ensembles are a result of altering \(D_b\), the RIS, or both, ranges of mean cold-pool \(u'\) are computed using subsets from each ensemble. Each ensemble subset consists of three members that either share the same RIS (Figs. 13a–c) or \(D_b\) (Figs. 13d–f). For example, in Fig. 13a, ranges are computed at each output time using only the three ensemble members that have graupel as the RIS, which means that the only difference in the microphysics schemes between these three ensemble members is \(D_b\). Before continuing with this analysis, the reader is cautioned that the goal here is relatively narrow: determine whether the increasing sensitivity to the microphysics with increasing LCL in this particular experimental setup is solely the result of one of the two microphysics alterations used. Given the small ensemble size (three members), more tests are needed to determine how applicable these results are beyond the parameter space examined here.

In general, sensitivity to both the raindrop breakup threshold and RIS characteristics increases with LCL. In Fig. 13a, it can be seen that, about 30 min after cold-pool onset, the largest ranges occur in the ensemble subset with the highest LCL (2000 m), which is consistent with the results presented earlier in this section. In the first ∼20 min, however, the trend of increasing subset range with LCL is less clear. Similar behavior is seen in the ensemble subsets that have hailMOR or hailMY as the RIS, though the pattern of increasing cold-pool variability with increasing LCL emerges more quickly after cold-pool onset (∼10 min for hailMOR and ∼15 min for hailMY; Figs. 13b,c). For the ensemble subsets that hold \(D_b\) fixed and only allow the RIS to vary, there is a clear trend of greater ensemble spread with higher LCLs for almost all times (Figs. 13d–f). Thus, it appears that beyond ∼20 min, ensemble spread increases with LCL regardless of whether the microphysical differences between the ensemble members arise from changing \(D_b\) or the RIS characteristics. Prior to ∼20 min, this pattern is less
clear when only $D_b$ is varied, especially when graupel is the RIS. Why is this the case? One possible explanation is that convective storms in environments with lower LCLs initially form larger raindrops owing to more active warm-rain processes during these earlier stages of storm development (Figs. 7 and 8). This likely results in increased sensitivity to raindrop breakup as the LCL is lowered, at least during the initial stages of convective storm development when warm-rain processes dominate near-surface precipitation formation. The dominance of warm-rain processes is supported by time series of process rates that show that accretion of cloud water by rain is the largest rain source within the ~40 min after model initiation, whereas the melting of RIS becomes the dominant source later on (not shown). This increased sensitivity to raindrop breakup with lower LCLs during the early part of the simulations partially counters the trend of increasing spread with higher LCLs. This increased sensitivity with lower LCLs disappears at later times once the simulations with higher LCLs start to produce larger raindrops owing to the melting of RIS (not shown). In the simulations using graupel as the RIS, it takes longer for appreciable
RIS fluxes into the melting layer to develop, relative to simulations using hailMOR or hailMY (e.g., Fig. 10a). Using the RIS fluxes as a guide as to how active cold-rain processes are, we can see that there are two distinct surface precipitation peaks for the simulations using graupel as the RIS: an earlier one influenced primarily by warm-rain processes (between 20 and 55 min in Fig. 10b) and a later one influenced by cold-rain processes that peaks shortly after the RIS flux into the melting layer peaks (after 55 min in Fig. 10). This clear distinction between the beginning of warm-rain processes and the arrival of melted RIS is much less pronounced in the simulations using hail-MOR (Fig. 10). Thus, the fact that the increasing sensitivity to raindrop breakup with decreasing LCL is most pronounced in the simulations using graupel as the RIS appears to be the result of a longer period where warm-rain processes dominate, relative to the other RIS characteristics used.

4. Discussion

a. Linking the microphysical sensitivity of cold pools to the LCL

To understand why cold pools are more sensitive to the microphysics as the LCL increases, the dominant microphysical processes that form and maintain the near-surface cold pool must be examined. Similar to Mallinson and Lasher-Trapp (2019), cumulative cooling amounts $Q_\phi$ from model initiation to the $M$th model output time are computed for a variety of phase changes using

$$Q_\phi = \sum_{i=0}^{M} \sum_{j=0}^{N} \rho_i L_{q,\phi(i)} \Delta V \Delta t,$$

