Identifying the microphysical sensitivities of mesoscale and synoptic precipitation using an ensemble framework

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IDENTIFYING THE MICROPHYSICAL SENSITIVITIES OF MESOSCALE 
AND SYNOPTIC PRECIPITATION USING AN ENSEMBLE FRAMEWORK

by

Lauriana Catherine Gaudet

A Dissertation
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ABSTRACT

Through ensemble sensitivity analysis, this dissertation aims to identify the amount of forecast uncertainty that stems from the representation of mixed-phase cloud microphysics within the Weather Research and Forecasting Model (WRF). The first research thrust focuses on how the evolution of ice crystal shape and choice of ice nucleation parameterization in the Adaptive Habit Microphysics Model (AHM) influences the lake-effect storm that occurred during Intensive Operating Period 4 (IOP4) of the Ontario Winter Lake Effect Systems (OWLeS) Field Campaign. This localized snowstorm produced total liquid-equivalent precipitation amounts up to 17.92 mm during a 16-hour time period, providing a natural laboratory to investigate the ice-liquid partitioning within the cloud and various microphysical process rates, as well as the accumulated precipitation magnitude and its associated spatial distribution. Two nucleation parameterizations were implemented, and aerosol data from a size-resolved Advanced Particle Microphysics (APM) model were ingested into the AHM for use in parameterizing ice and cloud condensation nuclei. Simulations allowing ice crystals to grow nonspherically produced 1.6–2.3% greater precipitation while altering the nucleation parameterization changed the type of accumulating hydrometeors. In addition, all simulations were highly sensitive to the domain resolution and the source of initial and boundary conditions.

The second research thrust aims to identify which microphysics processes may lead to the greatest forecast uncertainty in the OWLeS IOP4 lake-effect storm as microphysical processes within mixed-phase convective clouds can have cascading impacts on cloud properties and resultant precipitation. A microphysical ensemble composed of 24 simulations that differ in the
microphysics scheme as well as changes in the representation of aerosol and potential ice nuclei concentrations, ice nucleation parameterizations, rain and ice fall speeds, spectral indices, ice habit assumptions, and the number of moments is used for modeling hydrometeors in each adaptive habit model. Each of these changes to microphysics results in varied precipitation types at the surface; 15 members forecast a mixture of snow, ice, and graupel, seven members forecast only snow and ice, and the remaining two members forecast a combination of snow, ice, graupel, and rain. Observations from an optical disdrometer positioned to the south of the core of the lake-effect storm indicate that 92% of the observed particles were snow and ice, 5% were graupel, and 3% were rain and drizzle. Analysis of observations spanning more than a point location, such as polarimetric radar observations and aircraft measurements of liquid water content, and comparisons to the ensemble provides insight into cloud composition and processes leading to the differences at the surface. Ensemble spread is controlled by hydrometeor type differences spurred by processes or parameters (e.g., ice fall speed) that affect graupel mass.

The ensemble approach used to investigate system microphysical sensitivity in the second thrust is expanded in the third research thrust, where a stochastic perturbed parameterization (SPP) is implemented into WRF and the AHM to investigate the impact of microphysics process rate perturbations on high-intensity precipitation affecting New York State (NYS). This SPP methodology is used to investigate the impact of perturbations on the most active microphysics process rates in a synoptic rain storm with a tropical moisture connection that impacted NYS from 29–30 October 2017. These process rates include vapor deposition onto ice (IDEP) and snow (SNOWDEP), accretion of droplets by rain (CRACCR), and the melting of snow (SMELT). Nine tuning experiments with slightly different spatial, temporal, and amplitude autocorrelation parameters were conducted to elicit those most conducive to the
production of physically-sound ensemble spread (i.e., standard deviation) when perturbing IDEP. These parameters are used, along with random number seeds, to generate a stochastic pattern that perturbs the process rate in each model grid cell, thereby producing an ensemble including stochastic microphysics uncertainty. These SPP methods are compared to ensembles involving initial and boundary condition (IC/BC) uncertainty, the Stochastic Perturbed Physics Tendency (SPPT), independent SPPT (iSPPT) perturbation methods, and IC/BC ensembles combined with SPPT, iSPPT, and/or SPP. The performance of the four SPP ensembles are verified against NYS Mesonet observations of 2-m temperature, precipitation, and melting level. The impacts of these perturbations affect the precipitation forecast across the state, with the greatest changes in forecast spread residing in the upper-end of the forecast range. Unexpected relationships among process rates are uncovered when perturbations are applied to each process rate, which are explored further in this work through analysis and comparison of process rate spread and frequency. These relationships are also examined in low- and high-end precipitation regions, where perturbations that directly affect cold or warm cloud processes may non-linearly impact surface rainfall. The influence of SPP methods is tied back to thrusts 1 and 2 through the exploration of two lake-effect storms, including OWLeS IOP4 and a storm in December 2017. This analysis indicates that perturbations to ice deposition affect the QPF differently than other perturbations due to the impact this process has on other related in-cloud processes in both cases. As a whole, this dissertation contributes new knowledge about precipitation responses to the representation of microphysics and associated uncertainty in numerical weather prediction models.
Navigating through my Ph.D. program has been an incredibly supportive experience thanks to the people I surround myself with. I thank God every day for the blessings in my life, including the opportunity to advance my education to the highest level.

From day one, my advisor, Dr. Kara Sulia, has been there to answer every science question, discuss career paths and life, hand me a tissue when having a tough day, champion my successes, and continuously & gently push me. She always believed I was capable of earning this degree, even and especially when I didn’t think I was. I am absolutely blessed to have been advised by her. I would also like to thank my committee members including Dr. Ryan Torn, Dr. Justin Minder, and Dr. Fangqun Yu. My discussions with each of these fantastic scientists strengthened my critical thinking throughout the scientific process and helped me to learn more than I thought was possible. I would not have been able to complete this dissertation without their years of mentorship.

Sarah Long, a meteorologist I watched on my local news in my childhood was the first person to encourage me to not discount research. She was incredibly encouraging of me when I applied for my first research internship at Hobart and William Smith Colleges, where I truly found my research passion thanks to the wonderful advisement of Dr. Neil Laird. Before that point and specifically when I received the acceptance, I needed a conversation with my favorite professor and advisor from my undergraduate department, Dr. Janel Hanrahan. I remember being so nervous to accept the research offer, live away from home for a summer, and try to learn how to do something I had never done before; I was scared to fail. She recognized that and gently pushed me to leave my comfort zone. Her belief in me sparked a
belief in myself that ultimately has led me to where I am today. I am indebted to the support I received from Sarah & Dr. Hanrahan, the women who showed me I could, and Dr. Laird, the advisor who inspired me to be a curious scientist.

My parents have been my constant support system not only during my five years here in Albany, but my entire life. Before the pandemic pushed everyone to work from home, my office desk was covered in photos of my family and friends. I stuck a little sticky note on a picture of my parents that said, “You can do it!”, to look at when I had moments of doubt or stress. I looked at it often for inspiration; they never let me down. My sisters, Lizzie and Grace, have always inspired me to push myself and do my best so that I can show them that they can absolutely do hard things if they have passion and dedication. My Mom, Dad, Lizzie, and Grace have each wrapped me in warm, kind, and supportive love that consistently leaves me wanting to make them proud. I know I have through my work, but I also hope I have through my character.

I can’t imagine my time in the Department of Atmospheric and Environmental Sciences without the close friends I made there, including Vanessa Przybylo, Macy Testani, and Kaitlyn Fons. I hold many memories close to my heart, including our birthday month celebrations at Cheesecake Factory, hanging out on my front porch, and skiing & hiking in the Adirondacks. My research twin, Vanessa, is one of the people I have grown the closest to through all of the classes we have taken together and the memories we’ve made outside of our department’s hallways. There is truly no one else who I would have rather walked alongside with during the entirety of grad school.

My best friends, Jeremy Sousa and Dakota Crane, have been there for me in every tough moment to lift me back up & also to celebrate my successes. They know how to unlock my deepest laughter and are like family to me. They are an invaluable part of my life, as are
all of my friendships with those here in Albany and Maine that I hold close to my heart.

Some who go to graduate school are supported by someone they love. I am fortunate enough to have experienced that during the beginning and end of my time on the path to my Ph.D. But in the middle, I experienced heartbreak, as many also do during their lifetime. It was then that I decided to stay for my Ph.D. It was then that I chose myself. It’s why I’m sitting here today writing these words of thanksgiving. It’s also why I am now with the most caring, supportive partner I could have dreamed of, Arnold Kurbanovas. He has believed in my abilities, seen me struggle and excel, and has never wavered through the time we have been together. He truly wants what is best for me, even if it means a sacrifice of time, and I will forever be grateful for him.

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PREVIOUSLY PUBLISHED WORK

The materials in Chapter 2 and Chapter 3 have been peer-reviewed and published. The materials from these articles were included with electronic permission from the American Meteorological Society, which is included in Appendix B. These articles were incorporated into this dissertation as the work they include is an integral component of the work as a whole. Further, they build upon each other and are necessary stepping stones into Chapter 4. Since the author of this dissertation was the lead researcher and author for the published work, it is appropriate to include both articles within this dissertation. The articles can be accessed through the following citations:


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1. Introduction

The U.S.-Taiwan Partnership for International Research and Education (PIRE), the catalyst for the work presented herein, seeks to improve the understanding of high-impact weather events and communication of their associated societal risk in the northeastern United States (NEUS) and Taiwan. PIRE research questions are primarily concerned with the predictability of such impactful weather, which varies depending on the temporal and spatial scale of such an event. In addition, prediction skill depends on the accuracy of physical processes represented within numerical forecast models. This dissertation aims to address the potential impact of microscale physical processes within numerical weather prediction (NWP) models on precipitation forecasts.

1.1 Motivation and Objectives

The frequency of extreme hydrologic (e.g., precipitation and streamflow) events in the Catskill Mountains and Hudson River Valley in southern New York State (NYS) has been increasing between the months of June and October since the mid-1990s (Mantonse and Frei 2013). Extreme precipitation events in NYS and the remainder of the NEUS are attributed to extratropical storms, hurricanes or tropical storms, convection, or precipitation associated with a tropical moisture source (Howarth et al. 2019). Western NYS experiences the effects of lake-effect convective clouds initiated by Lake Ontario and Lake Erie, which pile a considerable amount of snow in a localized area over a relatively short time period (e.g., hours to days; Lang et al. 2018). Snowfall that affects a more widespread area tends to be produced by extratropical cyclones. These synoptic events can also generate widely ranging rainfall intensities during the warm and transition (e.g., spring, fall) seasons. Warm-season convective events tend to cause localized areas of intense precipitation on a spatial scale comparable to lake-effect snow. Hurricanes and tropical cyclones can ravage NYS as they approach or make landfall on the NEUS coastline; these do not occur frequently (less than
every 20 years along the southern NEUS coastline, and are therefore considered edge cases. However, events of tropical origin affecting the southeastern U.S. may be more likely to affect the NEUS if associated moisture is transported northward by large-scale flow. These events have the ability to disrupt daily life by reducing or inhibiting travel due to precipitation (e.g., Böcker et al. 2013) and potentially life-threatening flooding, among many other physical and health-related impacts.

Large uncertainties surrounding the representation of physics in numerical models currently exist, specifically when considering precipitation on the meso- and synoptic scales, and multiple hydrometeor phases (i.e., liquid and ice). Liu et al. (2011) found that planetary boundary layer, land surface, and radiation transfer schemes only weakly influence winter season precipitation forecasts in the western U.S., while microphysics schemes provide considerable uncertainty. This partially stems from an underdeveloped understanding of microphysical processes and their subsequent interactions in clouds, both in an observational and modeling sense. For example, there are wide-ranging differences among precipitation efficiencies in mesoscale winter storms (Reeves and Dawson 2013; McMillen and Steenburgh 2015; Bartolini 2019) and orographic precipitation events (Morales et al. 2019) when comparing multiple microphysics schemes or changing parameters within. These and many other studies have been conducted solely investigating the sensitivities of precipitation to physics parameterization choices in NWP. One component of PIRE research seeks to build upon the current understanding of microphysics uncertainty in a multi-faceted approach by identifying and improving upon NWP limitations. As such, this dissertation aims to address this physical uncertainty with focus on *microphysical* representation in NWP. To increase understanding of such processes and their effects on precipitating systems, identifying sensitivities to user-defined choices within microphysical models by means of both single and multi-microphysics ensembles is integral. Furthermore, PIRE seeks to better understand, predict, and respond to extreme weather events. Hence, this dissertation will not only edify the sensitivity of heavy precipitating events to microphysical processes, but upon investigating multiple events, will
also elucidate the microphysical influence(s) on the predictability of heavy precipitation in NYS.

1.2 Organization of Dissertation

The dissertation will be organized as follows. The remainder of Chapter 1 introduces the research questions that guide the work in Chapters 2, 3, and 4. Chapter 2 includes a literature review of lake-effect snow and assesses lake-effect forecast sensitivity to pristine ice crystal nucleation and mode of growth. Chapter 3 builds upon this research by addressing and including several additional sources of microphysics uncertainty, as well as measuring the sensitivity of the lake-effect forecast to these and to various microphysics schemes. The stochastic methods in which forecast uncertainty can be accounted for within NWP are discussed in Chapter 4. Then, microphysics uncertainty is addressed in a more systematic approach by means of those various stochastic perturbation methods to understand how specific microphysics processes lead to forecast uncertainty in both synoptic and mesoscale events. Each of these chapters includes a brief introduction, description of the numerical methods, simulation details and description, and analysis of results that are integral to each component of this research endeavor. The findings from Chapters 2–4 are discussed and final conclusions are outlined in Chapter 5.

1.3 Research Questions

To address the objectives of this dissertation, the following research questions will be addressed herein.

1. Does representing pristine ice nucleation with different parameterizations have impacts on a winter storm forecast?

2. Do changes in method of ice crystal growth (i.e., spherical or nonspherical) alter the forecast of a winter storm?
3. Do various representations of microphysics through changed parameters and parameterizations within two bulk microphysics schemes impact a winter storm forecast the same as choosing a different microphysics scheme?

4. What degree of uncertainty do microphysical processes introduce to a forecast and how does that uncertainty propagate through a cloud system?
2. Sensitivity of Lake-Effect Cloud Microphysical Processes to Ice Crystal Habit and Nucleation during OWLeS IOP4

2.1 Overview and Objectives

The accurate prediction of high-impact snowfall events depends on the parameterization of thermodynamic and microphysical processes, including the formation and subsequent growth of frozen hydrometeors. While synoptic and mesoscale dynamics provide the environmental conditions and ascent needed for mixed-phase cloud formation, surface precipitation quantities are dependent upon the liquid and ice water contents and hence the growth mechanisms of ice crystals, including vapor deposition and subsequent collection. Before crystals can undergo growth or decay, they must first nucleate.

This chapter aims to answer the first two research questions presented in Chapter 1.3 which are concerned with the impacts of different representation of pristine ice nucleation and ice crystal growth on the forecast of a winter storm. To accomplish this, Meyers et al. (1992) and DeMott et al. (2015), both introduced and discussed in Section 2.3.2, are used as the two pristine heterogeneous ice nucleation parameterizations while spherical and nonspherical growth are explored for the ice crystal growth mechanisms. Focus is solely placed on a lake-effect storm that occurred during the Ontario Winter Lake-effect Systems (OWLeS) field project (Kristovich et al. 2017), as its thermodynamic conditions support considerable ice nucleation and growth throughout its lifetime.

2.2 Background

2.2.1 Lake-Effect Snow

Lake-effect storms (LESs) are the dominant case study type within this dissertation. Lake-effect (LE) snow impacts the Great Lakes region during the fall and winter months when either an Arctic or continental Polar air mass traverses over the relatively warm lakes.
The airmass experiences localized supersaturation, and lapse rates steepen via low-level moistening and warming. Conditional instability is locally enhanced, favoring convection and leading to the formation of cumuliform clouds (Kristovich and Laird 1998). These clouds can organize into widespread cells or an organized cloud band depending on wind speed and direction relative to the long lake axis, presence of a secondary circulation due to thermal differences between the lake and land, and the influence of differential surface roughness on low-level convergence (Bergmaier et al. 2017). Note that the ascent associated with the secondary circulation may also assist with the triggering of convection and increase the lifespan of convective processes (Bergmaier and Geerts 2016; Bergmaier et al. 2017). When these clouds reach the downwind side of a lake, any present topography can contribute to further forcing for ascent, intensifying the storm (Ahrens 2013). Climatologically, LE clouds are more frequently observed during December, January, and February when the air-lake temperature difference is typically maximized (Laird et al. 2017). From October to March, LE clouds are present about 60–80% of days per month over the Great Lakes Region (Laird et al. 2017).

LESs generally produce low-density snow that leads to snow-to-liquid ratios (SLRs) much greater than the conventional 10:1 rule of thumb (Schmidlin 1993; Baxter et al. 2005). While it is common to observe SLRs exceeding 20:1 throughout the Great Lakes, this region also experiences the greatest variation in SLR; the SLRs for the 25th and 75th percentile are 10:1 and 20:1, respectively (Baxter et al. 2005). Some variability may be explained by ice cover changes as moisture availability is maximized when the lakes are ice-free, leading to considerable riming instead of additional primary or secondary ice nucleation processes or aggregation. Lake Ontario, the moisture source of interest in this work, and its immediate downwind regions climatologically experience SLRs of 12:1 in the fall and spring (e.g., October, November, March, April) and 16:1 in the winter (e.g., December, January, February). Note that these SLR values are inclusive of all snow-producing weather systems and as such are not representative of solely LESs.
Due to the high SLRs climatologically observed in the Great Lakes region, a substantial amount of snow can accumulate in a localized area over a short span of time (Ahrens 2013). Lang et al. (2018) analyzed numerous LES snowfall amounts during ten cold seasons (2003/2004–2013/2014) and determined that the mean snowfall downstream of Lake Ontario during this time period had maximum values ranging from 2.0–3.0 mm snow liquid water equivalent (SLWE) per LES event. On average, all Lake Ontario LESs produce greater than 55.3 mm SLWE per cold season in downstream regions, with accumulations nearing 130 mm SLWE in areas of higher terrain (e.g., Tug Hill Plateau).

LESs impact many facets of day-to-day life due to associated extreme snowfall. Schmidlin (1993) explored numerous societal and economic impacts of LE snow lee of Lake Erie during the extremely cold month of December 1989. During this month highway departments spent $371,000 (not accounting for inflation) on snow and ice removal, and operational costs at an Ohio lake port rose by 240% due to LESs. In addition, highway toll revenue likely decreases during LESs as a statistically significant negative correlation exists between snowfall amounts and total daily traffic counts of passenger cars in the Buffalo, NY region (Call 2011). There are also positive impacts of LE snow, namely related to winter recreation and contributions to meltwater in watersheds (Hall et al. 2018).

Forecasting cold-season LESs is challenging, as these storms are a dynamic mesoscale phenomena that can vary immensely on both small spatial and short temporal scales. Niziol et al. (1995) highlights the importance of accurately capturing various fields, such as small-scale features forced by a lake (e.g., thermal and frictional convergence zones) and lake properties that control heat and moisture fluxes, such as ice cover and water temperature, that lead to formation of an LES when trying to model these events. While it is possible to produce a forecast that is generally comparable to observations with high-resolution regional models fed by highly-resolved initial conditions for both land and lake surfaces, identification and improvements of the best performing parameterizations and schemes are still necessary within these models to gain greater accuracy with respect to forecasting the timing, duration,
location, and intensity of LESs.

2.2.2 Microphysics Uncertainty in a Lake-effect Storm: Ice Crystal Nucleation and Growth

The effect of ice microphysics on sedimentation properties has been studied in bulk microphysical parameterizations with spherical ice crystals (e.g., Hong et al. 2004). However, some bulk microphysics models treat ice crystal habit, or shape, in an empirical sense, prescribed as a function of size and temperature (Phillips et al. 2017) while some bin microphysics models predict the evolution of crystal shape explicitly (Phillips et al. 2018). Multi-moment bulk microphysical parameterizations have been developed that allow for the nonspherical growth of ice crystals (Harrington et al. 2013a,b; Tsai and Chen 2020). Through theoretical and applied studies, Sulia and Harrington (2011) and Sulia et al. (2013) determined that the habit of ice crystals is of utmost importance to track during periods of depositional ice growth. Habit evolution can have a substantial influence on cloud phase partitioning, such as ice and liquid mass, which can thereby influence hydrometeor sedimentation rates and other cloud properties. Nucleation-controlled variations in pristine ice number concentration \( N_i \) and subsequent depositional growth can impact ice mass and indirectly affect the degree of exaggeration of the crystal habit. Various parameterizations exist to represent ice nucleation; the choice of parameterization affects the number concentration of ice crystals in a volume due to the differing dependencies within the parameterization equations, with potential influences on sedimentation rates and cloud glaciation times, among other microphysical factors. Highly active cold-season storms with abundant moisture sources, namely LESs, offer a ripe opportunity wherein such interactive processes and their associated effects can be investigated.

While the mesoscale dynamics of LE clouds are foundationally understood, the effect of microphysical ice processes in numerical models is less so. As such, the purpose of this chapter is to diagnose the potential effects of ice crystal nucleation and mode of growth on
in-cloud LE microphysical processes and forecast precipitation magnitude, type, and spatial pattern. Harnessing a deeper understanding of why certain microphysical processes lead to varying numerical solutions is necessary when aiming to understand the discrepancies between model output and observations, and even among varying model solutions.

2.3 Model and Parameterization Descriptions

As the outlined research questions are concerned with microphysics sensitivities in NWP, this dissertation involves multiple microphysics schemes, various changes to parameterizations within, and uses multiple methods of stochastic perturbations to account for uncertainty. Those relevant to each chapter are expanded upon in their respective subsections. The microphysics schemes and parameterizations used in this chapter are further expanded upon in the following subsections.

2.3.1 Adaptive Habit Microphysics Model

Ice crystals can grow to relatively large sizes at the expense of liquid droplets in mixed-phase clouds via the Wegener-Bergeron-Findeisen process (Sulia and Harrington 2011). Due to enhanced depositional growth for nonspherical crystals, assuming spherical growth at all temperatures underestimates the final crystal mass, which ultimately affects ice and liquid water contents and subsequent precipitation processes. The Adaptive Habit Microphysics Model (AHM), the primary microphysics scheme used throughout this dissertation, combines vapor diffusional mass growth from the classical capacitance model (Pruppacher and Klett 1997) and aspect ratio ($\phi$) evolution based on the inherent growth ratio ($\Gamma$) of the crystal, which varies with temperature and describes the distribution of mass between the major and minor crystal axes. Harrington et al. (2013a) developed the AHM with four prognostic ice variables: mass, number, and spheroidal volume-weighted $a$- and $c$-axis length mixing ratios to predict ice crystal properties. Ice crystal shape is characterized as spheroidal by relating its $a$- and $c$-axes as $\phi = \frac{c}{a}$ where an oblate spheroid represents a platelike habit (i.e., $a > c$ thus $\phi < 1$), and a prolate spheroid represents a columnar habit (i.e., $c > a$ thus
By means of tracking $\phi$, the AHM predicts the evolution of ice crystal habit through a historical tracking parameter, which takes account of $\phi$ evolution through a temporal average of $\Gamma$, capturing the nonlinear growth via vapor diffusion and subsequent effect on phase partitioning (Sulia et al. 2013). This model has been tested in a parcel model framework (Harrington et al. 2013b), two-dimensional kinematic model (Sulia et al. 2013; Jensen et al. 2017), and both ideal and real Weather Research and Forecasting Model (WRF) simulations (Sulia et al. 2014; Sulia and Kumjian 2017a,b; Jensen et al. 2018; Gaudet et al. 2019; Sulia et al. 2021; Gaudet et al. 2021).