where $\rho$ is the air density, $\Delta q_{\phi(i)}$ is the change in the hydrometeor mass mixing ratio owing to phase change $\phi$, $L_{q,\phi}$ is the...
enthalpy associated with phase change $Q_f$, $\Delta V$ is the grid cell volume, and $\Delta t$ is the time between output file dumps. In the two sums, the $i$ index corresponds to the output time and the $j$ index corresponds to the spatial grid point, with $N$ being the total number of grid points. Examining $Q_f$ from various phase changes over the first hour after cold-pool onset agrees with the results from previous studies (e.g., James and Markowski 2010; Mallinson and Lasher-Trapp 2019) that the evaporation of rain $Q_{evap}$ produces the most near-surface cooling when compared with other phase changes (Fig. 14). Cloud evaporation becomes the dominant cooling mechanism above cloud base, and melting and sublimation become larger closer to the melting layer. Although cooling from cloud evaporation, melting, and sublimation increase at higher altitudes, these processes likely do not contribute directly to the negative $\theta'$ values in the near-surface cold pool. This is because parcels with negative $\theta'$ aloft will experience an increase in $\theta'$ as these parcels descend owing to a decrease in base-state $\theta$ at lower heights (e.g., Fig. 2), which likely results in minimal $\theta'$ values near the surface unless there is additional cooling closer to the ground (which, in this case, would come from rain evaporation based on Fig. 14). Switching our focus to measures of ensemble spread, ensemble standard deviations of rain evaporational cooling increase with LCL below ~1 km AGL, whereas the standard deviation of cooling
from the evaporation of cloud water and melting of ice do not systematically increase with LCL.

Given that rain evaporation is the dominant cooling mechanism in the lowest 500 m and that the ensemble standard deviation of rain evaporational cooling increases with higher LCLs, we will focus on rain evaporation to explain the increasing sensitivity of the cold pool to the microphysics with higher LCLs. To further explore cooling from the evaporation of rain, $Q_{evar}$ time series at 50 m AGL are computed for each ensemble member. Increasing the LCL increases both the amount of rain evaporational cooling and the ensemble spread of rain evaporational cooling (Fig. 15), which is consistent with the increases in cold-pool strength and spread with LCL shown in section 3.

To understand why the spread of $Q_{evar}$ increases with the environmental LCL, the rain evaporation time-tendency equation is examined. In the Morrison two-moment scheme, rain evaporation is handled using Eq. (4) from Morrison et al. (2009), which can be written as

$$\frac{\partial q_{e}}{\partial t} = q_{e} - q_{es} \frac{1}{\tau_{r}},$$

where $\partial q_{e}/\partial t$ is the rain mass time-tendency owing to evaporation, $q_{e}$ is the water vapor mass mixing ratio, $q_{es}$ is the equilibrium water vapor mass mixing ratio, $\tau_{r}$ is the phase relaxation time for rain, and

$$\Gamma = 1 + \frac{q_{v} L_{v}}{\Delta T c_{p}},$$

with $T$ being temperature, $L_{v}$ being the enthalpy change associated with vaporization, and $c_{p}$ being the specific heat capacity at constant pressure. Information about the rain PSD is contained in $\tau_{r}^{-1}$, which increases with increasing rain number mixing ratio $N_{tot}$ and number-weighted mean raindrop diameter $D_{n}$ [see Eq. (4) from Morrison et al. (2005) and Eq. (A5) from Morrison and Grabowski (2008)]. Similar to Eq. (1), the evaporation rate depends on an environmental control (how close the air is to saturation) as well as a microphysical control (raindrop characteristics). In Eq. (4), the former is related to the $q_{e} - q_{es}$ factor, whereas the latter is related to $\tau_{r}^{-1}$.

As mentioned in the introduction, we hypothesize that larger magnitudes of $q_{e} - q_{es}$ (which are associated with higher LCLs) will magnify any differences in the evaporation rates between ensemble members that are already present owing to differences in the rain PSDs that arise from the variations in the microphysics scheme. The ultimate result of this magnification is a larger sensitivity of the cold pool to the microphysics scheme in environments with high LCLs. From a statistical standpoint, this is similar to stating that multiplying a given distribution of $\tau_{r}^{-1}$ values by a larger $q_{e} - q_{es}$ factor (and dividing by a constant $\Gamma$) will result in a wider distribution of evaporation rates. To test this hypothesis, $Q_{evar}$ time series are again computed, but this time the cooling amounts are divided by $q_{e} - q_{es}$ at each grid point prior to computing the sums in Eq. (3). The result is $Q_{evar}$, time series that have the environmental control removed, so the differences in rain evaporational cooling are almost exclusively the result of differences in the rain PSDs (the microphysical control). Ensemble medians and standard deviations for these modified $Q_{evar}$ values are presented in Figs. 16 and 17. Without the environmental control, ensemble medians and standard deviations of

![Fig. 10. Precipitation fluxes for selected simulations: (a) RIS downward flux at $z = 4270$ m AGL, which is near the freezing level for a surface-based parcel lifted pseudoadiabatically and (b) domain-average surface precipitation rates. Solid and dashed lines represent simulations using the LCL = 500 m and LCL = 2000 m base states, respectively.](image-url)
the rain evaporational cooling amounts below ~2 km decrease as the LCL increases. This suggests that the greater evaporational cooling in the high-LCL ensembles is a result of lower relative humidities, not because the shape of the rain PSDs are more conducive to evaporation as the LCL is increased. In fact, there is some indication in Figs. 16 and 17 that the rain PSDs of the low-LCL ensembles are actually more favorable for evaporation than the high-LCL rain PSDs, and that the low-LCL rain PSDs are more variable between members within a given ensemble (hence the slightly larger standard deviations).

To further explore how the microphysics control varies with LCL, time series of various quantities related to the rain PSDs are examined (Fig. 18). In agreement with the results from Fig. 16, $\tau_{\text{e}}^{-1}$ values increase as the LCL decreases, which suggests that the rain PSDs actually favor increasing evaporation rates as the LCL decreases. This increase in $\tau_{\text{e}}^{-1}$ with decreasing LCL is the result of larger $N_{\text{tot}}$, values, which more than compensate for the very slight increase in $D_{n_{\text{e}}}$ with higher LCLs (Figs. 18c,e). The exact reason for this increase in $N_{\text{tot}}$, with decreasing LCL is beyond the scope of this article, but we speculate that this may be the result of many of...
applies when a completely different microphysics parameterization is used. For this sensitivity test, the predicted particle properties scheme (P3; Morrison and Milbrandt 2015; Milbrandt and Morrison 2016) is used in CM1, release 20.1. The principal difference between the Morrison two-moment scheme and P3 involves the treatment of ice particles. In the Morrison two-moment scheme, there are three predefined ice categories (pristine ice, snow, and rimed ice), and each category has fixed properties, such as bulk density and fall-speed parameters. Such an approach is an oversimplification, because unlike raindrops and cloud droplets, the density of ice particles can vary widely depending on the growth history of the particle (e.g., Pflaum and Pruppacher 1979). Further, ice can also assume many different shapes depending on their growth histories (e.g., Bailey and Hallett 2009). P3 partially alleviates this problem by using a predefined number of “free” ice categories with properties, such as particle density and fall-speed parameters, which evolve freely within the simulation. This is accomplished by predicting four mixing ratios for each ice category: total particle mass, particle number, rime mass, and rime volume. This approach allows for a more realistic treatment of ice hydrometeors within a given free category, and also removes the need for artificial conversion thresholds between ice categories.

Other than using P3, the CM1 configuration follows Table 1. A total of four ensembles are simulated with twelve members each. The four ensembles use the LCL = 500, 1000, 1500, and 2000 m thermodynamic base states. Each ensemble member uses one of three raindrop breakup thresholds (100, 280, and 500 μm), one of two rain PSD shape parameters (0 and 6), and an ice fall-speed multiplier of 0.5 or 1.5, which is used to emulate uncertainty in ice full speeds, similar to Stanford et al. (2019). All ensemble members use P3 configured with two free ice categories.

The results from these simulations are presented in Fig. 19. As seen in Figs. 19a and 19b, cold-pool strength tends to increase with LCL, as does the ensemble spread of cold-pool strength, at least during the first ~20 min after cold-pool onset, which is similar to the results we showed earlier for the Morrison two-moment scheme (e.g., Fig. 12). The P3 ensembles also show an increase in the ensemble median and ensemble standard deviation of rain evaporation at the lowest model level as the LCL increases, which also agrees with the ensembles using the Morrison two-moment scheme (Fig. 15). The equation for the evaporation of rain in the P3 scheme differs from the Morrison two-moment scheme, so removing the environmental control is not as simple as dividing the evaporation rates by $q_v - q_w$. Therefore, to determine why the rain evaporation ensemble median and standard deviation increase with LCL, total precipitation and characteristics of the rain PSD are examined, similar to Fig. 18. The decreasing precipitation and $\tau_r^{-1}$ values with increasing LCL both favor stronger cold pools for the low-LCL simulations, which suggests the observed increase in cold-pool strength with LCL can be attributed to the drier environmental conditions, not differences in the rain rate or rain PSD characteristics (Figs. 19e,k). The ensemble standard deviations of $\tau_r^{-1}$ show no clear trend as the LCL is changed (Fig. 19), which suggests that the increase in the ensemble standard deviations of rain evaporation with