### 2.3.2 Ice Nucleation Parameterizations

The formation of ice crystals has been modeled using distinct nucleation parameterizations representing different nucleation modes with varying dependencies (e.g., temperature, ice supersaturation, aerosol concentration) as a result of in-situ measurements and lab studies. Despite numerous field campaigns and laboratory studies focused on detailing nucleation processes (e.g., DeMott 1990, Meyers et al. 1992, Phillips et al. 2008, DeMott et al. 2010, Ardon-Dryer 2012, Murray et al. 2011, DeMott et al. 2015, Hiron and Flossman 2015, Solomon et al. 2015, among others), albeit with varying assumptions or goals of quantifying different aerosol inputs, the prediction of ice nucleating particles (INPs) remains challenging. Uncertainty is reflected in the varying forms of ice nucleation parameterizations modeling different or even combined nucleation modes (e.g., deposition, contact-freezing, immersion-freezing) aimed at representing the formation of ice crystals.

Pruppacher and Klett (1997) noted that certain ice nucleation modes may produce greater INP concentrations than others over a range of subfreezing temperatures; contact freezing nucleation is the dominant mode, followed by deposition and immersion freezing. However, more recent research has demonstrated that contact freezing is the least important mode of heterogeneous ice nucleation (Phillips et al. 2007), even when considering the direction of freezing (e.g., inside-out vs. outside-in, Phillips et al. 2017). Immersion
freezing has been suggested to be of greatest importance within mixed-phase clouds while deposition nucleation is expected to have a secondary contribution to \( N_i \) (Kanji et al. 2017). Condensation freezing has historically been treated as a combined nucleation mode (e.g., immersion-condensation freezing, Kanji et al. 2017). As such, the AHM includes the choices of condensation and immersion freezing nucleation as parameterized by DeMott et al. (2015) and condensation and deposition freezing by Meyers et al. (1992), hereafter DEM15 and MEY92, respectively.

The MEY92 parameterization was empirically developed from multiple continuous flow diffusion chamber INP concentration measurements and is inherently temperature dependent due to its saturation dependence. The number of predicted ice crystals nucleated via deposition-condensation freezing (\( L^{-1} \)) is given by

\[
N_{id} = \exp[-0.639 + 0.1296(100(S_i - 1))],
\]

where \( S_i \) is ice saturation, which varies spatially. The MEY92 parameterization is independent of aerosol concentrations. The observations from which the scheme was derived were surface-based, which was noted to be a potential source of error by MEY92. It is well-known that the number concentration of ice that results from nucleation via MEY92 is generally an overestimation compared to other schemes and observations (Prenni et al. 2007). MEY92 states that Eq. 2.1 should only be applied in the temperature range of \(-7 \) to \(-20^\circ C\), but can be extrapolated within reason outside of these temperatures. MEY92 allows ice nucleation below water saturation at all relevant temperatures, but de Boer et al. (2011), among others, question the existence of strong deposition nucleation at modest to moderate levels of supercooling. All possible misrepresentations of nucleation should be considered when interpreting the results presented in section 2.5.

The resulting INP number concentration (\( L^{-1} \)) from the nucleation of ice crystals by means of both condensation and immersion freezing can be modeled using the parameterization
which considers the material of aerosol particles ($n_a$) with diameters greater than 0.5 $\mu m$ as well as calibration factors ($cf$) for the laboratory instruments used to measure immersion freezing at 105% relative humidity with respect to liquid water, where $\alpha = 0$, $\beta = 1.25$, $\gamma = 0.46$, and $\delta = -11.6$. DEM15 introduced the $cf$ factor to correct for an instrumental bias, and while Garimella et al. (2018) found sensitivity of INP to $cf$ in climate models, DEM15 suggests that $cf = 3$ be used in cases with natural mineral dust. With the establishment of these two nucleation methodologies, next it must be determined from which data source the unknown variable ($n_{a>0.5\mu m}$) is defined.

2.3.3 Advanced Particle Microphysics Model

Levin et al. (2005) suggests that precipitation amounts and rates decrease as aerosol pollution increases within a cloud due to the aerosol indirect effect on cloud microphysics and precipitation. Ardon-Dryer (2012) showed that the onset of precipitation may be delayed with an increased amount of environmental aerosols. These and many other studies support the need for high-resolution aerosol data in numerical models due to their direct and indirect effects on cloud properties. The Advanced Particle Microphysics (APM) model was developed by Yu and Luo (2009) to explain observations of size-resolved atmospheric particles. The process of nucleation, condensation and evaporation, coagulation, local thermodynamic equilibrium, and dry deposition are considered within the APM, which can be used as an independent box model or coupled with other chemistry-focused models. It was first implemented into a global three-dimensional atmospheric composition model, Goddard Earth Observing System (GEOS)-Chem (Yu and Luo 2009) and later integrated with the chemistry-coupled WRF model (WRF-Chem, Luo and Yu 2011). The APM is optimized to simulate secondary particle formation and subsequent growth to sizes typical of CCN, with increased size resolution for
critical aerosol size ranges. Here, secondary particles refer to those formed from new particle formation (or particle nucleation) in the atmosphere, while primary particles include dust, sea salt, black carbon, and primary organic carbon. The APM uses 40 bins to represent secondary particles in the dry size range of 1.2 nm to 12 µm. While freshly nucleated particles are only a few nanometers, growth to CCN sizes (diameters ranging from < 0.2 to > 2 µm, Hindman et al. 1977) can occur. In sum, the APM treats CCN concentration as a function of the aerosol particle size distribution, composition, and liquid supersaturation (Luo and Yu 2011).

2.4 Data & Methodology

2.4.1 Implementation into the Adaptive Habit Microphysics Model

Both [MEY92] and [DEM15] were implemented into the AHM to test the subsequent sensitivity of sedimentation rates and precipitation accumulation amounts during intensive operating period 4 (IOP4) of the OWLeS field campaign. Unlike in previous studies using the AHM where ice nucleation was dependent upon the predetermined ice concentration and existing ice in a grid cell, these parameterizations developed from empirical data allow for a spatially and temporally evolving $N_i$. A nucleation rate is calculated in each grid cell via Equation 2.1 or 2.2, with extrapolation used if $-35 < T < -5^\circ$C and the ice supersaturation is $\geq 5\%$. Neither the MEY92 or DEM15 parameterizations consider the present ice number concentration before diagnosing the $N_i$ or INP, respectively, at the current timestep. This could lead to potential overprediction of ice number and mass within a cloud system. However, the DEM15 rate is applied only if there is enough cloud droplet mass to sustain immersion freezing processes. Therefore, no immersion freezing will ensue in unphysical conditions, where no droplets exist for INPs to be immersed within and subsequently induce freezing. Also, while secondary ice processes are represented within the AHM, even though the quantification of such processes is challenging due to limited understanding (Field et al. 2017), the associated effects are not investigated within this work.
For this work, the APM was run independently of the AHM in the WRF-Chem v3.7.1, using the same initialization time, simulation time period, and namelist options discussed in the next section (2.4.2). The APM-produced INP and CCN aerosol data were then updated within the AHM every three hours. While the background aerosol profile is reset every three hours, the changes from one time step to the next are negligible, so nudging is not performed on these data. Dust particles have a negligible contribution to CCN but are important for heterogeneous ice nucleation and so are considered the dominating environmental aerosol for ice nucleation. Due to unclear physics of ice nucleation of carbonarious aerosols, only the contribution of dust to ice nucleation is considered; this dust is not specifically defined as mineral dust by the APM. Although this is not a specific requirement for the DEM15 parameterization, the use of dust data is adequate relative to using all hydrophobic aerosol with no regard to composition. Dry dust with diameters larger than 0.5 \( \mu m \) act as initial input \( (n_a) \) into the DEM15 parameterization and are assumed to be an upper limit for \( N_i \) calculations by MEY92. Only 20% of the APM dust data are used in the AHM with this size threshold specified by DEM15. For a given supersaturation with respect to liquid, the CCN number provided by the APM is used to calculate cloud droplet number concentrations in the model. APM aerosol were treated as background in the AHM, meaning that no amount of aerosol was removed during CCN or INP activation or scavenging processes, or added during complete droplet evaporation or particle sublimation therefore removing consideration of any aerosol recycling processes.

To directly compare MEY92 to DEM15 at varying temperatures, the saturation vapor pressure with respect to liquid and ice are calculated for a range of temperatures. Assuming liquid water saturation, the ice supersaturation is calculated and used in the MEY92 deposition nucleation equation. In Figure 2.1, the DEM15 parameterization is evaluated with aerosol concentrations of 0.01 and 0.1 \( \# \) cm\(^{-3}\) for particles with diameters >0.5 \( \mu m \). The predicted \( N_i \) for each aerosol case stay consistently different for DEM15 with decreasing temperature. As the temperature decreases, there is an exponential increase in INP concentration, which
is a typical trend and not exclusive to \textit{MEY92} and \textit{DEM15} (Cziczo et al. 2017). An $N_i$ difference of about six orders of magnitude exists between \textit{MEY92} and \textit{DEM15} at warmer temperatures with this difference decreasing as temperatures cool. These results indicate that \textit{MEY92} nucleates a greater $N_i$ than \textit{DEM15} at all considered temperatures with INP concentrations representative of this LES event, discussed in section 2.5.3.

2.4.2 Experimental Setup

The LES of interest occurred during OWLeS IOP4, details of which are discussed in section 2.5. Numerical simulations of this LES and its associated microphysical characteristics are completed using version 3.7.1 of the WRF model. The simulations are run with three two-way nested domains centered at 43.605°N and 76.721°W varying in horizontal resolution from 25 km (Domain 1, D01), 5 km (Domain 2, D02), and 1 km (Domain 3, D03; Fig. 2.2), and 30 nonlinear vertical levels, extending to about 15 km. The time step is 150 seconds in D01, 30 seconds in D02, and 6 seconds in D03. D03 focuses on eastern Lake Ontario and its downwind regions; sensitivity tests determine negligible precipitation pattern differences when shifting this domain to include the entirety of Lake Ontario. Initial and boundary conditions are provided by the 12-km North American Mesoscale (NAM) Forecast System Analysis; offline tests indicate increased forecast proficiency of NAM IOP4 LES snowfall location relative to the 0.5° Global Forecast System Analysis data.

Each simulation is run for the period of 11–20 December 2013, allowing four days of model spin-up to capture a synoptic event (0600 UTC 14 December to 1600 UTC 15 December) that preceded the LES (1800 UTC 15 December to 0800 UTC 16 December). Ample spin-up time allows for accurate representation of this synoptic event, triggering the instability leading to the LES formation, while decreasing the spin-up time results in a poor spatial LES precipitation forecast. The Rapid Radiative Transfer Model adapted for global climate models (RRTMG; Iacono et al. 2008) is used to determine longwave radiative fluxes. The Dudhia scheme is chosen to calculate shortwave radiative processes (Dudhia...
Boundary layer physics are determined by the Yonsei University Scheme (YSU; Hong and Noh 2006a). The Kain-Fritsch cumulus scheme is used in D01 and D02 (Kain 2003) but turned off in D03 due to its high convection-allowing resolution. The aforementioned AHM is used as the microphysics option, within which ice nucleation varied between the MEY92 and DEM15 parameterizations, described in section 2.3.2. The four simulations of interest and their associated modeling options diverging from the namelist options discussed are summarized in Table 2.1. The labels $MEY92_H$, $MEY92_S$, $DEM15_H$, and $DEM15_S$ are used to refer to specific simulations and their model specifications. $MEY92$ and $DEM15$ refer to the parameterization used for ice nucleation within the AHM, Meyers et al. (1992) and DeMott et al. (2015), respectively. The $S$ (spheres) and $H$ (habits) subscripts on these labels refer to ice growth occurring spherically and nonspherically, respectively.

2.4.3 Quantitative Precipitation Estimates

Radar-derived precipitation data is the best option for model validation in this area of very limited in-situ ground observations. The 24-hr quantitative precipitation estimate (QPE) valid at 1200 UTC 16 December from the National Weather Service Advanced Hydrologic Prediction Service (AHPS) was used to evaluate modeled QPFs. For clarity, QPE and QPF are not interchangeable and refer to precipitation observations and forecasts, respectively. To build this dataset, precipitation estimates from the Next Generation Weather Surveillance Radar 88-D (WSR 88-D) were compared to reports of precipitation from rain gauges by the AHPS. Based on this comparison, a bias was computed and applied to the radar data. The radar and gauge precipitation data were then combined into the QPE field and monitored every hour. This AHPS QPE product has a spatial resolution of 16 km$^2$ and temporal resolution of 24 hours, where a hydrologic day runs from 1200–1200 UTC. Note that communication with staff at the AHPS has identified the lack of documentation on the $A$ and $b$ constants in the reflectivity-to-rainfall (Z-R) relationship developed by Marshall et al. (1947), $Z = AR^b$, used during a specific event. As a supplement to the AHPS observation, accumulated precipitation
was derived herein from the 0.5° plan position indicator (PPI) scans (fixed-elevation azimuthal scans of radar) provided about every five minutes by the KTYX radar (Montague, NY, located east of Lake Ontario) using the aforementioned Z-R relationship where $A = 75$ and $b = 2$ and were then interpolated to a 16 km² grid. These results are discussed in section 2.5.4.

As with observations, the daily precipitation accumulation maps for the model simulations presented in section 2.5 were produced for 1200 UTC 15 December to 1200 UTC 16 December. The accumulated precipitation was calculated in the AHM for MEY92 and DEM15 as a sum of rain and liquid-equivalent snow, ice, and graupel that precipitated to the surface; this is referred to as the explicit model precipitation. Using these forecasts instead of snowfall depth removes the uncertainty regarding the highly variable snow-to-liquid ratios in this region (Baxter et al. 2005) and allows for direct comparison to AHPS measurements and the KTYX-derived QPE. In addition to the daily QPEs, hourly snow-water liquid-equivalent measurements were recorded at two stations east of Lake Ontario during the OWLeS field campaign (Kristovich et al. 2017) operating between 5 December 2013 and 29 January 2014. The North Redfield station (43.62445°N, 75.87708°W, elevation of 385 m above sea level (ASL); Steenburgh et al. 2014a) and the Sandy Creek station (43.6402°N, 76.09715°W, elevation of 143 m ASL; Steenburgh et al. 2014b) measurements were used in analyses for both daily precipitation accumulation maps and a time series of precipitation.

Note that as radar is a remote sensing tool, its data quality issues are inherently problematic. These errors can be exacerbated by environmental conditions and mechanical specifications. The most obvious potential error source is the Z-R relationship, where $A$ and $b$ are constants that change substantially depending on the hydrometeor class and associated size distribution (Stout and Mueller 1968). Campbell et al. (2016) noted that during an earlier OWLeS IOP, setting $A = 75$, the constant more regularly used for snowfall in the Western U.S., and $b = 2$ allowed for better liquid-equivalent forecasts when compared to the station measurements in Sandy Creek and North Redfield, NY. As such, these constants are used in the derivations presented herein. This Z-R relationship is less reliable for a mixture of
hydrometeor types or when a transition is occurring from snow to rain, for example, as the set
dielectric constant cannot simultaneously account for both ice- and liquid-phase hydrometeors.
Of course, other problems may arise from radar, such as location and elevation, distance
of the sampling data, and coverage. To not only better elucidate these potential errors in
Z-R calculations, but to also better compare observed and modeled precipitation, QPFs are
calculated using the same Z-R relationship described above. Sulia and Kunjian (2017a,b)
show that an offline forward operator can produce modeled polarimetric radar quantities
Ryzhkov et al. (2016) from AHM model output. To better compare observed and modeled
precipitation, QPFs are calculated using the Z-R relationship described above. The derived
radar data from the forward operator is used to calculate the accumulated precipitation using
the same Z-R relationship as was used for the KTYX $Z_H$ data. While a loss of accuracy
is expected with this two-step derivation (i.e., model output to simulated radar reflectivity
to precipitation), the results of this test discussed in section 2.5.4 provide insight into how
the accumulation amounts from the derived radar data differ from the explicit modeled
precipitation quantities.

2.5 Case Study

The methodology outlined in section 2.4 is applied to investigate OWLeS IOP4. In this
section, OWLeS IOP4 will be introduced in both the synoptic and mesoscale senses through
NAM analysis and a combination of in-situ and remote observations. The dust conditions as
modeled by the APM are introduced to ground further discussion of the effects on ice crystal
nucleation and subsequent processes in the AHM. Then, the WRF simulations outlined in
Table 2.1 will be analyzed to further elucidate the microphysical structure of the storm as
well as the impacts that ice nucleation and subsequent growth mode have on the QPF.

2.5.1 Synoptic Conditions

As confirmed by the sensitivity to model spin-up, the OWLeS IOP4 case focused on
a locally confined, shallow cumuliform LE cloud that responded to the latent conditions
of the preceding synoptic circulation. 12-km NAM analysis shows that a trough at 500-hPa propagated eastward from 1800 UTC 15 December to 0600 UTC 16 December 2013, bringing with it increased absolute vorticity over Lake Ontario (Fig. 2.3). The circulation associated with a low-pressure system off the coast of Maine at 1800 UTC (Fig. 2.3) ushered in subfreezing temperatures at both the surface and 850-hPa into the eastern Great Lakes region (Fig. 2.4). As a result, there was a 16–20°C temperature difference between the lake-surface and 850-hPa, satisfying the accepted baseline 13°C minimum temperature difference needed for LES to develop (approximately the dry adiabatic lapse rate, Braham 1986), which allowed for the destabilization of the lower atmosphere and moisture and heat fluxes to propagate upwards. Weak westerly surface and 850-hPa winds (Fig. 2.4) over the relatively warm (i.e., 4.35°C) and ice-free (NOAA 2013) Lake Ontario allowed the overlying air mass to travel over the longest fetch of the east-west-oriented lake, maximizing the amount of potential heat and moisture fluxes.

2.5.2 Mesoscale Conditions and Observations

Multiple radiosondes were launched from three locations near Lake Ontario during IOP4 by mobile sounding teams led by Millersville University, SUNY Oswego, and Hobart and William Smith Colleges (Fig. 2.5). All soundings indicate that the atmosphere was nearly to completely saturated from the surface to approximately 700-hPa, where the capping inversion inhibited any additional vertical growth of the LES. The winds were primarily westerly at all sampled atmospheric levels indicating little to no directional shear. Surface winds ranged from 5–15 m/s, validating the aforementioned NAM analysis winds (Fig. 2.4) with a slight increase in magnitude. From these soundings, cloud base and top temperatures are estimated to be around −8 and −27°C, respectively. As seen in PPI scans of reflectivity (ZH) by the KTYX radar, the LES was well-organized from 0000-0700 UTC (Fig. 2.6a-h), with distinctly strong banding features from 0400-0700 UTC (Fig. 2.6e-h). During its greatest intensity, the ZH exceeded 35 dBZ (0500 UTC 16 December, Fig. 2.6f). The system intensity decreased as
the LES moved southward around 0600 UTC (Fig. 2.6g), rapidly decreased in strength at 0800 UTC (Fig. 2.6i), and lost all structure by 0900 UTC (Fig. 2.6j).

During IOP4, mobile surface snow observations were taken in Oswego, New Haven, Mexico, and Altmar, NY. The timing and types of precipitation observed at each location are outlined in Figure 2.7. Snow was observed at all locations, with Oswego, New Haven, and Mexico experiencing longer periods of time with dendritic crystals during either a portion of or the entire event. Graupel was reported in New Haven, Mexico, and Altmar, indicating riming at differing times and locations. The presence of graupel suggests the existence of liquid water in the cloud available for accretion and riming processes. The OWLeS King Air Mission Summary (Geerts 2013) notes a considerable amount of liquid water at the cloud top near 3 km, causing icing-induced instrument malfunction. Also included in the summary is the lack of liquid water over land, around 1.8 km above ground level. However, the liquid water content did reach up to 1.3 g m$^{-3}$ in the convective cells of the LES that had the ability to support high supersaturation production.

For the majority of its lifetime, the LES was precipitating directly over and to the east of Lake Ontario (Fig. 2.6), so it is not surprising that the maximum 24-hour accumulated liquid-equivalent precipitation of 17.92 mm reported by the AHPS was focused immediately east of Lake Ontario (Fig. 2.8a). The precipitation distribution follows an idealized simulation of a lake-effect band over an oval lake emulating Lake Ontario (Gowan et al. 2021), as the secondary circulation dramatically weakens upon landfall leading to an increase in hydrometeor fallout. The gradient of the precipitation was considerably tight, as much as 0.5 mm/km, in both the north-south and east-west directions. The precipitation was generally bounded between 43–44°N and 75–77°W. Precipitation south of 43°N is not included in the detailed event analysis. Liquid-equivalent data from Sandy Creek and North Redfield, NY vary slightly compared to the AHPS data (Fig. 2.8a). While the North Redfield station reported 16.76 mm of liquid-equivalent precipitation, within the 16–18 mm range measured by the AHPS, Sandy Creek reported 22.34 mm, which was 37–46% larger than the AHPS
range of 12–14 mm. Interestingly, a gauge-corrected NEXRAD $Z_H$-derived product provided by the National Center for Environmental Prediction (NCEP) was found by Welsh et al. (2016) to report about half of the nonspherical snow-water liquid-equivalent amounts observed at the Sandy Creek and North Redfield sites during an earlier OWLeS IOP. Based on this discrepancy and inherent data quality issues associated with radar retrievals discussed in section 2.4, caution is required when using these blended in-situ and remotely retrieved observations as ground truth. Figure 2.8b displays the QPE derived for this work from the 0.5° KTYX $Z_H$ during the same period. Although these data are not bias corrected by rain gauges, the result closely resembles that of AHPS, which is likely a consequence of the lack of gauges in this confined area.

As previously mentioned, the LES was well organized between 0000–0700 UTC 16 December. In Figure 2.9, modeled (shading) and observed (lines) precipitation intensity is compared between Sandy Creek (top) and North Redfield (bottom). The maximum and minimum accumulations from $MEY92_S$, $MEY92_H$, $DEM15_S$, and $DEM15_H$ serve as the bounds to the shaded range in Figure 2.9. Indicated by the observations, the precipitation was most intense between 0000-0700 UTC with the maximum one-hour accumulation at 0500 UTC. There was a sharp drop in accumulations afterward as the LES propagated south of the observation sites. All simulations lag the maximum precipitation by an hour at North Redfield but accurately capture the timing at Sandy Creek. All simulations under-forecast the precipitation at Sandy Creek before 0500 UTC. Both $MEY92$ simulations continue to under-forecast at both locations, but $DEM15_H$ generally over-forecasts after 0500 UTC at both locations and $DEM15_S$ forecasts very close to the observed precipitation at Sandy Creek but over-forecasts at North Redfield (individual simulation forecasts not shown). Despite the large spread in point hourly QPFs, the simulations capture the LES temporal evolution fairly well.
2.5.3 Dust Concentrations during IOP4

While large spatial and temporal variations in CCN and \( n_a \) exist regionally, there is no considerable variation in the immediate downwind region of Lake Ontario during IOP4. D03-averaged background CCN and \( n_a \) data from the APM from 1200–1200 UTC 15–16 December 2013 are provided in Figure 2.10 along with the modeled temperature at 0.32, 2.1, and 3.8 km above ground level. These altitudes are approximately at cloud base, mid cloud, and cloud top, respectively. Recall that \( n_a \) only consists of dust particles with diameters >0.5 \( \mu m \) and that dust particles have negligible contributions to CCN concentrations; therefore, these quantities are not closely related. The CCN concentration at 0.4% supersaturation is on the order of 100 cm\(^{-3}\) at the base and mid cloud, but decreases to less than 0.1 cm\(^{-3}\) at cloud top during the LES (Fig. 2.10, purple lines). This decrease with height is consistent with the findings of Luo and Yu (2011), albeit for the month of July. The \( n_a \) varies about 10\(^6\) kg\(^{-1}\) (1 cm\(^{-3}\)) at cloud base and decreases to about 10\(^5\) kg\(^{-1}\) (0.1 cm\(^{-3}\)) at mid cloud and cloud top (Fig. 2.10, green lines). These data are representative of the background CCN values used in all simulations, and the \( n_a \) values are used to constrain nucleation rates in \( MEY92_S \) and \( MEY92_H \) and calculate nucleation rates in \( DEM15_S \) and \( DEM15_H \). The temperatures are subfreezing during IOP4, ranging from \(-6\) to \(-10^\circ C\) at cloud base, \(-8\) to \(-22^\circ C\) at mid cloud, and \(-17\) to \(-27^\circ C\) at cloud top (Fig. 2.10, black lines). Temperatures at all vertical levels decrease throughout the event, with the mid cloud to cloud top cooling faster than the base. These temperature ranges cover all ice crystal growth zones, especially the dendritic growth zone and are also amenable to riming and aggregation processes. Nucleation rates for both \( MEY92 \) and \( DEM15 \) will increase with these decreasing temperatures as altitude increases (Fig. 2.1).

2.5.4 Precipitation: WRF Forecast vs. AHPS Observations

The AHPS data (Fig. 2.8a) is only available for accumulated precipitation over 24-hour periods. For further analysis and understanding of the spatial pattern of the QPFs, the
The LES simulation was split into 6-hour time periods (Fig. 2.11a). As expected, there was little to no precipitation between 1200–1800 UTC 15 December. While the LES initiated between 1800–0000 UTC, the QPF increased to a maximum of 10.6 mm. A QPF of 15.0 mm occurred between 0000–0600 UTC with a matching contribution south of the main area of interest between 0600–1200 UTC. All three remaining simulations (Table 2.1) follow this evolution, with variation in QPF magnitude. Both the rapid intensification and decay of the precipitation associated with the LES is elucidated in this evolution culminating in a total 24-hour QPF for each simulation valid at 1200 UTC 16 December in Figures 2.11b-e. Each simulation provides a QPF with maxima > 25 mm, ranging from 25.7 mm in MEY92S (Fig. 2.11d) to 41.3 mm in DEM15S (Fig. 2.11b).

The bulk of the forecast precipitation is downwind of Lake Ontario following the observations in Figure 2.8a overlaid in Figures 2.11b-e (white dashed contours), but the simulations include some widespread light accumulations (2–4 mm) throughout most of D03. Although the QPF magnitude is in major disagreement between each simulation and observations (about 97.5% greater than observations), the locations of maximum observed and modeled precipitation as defined as the area inside the innermost contour are relatively similar with the exception of MEY92S. DEM15 (Fig. 2.11b) provides the most accurate QPF in terms of the location of maximum precipitation, only 4.2 km from the observed maximum. The greatest distance of 23.4 km lies within the MEY92S QPF (Fig. 2.11d), whereas DEM15 and MEY92H (Fig. 2.11b,e) are 9.1 and 15.5 km from the observed maximum, respectively. This highlights a connection between the location of maximum QPF and habit in all simulations: nonspherical ice growth lends to a slightly better spatial forecast. Additionally, the DEM15 parameterization is more adept at location placement than MEY92 due to location of the graupel accumulation maxima (not shown). The split QPF maxima produced by all simulations except MEY92H (Fig. 2.11b,c,d) was a result of the continued, slightly less intense precipitation to the southwest of the main maximum during the southward movement of the storm. Lastly, the spatial distribution of precipitation
does not change drastically within the same nucleation parameterization. On average, the nonspherical ice growth method serves to increase the QPF: the average D03 QPF increases from 5.37 to 5.45 mm in MEY92 and from 5.37 to 5.50 mm in DEM15.

The 24-hour period of these forecasts allows for direct quantitative comparison to the AHPS observations in Figure 2.8a, keeping in mind that the precipitation may be underestimated. While the simulations seem to over-forecast the LES precipitation, each captures the location of the precipitation. A more quantitative approach to analyzing the precipitation magnitude and location with respect to AHPS observations is provided in Figure 2.12. Again, each simulation is forecasting more precipitation than what was reported by the AHPS. Both DEM15 simulations provide a solution that better matches the observations of the location of the average maximum precipitation (75.85°W), while the MEY92 simulations place the maximum to the east (75.7°W). While the absolute QPF maximum is greater in DEM15S (Fig. 2.11b) than DEM15H (Fig. 2.11c), nonspherical ice growth generally results in a greater averaged QPF due to the increase in north-south oriented spatial coverage of high QPF near the absolute maximum. The relationship between DEM15 and MEY92 is less clear as the relative amount of precipitation varies longitudinally (Fig. 2.12) with DEM15 greater west at roughly 75.80°W and MEY92 greater to the east. The greatest mean squared error (MSE) of 12.7 is between DEM15S and MEY92S and the least, 3.3, is between DEM15H and DEM15S, indicating that the greatest source of forecast variability stems from nucleation parameterizations with the secondary source emanating from the ice growth mode.

2.5.5 Precipitation: Derived Forecast vs. Derived KTYX Observations

As described in section 2.4.3 radar variables were computed from each model simulation. Observed and forward-operator-generated 0.5° $Z_H$ are compared during the LES lifetime on 16 December (Fig. 2.13). At 0000 UTC, all simulations produce an LE cloud band of relatively high $Z_H$ that is further south and more structurally banded compared to
observations. Between 0200–0600 UTC, there is an increase in \( Z_H \) just east of the lake in observations, and the simulation maxima move from over the lake to east of the lake. The simulations all over- and under-estimate \( Z_H \) to a varying degree in D03 at all analysis times (presented quantitatively below) with DEM15 too aggressive with \( Z_H \) and MEY92 presenting the opposite issue. Finally, the maximum \( Z_H \) values in DEM15 are greater than those in MEY92. Despite the discrepancy between the observed and simulated \( Z_H \) magnitudes, the simulations are able to generally capture the evolution of the LES. This increases confidence in the model to accurately forecast this LES and its associated physical processes.

The general similarities in reflectivity magnitudes between KTYX observations and WRF simulations (Fig. 2.13) give pause to the larger modeled precipitation values (Fig. 2.11 b–e) relative to the KTYX-derived precipitation (Fig. 2.8b) for all simulations. To identify the disconnect, the simulated \( Z_H \) at a scanning angle of 0.5° (i.e., Fig. 2.13) is converted to a reflectivity factor and used as an input to the aforementioned reflectivity-rainfall (Z-R) relationship to derive a secondary precipitation product for each simulation (Fig. 2.14). This derivation method allows for more of a one-to-one comparison between the precipitation derived from simulated \( Z_H \) and observed \( Z_H \) when used in the Z-R relationship. Note that the differences between the results in Figures 2.11 and 2.14 not only stem from their contrasting temporal and spatial resolutions but also the original data source; the model accumulates precipitation at every timestep (6s in D03) whereas precipitation is derived from the forward simulated \( Z_H \) each hour. Additionally, the QPE derived from the KTYX \( Z_H \) is computed for every scan, which occurs approximately every five minutes.

Immediately evident in each of the simulations in Figure 2.14 is the slight difference in DEM15 QPF and a substantial reduction in each MEY92 QPF compared to the associated explicit model forecasts in Figure 2.11b–e, bringing the MEY92 QPFs closer to the KTYX-derived observations (Fig. 2.8b). Within the simulated \( Z_H \)-derived QPF, the maximum forecast ranges from 10.8 mm in MEY92S (Fig. 2.14c) to 34.4 mm in DEM15S (Fig. 2.14a). With the exception of the high QPF over eastern Lake Ontario in the DEM15 simulations
(Fig. 2.14a,b), the spatial distribution of precipitation is relatively similar to the explicit model forecast, but the light accumulations are not as widespread in all simulations throughout D03. Recall that the simulated \( Z_H \)-derived QPF is calculated from forward-simulated \( Z_H \) values at a scanning angle of 0.5°. Since the lake is tens to hundreds of kilometers from KTYX, the sampled \( Z_H \) is in the LE cloud and not close to the surface where the accumulation is occurring, meaning that this Z-R relationship captures the cloud and not the QPF, to some degree. This is not representative of the surface accumulation since there are many sub-cloud processes that can affect the QPF, demonstrated by the surface precipitation values in Figure 2.11. However, this assumption that backscattering hydrometeors further from the radar will accumulate at the surface is embedded within the Z-R relationship, and therefore the KTYX-derived QPE as well.

One major difference between DEM15 and MEY92 is the presence of rain and graupel (Fig. 2.15), especially over Lake Ontario (Fig. 2.16e-h), during the lifetime of the LES. The rain and graupel aloft, most of which is not reaching the surface but sampled by the radar over the lake, causes the large uptick in \( Z_H \) values in DEM15 (Fig. 2.13) and therefore its derived QPF (Fig. 2.14a,b). The model QPF (Fig. 2.11) does not display the same signature because the amount of rain and graupel within the \( 0.5° \) scan exceeds the amount accumulating at the surface. To confirm this, a theoretical scanning angle of 0.01° was used to capture near-surface hydrometeors. With this low angle, the DEM15 D03-sum of derived QPF decreased by 13.3% due to reduced concentrations of rain and graupel near the surface (not shown). It is hypothesized that if the DEM15 simulation only produced snow, then the observed QPE (i.e., Fig. 2.8) and explicit model QPF (i.e., Fig. 2.11) may have resulted in similar values.

In the MEY92 simulations, ice and snow are the dominant hydrometeors, with negligible rain and small contributions from graupel (Fig. 2.15). In the DEM15 simulations, there is still a large amount of ice and snow but also much more rain and graupel. While MEY92 has an average hydrometeor mass accumulating at the surface comparable to DEM15 (Fig. 2.11b-e),
its derived precipitation forecast from the simulated radar is much lower than that of DEM15 (Fig. 2.14): the MEY92 LES is mostly comprised of hydrometeors (ice and snow) that have a lower backscattered power to the radar compared to those in DEM15 (ice, snow, graupel, and rain) and so result in relatively lower $Z_H$ values (Fig. 2.13), significantly decreasing the precipitation rate derived from the Z-R relationship. Liquid water is more reflective than ice, so any liquid water present can exacerbate QPE errors (Markowski and Richardson 2010).

Despite these differences, the QPFs derived from the modeled $Z_H$ are closer to the observations derived from KTYX $Z_H$; the explicit QPFs (Fig. 2.11) are around 97.5% greater than the AHPS QPE (Fig. 2.8), whereas the derived QPF (Fig. 2.14) are 1.2% less to 21.9–56.5% greater than the KTYX-derived QPE, with MEY92 providing a lesser QPF and DEM15, producing the greatest difference in QPF. The ability of the model to capture the $Z_H$ signature relatively well and produce derived forecasts close to KTYX-derived QPE for MEY92 suggests that the explicit model QPF (i.e., Fig. 2.11) may be closer to ground truth for this specific LES than the AHPS observations or KTYX-derived QPE (Fig. 2.8). This result implies that pertinent information is lost in the assumptions of the precipitation derivation, which is a function of the in-cloud hydrometeors (e.g., snow, ice, graupel, rain). It is difficult to express the size distributions of one hydrometeor type in two constant values in the Z-R relationship, never mind a mixture.

2.5.6 Microphysical Responses

As previously discussed, the inhomogeneous mixture of hydrometeors include contributions from rain, snow and ice, and graupel, which vary slightly among ice habit and greatly among nucleation sensitivity simulations (Fig. 2.15). When ice evolves nonspherically, the total amount of snow and ice accumulating at the surface decreases in MEY92 and increases in DEM15. In addition, the amount of snow and ice decreases and both rain and graupel increase when changing the nucleation parameterization from MEY92 to DEM15.

A surprising outcome from this precipitation breakdown is the presence of accumulated
rain in DEM15, which was not observed by OWLeS spotters at any of the locations from 2200–0700 UTC (Fig. 2.7). The timeseries of multiple hydrometeor classes that accumulated hourly provided in Figure 2.15 reveals that in DEM15 the majority of rainfall occurred almost entirely before 0100 UTC 16 December, with smaller amounts during the LES. The magnitude of accumulated rain as simulated in DEM15 was much less than that of snow and ice when the LES was of greatest intensity from 0100–0700 UTC (Fig. 2.15). Again, due to the diversity of hydrometeors in this LES and the lack of plentiful ground-based in-situ observations, quantifying the precipitation that accumulated on the ground proves to be challenging.

To better understand hydrometeor type differences between MEY92 and DEM15, microphysical properties are investigated. Due to similarities between hydrometeor types for a given nucleation parameterization, only the nonspherical results between MEY92 and DEM15 are assessed. Cross sections of the LES at 0500 UTC 16 December are provided in Figure 2.16. Differences exist among each due to the variance of microphysical properties. The main contributor to these differences lie within the INP number concentration. As discussed previously, the MEY92 parameterization nucleates a greater number of ice crystals than that of DEM15 (Fig. 2.1); this holds true in the simulations. The immersion freezing nucleation rate in the DEM15 scheme (Fig. 2.17a, green) is lesser than the deposition-condensation freezing nucleation rate in the MEY92 scheme (Fig. 2.17b, gold). As such, the ice mass and $N_i$ are greater in MEY92 than in DEM15 (Figs. 2.16a,b,k,l; 2.18).

Aggressive ice formation by MEY92 potentially leads to preferential growth of ice at the expense of liquid drops. This decreases the number of cloud drops, reducing autoconversion processes substantially. A lack of small cloud and large rain droplets (Fig. 2.16e,i) effectively reduces the riming processes within the cloud and the rain accumulating at the surface. Thus, many ice crystals will dominate depositional growth at the expense of available moisture in the cloud and sediment as ice and aggregate snow. The snow mass is slightly greater in MEY92 (Figs. 2.16c,d) due to increased aggregation of ice by snow (Fig. 2.17, purple). Conversely,
DEM15 nucleates fewer INP and the initiation of ice depends on the existence of cloud droplets within the cloud. Therefore, less ice nucleates (Fig. 2.17 green) based on the lower initial INP, compared to MEY92 (Fig. 2.17 gold). Droplets can still grow in the presence of this ice, reaching sizes representative of rain, ultimately triggering autoconversion (Fig. 2.17 blue). The strong presence of liquid water in the cloud is conducive to riming processes. A deeper look into the process rates between MEY92 and DEM15 indicates that there is a greater conversion rate to graupel after riming processes (Fig. 2.17 red), and subsequent deposition of graupel (Fig. 2.17 black) due to the greater amount of available liquid (Fig. 2.18 pink and black) and vapor (not shown) in the DEM15 simulations. Ultimately, this results in less snow and ice, more rain, and more graupel (Figs. 2.15 2.16 2.18). The number of nucleated ice crystals in a mixed-phase cloud with supercooled liquid has a strong effect on the hydrometeor types that grow in the cloud and subsequently sediment. Therefore, due to the sometimes extreme differences in nucleated ice number, hydrometeor differences that extend from in the cloud down to the surface exist between MEY92 and DEM15. Finally, the nonspherical simulations experience greater ice-snow aggregation rates (Fig. 2.17 purple dashed) due to the increased ice mass via depositional growth.

Cross sections highlight that MEY92 has a greater $N_i$ (Fig. 2.16k,l), by a few orders of magnitude, and ice mass (Fig. 2.16a,b) compared to DEM15, especially over Lake Ontario. A D03 sum of mixing ratios during the entire LES event shows that the MEY92 simulations have more ice and snow during the LES, but there are more cloud droplets, rain, and graupel in the DEM15 simulations (Figs. 2.15 2.18); these differences are also evident in the cross sections at 0500 UTC (Fig. 2.16a-j). As seen in Figure 2.17, DEM15 has an autoconversion rate about two orders of magnitude greater than that of MEY92 (Figure 2.17 blue) which can be directly related to the abundance of cloud drops in both DEM15 simulations (Fig. 2.18a, black). With more rain (Fig. 2.18a, pink), the collection of droplets by snow to form graupel (riming) is also larger in DEM15, with subsequent increases in graupel deposition (Fig. 2.17 black). The depositional growth rate for nonspherical ice crystals is greater than that for spherical ice.
crystals (not shown), leading to greater ice mass (Fig. 2.18, blue) and exaggerated habits (Fig. 2.16m,n) in the nonspherical simulations. The ice crystals at this time are mostly plates with some pockets of columns in $DEM_{15_H}$ (Fig. 2.16n) but are largely plates in MEY92 with some possible dendrites as suggested by $\phi << 1$ (Fig. 2.16m). With all of these factors combined, it is not surprising that the $DEM_{15_H}$ simulation produced the greatest average precipitation forecast (Fig. 2.11c) with the relatively large presence of rain and graupel in addition to efficient depositional growth.

The LES in IOP4 responds systematically to changes to ice nucleation parameterization and crystal growth within the WRF model. To better quantify these responses, percent errors are provided in Table 2.2 for precipitation, mixing ratios, and sedimentation rates with MEY92 as the control simulation due to its independence from aerosol data used in its nucleation parameterization and its spherical mode of ice growth. As previously discussed, MEY92 nucleates a greater number of ice crystals than DEM15 in both spherical and nonspherical simulations. There is more rain and graupel mass and therefore greater associated sedimentation rates in DEM15 likely due to the aforementioned increased autoconversion. With a decrease in ice crystal number, the sedimentation rates of ice and snow are also comparatively lower in DEM15. There are also intriguing microphysical relationships valid for both MEY92 and DEM15 when ice evolves nonlinearly. Ice, snow, and graupel mass increase whereas rain mass decreases with nonspherical growth. Ice mass increases as a direct result of the increased depositional growth rate, which then increases the sedimentation rates for ice and snow, but only in DEM15. The snow sedimentation rate increases in MEY92 as well, but the ice sedimentation rate decreases suggesting subsequent processes such as aggregation may be overtaking the mass effect. In addition, the crystals have a nonspherical habit ($\phi < 1$ or $\phi > 1$) with different levels of exaggeration due to this growth. The rain sedimentation rate likely decreases due to the growth of ice; vapor is now preferentially growing crystals at the expense of smaller droplets affecting subsequent processes such as autoconversion.

There is an unexpected response in the decrease of $N_i$ with nonspherical growth in
MEY92 by 9.9% (Table 2.2). The nucleation parameterization is not manipulated with this habit change as all particles are nucleated with $\phi = 1$. Referring back to Equations 2.1 and 2.2 it is evident that these differences must stem from changes in ice supersaturation and temperature, respectively. The driving force of existing temperature differences is increased latent heating as a result of the greater depositional ice growth (Table 2.2) in the nonspherical simulations. This growth also serves to decrease the ice supersaturation through increased uptake of vapor by ice crystals. Between 1200 UTC 15 December and 1200 UTC 16 December where there were pristine ice crystals in D03, the $MEY92_H$ simulation is, on average, 0.046°C warmer than the $MEY92_S$ simulation, and the ice supersaturation decreased by 0.023%. The slightly warmer temperatures and lesser ice supersaturations fed into the nucleation parameterizations lead directly to smaller nucleation rates in the nonspherical simulation. Offline tests demonstrate that a supersaturation difference of this magnitude has the ability to suppress $MEY92_N$ nucleation by $1 - 100$ kg$^{-1}$, depending on the ambient ice supersaturation. A similar pattern is observed for DEM15 simulations due to their temperature dependence. Finally, the accumulated precipitation responds similarly in the AHM: average precipitation increases by up to 0.8% when changing parameterizations from MEY92 to DEM15 and increases by 1.6–2.3% with nonspherical ice growth (Table 2.2).

### 2.6 Summary

The Meyers et al. (1992) and DeMott et al. (2015) ice nucleation parameterizations with background IN and CCN sources provided by the Advanced Particle Microphysics (APM) model (Luo and Yu 2011) were implemented into the AHM to investigate their influence on cloud properties and sedimentation processes. Historically, WRF microphysics options do not allow for the nonlinear evolution of nonspherical growth, which has the potential to impact the forecast accuracy of high-impact cold-season events. However, note that the AHM is now available via the new Ice-Spheroids Habit Model with Aspect-Ratio Evolution (ISHMAEL; Jensen et al. 2017), released in version 4.1 of WRF. With increasing computational efficiency,
it is reasonable to make use of the AHM in mesoscale modeling. The choice of ice nucleation parameterization resulted in a greater QPF difference compared to the ice crystal growth process due to the increase in hydrometeor diversity that composed the LES when employing DeMott et al. (2015). The presence or lack of homogeneity among the hydrometeors stemmed from the number of nucleated crystals ($N_i$), which either depleted the number of cloud droplets to grow ice in MEY92 simulations (i.e., glaciation) or allowed for simultaneous growth of ice and cloud droplets in DEM15. The resulting $N_i$ from the individual nucleation parameterizations significantly impacted concentration-dependent microphysical process rates such as aggregation, riming, and deposition, significantly altering the mixture of hydrometeors, sedimentation rates, radar reflectivity calculations, and precipitation quantities. Hence, the analysis in this work should provide not only insight, but caution on the cascading influence of microphysical processes on the system as a whole. In this regard, direct observations of $N_i$ are important to constrain and improve the model. The secondary controlling difference among the simulations of nonspherical ice growth increased the ice mass in the LES and its associated QPF. Validating the QPFs proved difficult due to the sparseness of ground-based in-situ precipitation measurements. Skepticism was placed on radar-derived precipitation in IOP4 due to the mixture of hydrometeors in this LES leading to less reliable constants in the Z-R relationship. This suggests that the explicit model QPFs may be more representative of ground truth than the radar-derived estimates. Further research is necessary to increase confidence in such precipitation datasets during events where in-situ observations are relatively limited, leading to more robust forecast verification and model validation. It is important to note that these conclusions should not be extrapolated and applied to other cold-season LES cases, as they are specific only to this 15–16 December 2013 case. Analysis of multiple LES is necessary to take the next step in understanding how best to model these events to elicit the best forecast in terms of timing, location, and magnitude of precipitation.
### 2.7 Tables

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<th>APM CCN</th>
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Table 2.1: Reference table of all model simulations discussed in this work.
### Table 2.2: Percent error in D03 summed quantities compared to a simulation run with MEY\textsuperscript{92} nucleation and spherical ice growth where \( n_i \) is \( N_i \), \( Q_i \) is ice mass mixing ratio, \( Q_s \) is snow mass mixing ratio, \( Q_g \) is graupel mass mixing ratio, \( Q_r \) is rain mass mixing ratio, \( i\text{Dep} \) is ice deposition rate, \( i\text{Sed} \) is ice sedimentation rate, \( s\text{Sed} \) is snow sedimentation rate, \( g\text{Sed} \) is graupel sedimentation rate, and \( r\text{Sed} \) is rain sedimentation rate.