![Ensemble Standard Deviations](image)

**Fig. 12.** As in Fig. 5, but for the ensemble standard deviations. Black dots indicate output times where the ratio of the LCL = 2000 m standard deviation to the LCL = 500 m standard deviation is greater than 1 and statistically significant using a bootstrap resampling test with a significance level of 0.05.

the smaller drops in the high-LCL simulations evaporating before reaching the lower levels of the model owing to the deeper subcloud layer. This would also contribute to the slight increase in surface precipitation as the LCL decreases (Fig. 18a). In turning to the ensemble standard deviations in Fig. 18, we can see that the ensemble spread of $\tau_r^{-1}$ decreases with LCL during the first ~20 min after cold-pool onset, which agrees with the small increase in the ensemble standard deviation of $Q_{\text{evap}}(q_v - q_w)$ as the LCL decreases (Fig. 16b). These results suggest that while the environmental control favors increased evaporation as the LCL increases, this trend is partially countered by a microphysical control that favors increased evaporation as the LCL decreases. Furthermore, the increase in the ensemble spread of evaporation rates with LCL appears to be driven by differences in the environmental control on evaporation between the various ensembles given that the ensemble spread of the microphysical control on evaporation ($\tau_r^{-1}$) increases with decreasing LCL.

**b. Sensitivity to the microphysics parameterization**

This section explores whether the increase in sensitivity to the microphysics parameterization with increasing LCL...
increasing LCLs is the result of drier conditions in the high-LCL ensembles, not differences in the ensemble spread of rain PSD characteristics (Fig. 19d). All these observations agree with those presented earlier for the Morrison two-moment scheme (Fig. 18), which suggests that the same physical mechanism is at play here even though a different microphysics scheme is used.

There is one notable way that the P3 ensembles differ from the Morrison two-moment ensembles. The ensemble standard deviations for the mean cold-pool $u'$ all quickly converge by $\sim 20$ min after cold-pool onset in the P3 ensembles (Fig. 19b), which is not the case in the Morrison two-moment ensembles. This appears to be because the majority of the precipitation falls in the first $\sim 15$ min after cold-pool onset (Fig. 19e), which differs from the simulations using the Morrison two-moment scheme (Fig. 18a). The lack of rain at later times in the P3 simulations results in reduced rain evaporation relative to the simulations using the Morrison two-moment scheme (cf. Fig. 15a and Fig. 19c), which contributes to weaker cold pools at later times with smaller ensemble spreads. This difference does not change the fact that ordinary convection in an environment with a higher LCL is more sensitive to the microphysics owing to the greater evaporation potential of these environments.

### c. Other sensitivity tests

As mentioned in section 2a, there is considerable sensitivity of the initial convective cell in a cloud model to the initiation method. Sensitivity tests using the LCL = 500 m and LCL = 2000 m ensembles with different initiation methods are performed to determine if changing the initiation method changes our results. Four initiation methods are tested: (i) 2-K warm bubble that does not maintain the environmental relative humidity profile, (ii) low-level convergence using a maximum convergence of $2 \times 10^{-3}$ s$^{-1}$ (Loftus et al. 2008), (iii) updraft nudging using an updraft maximum $w_{\text{max}}$ of 5 m s$^{-1}$ (Naylor and Gilmore 2012), and (iv) updraft nudging with $w_{\text{max}} = 10$ m s$^{-1}$. In all the sensitivity tests, the spread of mean cold-pool $\theta'$ and the spread of $Q_{\text{evar}}$ generally increase with LCL (Fig. 20). Removing the environmental control from $Q_{\text{evar}}$ by dividing by $q_v - q_w$ either causes the spread of $Q_{\text{evar}}$ to decrease as the LCL increases.