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<th>( Q_i )</th>
<th>( Q_s )</th>
<th>( Q_g )</th>
<th>( Q_r )</th>
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Percent Differences
2.8 Figures

Figure 2.1: Meyers et al. (1992) predicted ice parameterization for deposition-condensation nucleation compared to the DeMott et al. (2015) parameterization for ice nucleating particle number prediction by means of immersion-condensation freezing, respectively ($\#L^{-1}$). Two concentrations of dust $>0.5 \mu m$ at standard temperature and pressure are considered for DEM15: 0.01 (orange) and 0.1 cm$^{-3}$ (blue).
Figure 2.2: Nested domains for all WRF simulations.
Figure 2.3: NAM analysis of mean sea-level pressure (hPa) in intervals of 2 hPa (first column) and 500-hPa geopotential heights (m) and absolute vorticity (s$^{-1}$, second column) at 1800 UTC 15 December 2013 (first row), 0000 UTC 16 December 2013 (second row), and 0600 UTC 16 December 2013 (third row).
Figure 2.4: NAM analysis of temperature (°C) and wind (m/s) at the surface (first column) and 850-hPa (second column) at 1800 UTC 15 December 2013 (first row), 0000 UTC 16 December 2013 (second row), and 0600 UTC 16 December 2013 (third row).
Figure 2.5: Skew T-logp diagrams (temperature (red), dewpoint temperature (green), and wind barbs (full and half barbs represent 5 and 2.5 m/s, respectively)) at three locations marked on the map (bottom right) by the following mobile observing teams: Millersville University (first row) at 2055 UTC 15 December and 0215 UTC 16 December, SUNY Oswego (second row) at 2315 UTC 15 December and 0215 UTC 16 December, and Hobart and William Smith Colleges (HWS, bottom left) at 2316 UTC 15 December.
Figure 2.6: NEXRAD (KTYX) 0.5° reflectivity at times closest to (a) 0000, (b) 0100, (c) 0200, (d) 0300, (e) 0400, (f) 0500, (g) 0600, (h) 0700, (i) 0800, and (j) 0900 UTC 16 December 2013. Black line on (f) corresponds to location of cross sections at 0500 UTC 16 December in Figure 2.16.
Figure 2.7: A timeline of precipitation types observed by OWLeS spotters between 2200 UTC and 0700 UTC at Oswego, New Haven, Mexico, and Altmar, NY. Snow is denoted by blue and graupel by green. Unless otherwise noted, the presence of colored bars represents the observation of that hydrometeor via the key. A map of spotter locations is provided for spatial reference.
Figure 2.8: Quantitative precipitation estimates for the time period of 1200 UTC 15 December to 1200 UTC 16 December 2013 from (a) AHPS with daily snow-water liquid-equivalent measurements at the Sandy Creek and North Redfield stations, denoted by western and eastern triangles, respectively and (b) the KTYX 0.5° $Z_H$ derivation. The provided color scale is representative of both the AHPS and station observations.
Figure 2.9: Time series between 1200 UTC 15 December and 1200 UTC 16 December of hourly snow-water liquid-equivalent precipitation measurements (solid) at the Sandy Creek (top) and North Redfield (bottom) stations compared to the maximum and minimum simulated hourly accumulations (bounding the shaded area) from the $MEY92_s$, $MEY92_H$, $DEM15_s$, and $DEM15_H$ simulations.
Figure 2.10: Evolution of (top panel) average background cloud condensation nuclei (CCN) at 0.4% supersaturation (purple, cm$^{-3}$) and number concentration of dust > 0.5 µm ($n_a$, green, kg$^{-1}$) as simulated by the APM and (bottom panel) temperature (°C) at 3.8 (approximately cloud top, dotted), 2.1 (approximately mid cloud, solid), and 0.32 km (approximately cloud base, dashed) above ground level in Domain 3 from 1200 UTC 15 December to 1200 UTC 16 December 2013.
Figure 2.11: 24-hour model QPF (mm) valid at 1200 UTC 16 December for Domain 3, which includes the geographic area shown in each of the panels above. The 24-hour temporal evolution of model precipitation accumulation for MEY92S in Domain 3 is provided in (a). From left to right, QPFs represent accumulations between 1200-1800 UTC 15 December, 1800 UTC 15 December-0000 UTC 16 December, 0000-0600 UTC 16 December, and 0600-1200 UTC 16 December. QPFs in panels (b) and (c) are modeled with DeMott et al. (2015) and panels (d) and (e) are modeled with Meyers et al. (1992). The first column (b, d) is run with spherical ice growth and the second column (c, e) is run with nonspherical ice growth. The AHPS observations are provided on each panel (white dashed contour) in the interest area for QPE 4–18 mm for spatial reference; the dashed box over the colorbar in panel (b) represents this range. Refer to Figure 2.8a for specific magnitudes.
Figure 2.12: 24-hour liquid-equivalent precipitation (mm) valid at 1200 UTC 16 December 2013 averaged between 43 and 44°N in D03 for the explicit model QPFs from $MEY92_H$, $MEY92_S$, $DEM15_H$, $DEM15_S$ in addition to AHPS observations.
Figure 2.13: PPIs of 0.5° reflectivity (dBZ) at 0000 UTC (first column), 0200 UTC (second column), 0400 UTC (third column), and 0600 UTC (fourth column) 16 December 2013 observed by KTYX (first row) and simulated by DEM15S (second row), DEM15H (third row), MEY92S (fourth row), and MEY92H (fifth row).
Figure 2.14: 24-hour QPF derived from simulated radar reflectivity for D03, valid at 1200 UTC 16 December. (a) and (b) are modeled with DeMott et al. (2015) and (c) and (d) are modeled with Meyers et al. (1992). The first column (a, c) is run with spherical ice growth and the second column (b, d) is run with nonspherical ice growth. Derived data interpolated onto a 4 km grid.
Figure 2.15: Evolution of rain (purple), ice and snow (turquoise), and graupel (green) accumulated at the surface in Domain 3 from 1800 UTC 15 December to 0800 UTC 16 December 2013 for DEM$_{15S}$ (first row), DEM$_{15H}$ (second row), MEY$_{92S}$ (third row), and MEY$_{92H}$ (fourth row). Total accumulation magnitudes (mm) of each hydrometeor class are provided in the legends of each subplot for the presented time period. Note that these bars are stacked and not accumulating, and so where the bar begins relative to where it end must be considered when determining the magnitude.
Figure 2.16: Cross section (43.5°N) of (a,b) ice mixing ratio (g kg$^{-1}$), (c,d) snow mixing ratio (g kg$^{-1}$), (e,f) rain mixing ratio (g kg$^{-1}$), (g,h) graupel mixing ratio (g kg$^{-1}$), (i,j) cloud mixing ratio (g kg$^{-1}$), (k,l) $N_i$ (#/L), and (m,n) aspect ratio with contoured temperature (°C) for both $MEY92_H$ (first column) and $DEM15_H$ (second column) at 0500 UTC 16 December 2013.
Figure 2.17: Autoconversion (blue), immersion freezing nucleation (green), deposition nucleation (gold), graupel deposition (black), riming (red), and ice-snow aggregation (purple) rates (g kg\(^{-1}\) s\(^{-1}\)) summed through D03 for (a) DEM15 and (b) MEY92 between 1800 UTC 15 December - 0800 UTC 16 December 2013. Spherical rates are denoted with solid lines and nonspherical rates are denoted with dashed lines.
Figure 2.18: Hourly ice (blue), snow (green), rain (pink), cloud (black), and graupel (red) mixing ratios (g kg\(^{-1}\)) summed through D03 for (a) DEM15 and (b) MEY92 between 1800 UTC 15 December - 0800 UTC 16 December 2013. Mixing ratios for spherical ice growth are denoted with solid lines and those for nonspherical growth are denoted with dashed lines.
3. Assessment of a Microphysical Ensemble Used to Investigate the OWLeS IOP4 Lake-Effect Storm

Chapter 2 investigated the 15–16 December 2013 lake-effect storm that resulted in heavy precipitation east of Lake Ontario observed during IOP4 of the OWLeS field campaign. This investigation elucidated the sensitivity of the quantitative precipitation forecasts to the microphysical attributes of the system. This was accomplished through analysis of nucleation and ice particle shape parameterizations. That work is expanded upon here in Chapter 3 to further analyze the microphysical sensitivities of this case, but across a broader spectra of simulations and variables.

3.1 Overview and Objectives

This chapter seeks to address the third research question outlined in Chapter 1.3, which aims to determine if altered microphysics parameters and parameterizations affect a winter storm forecast to the same degree as changing the microphysics scheme. The chosen winter storm is OWLeS IOP4, as was investigated in Chapter 2. Through answering this research question, a better understanding of the sensitivity to various microphysics processes and schemes themselves is gained.

3.2 Background

Parameterized physical processes within NWP schemes have varied forecast impacts, which have been investigated via sensitivity studies and/or ensembles. Many studies have investigated the usefulness and skill of ensembles derived from initial condition uncertainty (IC; Golding et al. 2016), physics uncertainty (PHYS), or a combination of both (IC-PHYS; e.g., Stensrud et al. 2000, Fujita et al. 2007; Golding et al. 2016). PHYS ensembles can include uncertainties in one or many processes in the land surface, the boundary layer, radiative transfer, cloud microphysics, and cumulus parameterizations. Although results
can differ depending on the season (e.g., warm vs. cold; Stensrud et al. 2000; Meng and Zhang 2007), some PHYS ensembles provide a larger envelope of solutions (i.e., forecast spread) encompassing atmospheric variability in thermodynamic variables such as potential temperature and dewpoint temperature, compared to IC ensembles (Fujita et al. 2007). An ensemble forecast that is reliable and encompasses atmospheric variability should randomly sample from the same probability density function (PDF) as the observation (Hamill 2001). Interestingly, IC-PHYS ensembles surpass the capabilities of individual ensembles due to representation of different portions of the atmospheric PDF; IC-PHYS returns the largest forecast spread in thermodynamic variables while also following closest to observations (Fujita et al. 2007). However, situations may arise where model error leads to forecast biases, potentially skewing the range of forecast possibilities. Meng and Zhang (2007) demonstrated that a combination of cumulus schemes both with and without PHYS model error strengthens ensemble performance due to reduced model biases. Saslo and Greybush (2017) used an ensemble-based framework focused on IC and boundary condition (BC) perturbations, different combinations of microphysics and boundary layer schemes, and data assimilation within LES forecasts downwind of Lake Ontario. Changes in ICs and BCs as well as various environmental variables, such as low-level wind, largely influenced precipitation forecasts. The PHYS ensembles suggested that different physics scheme choices can lead to varied precipitation intensities.

Considerable uncertainties surrounding physics representation in NWP currently exist, specifically when considering precipitation on the meso- and synoptic scales and hydrometeor phases (i.e., liquid and ice). Liu et al. (2011) found that planetary boundary layer, land surface, and radiative transfer schemes only weakly influenced cold-season precipitation forecasts, while microphysics schemes provided considerable uncertainty. This partially stems from an underdeveloped observational understanding of microphysics due to the innate difficulty with such investigations, which affects the representative parameterizations. Liu et al. (2011) noted that inconsistencies are even evident in the implementation of the
same exact parameterizations, such as the Bigg (1953) method to represent the freezing of rain, among different schemes. For example, wide-ranging differences among precipitation efficiencies (e.g., creation and growth of graupel) in mesoscale winter storms were discovered when comparing multiple microphysics schemes (Reeves and Dawson 2013; McMillen and Steenburgh 2015; Bartolini 2019). These and many other studies have been conducted solely investigating precipitation sensitivity to physics choices in NWP. Identification of sensitivities to user-defined choices within microphysical models by means of both single and multi-model ensembles is integral to build upon understanding of such processes and their effects on precipitating systems, as well as to recognize which processes produce forecast uncertainty.

Chapter 3 explores the ensemble spread produced when using different microphysics, either by varying schemes (e.g., Morrison et al. 2009; Thompson et al. 2008) or altering a parameter or process physics (e.g., vapor deposition rate) within a microphysics scheme. It also builds upon the exploration of LES quantitative precipitation forecast (QPF) sensitivity to the choice of ice nucleation parameterization and subsequent spherical or nonspherical mode of growth in Chapter 2 (Gaudet et al. 2019). Only slight forecast differences existed among the QPF magnitude, but there were intriguing changes in the hydrometeor distribution and spatial QPF that open the door for further investigation.

3.3 Model and Parameterization Descriptions

Within this chapter, the same version of the AHM is used as in Chapter 2 (Section 2.3.1). Additionally, unless otherwise noted, the experimental setup is that described in Section 2.4.2. Finally, microphysics schemes were added to the analysis to obtain a better grasp on microphysics uncertainty; those schemes are identified and discussed below.

3.3.1 National Taiwan University Microphysics Model

Like the AHM, the three-moment National Taiwan University (NTU) model used herein allows for the evolution of ice crystal habit following the parameterization of Chen and Lamb (1994b). It also allows for snow shape to vary, with the assumption that snow is an
oblate spheroid. The NTU model describes habit with a single variable, the volume-weighted aspect ratio \(^{(Tsai \text{ and Chen} \ 2020)}\). Bulk volume and mass are tracked separately to provide a variable bulk density for ice, snow, and graupel. Additionally, the calculation of fall speeds and collision efficiencies depend on the shape and density of ice and snow \(^{(Tsai \text{ and Chen} \ 2020)}\). The default setup of the NTU model (NTU-DEF) is outlined as follows. The initial cloud condensation nuclei (CCN) distribution is homogeneous in the horizontal and decreases exponentially in the vertical with a scale height of 3.57 km except for the lowest three sigma levels, or below 850 hPa \(^{(Cheng \text{ et al.} \ 2007)}\). CCN composition is assumed to be ammonium sulfate, while its size distribution is trimodal lognormal of clean continental type \(^{(Whitby \ 1978)}\). The primary production of ice crystals follows \(^{(DeMott \ et al. \ 2010)}\) for deposition and condensation-freezing nucleation with a given potential IN number concentration of 400 L\(^{-1}\) \(^{(Georgii \text{ and Kleinjung} \ 1967; \text{Chen and Lamb} \ 1994a)}\). Also, raindrop fall speed calculation matches that of \(^{(Chen \text{ and Liu} \ 2004)}\), and the representation of crystal properties (nonspherical shape and variable apparent density) is based on the bulk parameterization of adaptive growth habit together with the triple-moment bulk closure method \(^{(Chen \text{ and Tsai} \ 2016)}\). The fall speeds for solid-phase hydrometeors (pristine ice, snow aggregates, graupel, and hail) follow the theoretical parameterization of \(^{(Mitchell \text{ and Heymsfield} \ 2005)}\).

This NTU scheme and multiple variants thereof (discussed below) are added to the four AHM variants in Chapter 2 to comprise an ensemble of simulations. Additionally, publicly available WRF microphysical options are included as members of this ensemble, discussed next.

### 3.3.2 Publicly Available WRF Microphysics

WRF version 3.7.1 includes several microphysics schemes. The following schemes are also used in this analysis: Purdue Lin \(^{(Chen \text{ and Sun} \ 2002)}\), WRF Single-moment 6-class \(^{(WSM6; \text{Hong and Lim} \ 2006)}\), Goddard \(^{(GCE; \text{Tao et al.} \ 1989 \text{ and } 2016)}\), WRF Double Moment
6-class (WDM6; Lim and Hong 2010), Morrison 2-moment (M2M; Morrison et al. 2009), Milbrandt-Yau Double Moment (MY2; Milbrandt and Yau 2005a,b), Thompson (THOM; Thompson et al. 2008), and CAM V5.1 2-moment 5-class (CAM; Eaton 2011). The numerous combinations of physical process representation within these schemes makes it difficult to attribute a specific physical process to the largest discrepancy in a forecast, if the response is indeed linear. The aim of this work is not this type of attribution, but instead to understand the underlying variability derived from microphysics during a mesoscale winter precipitating event.

3.4 Data and Methodology

As presented in Chapter 2, Gaudet et al. (2019) investigated the LES sensitivity to ice nucleation and growth mode using the AHM. The assemblage of models outlined in Section 3.3 is used as a framework to initially identify which processes and parameters contribute to forecast variations. This sort of analysis, investigating an event through multiple simulations using various physics schemes, is considered to be a multi-physics ensemble approach. As such, the 24-member ensemble used herein follows other similar multi-physics ensemble investigations in which the total number of members ranges from eight to 48 (Jankov et al. 2017; Imran et al. 2018; Yang et al. 2019).

3.4.1 Microphysical Ensemble Composition

In addition to using publicly available WRF microphysics modules, potential sources of uncertainty including ice nucleation, mode of ice crystal growth, aerosol concentration, potential IN concentration, fall speeds, and spectral indices were isolated and changed within the AHM and NTU to build a microphysical ensemble. These were chosen based on existing nucleation and growth sensitivities identified in Gaudet et al. (2019) and a pre-constructed ensemble from NTU. The 24 ensemble simulations and their associated modeling options diverging from the standard namelist are summarized in Table 3.1. Members 1–4 are referred to as AHM, 5–12 as public, and 13–24 as NTU in the remainder of this work. Public members
were used without any modification.

AHM ensemble member perturbations use a combination of Meyers et al. (1992), MEY92, or DeMott et al. (2015), DEM15, ice nucleation parameterization with spherical (AHM-MEY92S, AHM-DEM15S) or nonspherical (AHM-MEY92H, AHM-DEM15H) ice growth. Nonspherical ice growth is calculated and tracked in the AHM through volume-weighted major and minor crystal axis lengths and ice crystal bulk density. A thorough description of the AHM and nucleation parameterizations is provided in Chapter 2.3. The NTU ensemble is built from individual changes to the various representations of specific microphysical processes and parameterizations within NTU-DEF. Initial condensation nuclei distributions are separately changed to marine and polluted types in NTU-MAERO and NTU-PAERO, respectively (Whitby 1978, cf.). The given potential IN concentration is 4 L$^{-1}$ in NTU-INL and 40000 L$^{-1}$ in NTU-INH. Raindrop fall speed calculation uses the empirical relation $v = 841.997D^{0.8}$ in NTU-RFS (Liu and Orville 1969). Variations of spectral index ($\alpha$, shape parameter of the size spectrum) are diagnosed from size in NTU-DSI or fixed as constants ($\alpha = 3$ for pristine ice, $\alpha = 0$ for other hydrometeor categories) in NTU-FSI, which employs a bulk 2-moment method. Ice fall speed calculations are replaced with empirical size relations such as $v = aD^b$ in NTU-FRFS, where $a$ and $b$ are constants ($a = 700$, $b = 1$), $v$ is the fall speed of cloud ice, and $D$ is the spherical equivalent diameter. Pristine ice and aggregate shape is assumed spherical in NTU-SPH; this assumption is combined with the bulk 2-moment method in NTU-2SPH. Finally, traditional parameterizations of crystal properties (spherical with fixed density) and fall speed calculations (the same as used in NTU-RFS and NTU-FRFS) together with the bulk 2-moment method define NTU-2TRAD.

Each ensemble member was run with WRFv3.7.1 for 12 – 17 December 2013, allowing for sufficient spin-up time before the LES observed during OWLeS IOP4 initiated around 1800 UTC 15 December and dissipated around 0900 UTC 16 December. All LES simulations are run with three, two-way nested domains centered at 43.605°N and 76.721°W, seen in Fig. 3.1a, varying in horizontal grid spacing from 25 km (Domain 1, D01), 5 km (Domain 2,
D02), and 1 km (Domain 3, D03), and 30 nonlinear vertical levels, extending to about 15 km. Other than microphysics, all remaining physics namelist options are outlined in Table 3.2.

3.4.2 Machine Comparison

The University at Albany, SUNY (UA) and NTU simulated WRF on two separate machines to produce the ensemble members listed in Table 3.1. UA simulated members 1–5 while NTU simulated both member 5 and members 13–24. Member 5 was intentionally run on both UA and NTU machines to perform a quantitative comparison and ensure that any differences in the following analysis are solely a result of microphysical perturbations, rather than machine hardware/software differences. A Spearman correlation coefficient of 0.9985 with a p-value of 0 indicated no statistically significant difference between member 5 QPFs in D03. This specific test does not assume a normal data distribution.

Additionally, the Spearman correlation coefficients computed for each mass mixing ratio in D03 is as follows: 0.98 for ice, 0.97 for snow, 0.48 for graupel, 0.97 for cloud, and 0.97 for rain mass mixing ratios. The data in Fig. 3.2 show the differences between the UA and NTU member 5 mixing ratios (M2M\textsubscript{NTU}−M2M\textsubscript{UA}) at each grid point in D03 every 3-h from 1200 UTC 15 to 1200 UTC 16 December 2013. Fig. 3.2 demonstrates that snow and cloud mass differences dominate, while ice and rain differences have lesser contributions. On average, these discrepancies are on the order of 1% of the total forecast for ice and rain, 0.1% for cloud, and 0.01% for snow. The only exception is graupel, with differences ranging between 14.8–17.4%. A possible explanation of this relatively large difference is the low occurrence (zeroth moment) of graupel in M2M (as judged by Fig. 3.9). While forecasts of the same member are not compared again in this work, readers should be aware that there is variation in the graupel forecasts. All hydrometeor difference distributions center around zero, implying that a balance exists between the number of gridpoints in D03 forecasting more or less liquid or frozen mass relative to the NTU-simulated member 5. Since the differences in the remaining hydrometeor mixing ratios vary at each 3-h output and do not increase or
decrease throughout time, it is appropriate to run the simulations on separate machines.

3.4.3 Observational & Validation Datasets

Several observational datasets are available through the National Center for Atmospheric Research (NCAR) Earth Observing Laboratory (EOL) for OWLeS. Table 3.3 includes the instruments, their deployment locations (Fig. 3.1b), and observation types used to analyze IOP4. Hourly measurements of snow-water liquid-equivalent (SWLE) precipitation and 6-h snow depth were recorded at two stations, North Redfield (Steenburgh et al. 2014a) and Sandy Creek (Steenburgh et al. 2014b), east of Lake Ontario. To provide a more spatially extensive accumulation dataset, a radar-derived and rain gauge-corrected 24-h quantitative precipitation estimate (QPE) valid at 1200 UTC 16 December 2013 was obtained from the Advanced Hydrologic Prediction Service (AHPS, National Weather Service 2020). As these data are not directly measured at the surface, the magnitude of the QPE is relatively uncertain. Therefore, the AHPS data are only used for forecast location validation.

Center for Severe Weather Research (CSWR) Doppler on Wheels (DOW, Wurman 2001) polarimetric X-band radar data provide observations to infer microphysical information about the LES. Out of the three DOWs deployed during IOP4, DOW7 provided the best coverage of the LES, especially over Lake Ontario. As such, only the DOW7 data are used herein and are supplemented by operational KTYX (NOAA 2014) 0.5° plan position indicator (PPI) scans. Four micro rain radars (MRRs, Steenburgh et al. 2014c) were deployed east of Lake Ontario allowing for analysis of LES structure and characteristics with increasing inland distance. These raw data were processed with the Maahn and Kollias (2012) algorithm and averaged to a time resolution of 60-s, as in Minder et al. (2015). The Mobile Integrated Profiling System (MIPS) was also operational during OWLeS, providing data used herein from the Particle Size Velocity (PARSIVEL) optical disdrometer (Phillips and Knupp 2014a) and the X-band profiling radar (XPR, Phillips and Knupp 2014b). The disdrometer was designed to measure rain characteristics and therefore is built on assumptions such as sphericity for
particles < 1 mm. While it can and has been used to characterize snow, these assumptions can cause data issues particularly for particles with a diameter < 1 mm (Yuter et al. 2006). MIPS was deployed at SUNY Oswego on the southern shore of Lake Ontario (Fig. 3.1b, star) due to the likelihood it would detect the LES convective core. However, the storm developed north of the operational forecast location, leaving the MIPS instruments too far south to observe the LES convective core for a majority of its lifetime. To mitigate some issues related to the simulated cloud location within comparisons of the ensemble and MIPS observations, ensemble data were averaged over a 20×20-km area surrounding the MIPS location. Finally, the University of Wyoming King Air (UWKA) flew through the LES in both across and along band directions. Aircraft measurements of liquid water content (LWC) were provided by the Gerber Particle Volume Monitor (PVM, University of Wyoming - Flight Center 1977). This suite of observations is used to (1) serve as a reference point for the microphysical ensemble simulations outlined in Section 3.4.1 and (2) investigate the observations collected during IOP4, an overview of which is presented in Sections 2.5.1 and 2.5.2 but is also summarized in the following section.

3.5 Precipitation Observations and Forecasts

A departing cold front associated with a low-pressure system off the New England coast introduced an arctic air mass over the eastern Great Lakes. Strong LE convection initiated over Lake Ontario at 1800 UTC 15 December 2013 and continued until about 0900 UTC 16 December 2013, dumping roughly 18 mm of SWLE near the Tug Hill Plateau (THP, Fig. 3.1b), according to the AHPS estimates. A thorough description of the associated synoptic and mesoscale features is available in Chapter 2.5. An in-depth analysis of the OWLeS IOP4 observations and the ability of the ensemble to accurately simulate the LES properties leading to the precipitation forecast follows.
3.5.1 Assessment of Ensemble Forecast Spread and Error

Spearman correlation coefficients were calculated between each ensemble member and the remaining 23 members for the 24-h QPF throughout D03 valid at 1200 UTC 16 December 2013 (Fig. 3.3). The smaller the correlation, the greater potential difference in the spatial QPF pattern (see Fig. 3.6) with an increased likelihood that a member substantially increases the ensemble spread. In Fig. 3.3, all NTU members except for NTU-FRFS and NTU-2TRAD are clustered toward higher correlation coefficients when compared to other NTU members, indicating that they are relatively similar. However, they show some of the lowest values when compared to the public members. AHM members using DEM15 are clustered toward higher correlation values, but those using MEY92 provide greater QPF differences as indicated by their slightly reduced correlations. Additionally, decreases in correlation coefficient associated with the ice nucleation parameterization changes in the AHM point toward IN concentration potentially controlling some forecast variation. Since correlation coefficient is a proxy for spatial QPF differences among ensemble members, any disparity in correlation coefficient between the AHM-MEY92 and AHM-DEM15 members and the remaining ensemble members stems from the choice of nucleation parameterization. This choice ultimately alters the forecast enough to cause differences between the median correlation coefficient in both AHM-MEY92 members (0.86) and both AHM-DEM15 members (0.92). Finally, the publicly available microphysics schemes in WRF, such as LIN and WDM6, have some of the lowest correlation coefficients, indicating that a change in microphysics scheme may elicit greater ensemble spread than a physical parameter change within the AHM or NTU. This is not a surprising result as physical process representation varies extensively from one scheme to another, making it difficult to pinpoint the root cause for the spread. Smaller correlation coefficients increase forecast spread, which helps identify potential forecast uncertainties and widen the envelope of event forecasts, and also indicate sensitivity to microphysics; identifying that sensitivity is the purpose of this study. This ensemble provides enough variation to warrant an investigation into the reasons driving those forecast differences.
To assess forecast accuracy during 1200 UTC 15 – 1200 UTC 16 December 2013, the hourly SWLE observations at Sandy Creek and North Redfield, NY were resampled to 3-h accumulations and compared to each member’s 3-h liquid-equivalent QPF both qualitatively and quantitatively. A time series of observations and forecasts (not shown) indicates that most ensemble members overestimate the precipitation at North Redfield before the peak precipitation at 0600 UTC by as much as 5.0 mm while the opposite problem exists at Sandy Creek, underestimating by as much as 6.3 mm. At both locations, public members exhibit a substantial forecast range (i.e., 1.1–9.6 mm at Sandy Creek, 1.7–14.5 mm at North Redfield), AHM members tend toward a relatively moderate forecast range (i.e., 5.0–10.7 mm at Sandy Creek, 8.6–16.3 mm at North Redfield), and the NTU members provide the greatest SWLE forecast (i.e., 6.5–14.8 mm at Sandy Creek, 13.1–17.6 mm at North Redfield), which matches best with the observations at 0600 UTC 16 December (i.e., 15.0 mm at Sandy Creek, 14.7 mm at North Redfield). To assess how these member forecasts compare to observations over the duration of the event, a root mean square error (RMSE, Fig. 3.4) is calculated from eight observed and simulated values. The closer to zero the RMSE, the less the observations and forecasts deviate, while RMSE > 0 means that the QPF was either under or over the observed amount. The RMSE values in Fig. 3.4 indicate a range of imperfection within the ensemble at both locations, ranging from 1.1–5.4 mm at Sandy Creek and 0.4–4.6 mm at North Redfield. Note that the mean absolute error (MAE) ranges from 0.71–2.88 mm at Sandy Creek and 0.30–1.95 mm at North Redfield. At North Redfield, the minimum RMSE and MAE are associated with MY2 (9) and the maximum RMSE and MAE are from WDM6 (11). Although the same is not true at Sandy Creek, the members with maximum (WDM6, 11) and minimum RMSE (NTU-2SPH, 13) only marginally differ from the members with the maximum and minimum MAE. A majority of NTU members have RMSE values lesser than the median and lower quartile at both Sandy Creek and North Redfield. The large spread among public members indicates a high uncertainty in bulk microphysical treatments. Interestingly, NTU-FRFS (16) has RMSE values on par with most AHM and public members.
at both Sandy Creek and North Redfield. As introduced in section 3.4.1, NTU-FRFS replaces ice fall speed calculations with empirical size relations, which signifies that simplifying this calculation adversely impacts QPF error due to a mass flux change toward the surface. At Sandy Creek, most NTU members best forecast 3-h QPF (RMSE closer to zero) while a majority of public members are furthest from observations, which is a factor of spatial forecast differences\(^1\) in the 3-h QPF among the ensemble members. The distribution of RMSE at North Redfield is slightly different; while NTU members provide relatively low RMSE compared to almost all public members and both AHM-MEY92 members (1 & 2), the lowest RMSE is from a public member, MY2 (9). This analysis indicates which clusters of the ensemble lead to the greatest forecast error while also exemplifying the spatial variability of ensemble verification between Sandy Creek and North Redfield.

### 3.5.2 Spatial and Temporal Characteristics

Following the ensemble member intercomparison and member comparison to system-wide observations, further assessment of ensemble predictability and microphysical investigations are performed through analysis of IOP4 using the suite of observations outlined in Section 3.4.3. As the system passed over the eastern shore of Lake Ontario, the MIPS disdrometer (see Fig. 3.1b for location) indicated upticks in precipitation intensity (Fig. 3.5a) ranging from 1–5 mm hr\(^{-1}\) around 2215 and 2315 UTC 15 December, as well as 0100, 0200, 0330, and slightly before 0530 UTC 16 December, which coincide with increases in reflectivity, ranging from 10–25 dBZ (Fig. 3.5b, stars). Precipitation intensifies slightly before and immediately after 0600 UTC 16 December, peaking at 23.5 mm hr\(^{-1}\). This is considerably larger than the preceding intensity observations because the number of particles observed by the disdrometer more than doubled and increased in diameter (not shown). The precipitation intensity peak also coincides with a reflectivity maximum of 38.6 dBZ. Based on analysis of KTYX 0.5° PPI scans (Fig. 3.5c, d), the cloud band propagated southward before 0600 UTC and brought

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\(^1\)Defined as the longitudinal and/or latitudinal differences relative to where the forecast field is located for each respective ensemble member.
with it large reflectivity values and the sudden increase in heavy precipitation. Lighter precipitation was observed earlier because the disdrometer was sensing precipitation on the periphery of the quasi-zonal convective core (Fig. 3.5c,d).

24-h QPE provided by the AHPS and 24-h QPFs for all ensemble members valid at 1200 UTC 16 December 2013 are presented in Fig. 3.6. Each member forecast captures LES precipitation downwind (i.e., east) of Lake Ontario, with some variance in latitudinal placement. Although the QPFs are about double the AHPS observations (Fig. 3.6 upper left panel), of which the validity is questionable (see Chapter 2.4.3), some agreement exists among all members as to the expected magnitude of precipitation during IOP4. All AHM and NTU members produce a thin band of precipitation southwest of the main area of interest, which was not present in the observations. The mean QPF (D03 average of all horizontal grid points) ranges from 3.5 mm (WDM6) to 6.1 mm (NTU-FRFS); NTU and AHM members generally produce greater mean precipitation than the public members (Fig. 3.6). While the ensemble accurately forecasts the location of maximum precipitation, the abundance of precipitation elsewhere reduces confidence that this ensemble is able to completely represent IOP4. The following analyses will provide insight into the sources of ensemble forecast variation and how those contribute to the inability to accurately forecast QPF.

During 1800 UTC 15 – 1200 UTC 16 December, measurements of snow totaled 300 mm (24 mm SWLE) at Sandy Creek and 420 mm (22.5 mm SWLE) at North Redfield. The snow-to-liquid ratios (mm mm$^{-1}$) were 12.5 and 18.67 (within the climatological range in upstate NY, Baxter et al. 2005), respectively, confirming that the accumulated snow had a greater water content at Sandy Creek. So, the snow accumulations increased and SWLE decreased slightly with inland distance. From analysis of almost 30 additional OWLeS-observed LES events, Minder et al. (2015) found that it was common for these storms to become less convective and show characteristics of a convective-to-stratiform transition with increasing inland extent. Unsurprisingly, the MRR data also suggest that such a transition may have occurred in IOP4. Contoured frequency with altitude diagrams (CFADs, Yuter and
Houze (1995) of effective reflectivity \( (Z_e) \) normalized by the number of observations taken by vertically pointing MRRs deployed at Sandy Island Beach, Sandy Creek, North Redfield, and the upper plateau during IOP4 are provided in Fig. 3.7. The CFAD construction follows the detailed methodology of Minder et al. (2015). Note that data with low observation counts (defined as below the 5th percentile of the total counts at each site) are not shown. Along with a general decrease in maximum reflectivity at all altitudes the LES echo top lowers (Figs. 3.7a–d), indicative of weakening convection as upward vertical motion becomes less intense (Figs. 3.7e–h). The negative tilt of the modal \( Z_e \) with altitude in all CFADs suggests either melting processes or a size increase of particles detected by the MRRs within the LES (Minder et al. 2015). As the subfreezing temperatures present throughout the atmospheric column during IOP4 would not allow for considerable melting, the tilt of the modal \( Z_e \) is likely the product of efficient hydrometeor growth processes.

At Sandy Island Beach and Sandy Creek, the modal \( Z_e \) in the lowest 1 km of the cloud is \( > 20 \text{ dBZ}_e \) and decreases to about 15 \( \text{ dBZ}_e \) at North Redfield and upper plateau. The larger modal \( Z_e \) at lake-proximate locations likely corresponds with an increase in particle density leading to a larger dielectric constant, hydrometeor number concentration, hydrometeor size, or a combination of these (Figs. 3.7a–d). The shifted frequency distributions to smaller \( Z_e \) suggests a lower concentration of hydrometeors with less LWC at the eastern-most locations. Additionally, increases in particle density may be supported by increased LWC; an east-west UWKA flight leg at an average altitude of 1.68 km confirms that while there is greater variability in LWC measurements near Lake Ontario, LWC generally decreases with increasing distance from the lake (Fig. 3.8). This corroborates the manual snow observations: a greater amount of SWLE was observed at Sandy Creek than at North Redfield, meaning that the densities of frozen hydrometeors were greater and/or more cloud liquid water was present at Sandy Creek, as evidenced by the large frequency of high \( Z_e \) (Fig. 3.7b). Meanwhile, precipitation processes were efficient at North Redfield due to a greater observed snow accumulation with a relatively shallower vertical cloud extent and decreased modal \( Z_e \).
Furthermore, Figs. 3.7e–h highlight the 5th and 95th percentile Doppler radial velocities\footnote{Here, radial velocity as detected by the MRR is defined as the Doppler velocity contributed to by both hydrometeors and air motions, meaning that situations could arise where the hydrometeors and air motions are moving in opposing directions.} (i.e., hydrometeor vertical motion) observed by each MRR throughout the vertical extent of the LES. The intensity of the hydrometeor vertical motion decreases with increasing inland extent. The prevalent upward hydrometeor motion coupled with the direct moisture source at locations closest to Lake Ontario may sustain a greater supersaturation and particle residence time in the cloud system, resulting in greater particle growth and density changes via deposition, aggregation, and/or riming. Since riming would increase particle density and thereby downward hydrometeor motion, it is postulated that riming led to the notable difference in this motion between the near-lake Sandy Island Beach MRR observations (Fig. 3.7e) and those at the upper plateau (Fig. 3.7h). Analysis of NTU members (not shown) support this hypothesis, as graupel accretion rates among the members increase from the upper plateau to Sandy Creek by 58.2%, but then decrease slightly by 5.3% at Sandy Island Beach; despite that reduction, the accretion rate at Sandy Island Beach ($3.37 \times 10^{-9}$ kg kg$^{-1}$ s$^{-1}$) surpasses that at upper plateau ($2.25 \times 10^{-9}$ kg kg$^{-1}$ s$^{-1}$). While graupel density differences of $<1\%$ do not sufficiently support differences in precipitation accumulation at the surface, the accretion increases do support these differences. Furthermore, NTU member hail (large graupel that exceeds the Shumann-Ludlum limit during growth, Tsai and Chen\cite{tsai2020} mass-weighted fall speeds are almost 300% greater at lake-proximate locations. Due to these effects, spatial characteristics of QPF also depend on proximity to Lake Ontario, as this can control the vertical extent of the LES and its convective intensity, which in turn influences hydrometeor growth and sedimentation.
3.6 Analysis of Precipitation Type

Ensemble members can be grouped into three subsets based on precipitation types accumulating at the surface (Fig. 3.9) during the 24-h period ending 1200 UTC 16 December: snow and ice (SI); snow, ice, and graupel (SIG); and snow, ice, graupel, and rain (SIGR). An ensemble member is placed into a group if at least 10% of the D03-averaged accumulation is attributed to any of these precipitation types. Seven members predict SI (AHM-MEY92H, AHM-MEY92S, M2M, CAM, THOM, WDM6, and NTU-FRFS), 15 forecast SIG (GCE, LIN, MY2, WSM6, all NTU members except for NTU-FRFS), and two predict SIGR (AHM-DEM15H, AHM-DEM15S). Autoconversion of cloud droplets to rain and melting of ice crystals at any near-surface and in-cloud grid point where the temperature is above freezing are sources of rain in SIGR simulations.

3.6.1 Ensemble Representation of Graupel Processes

As with other ice-phase hydrometeors, there are several differences in how each of these microphysics models represent the same graupel production or growth processes, if they are represented at all. CAM is the only member that does not explicitly model graupel. Parameterizations used to represent certain physical processes, such as the initiation and growth of graupel, and the manner in which they were implemented into the schemes can largely influence graupel production (Liu et al. 2011; Reeves and Dawson 2013; McMillen and Steenburgh 2015). First, there are differences in the graupel particle size distribution (PSD) intercept parameter: LIN, WSM6, WDM6, and GCE assign a constant value ($4.0 \times 10^4$ m$^{-4}$ in LIN and $4.0 \times 10^6$ m$^{-4}$ in WSM6, WDM6, and GCE), whereas M2M, MY2, THOM, and all AHM and NTU members calculate a value that is based on the graupel mixing ratio and number concentration, in addition to cross-sectional area in the NTU members. Additionally, there are many potential graupel sources, including riming, the freezing of rain, and various combinations of collection between frozen hydrometeors as well as between frozen and liquid hydrometeors. There are criticisms of how these processes are coded within the
microphysics models, the efficiency of the collection processes, and if some processes (e.g.,
collection of snow by graupel) should even be included within the graupel production terms
(Liu et al. 2011). MY2 imposes a threshold for conversion of snow to graupel that is different
than the other ensemble members; the conversion only occurs when the snow riming rate is
at least three times greater than the snow deposition rate (Milbrandt and Morrison 2013).
THOM, forecasting 0.55% of its QPF as graupel, allows the freezing of rain to contribute to
either cloud ice or graupel, depending on the size of the rain (Thompson et al. 2008). AHM
members add all frozen rain mass to cloud ice, whereas LIN, WSM6, WDM6, M2M, MY2,
GCE, and NTU members add it to graupel. The only member that includes collection of
snow by graupel is LIN. All members include collection of rain by snow, but THOM does not
instantly convert rain to graupel.

The combination of a low graupel PSD intercept parameter, all frozen rain converted
to graupel, the inclusion of graupel and snow collisions, and highly efficient rain and snow
 collisions resulted in the considerable graupel production accounting for 87.6% of QPF in LIN.
NTU-FRFS has slower ice fall speeds, which consequently leads to considerably less graupel
production through lessened riming processes. Therefore, the riming efficiency from either
the collision efficiency or the fall speed may be too high, as they lead to very active graupel
production in all other NTU members. It is less clear why MY2, forecasting 68.9% of its
QPF as graupel, followed closely to LIN, seeing as there was no consideration of graupel and
snow collisions and the member had a PSD intercept parameter that matched the value of
$4.0 \times 10^6 \text{ m}^{-4}$ as in WSM6, WDM6, and GCE. However, increases in graupel production are
also evident when simulating OWLeS IOP2b using the MY2 microphysics scheme (Bartolini
2019). Since there are differences in these microphysical models that extend beyond the
representation of graupel, there were likely processes occurring in other hydrometeors that
led to cascading effects on graupel. For example, graupel is present in the AHM-DEM15
simulations because the choice of ice nucleation parameterization from DeMott et al. (2015)
initiated less pristine cloud ice, allowing for the simultaneous growth of ice and cloud droplets,
eventually leading to riming processes (Chapter 2, Gaudet et al. 2019). Implementation differences that can lead to considerable changes in mass transfer and ultimately govern precipitation type are important to keep in mind when comparing model output that make use of different microphysics schemes, such as those in this work.

3.6.2 Precipitation Type Verification and Effects

Precipitation type was classified at the surface by means of Meteorological Terminal Aviation Routine Weather Report (METAR) codes recorded by the MIPS disdrometer. During IOP4, the following METAR codes were recorded: light, moderate, and heavy snow (-SN, SN, +SN, respectively), light and heavy soft hail (-GS, +GS, respectively), moderate hail (GR), light and heavy drizzle with rain (-RADZ, +RADZ, respectively), and light, moderate, and heavy drizzle (-DZ, DZ, and +DZ, respectively). Subcategories of hydrometeors and their respective intensities were merged into larger groups; snow combines -SN, SN, and +SN, graupel includes -GS, +GS, GR, and rain accounts for -RADZ, +RADZ, -DZ, DZ, and +DZ. Between 2127 UTC 15 December and 0657 UTC 16 December, the report count of each code was summed and added to their respective major hydrometeor group. The counts were weighted by the precipitation intensity of each major category, effectively calculating the amount of precipitation each hour while removing the assumption that all hydrometeor categories are contributing to the accumulation equally. The percent contribution of each hydrometeor category was computed for the disdrometer observations during the aforementioned period and for each of the ensemble members as an average within a 20 km $\times$ 20 km bounding box surrounding the MIPS site during the time period of 2100 UTC 15 December – 0600 UTC 16 December (Fig. 3.10). According to the recorded METAR codes, 92% of precipitation observed at the MIPS site (Fig. 3.1b) was snow and ice, with a 5% contribution from graupel and the remaining 3% from rain and drizzle. With the exception of NTU-FRFS, NTU members stray the furthest from observations, with forecasts of snow and ice ranging from 5%–18%, an exorbitant graupel forecast of 82%–95%, and rain and drizzle
ranging from 0%–1%. As touched upon previously, the reduced graupel contribution in NTU-FRFS points toward a riming efficiency that is unrepresentative of this event in the remaining NTU members. GCE, LIN, MY2, WDM6, WSM6, and AHM-DEM15 members also produce an aggressive amount of graupel at the MIPS site (Fig. 3.10), ranging from 29% (WDM6) to 100% (LIN) of the total accumulation, for reasons discussed earlier in this section. Ensemble members providing a solution closer to observations included AHM-MEY92 members, M2M, CAM, and THOM with snow contributions around 99%. While these amounts leave little room for graupel, drizzle, and rain, they are far from the extremely unlikely forecasts calling for an equal or dominant contribution from graupel. However, NTU-FRFS best captured the relative hydrometeor contributions, with a 90% forecast of snow, 10% forecast of graupel, and no prediction of rain and drizzle. However, this member was also the one of the only NTU members to have an RMSE above the median at both Sandy Creek and North Redfield (Fig. 3.4). Though this analysis is a point comparison due to the deployment of a single disdrometer, it is a step toward understanding surface precipitation types. As the majority of these data were observed while the LES convective core was to the north of the MIPS site, the hydrometeor composition may not be fully representative of that portion of the LES producing the greatest amount of precipitation. This can lead to discrepancies among the following analyses, in which MIPS observations do not prompt the same conclusions (e.g., LES only composed of snow and ice) as domain-wide comparisons (e.g., 99.6% graupel for LIN at the MIPS site, but <87.6 graupel for LIN on average for D03).

Additional understanding of the dominant hydrometeor species accumulating at the surface stems from the joint particle size-velocity distribution (Fig. 3.11a). However, uncertainties within these disdrometer data exist due to observational noise, sampling effects, and assumptions about the type of particles being sensed. While research shows these uncertainties can be quantified for both snow (Battaglia et al. 2010) and rain (Jaffrain and Berne 2011) events, a standard does not exist for uncertainty quantification during mixed-phase events such as IOP4. Due to this unknown effect, uncertainties exist within
these disdrometer data but the actual quantity of which is not accounted for in this work. The greatest number of particles converge around diameters roughly at 1.5 mm and fall speeds of 0.5 m s\(^{-1}\). The extension of a high incidence of particles with diameters > 4 mm may be skewed by the issues of oversizing snow particles with an equivalent spherical diameter < 2 mm (Battaglia et al. 2010). Observations of graupel tend to be in the tail of the fall velocity distribution (> 3 m s\(^{-1}\)) but do not have much bearing on the total joint distribution since they were infrequently observed. To further understand the particles falling during the LES core passage, which may be representative of some LES convective cores influencing areas east of Lake Ontario earlier in its lifetime, a difference joint distribution normalized by the average particle count during each respective time period was calculated between 0600–0655 UTC (high intensity precipitation) and 0300–0400 UTC (low-moderate intensity precipitation) 16 December (Fig. 3.11b). The latter period shifts the joint distribution to faster velocities, which is hypothesized to correspond well with potentially rimed particles falling at faster speeds due to the precipitation intensification during this time (Fig. 3.5a).

Both observed and simulated precipitation type mixtures at the ground stem from in-cloud liquid-ice partitioning differences. The presence, or lack thereof, of certain species (e.g., liquid water) can alter remotely retrieved cloud location and expanse due to properties such as particle density and composition. As an example of remotely sensed differences, point probabilities of simulated \(Z_H > 15\) dBZ interpolated to a 0.5\(^{\circ}\) PPI scan in D03 at 0600 UTC 16 December are provided for both the entire ensemble and each hydrometeor group and are compared to KTYX-observed 15 dBZ contour in the 0.5\(^{\circ}\) PPI scan in Fig. 3.12. AHM and NTU members derive simulated \(Z_H\) by means of the polarimetric radar operator developed by Ryzhkov et al. (2011) while public members use \(Z_H\) calculations provided by the Python package WRF-Python (Ladwig 2017). To calculate these probabilities at each grid point in D03, the number of ensemble members with simulated \(Z_H > 15\) dBZ (\(N_{Z_H > 15\ dBZ}\)) was divided by the total number of members in the ensemble, \(N_{Z_H > 15\ dBZ}/24\), (Fig. 3.12a) or divided by the total in each respective hydrometeor group, \(N_{Z_H > 15\ dBZ}/N_{h_{\text{group}}}\) (Fig. 3.12b–d). The resulting
value at each grid point is considered to be the probability of that $Z_H$ threshold being reached or surpassed and is contoured in Fig. 3.12.