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**Fig. 13.** Range of mean cold-pool $\theta'$ using a subset of the members in each ensemble. Each subset includes those members that have (a) graupel as the RIS, (b) hailMOR as the RIS, (c) hailMY as the RIS, (d) $D_b = 105 \mu$m, (e) $D_b = 300 \mu$m, and (f) $D_b = 510 \mu$m. Each subset contains three of the nine ensemble members.
or greatly reduces the differences in spread relative to the unmodified $Q_{evar}$ values (Fig. 20c). Because the inflow layer depth can change with the initiation method using our base states (see Fig. 12 from Murdzek et al. 2021), the results from these sensitivity tests suggest that our qualitative results are not impacted by slight changes to the inflow layer, which further suggests that not controlling for reversible CIN [which can also influence inflow layer depth, see Murdzek et al. (2021)]
did not greatly impact our results. We also tested a 1-K bubble that does not maintain the environmental relative humidity profile (not shown), but this method was too weak to produce strong convection when using the LCL = 500 m base state (the LCL = 500 m simulations in this test only had a peak updraft speed of \( \sim 35 \, \text{m s}^{-1} \), whereas the LCL = 2000 m simulations had a peak updraft speed of \( \sim 55 \, \text{m s}^{-1} \)). Altogether, these tests suggest that our qualitative results presented earlier are not sensitive to the choice of initiation method.

Another set of sensitivity tests is used to determine if our results change as the horizontal grid spacing is altered. Two sensitivity tests are performed, again using the LCL = 500 m and LCL = 2000 m ensembles. The first test uses a horizontal grid spacing of 1 km and a vertical grid spacing that is a factor of 2 greater than that of the original ensembles. The goal of this sensitivity test is to determine if our results hold for a model setup that is similar to operational, high-resolution forecasting models [e.g., the Warn-on-Forecast system (Lawson et al. 2018)]. The second test uses a horizontal grid spacing of 250 m with the same vertical grid as the original ensembles. The goal of this sensitivity test is to determine if our results hold for a model setup that is similar to operational, high-resolution forecasting models. The result of both of these sensitivity tests are, like the other sensitivity tests, qualitatively similar to the original set of ensembles (Figs. 21g-I). Thus, our results appear to be insensitive to variations in the LFC and the presence of weak vertical wind shear.

5. Conclusions

The objective of this study was to determine how and why there are changes in the sensitivity of convective cold pools to the microphysics parameterization in environments with different LCLs, and whether these results were robust given different model configurations. To answer these questions, seven perturbed-microphysics ensembles with nine members each were run. Each perturbed-microphysics ensemble used a...
different horizontally homogeneous base state with a different LCL, and each ensemble member was simulated using CM1 with a different variation of the Morrison two-moment scheme. Microphysics scheme variations employed different raindrop breakup thresholds or different RIS characteristics. Sensitivity to the microphysics was assessed using the ensemble standard deviation of three cold-pool properties (minimum 50-m $\theta'$, average cold-pool $\theta'$, and cold-pool fractional area), and changes

**3600.0 s Ensemble Statistics**

![Graph](image)

**Fig. 16.** As in Fig. 15, but with all rain evaporational cooling rates divided by $q_v - q_w$ prior to computing $Q_{evar}$.

![Graph](image)

**Fig. 17.** As in Figs. 14c and 14d, but with all rain evaporational cooling rates divided by $q_v - q_w$ prior to computing $Q_{evar}$. 

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in sensitivity with LCL were determined by comparing ensemble standard deviations between various ensembles.

Similar to past studies, we found that cold-pool strength increases with increasing LCLs, more aggressive raindrop breakup, and faster falling RIS. For the research questions posed in the introduction, we offer the following answers:

1) Cold pools of ordinary convective storms were more sensitive to the microphysics as the LCL was raised. This was corroborated by a statistically significant increase in the ensemble standard deviations of the cold-pool properties from the LCL = 500 m to LCL = 2000 m ensemble at several output times.

2) Physically explaining the results in answer 1 is focused on rain evaporation, which had the largest microphysical contribution to cooling below cloud base. Rain evaporation increased with LCL owing to drier conditions (the environmental control), even though rain PSDs at the lowest model level in the low-LCL ensembles were more favorable for evaporation owing to the presence of more numerous drops (the microphysical control). This shows that the environmental control dominates the microphysical control and is responsible for the increase in cold-pool strength with LCL. Cold pools in the high-LCL ensembles are more sensitive to the microphysics owing to lower relative humidities in the PBL, which magnify differences in evaporation rates between ensemble members that were already present owing to the different microphysics scheme variations used (e.g., different raindrop breakup threshold or RIS characteristics).

3) These results did not qualitatively change when using a completely different microphysics parameterization (P3), different initiation methods (warm bubble, low-level convergence, or updraft nudging), horizontal grid spacings between 250 and 1000 m, a different base state formulation where the LFC is not held constant, or the presence of weak vertical wind shear in the environment.