With the exception of SIGR due to the low number of members in its group, each hydrometeor group is well within the observed 15 dBZ contour (Fig. 3.12 black contour). However, differences exist among the relative LES positioning. The western LES position is slightly to the south of observations in SI and marginally to the north in SIGR. Another interesting feature is the spatial expanse of the 50% probabilities (Fig. 3.12 cyan contour) among the groups. The entire ensemble forecast fills 71.3% of 15 dBZ KTYX reflectivity contour (Fig. 3.12a, black), which represents 60.8% of the total area forecast to reach the 15 dBZ threshold (cyan). SI fills 84.2% of the observed contour (Fig. 3.12b), but that only comprises 51.3% of its total forecast area. Similarly, SIGR filled 83.4% of the observed contour (Fig. 3.12d), but that only represented 46.1% of its vast forecast area. 59.3% of the observed contour was filled by SIG (Fig. 3.12c), which accounted for 62.0% of its total forecast area. Even though the areal extent of the SIG forecast (Fig. 3.12c) is less than the full ensemble (Fig. 3.12a), a greater portion of its total forecast area falls within the observed contour. In both quantitative and qualitative lenses, ensemble members in SIG best match the observations at this time due to the less expansive radar echoes to the north and south of the main LES. This confirms that precipitation type (e.g., SI, SIG, SIGR; Fig. 3.9) within the cloud system does have an influence on the spatial extent and location of the LES, specifically when graupel and/or rain are prevalent.

While low-level KTYX PPI analysis provides an overview of the system, the MIPS XPR can resolve details about the vertical profile of reflectivity at the MIPS location, near-surface (which is missed by KTYX) through cloud-top. The vertical geometry also provides an opportunity to parse the dynamic vertical structure. The interquartile range (IQR) of hourly $Z_e$ data $\geq -5$ dBZ$_e$ observed by the XPR is provided in Fig. 3.13. Note that since the LES is mixed-phase, X-band attenuation of any liquid present in the cloud impact these $Z_e$ data. However, any attenuation is likely minimal given that the sensible
precipitation is primarily frozen. During the majority of the LES lifetime, there is an increase in $Z_e$ with increasing proximity at varying levels near the surface (0.5~1 km), suggesting hydrometeor growth, followed by a decrease in $Z_e$ toward the surface (Fig. 3.13a–h) suggesting sublimation/evaporation. Between 0500–0650 UTC (Fig. 3.13, j) there is a pronounced $Z_e$ signature maximizing at approximately 2 km, followed by a sharp decrease near 1.5 km between 0500–0600 UTC (Fig. 3.13). Discussion of how these $Z_e$ data compare to process rates leading to particle growth and decay within the ensemble follows below. The increased altitude at which the maximum $Z_e$ is found during 0500–0650 UTC emanates from the collocation of the MIPS deployment site (Fig. 3.5d) and the relatively intense LES convective core at the end of its lifespan. However, the $Z_e$ decrease near 1.5 km in Fig. 3.13 is an artifact of the hourly time intervals; it exists solely because of the arrival of the LES core slightly before 0600 UTC. The level of maximum $Z_e$ during 0500–0650 UTC corresponds with that of the largest radial velocity observed during IOP4, 5 m s$^{-1}$ (not shown). Therefore, hydrometeor lofting is suggested by the collocation of strong radial velocities, considerably increased $Z_e$ especially at relatively higher altitudes, and a decrease of $Z_e$ below due to hydrometeor displacement.

The 3-h XPR median and IQR show smoothed signatures of those seen in the 1-h XPR data (Fig. 3.13), including $Z_e$ increasing toward the surface from 3 km to about 0.7 km during the two 3-h time periods spanning 2100 UTC 15 December to 0300 UTC 16 December (Fig. 3.14). A similar signature exists during 0300–0600 UTC from 2 km to 0.7 km, but with a layer of increasing $Z_e$ from 3.7 km toward 2.5 km, that then decreases toward 2 km. The $Z_e$ signatures are associated with the average in-cloud microphysical processes output by AHM and NTU ensemble members including accretion, deposition, condensation, evaporation, and sublimation that lead to changes in particle size and potentially number concentration, ultimately affecting $Z_e$. Vertical profiles of the aforementioned process rates at the MIPS site for each 3-h time period are overlaid on each panel, along with the profile of their overall sum. In this way, the vertical change in process structure is compared to the change in the
median of XPR $Z_e$ with height. While not a one-to-one comparison, it allows for further understanding of the potential effect of such hydrometeor growth and decay processes that likely affected the XPR data.

During the first two 3-h time periods (Fig. 3.14a,b), accretion (blue line) and deposition and condensation (orange line) rates maximize around 1.2 km followed by a decrease toward the surface, as evaporation and sublimation (green line) overtake the process rate sum below 0.7 km. The vertical level at which the process rate sum becomes negative is approximately where the $Z_e$ starts to decrease toward the surface. This confirms the hypothesis that sublimation and deposition processes serve to reduce the $Z_e$ toward the surface. While the final time period has the additional layer of $Z_e$ increase around 2.5 km followed by a decrease toward 2 km due to hydrometeor lofting, the overall signature below also corresponds with accretion, deposition, and condensation rates increasing $Ze$ toward the surface while below 0.7 km $Z_e$ decreases as growth rates slow and evaporation and sublimation rates increase toward the surface.

3.6.3 Contrasting the Effects of Ice Nucleation Parameterizations and Ice Nucleating Particle Concentrations

Questions may be brought forth as to why there are greater hydrometeor differences between the AHM-MEY92 and AHM-DEM15 members than between the NTU-INH and NTU-INL members due to the differences in ice nucleation rates (AHM-MEY92, AHM-DEM15) and INP concentration (NTU-INH, NTU-INL). Nucleation rates and INP concentration both impact the number concentration of the pristine ice number concentration, but a considerable impact on the hydrometeor composition forecast is only evident when employing different nucleation parameterizations. To understand why there is an apparent insensitivity to INP concentrations within NTU, it is helpful to first assess the differences in the pristine ice mass nucleation rate between these simulation pairs (Fig. 3.15). The ice nucleation rate differences between the NTU members are three to four orders of magnitude less than those between the
AHM members. Note that larger differences between members indicate greater disparities between the amount of nucleated pristine ice mass which has lasting impacts on the ice-liquid mass partitioning due to the vapor competition effect (Gaudet et al. 2019). The nucleation rate differences are comparatively low between the two NTU members (ranging between $10^{-6}$–$10^{-4}$ g kg$^{-1}$ s$^{-1}$), which explains why changes to the hydrometeor type forecast seen between the AHM members are not present between NTU-INH and NTU-INL. Furthermore, this signifies that changes in ice nucleation parameterizations lead to greater forecast uncertainty within IOP4 than the INP concentrations tested herein.

Now it is understood why similar differences in hydrometeor types are not present between NTU-INH and NTU-INL, but it would be advantageous to investigate why changes to INP concentration do not lead to forecast differences. Within the NTU implementation of the DeMott et al. (2010) nucleation parameterization, the nucleation rate is limited by the INP concentration and the maximum ice number. As such, the output from the nucleation parameterization is calculated and then compared to the INP concentration. Then, the nucleation rate is calculated from the lower value of the two divided by the model timestep. If the nucleation rate is less than the INP concentration, the number concentration of nucleated ice crystals is not impacted. This is also paired with a comparison to the maximum ice number. Fig. 3.16 provides information about the INP concentration and initiation rate of pristine ice throughout IOP4 for not only NTU-INH (INP = 40000 L$^{-1}$) and NTU-INL (INP = 400 L$^{-1}$), but also NTU-DEF (INP = 4 L$^{-1}$). Note that the INP concentrations are several orders of magnitude greater than the nucleation rates in all three members, indicating that they would not limit the rates. The lack of influence on the nucleation rates is also indicated by the relative similarity of these rates among the three members, with differences only on the order of $10^{-1}$ g kg$^{-1}$ s$^{-1}$ which likely stem from the limiting factor of the maximum ice number.
3.7 Microphysical Features

Now that an understanding of surface precipitation type has been established, it will be helpful to explore liquid-ice partitioning within the cloud through remote and in-situ observations. Analysis of both observed DOW7 and PVM data as well as concurrent comparison to the ensemble will allow for key inferences to be made.

3.7.1 DOW7 Polarimetric Data Analysis & Comparison

Polarimetric data collected by DOW7 (situated on the southeastern shore of Lake Ontario, Fig. 3.1b) during a majority of the LES lifetime allowed for cross-band analysis via 0° azimuthal cross sections. To efficiently evaluate more than one analysis time, CFADs, following the methodology discussed in section 3.5.2, were computed from these cross sections at 30-min intervals during 0000–0600 UTC 16 December. Forward simulation of polarimetric variables (Ryzhkov et al. 2011) was only completed for the AHM-MEY92H and AHM-DEM15H simulations due to the availability of hydrometeor shape information required for computation of polarimetric variables, such as differential phase shift ($K_{DP}$), differential reflectivity ($Z_{DR}$), and correlation coefficient ($\rho_{hv}$).

Much like the XPR (Fig. 3.13), the DOW7 CFAD in Fig. 3.17a indicates an increase of horizontal reflectivity ($Z_H$) with decreasing altitude to the surface, which is a classic signature of hydrometeor growth. At each altitude below 3 km, the upper range of reflectivity values in AHM-MEY92H (Fig. 3.17b) matches best to the DOW7 CFAD. Meanwhile, AHM-DEM15H (Fig. 3.17c) simulates $Z_H$ values close to double those observed in the 0–3 km layer. Through calculation of the individual contributions of ice, snow, graupel, and rain to the simulation of horizontal reflectivity for both AHM-MEY92H and AHM-DEM15H, it was found that the higher-end $Z_H$ field simulated by AHM-MEY92H is most impacted by snow and ice, whereas the signature of $Z_H > 20$ dBZ simulated by AHM-DEM15H is dominated by snow and graupel (not shown).

Observed $K_{DP}$ frequencies center around 0° km$^{-1}$, but extend to larger positive and
negative values throughout the profile (Fig. 3.17d). $K_{DP}$ values of 0° km$^{-1}$ imply that a
differential phase shift did not occur in the presence of spherical particles while positive
(negative) $K_{DP}$ values indicate that the horizontal (vertical) phase shift is larger than the
vertical (horizontal), indicative of nonspherical particles. AHM-MEY92H has frequencies
of $K_{DP}$ extending past 2° km$^{-1}$ in the 1–3 km layer due to the presence of oblate and
prolate ice crystals (Fig. 3.17e). In the 0–1 km layer, these frequencies start to decrease in
magnitude likely due to aggregation scavenging these crystals, moving them to the snow
category, which does not consider shape. Within AHM-DEM15H, $K_{DP}$ values are centered
at 0° km$^{-1}$ throughout the 0–5 km layer (Fig. 3.17f) since quasi-spherical ice crystals were
prominent (not shown), resulting in a negligible phase shift.

DOW7 $Z_{DR}$ primarily ranges from 0–1 dB up to 2 km with some less frequently observed
positive and negative values throughout the lowest 4 km layer (Fig. 3.17g). Note that due to
the relatively low modal reflectivity (Fig. 3.17a), the $Z_{DR}$ data (Fig. 3.17g) are less reliable
and potentially dominated by noise, therefore resulting in too high of a frequency near
0 dB. Observations above 3 km suggest low concentrations of nonspherical particles while
increased frequencies of 0 dB below this level are indicative of these nonspherical particles
aggregating efficiently. Generally, aggregation serves to decrease the exaggerated difference
between the horizontal and vertical dimension of the aggregate snow particle (Przybylo et al.
2019), moving the differential reflectivity closer to 0 dB. However, graupel particles can also
produce $Z_{DR}$ ranging from −0.5 to 1–2 dB (Straka et al. 2020). Within AHM-MEY92H,
a primary concentration around 0 dB exists in the lowest 2 km, but larger frequencies of
values up to 6 dB are present, primarily in the lowest 4 km (Fig. 3.17h). This suggests the
considerable presence of nonspherical ice particles that have a greater horizontal backscatter.
AHM-DEM15H has too large of a frequency of $Z_{DR}$ near 0 dB above 3 km, but it does not
present the issue of relatively large frequencies of high $Z_{DR}$ near the surface (Fig. 3.17j). Also,
both simulations produce $Z_{DR} < 0$ dB above 2 km, which better represents observations.
Finally, note that AHM-DEM15H concurrently shows high $Z_{DR}$ and $K_{DP}$ around 0° km$^{-1}$. 

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This is possible due to the different dependencies of these polarimetric variables; $Z_{DR}$ could be responding to a small concentration of nonspherical particles, which would not be large enough for an appreciable $K_{DP}$ signal.

Lower frequencies of observed $\rho_{hv}$ extend down to 0.90, with higher frequencies clustered roughly above 0.98 in the lowest 1 km layer (Fig. 3.17). Extending to the 1–4 km layer yields $\rho_{hv} > 0.98$. Therefore, hydrometeors sensed by the DOW are relatively homogeneous above 3 km and become increasingly varied toward the surface. The overwhelming presence of snow and ice observed by the disdrometer (Fig. 3.10) fits well with the narrative of the DOW7 frequency of $\rho_{hv}$ in the lowest layer. AHM-MEY92H has a wider $\rho_{hv}$ distribution due to the largely ice-dominated cloud system it simulates (Fig. 3.17k). The greater distribution of ice aspect ratios (not shown) results in a population of ice crystals of various habits that overtakes the particle shape dependence of $\rho_{hv}$. Through box model simulations, Sulia and Kumjian (2017a) found that larger nonspherical ice concentrations can cause greater extremes in $\rho_{hv}$, perhaps explaining the breadth of the AHM-MEY92H distribution. The highest frequencies of the AHM-DEM15H distribution (Fig. 3.17) are more narrowly concentrated to $\rho_{hv} > 0.95$, resembling the rightmost distribution of DOW7 (Fig. 3.17). The $\rho_{hv}$ values are closer to unity in AHM-DEM15H because, in addition to the greater abundance of spherical rain, the modal ice aspect ratio only varies between 0.1 and 1 (not shown). However, the different hydrometeor composition in AHM-DEM15H serves to decrease $\rho_{hv}$.

Neither AHM-MEY92H nor AHM-DEM15H are fully comparable to the DOW7 polarimetric observations as the simulations tended to be on either extreme of the observations. Considerable concentrations of nonspherical ice in AHM-MEY92H are likely causing strong $K_{DP}$ and $Z_{DR}$ returns. If more ice to snow conversion through processes such as aggregation occurred within AHM-MEY92H, the resulting $K_{DP}$ and $Z_{DR}$ fields may be more comparable to observations. This can be further explored using the updated version of the AHM that includes an improved methodology of ice-ice aggregation and as such has shown impacts to simulated polarimetric quantities in an idealized squall-line simulation (Sulia et al. 2021).
3.7.1.1 Impact of Improved Aggregation Methods on Polarimetric Quantities

To investigate the aforementioned hypothesis, the AHM coupled with the Ice Particle and Aggregate Simulator (IPAS; Schmitt and Heymsfield [2014]) is used. IPAS is a box model used to investigate the aggregation of ice crystals and was extended by Przybylo et al. (2019) to output statistically robust lookup tables for quantities related to single monomer aggregation, such as bulk aggregate a and c axis lengths and density. Based on the monomer ice characteristics, the AHM retrieves the associated aggregation characteristics from the corresponding lookup tables and thereafter snow is able to evolve nonspherically. In the current state of the AHM coupled with IPAS aggregation, snow can only be created through ice-ice aggregation, thereby neglecting collection processes, and accretion processes onto ice and snow are turned off.

The AHM was run with IPAS turned on using Meyers et al. (1992) and DeMott et al. (2015) ice crystal nucleation and nonspherical evolution. A handful of model setup parameters differed from AHM-MEY92H and AHM-DEM15H; IPAS was integrated into WRF version 3.9 (as opposed to WRFV3.7.1 used herein) and due to model instability, the model timestep was reduced from 150s to 100s and the namelist parameter \( \text{epssm} \) was set = 2. Due to existing model issues related to ingesting APM data when IPAS aggregation is turned off in this new version, the IPAS simulations are compared to the existing AHM-MEY92H and AHM-DEM15H simulations. The model time step, stability parameter, and model version likely spur slight differences as compared to the existing simulations, but it is beyond the scope of this work to debug this version of the model. Finally, the model output is converted to polarimetric quantities through the forward simulator used within the previous section.

Sulia et al. (2021) assessed changes to polarimetric quantities when involving IPAS aggregation, which spurred and supports the following investigation. CFADs were created using the same methods as in the previous section and the median values in each 1 km altitude bin were recorded. Fig. 3.18 shows the differences between the observed and simulated median for \( Z_H \), \( Z_{DR} \), \( K_{DP} \), and \( \rho_{hv} \). In each panel, simulations allowing nonspherical ice growth...
with either nucleation parameterization and IPAS aggregation turned on or off are included (MEY92H-IPAS-ON, DEM15H-IPAS-ON, MEY92H-IPAS-OFF, DEM15H-IPAS-OFF). The closer to the dashed zero line, the better a simulation captures the observations. The presented hypothesis only questioned the response of polarimetric quantities simulated from MEY92H to improved aggregation methods, but those from DEM15H are also included in this analysis for completeness.

The only consistent response in both MEY92H-IPAS-ON and DEM15H-IPAS-ON is the reduction of $Z_H$. As the majority of the median $Z_H$ signature is derived from snow (not shown) and since $Z_H$ is highly dependent on particle size, it is helpful to look at the a and c axis lengths of snow in Fig. 3.19. The a axis is larger than the c axis for both MEY92H-IPAS-ON and DEM15H-IPAS-ON. In both nucleation schemes, the snow radius with IPAS-OFF is larger than the snow a axis with IPAS-ON, meaning that $Z_H$ will be greater with IPAS-OFF even with slightly increased snow number concentrations in IPAS-ON (not shown). The increased snow number concentrations introduce a heightened vapor competition for snow deposition processes, leading to less mass transfer to snow particles and consequently a particle size distribution representative of smaller radii. Furthermore, IPAS-OFF does not allow for subsequent collection processes within the snow category [Sulia et al. 2021] which also suppresses the size of snow.

The remaining polarimetric quantities have varied responses in each nucleation parameterization due to the differences in precipitation type; MEY92H-IPAS-OFF is dominated by snow and ice whereas DEM15H-IPAS-OFF is a mixture of snow, ice, graupel, and rain (Fig. 3.9). This composition does not change in MEY92H-IPAS-ON, but in DEM15H-IPAS-ON the amount of snow reduces while that of graupel and rain increases (not shown). These precipitation type differences at the surface extend to hydrometeors in the LES cloud, affecting polarimetric quantities. $Z_{DR}$ increases and worsens with MEY92H-IPAS-ON, but only below 2 km (Fig. 3.18b). This is related to the detection of oblate snow, overtaking any effect from monomer nonspherical ice. $Z_{DR}$ in DEM15H-IPAS-ON also increases below 3 km
(Fig. 3.18f), although to a lesser degree likely indirectly (i.e., through $Z_H$) due to a lower snow concentration. The $Z_{DR}$ increase when using IPAS aggregation was also noted by Sulia et al. (2021). $K_{DP}$ is markedly better and reduced in MEY92H-IPAS-ON, almost exactly matching observations while it is only negligibly worse in DEM15H-IPAS-ON. $K_{DP}$ improves in MEY92H-IPAS-ON as snow is now nonspherical and thereby produces a phase shift. It overtakes the impact of ice due to its comparatively larger size. Finally, $\rho_{hv}$ is slightly better in MEY92H-IPAS-ON and, again, slightly worse in DEM15H-IPAS-ON. The reduction of $\rho_{hv}$ in MEY92H-IPAS-ON likely relates to the new shape information from snow whereas the response in DEM15H-IPAS-ON is related to the increased heterogeneity of hydrometeors.

The polarimetric quantities respond differently when using IPAS aggregation within the AHM, due to the hydrometeor composition as a direct effect of the chosen ice nucleation parameterization. It is most evident that the new shape information provided by snow overtakes the polarimetric signatures, for better or worse. Overall, the better representation of aggregation substantially reduces the median $K_{DP}$ error, but worsens the $Z_{DR}$ error in the lowest 2 km. It will be interesting to follow-up on how these responses change again once collection processes are considered after further model development. With much of the focus on frozen hydrometeors, attention is now shifted to the present differences in LWC among the ensemble members and how those compare to in-cloud observations.

3.7.2 PVM LWC Analysis & Comparison

For each ensemble member, LWC values at each of the grid points with the same latitude, longitude, and height of 11 UWKA flight legs perpendicular to the southern shoreline of Lake Ontario were aggregated into distributions to understand the range of liquid present in the cloud system (Fig. 3.20a). The 0000 UTC 16 December output is used for this analysis as it is closest to the UWKA flight time. To compare the PVM LWC data to the ensemble forecast LWC, the PVM data were resampled by a frequency calculated by dividing the ensemble member grid spacing (1 km) along the simulated flight path by the
average UWKA airspeed (approximately 90 m s\(^{-1}\)). Throughout the 11 flight paths spanning approximately three altitudes and legs (Fig. 3.20b), the PVM measures LWC ranging from 2.24\(\times\)10\(^{-3}\) \(\sim\) 4.94\(\times\)10\(^{-1}\) g m\(^{-3}\). LWC within this range was measured 73\% of the time during its operation on the flight legs. Simulated LWC values below the lower PVM measurement threshold (2\(\times\)10\(^{-3}\) g m\(^{-3}\), Gerber n.d.) are ignored (Fig. 3.20a). 79\% of ensemble members simulated a median within the observed IQR. Five of these members (MY2, NTU-2SPH, NTU-FSI, NTU-PAERO, NTU-2TRAD), all of which are in the SIG group, have distributions that extend outside of the observed IQR. As these members best simulated the persistence of LWC, it is likely that this presence of LWC allowed for graupel production to occur. Note that not all SIG members are comparable to the observed LWC distribution, meaning that graupel production was likely not as zealous as those forecasts suggest. This comparison to observations encapsulates the difficulty of fully capturing the liquid-ice partitioning in the cloud system.

As in Garvert et al. (2005) and Morrison et al. (2015), comparisons are made between the observed and average LWC for each of the 11 flight legs to delve into the variation of LWC (Fig. 3.21). These model data are not imposed with the lower limit of 2\(\times\)10\(^{-3}\) g m\(^{-3}\) so that it is easier to see which members produced LWC and allowed its persistence during each flight leg. The average flight altitudes were 2.83 km for flight legs 1–3, 3.12 km for legs 4–6, 1.69 km for legs 7–9, and 1.68 km for legs 10–11. The observations on the top row of Fig. 3.21 indicate that the average LWC is of similar magnitude during the first five flight legs, around 2.9\(\times\)10\(^{-1}\) g m\(^{-3}\). Flight leg 6 did not have any observations > 2\(\times\)10\(^{-3}\) g m\(^{-3}\), which was likely due to the combined effect of the aircraft flying slightly above the cloud top and the flight leg located the furthest inland of those included in this analysis. LWC values decreased by an order of magnitude at the flight levels of 1.69 and 1.68 km, ranging from 2.41\(\times\)10\(^{-2}\) to 6.74\(\times\)10\(^{-2}\) g m\(^{-3}\) in flight legs 9 and 8, respectively. As with Fig. 3.20 each of the ensemble members represents the observed LWC to a different extent and interesting new details are elucidated by Fig. 3.21. On average, legs 1–3 were simulated approximately one
order of magnitude less than observations. The ensemble members with LWC present did not adequately capture the highest LWC values in flight legs 4 and 5 due to the altitude increase, which was not well resolved at this time in the ensemble. LWC was absent from nine members during leg 4 and 12 members during leg 5. Only leg 7 was well-simulated by almost the entire ensemble, except for NTU-FRFS and both AHM-MEY92 members. AHM-MEY92S does not allow for LWC persistence due to its abundance of frozen hydrometeors (Fig. 3.9). However, LWC does persist in AHM-MEY92H specifically in the lower altitude flight legs 8–10. The AHM-DEM15 members allow for greater persistence of LWC, but still forecast up to one order of magnitude less LWC in legs 1–3, are on par with leg 7, and again produce up to four orders of magnitude less LWC in legs 8–11. With the exception of CAM and MY2 during flight legs 1 and 2, all public members either produce far too little or no LWC. CAM, GCE, LIN, and MY2 compare much better to observations during the lower altitude flight legs 7–11. With the exception of NTU-FRFS, NTU members are able to resolve LWC for flight legs 1–3 and 7–11, but do not systematically over or under produce LWC, except for at the highest flight levels (flight legs 7–9). A majority of NTU members allow enough in-cloud persistence of LWC to be comparable to the observations, which is notable considering their under performance in the precipitation-type comparative analysis. Similar to the findings of Bartolini (2019), the relationship between LWC and the prediction of graupel is complex.

3.8 Summary

A 24-member microphysical ensemble was built from multiple microphysics schemes available within WRF v3.7.1 and two bulk adaptive habit models, each with varied parameters and representations of physical processes within, including aerosol and potential ice nuclei concentrations, ice nucleation parameterizations, rain and ice fall speeds, spectral indices, ice habit assumptions, and 2- or 3-moment methods of modeling ice-phase hydrometeors. The ensemble was used to investigate microphysical characteristics and resultant precipitation observed during OWLeS IOP4 with operational and research radar observations as well
as in-situ surface and aircraft observations. The eight simulations using publicly available microphysics schemes and the 12 members using a bulk adaptive habit model were run at National Taiwan University (NTU). The remaining four simulations using a different bulk adaptive habit model were run at the University at Albany, SUNY (UA). For this reason, a machine difference was conducted for one of these simulations at both UA and NTU. The analysis determined existing differences between these simulations to be negligible, giving credence to continue using the other “remotely” simulated ensemble members.

The 24-h QPF valid at 1200 UTC 16 December 2013 of each ensemble member was statistically compared to those of the remaining ensemble members to assess the present forecast spread and member intercomparison. The RMSE of each member was also investigated to assess the ensemble accuracy at Sandy Creek and North Redfield, NY. Almost all NTU members except for NTU-FRFS resulted in lower forecast errors than most ensemble members at Sandy Creek and errors below the median at North Redfield.

Several remote and in-situ observations were analyzed to stitch together the in-cloud microphysical processes and surface precipitation. Analysis of MRR data suggest particle growth and/or aggregation at all four sites as well as increased downward hydrometeor vertical motion with increasing proximity to Lake Ontario due to increased riming. Collectively, the ensemble was able to detect areas highly impacted by precipitation as well as correctly simulate LES morphology. The ensemble tended to produce a QPF with two maxima, but only one directly east of Lake Ontario was observed.

The most intriguing result was the various mixtures of hydrometeor types that were forecast to accumulate at the surface: seven members produced snow and ice, 15 produced snow, ice, and graupel, and two forecast snow, ice, graupel, and rain. A disdrometer stationed south of the convective core for the majority of the LES lifetime predominantly observed snow, with <8% attributed to graupel and/or rain. As the convective core passed over the MIPS deployment site, the disdrometer detected increased fall velocities of larger hydrometeors, as indicated by its particle size distributions and joint-distributions of equivalent spherical
diameter and fall velocity. Within the ensemble, graupel was either grossly overforecast (AHM-DEM15H, AHM-DEM15S, GCE, LIN, MY2, WDM6, WSM6, and all NTU members except NTU-FRFS) or underforecast (AHM-MEY92H, AHM-MEY92S, M2M, CAM, THOM, NTU-FRFS) during the LES event. The same ensemble members that did not predict enough graupel as compared to the disdrometer observations also forecast the most snow. Ensemble members forecasting SI and SIGR increased the areal coverage of the simulated radar reflectivity in D03, thereby slightly changing the locales affected by precipitation.

The signature of hydrometeor growth and/or aggregation observed in the MRR data was also present in the MIPS XPR effective reflectivity data. Near the peak-intensity of the LES the XPR data showed considerable variability in the vertical, suggesting lofting via strong upward vertical motion, decreasing effective reflectivity in the low-levels and increasing effective reflectivity aloft due to the upward flux of hydrometeor mass. Earlier XPR CFAD signatures are confirmed by DOW7 reflectivity vertical profiles, which are similarly compared to the forward operator-simulated polarimetric quantities of AHM-MEY92H (SI) and AHM-DEM15H (SIGR). This analysis elucidated the ability of both simulations to capture some of the observed polarimetric signatures, but neither was fully representative of the observations.

Lastly, in-situ LWC data from 11 UWKA flight legs were compared to the LWC in the ensemble, demonstrating the ability of some SIG members to model LWC distributions comparable to observations. The ensemble members struggle to capture the variability of these LWC data during the first five flight legs, but resolve the lack of LWC in the sixth. Some public members and the majority of NTU members are able to model LWC on the order of the observed magnitude during the final 5 flight legs. Note that the results of this analysis strongly depend on the location of the modeled LES, the number of vertical levels in the simulation, and the output time of the model relative to the observation time. Herein, all of these dependencies may have affected the comparison to observations, especially since the observation times were offset up to approximately one hour from the forecast time and location differences existed even among the members.
Processes that directly (through parameterizations) or indirectly affect the creation or growth (e.g., riming) of graupel lead to hydrometeor type differences within the ensemble. The NTU microphysics scheme was most sensitive to the change of ice fall speed parameterization (NTU-FRFS), as use of the empirical size relation reduced riming rates, allowing for in-cloud persistence of snow and ice and depletion of LWC. This resulted in a poor comparison to in-cloud observations and 3-h QPF, but the best ensemble member comparison to precipitation type as observed by the MIPS disdrometer. The remaining NTU members were relatively insensitive to the changes made within the scheme, which resulted in forecasts of SIG and did not negatively affect the RMSE, as this group provided some of the lowest RMSE at both Sandy Creek and North Redfield. Additionally, the faster ice fall speeds indirectly resulted in LWC magnitudes that were on par with observations. Public schemes provided numerous forecast differences due to different numbers of moments, parameters and parameterization choices, and hydrometeor definitions. This led to a wide range of RMSE, resulting in both the lowest and highest RMSE at North Redfield. These members forecast either SI or SIG; those forecasting SI have poor LWC persistence compared to observations, while members forecasting SIG perform slightly better. Finally, AHM-MEY92 members produced greater RMSE at both locations and poor representation of LWC due to their forecasts of SI. AHM-DEM15 members have lower RMSE at both locations due to their forecasts of SIG, allowing LWC magnitudes to be more comparable to observations.

This work has identified considerable sensitivities of in-cloud hydrometeor partitioning extending to surface precipitation type during a cold-season event, as a direct result of microphysical processes in bulk models. Ensemble difficulty in correctly diagnosing hydrometeor type for IOP4 had implications on remote sensing of cloud LWC and precipitation magnitude, among other characteristics, contributing to the forecast spread. However, comparisons to remote and in-situ observations indicated that at times the ensemble was able to capture some characteristics (e.g., spatial, microphysical) of the storm. Even slight changes or seemingly minute choices made within the bulk microphysical models that comprise this ensemble had
considerable impacts on this LES forecast.

The work in this chapter explored many different microphysics schemes and parameters that ultimately led to forecast sensitivity within IOP4, whether that was through the QPF or precipitation type. Precipitation and hydrometeor type differences also led to impacts on remote sensing. Vastly different forecasts can be produced solely based on the way in which microphysics is parameterized, which elucidates just how broad the cone of forecast uncertainty can be. Additionally, there is an incredible amount of microphysics variability across all in-cloud temperatures; even if frozen hydrometeors are parameterized to mirror observations, the same may not be true for liquid hydrometeors. However, some of the changes made between members in this work also highlighted forecast insensitivity, such as in NTU-INL and NTU-INH, indicating that the potential IN concentrations within these members were likely inflated for this particular case study. With that said, the NTU members were very similar among each other suggesting that self-contained model adjustments are less impactful to the overall forecast, as compared to changes among entire microphysics schemes. Changes to microphysics processes within a single scheme continue to be explored in Chapter 4 through stochastic methods.
### 3.9 Tables

<table>
<thead>
<tr>
<th>No.</th>
<th>Name</th>
<th>Reference</th>
<th>Setup (option)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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<td>Harrington et al. (2013a,b)</td>
<td>Non-spherical ice w/ Meyers</td>
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<td>Semi-2M(10)</td>
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<td>Chen and Sun (2002)</td>
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<td>NTU-2SPH</td>
<td>Tsai and Chen (2020)</td>
<td>Spherical ice crystal with 2M</td>
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<td>Tsai and Chen (2020)</td>
<td>Spherical ice crystal</td>
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<td>Tsai and Chen (2020)</td>
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<td>Tsai and Chen (2020)</td>
<td>Fixed relations of fall speed</td>
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<td>NTU-2TRAD</td>
<td>Tsai and Chen (2020)</td>
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Table 3.1: Reference table of all members comprising the UA-NTU ensemble with their associated name and change, if any, to their respective microphysics code. If applicable, the WRF microphysics option is provided for all public members in parenthesis in the Setup column.
### Table 3.2: Reference table of the physical scheme setup for WRF simulations discussed in this dissertation.

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<tr>
<th>Physical Process</th>
<th>Scheme</th>
<th>Reference</th>
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<td>Shortwave Radiation</td>
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<td>Boundary Layer</td>
<td>YSU</td>
<td>Hong and Noh (2006b)</td>
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<td>Cumulus (Only D01, D02)</td>
<td>Kain-Fritsch</td>
<td>Kain (2003)</td>
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### Table 3.3: Instruments deployed during OWLeS IOP4 that provided data used for analysis in this work.

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<th>Observation-type used</th>
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<td>PPI scans</td>
<td>Polarimetric</td>
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<tr>
<td>MRR</td>
<td>Fig. 3.1b, circles</td>
<td>Vertically pointing</td>
<td>Effective reflectivity, vertical velocity</td>
</tr>
<tr>
<td>XPR</td>
<td>MIPS, Fig. 3.1b, star</td>
<td>Surface</td>
<td>Effective reflectivity, Radial velocity</td>
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<tr>
<td>PARSIVEL Disdrometer</td>
<td>MIPS, Fig. 3.1b, star</td>
<td>Surface</td>
<td>Particle size and Velocity</td>
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<tr>
<td>UWKA PVM</td>
<td>Fig. 3.20b</td>
<td>Aircraft</td>
<td>Liquid water content</td>
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Figure 3.1: (a) Nested domains used in WRF ensemble and (b) Domain 3 with location of OWLeS IOP4 deployment sites for: (circles) Micro Rain Radars at Sandy Island Beach (SIB), Sandy Creek (SC), North Redfield (NR), and the upper plateau (UP); (star) MIPS instrument suite; and (triangle) Doppler on Wheels 7 (DOW7). Topography is contoured every 50 m beginning at 100 m, with the Tug Hill Plateau (THP) annotated at the highest elevation shown.
Figure 3.2: Violin plot of mass mixing ratio (q) differences (g kg$^{-1}$) between NTU- and UA-simulated member 5 for ice (qi), snow (qs), graupel (qg), cloud (qc), and rain (qr) mixing ratios at each grid point in D03 and at 3-h intervals during the time period of 1200 UTC 15 to 1200 UTC 16 December 2013. The median (horizontal white line) and distribution of differences (shading) is provided by a kernel density plot for each mass mixing ratio. The vertical lines of each plot represent the range of differences.
Figure 3.3: Spatial correlation coefficients between 24-h QPFs valid at 1200 UTC 16 December 2013 of each ensemble member in D03. The correlation is annotated and shaded by color for each ensemble member on both axes. AHM, public, and NTU members are grouped together on both axes by the use of horizontal and vertical white space. Members follow the order that they appear in Table 3.1 for the x- (left-to-right) and y-axes (top-to-bottom).
Figure 3.4: Root mean square error (RMSE, mm, grey) and mean absolute error (MAE, mm, light orange) of SWLE precipitation between observations at Sandy Creek and North Redfield, NY and individual ensemble members from 1200 UTC 15 to 1200 UTC 16 December 2013. The interquartile range is represented by each box, the median is the horizontal line within the box, and the remainder of the distribution is denoted by the lines extending from each box. Individual member RMSE and MAE are overlaid as green, pink, and orange circles denoting AHM, public, and NTU members, respectively. Annotated numbers correspond to the simulation number in Table 3.1.
Figure 3.5: (a) Intensity (mm hr$^{-1}$) and (b) reflectivity (dBZ) derived by the MIPS disdrometer during the period of 2127 UTC – 0700 UTC 16 December 2013. Vertical dashed green lines correspond to the 0.5° KTYX horizontal reflectivity (dBZ) PPIs valid at (c) 03:31:52 UTC and (d) 06:09:43 UTC 16 December 2013. The stars in panel (b) indicate the reflectivity enhancements associated with the increases in precipitation intensity at the following times: 2215 and 2315 UTC 15 December 2013 and 0100, 0200, 0330, and around 0530 UTC 16 December 2013. The black star on panels (c) and (d) indicates the location of the disdrometer and other MIPS instruments.
Figure 3.6: 24-h model QPF (mm) in D03, valid at 1200 UTC 16 December for each ensemble member outlined in Table 3.1. Respective mean and maximum QPF (mm) provided at the top of each panel. AHPS QPE are presented in the first panel.
Figure 3.7: CFADs of (a–d) effective reflectivity ($dBZ_e$) and (e–h) Doppler radial velocity (m s$^{-1}$) measured by MRRs from 15 December 2013 1800 UTC to 16 December 2013 0630 UTC at (a,e) Sandy Island Beach, (b,f) Sandy Creek, (c,g) North Redfield, and (d,h) the upper plateau in New York. The beige shading at the bottom of each panel indicates the terrain height at each site. The bin sizes for the reflectivity and Doppler radial velocity CFADs at each site are 200 m $\times$ 1 $dBZ_e$ and 200 m $\times$ 0.5 m s$^{-1}$, respectively, where the vertical spacing is 200 m. The dashed lines on each panel are the 5th and 95th percentile of the (a–d) reflectivity and (e–h) radial velocity at each height.
Figure 3.8: UWKA-measured LWC (g kg⁻¹) versus longitude during an east-west UWKA flight transect during flight transect 11, 0115 UTC - 0143 UTC 16 December 2013, approximately 1.68 km AGL. The dots represent each 1-s observation of LWC during the flight leg. The solid black line represents the median LWC and the grey fill represents the interquartile range, both of which are calculated within 0.2° longitude bins.
Figure 3.9: Barplot of 24-h D03-average QPF (mm) for each ensemble member, valid at 1200 UTC 16 December 2013. The contribution of snow and ice, rain, and graupel in each QPF are represented by turquoise, purple, and green bars, respectively. Note that these bars are stacked and not accumulating, and so where the bar begins relative to where it ends must be considered when determining the magnitude.
Figure 3.10: Percent of total accumulations broken down by precipitation type observed by the disdrometer and forecast by each ensemble member. The disdrometer data are valid during disdrometer observation period of 2127 UTC 15 December to 0657 UTC 16 December 2013 and the ensemble time period is valid during 2100 UTC 15 December to 0900 UTC 16 December 2013. The percentage of snow and ice, graupel, and rain and drizzle both observed and forecast by each member are represented by turquoise, green, and purple bars, respectively. Note that these bars are stacked and not accumulating, and so where the bar begins relative to where it ends must be considered when determining the magnitude.
Figure 3.11: Joint particle equivalent spherical diameter (mm) and velocity (m s\(^{-1}\)) distribution observed by the disdrometer (a) aggregated during the time period of 0000 UTC – 0657 UTC 16 December 2013 and (b) as a difference between the time periods of 0600–0655 UTC and 0300–0400 UTC. The data are normalized by the average particle count observed during each respective time period before calculating the difference shown in (b).
Figure 3.12: Point probabilities of $Z_h > 15$ dBZ interpolated to the 0.5° PPI scan strategy at KTYX at 0600 UTC 16 December 2013 for (a) all simulations ($N=24$), as well as simulations that produce (b) snow and ice ($N=7$), (c) snow, ice, and graupel ($N=15$), and (d) snow, ice, graupel, and rain ($N=2$). Superimposed on each panel is the KTYX-observed 15 dBZ contour (black) at the 0.5° PPI scan and 50% point probability contour (cyan).
Figure 3.13: Vertical profiles of the interquartile range (shaded grey area) and median effective reflectivity (dBZe, solid black line) measured by the MIPS XPR are plotted for $Z_e \geq -5$ dBZe. Each panel represents XPR data from the time periods of (a) 2132 UTC – 2200 UTC, (b) 2200 – 2300 UTC, (c) 2300 UTC – 0000 UTC, (d) 0000 UTC – 0100 UTC, (e) 0100 UTC – 0200 UTC, (f) 0200 UTC – 0300 UTC, (g) 0300 UTC – 0400 UTC, (h) 0400 UTC – 0500 UTC, (i) 0500 UTC – 0600 UTC, and (j) 0600 UTC – 0650 UTC.
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Figure 3.15: The absolute value of the difference in the D03- and column-mean pristine ice mass nucleation rate (g kg$^{-1}$ s$^{-1}$) between AHM-MEY92H and AHM-DEM15H (solid line) and NTU-INH and NTU-INL (dashed line) throughout IOP4.

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Figure 3.18: Temporal and D03-averaged vertical profiles of the difference between the observed and simulated CFADs for a,e) horizontal reflectivity, b,f) differential reflectivity, c,g) differential phase shift, and d,h) correlation coefficient for (top row) MEY92H and (bottom row) DEM15H with IPAS aggregation on (solid line) and off (dashed line).
Figure 3.19: Temporal and D03-averaged vertical profiles of snow axis length (mm) for the a (solid line) and c (dotted line) axes when IPAS aggregation is used and the equivalent spherical radius (dashed line) of snow when IPAS aggregation is not used. Lengths are shown for simulations using MEY92 (pink) and DEM15 (green) nucleation parameterizations with nonspherical ice growth.
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Figure 3.21: Heatmap of average observed and simulated LWC for the 11 flight legs analyzed in Fig. 3.20. Flight legs are represented on the x-axis, with (top row) UWKA PVM observations, (second row) the ensemble mean LWC, and (remaining rows) the average LWC values for each ensemble member along the same flight path at 0000 UTC 16 December 2013. Values are annotated on each box of the heatmap. Grey-filled boxes indicate a lack of observed or simulated LWC values > 0 g m$^{-3}$. 

Chapter 3 analyzed the impacts of choosing different microphysics schemes, parameters, and parameterizations on the same lake-effect storm investigated in Chapter 2. Through consideration of changes to the QPF and hydrometeor types, as well as comparison to in-situ and remote observations, it was determined that changes to overall microphysics schemes lead to the greatest forecast differences in the OWLeS IOP4 case. Additionally, changes to any parameters that had a direct or indirect influence on graupel mass also led to forecast uncertainty by means of hydrometeor type diversity, which was at times wrapped into existing microphysics scheme differences. To further investigate other microphysical processes that may impact the overall precipitation forecast, stochastic methods are used and applied to individual processes within the AHM. This work aims to identify (1) how stochastic perturbations lead to forecast uncertainty and (2) the way in which forecast uncertainty propagates throughout the cloud system.

4.1 Overview and Objectives

High-impact weather events have significant regional consequences, so it is necessary to gain a holistic understanding of their associated forecast uncertainty. As discussed below in Section 4.2, a body of work exists concerning the uncertainty that initial and boundary conditions impose on a weather predictions. More recently, attention has shifted toward the representation of model error in weather forecasts and quantification of its impact on forecasts. Even with perfect initial conditions, forecasts would not be completely accurate due to model error. Model error exists due to the discretization of the equations of motion, lack of representation of subgrid scale processes, and assumptions made within parameterizations that represent atmospheric processes in the boundary layer and those involved in convection, cloud microphysics, and radiation, among others. Herein, focus is placed on the representation
of model error associated with cloud microphysics, to build upon the work in Chapters 2 and 3 which identified sensitivities of a lake-effect storm forecast to microphysics parameterizations. Microphysics error is represented by two stochastic perturbation methods outlined below in Section 4.3: independent stochastic perturbed parameterization tendencies and stochastic perturbed parameters.

Several research questions will be addressed through this work, which stem from the fourth and final research question outlined in Chapter 1.3: What degree of uncertainty do microphysical processes introduce to a forecast and how does that uncertainty propagate through a cloud system? To answer this question, various stochastic perturbation methods are explored and compared, and the impacts of these perturbations to microphysics in particular are assessed by focusing on surface rainfall forecast characteristics during a synoptic rain storm. First, this research aims to understand if and why high-impact forecasts are affected by stochastic microphysics perturbations. Through applying perturbations to specific microphysics processes within a microphysics scheme, the focus turns to identifying the consequential impacts to the remaining processes within the storm system and to the QPF. Additional cases are explored using some of these methodologies to understand if the results can be extended to similar and/or different weather types.

4.2 Background

All weather forecasts are associated with both practical and intrinsic predictability, where practical predictability involves two types of uncertainties: IC and model error. Impacts of IC uncertainty on a deterministic forecast was most notably brought to light by Lorenz (1963), in which he highlighted the considerably different solutions of two ordinary nonlinear differential equations initialized with slightly different conditions. The uncertainty in the true current state of the atmosphere was emulated through very small relative changes (i.e., perturbations) in the ICs, thereby representing the inability to observe every point on earth without error. Small-scale errors in the ICs quickly grew upscale, resulting in different final
states and the identification of predictability limits for meteorological events occurring on
various spatial scales (Lorenz 1969). Inspired by Lorenz’s seminal work, forays into ensemble
prediction began with a specific focus on IC uncertainty and its impacts on large-scale
phenomena and long-term prediction (Palmer 1993; Toth and Kalnay 1993 among others). 
Shortly after IC-based ensemble forecasting became commonplace at meteorological centers
around the world (Sivillo et al. 1997), more attention was placed on the impacts of model
error on forecasts.