We also found that the increase in cold-pool sensitivity to the microphysics with higher LCLs generally does not appear to depend on whether the raindrop breakup threshold or RIS characteristics are varied within the perturbed-microphysics

![Figure 18](image-url)
Fig. 19. Ensemble (left) medians and (right) standard deviations for simulations using the P3 microphysics parameterization: (a),(b) magnitude of average cold-pool $u'$; (c),(d) cumulative evaporation amounts $Q_{\text{evap}}$; (e),(f) cumulative total precipitation; (g),(h) mass-weighted mean rain number mixing ratio $N_{\text{tot},r}$; (i),(j) mass-weighted mean of the number-weighted mean raindrop diameter $D_{n,r}$; and (k),(l) mass-weighted mean inverse phase relaxation time for rain $\tau_{-1,r}$. The $N_{\text{tot},r}$, $D_{n,r}$, and $\tau_{-1,r}$ values are computed using grid points at the lowest model level (50 m AGL) where the rain mass mixing ratio exceeds 0.1 g kg$^{-1}$. Black dots in (b),(d) indicate output times where the ratio of the LCL = 2000 m standard deviation to the LCL = 500 m standard deviation is greater than 1 and is statistically significant using a bootstrap resampling test with a significance level of 0.05.
ensemble, at least for times greater than 20 min after cold-pool onset. There was a tendency, however, for low-LCL ensembles to be more sensitive to raindrop breakup than the high-LCL ensembles early on, likely owing to more active warm-rain processes in the low-LCL simulations during these initial stages of storm development. More active warm-rain processes would initially be expected in low-LCL simulations owing to the greater warm-cloud depth. The more active warm-rain processes during the initial stages of storm development in the low-LCL simulations can also explain why the low-LCL simulations formed cold pools faster than their high-LCL counterparts.

These results come with a couple of caveats. First, the base states used here featured well-mixed PBLs, so the LCL was

FIG. 20. Time series of ensemble standard deviations of (left) mean cold-pool $\theta'$; (center) cumulative rain evaporational cooling $Q_{evar}$ at 50 m AGL; and (right) $Q_{evar}$ at 50 m AGL with evaporational cooling rates divided by $q_v - q_s$ prior to computing $Q_{evar}$. Ensembles use the LCL = 500 m and LCL = 2000 m base states with the following initiation methods: (a)–(c) a 2-K warm bubble that does not conserve relative humidity, (d)–(f) low-level convergence, (g)–(i) updraft nudging with $w_{max} = 5$ m s$^{-1}$, and (j)–(l) updraft nudging with $w_{max} = 10$ m s$^{-1}$. Black dots indicate output times where the ratio of the LCL = 2000 m standard deviation to the LCL = 500 m standard deviation is greater than 1 and is statistically significant using a bootstrap resampling test with a significance level of 0.05.
directly related to the PBL relative humidity profile. Therefore, our results may not hold in situations where the LCL is not directly related to the PBL relative humidity. Second, precipitation rates stayed nearly constant as the LCL changed. Precipitation rates can also influence cold-pool strength, with larger precipitation rates favoring stronger cold pools. Thus, our results may change if the precipitation rate changes significantly with LCL, especially if larger precipitation rates are associated with lower LCLs.

As noted in the answer to our last research question, the results of this study appear to be fairly robust, at least for ordinary convective storms. Work is ongoing to expand the method used here to other storm modes (e.g., supercells) and determine whether reducing the sensitivity of the cold pool to the microphysics also reduces the sensitivity of storm hazards (e.g., tornadoes) to the microphysics. Taken altogether, this work will be beneficial in understanding how the predictability of convective storms and their hazards change in different environments.

Fig. 21. As in Fig. 20, but for ensembles using (a)–(c) 1000-m horizontal grid spacing with a vertical grid spacing increased by a factor of 2, (d)–(f) 250-m horizontal grid spacing, (g)–(i) a different set of thermodynamic base states where the LFC varies with the LCL [as in McCaul and Weisman (2001)], and (j)–(l) a base-state environment with winds in the $x$ direction that vary linearly from $-3.75$ to $3.75 \text{ m s}^{-1}$ in the 0–6-km layer.
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Data availability statement. CM1 source code, namelist files, analysis code, and statistical (60-s) output used for this project are available to the public through the Penn State Data Commons (https://doi.org/10.26208/fgce-5686). Base-state generation code can also be found on GitHub (https://github.com/ShawnMurd/MetAnalysis).

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