Great strides have been made within the modeling community over the past several
decades to improve deterministic forecasts and develop ensemble forecasts for high-intensity
rainfall events. As increasingly high-resolution forecasts have become feasible with growing
computational power, the disadvantages of using deterministic parameterizations of processes
that may be resolved in these simulations is becoming apparent (Palmer 2012). Considerable
uncertainty clearly still exists within NWP, namely lying in the assumptions and parameter-
erizations of subgrid scale processes and their impact on the resolved scale (Palmer 2012).
Only within the past few decades have the impact of these uncertainties on forecasts been
investigated in earnest, most popularly by stochastic perturbations. Buizza et al. (1999b)
applied stochastic perturbations with specified amplitude, spatial, and temporal autocorrela-
tion parameters to variables such as wind, temperature, and specific humidity at all model
levels to build an ensemble. Berner et al. (2011) followed a tangential methodology in which
a two-dimensional stochastic forcing pattern with spatial and temporal correlation was used
at all vertical model levels to perturb various basic atmospheric state variables; however, the
ensemble spread did not encompass all forecast possibilities (i.e., underdispersive). Stensrud
et al. (2000) suggested that a more dispersive ensemble could be created if it were composed
of significantly different physical schemes or processes within a single-model framework due
to less correlated forecasts. This hypothesis was supported with the ensembles developed by
Yussouf and Stensrud (2012) by combining various hydrometeor intercepts with ice-phase
(e.g., hail/graupel, snow) densities used within a microphysics scheme that resulted in more
accurate ensemble-mean precipitation, winds, temperature, and accumulated rainfall compared to a single-parameter ensemble. Continued exploration of PHYS and multi-parameter ensembles was highly encouraged by Stensrud et al. (2000) due to the plethora of uncertainties associated with physics schemes and the parameterizations therein.

Stochastic perturbed parameterization tendencies (SPPT) have been used to randomly perturb various tendencies outside of NWP parameterization schemes, such as time tendencies of potential temperature, wind components, and water vapor. SPPT has been found to reduce some systematic biases and also improve ensemble reliability by increasing forecast spread of variables including 2-m temperature, relative humidity, 10-m wind, and precipitation, among others (Bouttier et al. 2012). Even without acting upon hydrologic species, Bouttier et al. (2012) found that SPPT is able to elicit spread among precipitation forecasts due to indirectly enhancing rain evaporation. They note, however, that applying SPPT over a prolonged forecast period (i.e., > 24-h) may lead to over-dispersive and/or unrealistic forecasts as the effect of SPPT was observed to grow quickly. Lupo et al. (2020) also employs SPPT, along with independent SPPT, to delve into the sensitivity of a few heavy rainfall events to these perturbation schemes and the parameters used to construct them. They found that setting the time and amplitude stochastic parameters to be relatively large resulted in greater rainfall spread (i.e., standard deviation) because the high amplitude perturbations acted upon the tendencies over a longer time period. This study provides motivation to ensure appropriate parameters are chosen in creation of the stochastic pattern in this work.

Perturbing physical tendencies and/or parameters within parameterization schemes has been a more recent application of stochastic perturbations. In addition to atmospheric and oceanic ICs, Torn (2016) stochastically perturbed drag and enthalpy exchange coefficients to assess their impact on hurricane intensity forecasts. The lack of forecast variability in response to exchange coefficient perturbations was suggested to be related to the lack of spatial correlation in the perturbation pattern. Temporal and spatial correlations vary in stochastic perturbations: studies have involved neither, one or the other, or both. Juricke
et al. (2013) used all three methods when perturbing the sea ice thickness parameter (one that is not readily measured/constrained) in a coupled sea ice and ocean model. While all perturbation types resulted in a change of total sea ice volume and total sea ice area, the greatest impact came from including both a spatial and temporal correlation. Stochastic perturbations have also been applied to a convective parameterization, leading to increased spread among tropical cyclone tracks and intensity while limiting track errors (Snyder et al. 2011). However, as the perturbations led to a greater occurrence of tropical cyclone genesis, the false alarm rate increased for additional cases. Indeed, at times there may be a trade off where the added forecast value lies.

Griffin et al. (2020) investigated the impact of perturbations to the graupel spectra y-intercept parameter, the cloud water gamma distribution shape parameter, and the vertical velocity used within the cloud condensation nuclei (CCN) and ice nuclei (IN) activation calculation in a five-member ensemble using the Thompson et al. (2008) microphysics scheme. As these perturbations can only act when and where clouds are present within the domain, the resulting feedbacks can take longer (e.g., > 24 hours) to influence the overall forecast than solely including IC uncertainty would. However, if the aim is to focus on a process level understanding of how and why these microphysics perturbations lead to forecast spread, this should be a nonissue. The recent findings provide the necessary exploratory research needed before subscribing to the Palmer (2012) argument that stochasticity needs to be built into probabilistic models rather than being tacked on as an optional component. Before this can occur at the development level, we first need to understand how stochastic parameterizations affect precipitation forecasts at the process level. Hence, to add to the existing body of work, this chapter will begin to edify the importance and sensitivity of heavy precipitating events to microphysical processes. Palmer (2012) notes that process-level stochastic parameterization development may be produced with a sole focus on improving deterministic forecasts, but the research herein instead aims to understand the impacts of these perturbations on cloud systems and their resultant precipitation.
4.3 Stochastic Perturbation Methods

Stochastic perturbations are often used to represent model error in multiple components of NWP models. Berner et al. (2011) implemented a suite of these into WRF, including SPPT (Palmer et al. 2009), independent SPPT (iSPPT; Christensen et al. 2017), and Stochastic Perturbed Parameters (SPP). Each perturbation method makes use of a stochastic pattern dependent on three user-defined auto-correlated parameters: gridpoint standard deviation (i.e., amplitude), length-scale, and time-scale. The amplitude is sampled from a Gaussian distribution with a prescribed standard deviation and is bounded between a range of $\pm \sigma$, where $\sigma$ is the pre-defined standard deviation. The chosen length-scale should act on large spatial scales relative to the resolution of the innermost domain so perturbations are not acting as white noise. Furthermore, the time-scale should be long enough to allow perturbations to fully affect the system. While vertically invariant, the pattern evolves in horizontal space and time depending on the set parameter space according to an autoregressive model (Romine et al. 2014). Lastly, stochastic patterns as described and used by Berner et al. (2011) are generated on the outermost domain and interpolated to the innermost domain to retain consistency and ensure no issues at domain boundaries.

4.3.1 Stochastic Perturbed Physics Tendency

SPPT was based on the work of Buizza et al. (1999b), but was updated to allow for a spatially and temporally correlated evolution of perturbations and a univariate Gaussian distribution (Palmer et al. 2009). SPPT was developed to apply stochastic perturbations to the total tendencies of potential temperature, water vapor mixing ratio, and both $u$ and $v$ wind components (Palmer et al. 2009). These tendencies are summed from multiple physics schemes, including the planetary boundary layer, radiation, convection, and surface layer, to account for the uncertainty associated with existing parameterizations in each.
4.3.2 Independent Stochastic Physics Tendency

Perturbations can be separated out from the entire SPPT suite in WRF by means of independent SPPT (iSPPT) perturbations to tendencies (e.g., potential temperature, water vapor mixing ratio, zonal wind, and meridional wind) associated with the planetary boundary layer, radiation, convection, and surface layer parameterizations. It has been of interest to perturb the tendencies from these parameterizations independently to quantify the sensitivity of forecasts to specific parameterizations. Since there is interest in how perturbations to microphysics may affect probabilistic forecast uncertainty, Lupo et al. (2020) implemented the iSPPT framework to be applied to WRF microphysics (iSPPT\textsubscript{MP}) and investigated probabilistic QPF sensitivity to stochastic perturbations applied to microphysics tendencies. This perturbation method is also used in this chapter.

4.3.3 Stochastic Perturbed Parameter

Intrinsic uncertainty is associated with parameterized sub-grid scale processes within NWP models. The uncertainties focused on in this dissertation are related to cloud microphysics processes. Their uncertainty source is twofold, in that these processes cannot be fully resolved on a standard model grid and the parameterizations developed from in-situ and laboratory studies may be unable to robustly represent the process of interest, as microphysics processes do not happen in isolation from each other (e.g., ice/snow melting and collection). Furthermore, spatial and seasonal limitations of these studies inhibit the globalization of these parameterizations.

The uncertainty associated with the parameterizations of such processes can be directly accounted for through stochastic perturbations, such as SPP. Using this method, perturbations from the stochastic pattern can be applied to a specific variable, tendency, or process at multiple vertical levels throughout the simulation. It has most recently been used to assess parameter uncertainty at its source in both convection and planetary boundary layer schemes within WRF; Jankov et al. (2017) found that when coupled with stochastic perturbation
techniques that account for other uncertainties (e.g., SPPT), verification metrics improve slightly. This study demonstrates the ease in which this method can be applied to other variables, tendencies, and parameters within WRF.

Once the stochastic pattern is passed into the scheme of interest, SPP can be used by treating the perturbation to a variable as multiplicative. Consider a variable \( R \) that represents a constant value, process rate, or tendency within a scheme. After \( R \) is defined or computed in a scheme, the SPP method is applied to \( R \) at each grid point, as

\[
R^* = R(1 + p),
\]

where \( R^* \) is the newly perturbed variable and \( p \) is the stochastic pattern value at that grid point. \( R^* < R \) where \( p < 0 \) and \( R^* > R \) where \( p > 0 \), while the magnitude of the change \( (R^* - R) \) is dependent on \( p \). This dependence highlights the need for an appropriate parameter space to perturb the variable(s) of interest, as discussed earlier in this section.

4.4 Data and Methodology

4.4.1 Implementation

Stochastic perturbation methodologies, such as SPPT, iSPPT, and SPP, were implemented into WRF by Berner et al. (2011), and iSPPT to microphysics (iSPPT\(_{MP}\)) was implemented by Lupo et al. (2020). Herein, SPP has been implemented into the AHM so that no explicit perturbations occur outside of the microphysics scheme. The associated stochastic perturbation pattern (Fig. 4.1a) is generated via a random number seed fed into the code developed by Berner et al. (2011), discussed in Chapter 4.3 and evolves on a user-defined spatial and temporal scale, which will be defined through tuning experiments in Section 4.4.4 following Buizza et al. (1999b) and Lupo et al. (2020). At any given time, the pattern is the same in all domains; therefore, it is important to consider the scale of the phenomena of interest when determining the spatial autocorrelation of the pattern, as perturbing with white noise is not the aim of this research.
Stochastically perturbing moisture tendencies outside of microphysics schemes as in Buizza et al. (1999b) and Lupo et al. (2020) can lead to artificial moisture sinks and sources, ultimately violating mass and energy conservation due to the lack of a saturation adjustment. In contrast, SPP is applied herein to various process rates within the AHM to allow for the appropriate conservation at each grid point and model time step. These types of perturbations to microphysics parameters and processes have generated considerable interest in the NWP community, as evidenced by the numerous studies published in the past decade (e.g., Jankov et al. 2017; Ollinaho et al. 2017; Jankov et al. 2019; Stanford et al. 2019; Griffin et al. 2020; Thompson et al. 2021). As an example of how these perturbations work, consider an arbitrary process rate \( PR_x \) that is perturbed via SPP. Depending on the stochastic pattern value, a positive or negative perturbation is applied to \( PR_x \), with restrictions in place to prevent an unphysical sign reversal. This would happen if the stochastic pattern \(-1\) thereby forcing a process like ice deposition to instantly become sublimation, which is not physical in an ice supersaturated environment. \( PR_x \) is computed as usual in the AHM, immediately followed by a multiplicative perturbation \( PR_x = PR_x \times (1 + r(i, k)) \), where \( r \) is the stochastic pattern value, which redefines \( PR_x \) based on the perturbation pattern (Fig. 4.1a) at each grid point and time step. By perturbing rates such as \( PR_x \) within the AHM, updated quantities such as vapor mass and temperature, among others, are correctly evolved allowing for a much more physical evolution of process-level uncertainty.

4.4.2 Experimental Setup

The PIRE Climate Group found that the frequency and magnitude of extreme precipitation events occurring during the fall season (i.e., September, October, and November) has increased in the NEUS due to a heightened association between these events and tropical moisture (Howarth et al. 2019). To align this foundational work with those PIRE-related findings, the initial case study focuses on a heavy rainstorm occurring on 29–30 October 2017 with tropical moisture connections that impacted the majority of NYS. Over a span just shy
of two days, the associated rainfall exceeded 100 mm in several locations (Fig. 4.1b).

To study the sensitivity of the storm to microphysics process uncertainty, the WRFv3.7.1 coupled with the AHM is run for a 60-hr simulation period of 1200 UTC 28 October – 1800 UTC 30 October 2017, allowing for 12 hours of model spin-up. Two nested domains (Fig. 4.1a) are centered on NYS to leverage verification with the NYSM, vary in horizontal grid spacing from 15 km (Domain 1) and 3 km (Domain 2), and include 60 nonlinear vertical levels, extending to about 16 km. The time step is 30 seconds in the outermost domain and 6 seconds in the innermost domain. Initial and boundary conditions are forced using the Global Forecasting System (GFS) analysis data. The AHM is the microphysics option used in this study; all remaining physics options are outlined in Table 4.1. All simulations discussed herein were run on the NCAR Cheyenne supercomputer (CISL 2019).

In this study, multiple ensembles are used to explore the impacts of stochastic perturbations on ensemble forecast spread (see Appendix A). With the exception of the tuning experiments, each ensemble is comprised of 15 members, where each member is defined by a different stochastic pattern (e.g., Fig. 4.1a) generated using a random number seed. In addition to the 15 members comprising each ensemble, a control member is generated wherein no stochastic pattern is applied. Operational ensembles include a wide range of ensemble members (e.g., 20–250), but ensembles used in exploratory research may include as little as a handful of members. Necker et al. (2020) highlighted the dependence of statistical quantities such as correlations and ensemble bias on the number of included members, but noted that a sampling error correction sufficiently reduces spurious correlations and bias when using a reduced member ensemble. It is probable that sampling errors are embedded in each of these ensembles due to their relatively small size, which should be taken into consideration in the analysis.

The top four most active process rates that undergo conservation checkpoints in the AHM were identified within the control simulation and became the focus of the process rate uncertainty analysis through direct perturbation within the AHM. Stochastic perturbations
to ice (IDEP) and snow (SDEP) deposition, rain accretion of cloud droplets (CRACCR), and the melting of snow (SMELT) are completed to assess the potential nonlinear feedbacks among other process rates and resultant precipitation. These four process rates and the hydrometeor categories they directly affect are outlined in Table 4.2. The perturbations to these process rates provide insight into microphysics scheme sensitivities, which can be used to determine the microphysical processes that may be important sources of forecast sensitivity in certain weather events. A 15-member ensemble exists for iSPPT$_{MP}$ as well as for SPP applied to each of the four process rates in Table 4.2, resulting in a total of 5 ensembles focused on microphysics perturbations, four of which are AHM process-level ensembles.

4.4.3 Observational & Validation Datasets

In this study, NYS Mesonet (NYSM, Brotzge et al. 2020) data are used to delve into in-situ and remote measurements that are applied to ensemble tuning and verification during the heavy rainfall event on 29–30 October 2017 as well as a lake-effect event occurring on 15–16 December 2017. The NYSM is an unparalleled source of high resolution weather data that is ripe for numerous applications within the weather and climate enterprise. The dense standard network of 125 weather stations (as of late 2017) provides a rich dataset involving spatial variability and surface-level details that would have otherwise been missed using other observation networks, such as the Automated Surface Observing System (ASOS) network. 120 NYSM sites reported data during the October case and 119 during the December 2017 case (Fig. 4.1b). The distance between each NYSM site is approximately 30 km, on average, which is an order of magnitude less resolved than the 3 km grid spacing in the innermost domain of the WRF simulations. The NYSM observations are considered to be ground truth; the instrument precision of precipitation varies ±0.1 mm and 2-m temperature varies ±0.3° C at 0° C (Brotzge et al. 2020). Note that while these observations are very reliable, they are single point measurements that could be missing other localized phenomena. Additionally, the NYSM site locations are used in several ensemble analyses to retain specific focus on
The observations at each site are compared to those at the closest WRF grid point, with an average distance between those two locations of 1.3 km. No interpolation or averaging is considered. The standard meteorological variables reported every 5-min are resampled to the WRF output frequency of 1-h by summing the accumulated rainfall and averaging the other variables, which are used in several ensemble verification analyses. In addition, atmospheric sounding data obtained from the University of Wyoming are used to analyze the lake-effect storm thermodynamics in section 4.6.

4.4.4 Stochastic Parameter Tuning Experiments

This work aims to understand the degree of uncertainty that microphysical processes introduce to a forecast, specifically on the synoptic scale. Historically, the parameters used to generate the stochastic pattern have been either systematically evaluated (Buizza et al. 1999b; Lupo et al. 2020) or empirically chosen (Romine et al. 2014; Thompson et al. 2021). Herein, a systematic approach is followed to properly tune these parameters toward those of appropriate space and time scales. To accomplish this, nine SPP ensemble experiments with five members each involving slightly different spatial, temporal, and amplitude autocorrelation parameters (Table 4.3) were carried out by stochastically perturbing IDEP (SPP$^{IDEP}$) within the AHM. These parameter sets are based off of the work of Lupo et al. (2020). Only five members were used in these tuning experiments due to computational time restraints and storage limits. Each experiment was labeled according to the change relative to the reference experiment (REF) and the new magnitude. Amplitude changes are accounted for in A0.3 and A0.4, length-scale changes in L45km and L500km, time-scale changes in T900s and T21600s, and combinations of those changes, with an increase in amplitude and time-scale (IAT), and IAT plus a decrease in length-scale (IATDL). Examples of the stochastic pattern in each experiment are provided in Fig. 4.2.

These tuning experiments help determine which parameter combinations produce the most desirable metrics; hence, ensemble forecast spread$^{\dagger}$, RMSE, and mean error (see$^{\dagger}$Defined for this analysis as the square root of the ensemble-mean variance (as in Fortin et al. 2014)).
Appendix A] of the hourly rain rate, 2-m temperature, and 10-m wind are computed relative to the closest NYSM observations of the same parameter (Fig. A3). Comparing the RMSE to the forecast spread allows for insight into the ensemble reliability, as it is assessing forecast dispersion. In an ideally dispersive ensemble, the RMSE and spread should match as that indicates the ensemble spread will encompass the observations, even when accounting for forecast errors. The rain rate, 2-m temperature, and 10-m wind in Fig. A3 all have RMSE values that exceed the ensemble spread, indicating an underdispersive ensemble. However, there are slight differences among the tuning experiments in each of these variables. Out of the three, the rain rate RMSE and spread in each of the tuning experiments have the greatest variation across the experiments. This signifies that rain rate is relatively sensitive to the choice of stochastic pattern parameters, which is important to understand as rain rate and the event-total QPF are used for diagnostic analysis throughout the remainder of this research. Furthermore, rain rate spread peaks between 0000–0300 UTC 30 October, which is when the majority of the most intense precipitation rates are forecast in the control simulation, discussed below. Note that the rain rate mean error is > 0 mm after 1300 UTC 29 October (Fig. A3d, black), indicating that the average forecast across all NYSM sites tends toward a wet bias in all tuning experiments. The ensemble spread of 2-m temperature stays below 0.5°C throughout the forecast period, with mean errors ranging between 0.4–0.8°C between 1200 UTC 29 October – 0400 UTC 30 October that drop as low as 0.2°C in the subsequent time period. The 10-m wind RMSE (Fig. A3c) and mean error (Fig. A3f) steadily increase throughout the simulation. The mean error indicates that the wind is over-forecast anywhere between 1.5–3.5 m s⁻¹ with very slight variation among tuning experiments, as compared to NYSM 10-m wind observations. The 10-m wind ensemble spread increases until about 0700 UTC 30 October, but stays below 1 m s⁻¹. This analysis elucidates that the parameters used to generate the stochastic pattern do not considerably impact the ensemble spread of either 2-m temperature or 10-m wind, but they do slightly increase variability of rain rate spread.

There is not much variation to note in the NYSM site mean rain rate throughout the
event (Fig. 4.4) as the mean smooths out the small differences spurred by the perturbations. However, variation among the tuning experiments is present in the rain rate ensemble spread (Fig. 4.4). Relative to REF, the changes in the stochastic parameters did not uniformly affect the rain rate spread during the event. Instead, rain rate spread is seen to be greater or less than that of REF during different forecast periods, suggesting that no one combination of parameters leads to a definite spread response. Through this comparative analysis alone, it is unclear which experiment provides the best spread characteristics. For that determination, rank histograms are used.

Since the mean forecast is not overtly affected by stochastic parameters, but the ensemble spread is dependent, the nature of the QPF spread relative to NYSM observations is explored for each tuning experiment through rank histograms (Fig. 4.5). The rank histogram associated with each tuning experiment has a U-shape (highest frequencies in bins 1 and 6), rendering the ensemble underdispersive [Hamill 2001], which is to be expected when initial or boundary condition perturbations are excluded. Table 4.3 notes the percentage of observations found within the ensemble forecast. Specifically, 24.6% of observations fall within the REF experiment forecast spread. When decreasing the amount of time the perturbations affect the process rate in the T900s experiment, the percentage drops to 23.4%. However, the greatest dispersion out of all tuning experiments, which includes 26.5% of all observations within the forecast range, is achieved when increasing both the amplitude and time scale and decreasing the length scale (IATDL). The advantage of this combination makes sense, as the resultant pattern effectively leads to larger magnitude perturbations affecting smaller regions over a longer time period. For this reason, the IATDL parameters \(a = 0.4, \ L = 45 \text{ km}, \ T = 21600 \text{ s}\) are used to create the perturbation pattern used in all stochastic ensembles (Table 4.2).

Overall, the tuning experiments do not provide nearly enough dispersion to be considered useful operational guidance for precipitation forecasting. With that said, the aim of this work is not to develop a new method for operational forecasting, but to understand the impacts of
SPP methods on microphysical processes and resultant precipitation. Here, it is helpful to assess the dispersion of the ensemble to grasp the impact of these perturbations to deterministic and probabilistic verification as those metrics can help identify the advantages/disadvantages of including these types of perturbations. Another concern lies in that the dispersion differences among the tuning experiments, which are driven by changes to the stochastic pattern, are not substantial. These differences may be small due to the stochastic parameter space that was explored, but they also may be indicative of an upper dispersion limit that exists when perturbing microphysics tendencies within this storm (i.e., the microphysical nature of the processes lead to smaller differences). If so, these results suggest that while perturbing microphysics leads to a small amount of forecast uncertainty, adding microphysics perturbations to IC/BC ensembles may not result in more forecast uncertainty. In other words, the additive effect of microphysics perturbations to IC/BC may be small or nonexistent, as seen in the following section.

4.5 Initial Case Study of Stochastic Perturbations within the AHM

A low-pressure system tracked up the east coast of the U.S., impacting NYS and western New England with widespread 17 m s\(^{-1}\) wind gusts and significant rainfall, leading to flash flooding \(\text{\cite{NWS2017}}\). While the low-pressure system was propagating through NYS and simultaneously undergoing bombogenesis, a record low pressure of 976 hPa during the month of October was set at 0600 UTC 30 October 2017 at the Albany International Airport in Albany, NY \(\text{\cite{NWS2018}}\). 40.4 mm of precipitable water (PWAT) was observed from the 0000 UTC 30 October sounding launched 7 km away at the Albany Weather Forecast Office, which is slightly above the climatological daily maximum (39.1 mm) and the maximum moving average at this location (37.6 mm; \text{\cite{SPC2019}}); the remnants of Tropical Storm Philippe contributed to this moisture availability. These and other meteorological factors coupled with an amplified trough west of this system resulted in the Weather Prediction Center (WPC) highlighting flash flooding potential, especially enhanced amounts over the Catskill Mountains.
where the moisture flux was orthogonal to the mountain range (WPC 2017). Attention on the Catskill Mountains was appropriate, as 170.3 mm of rain fell at the Tannersville NYSM site (Fig. 4.1b). Rainfall accumulation was widespread throughout NYS, with a swath of observations >70 mm oriented with a northwestern tilt from east of Lake Ontario to New York City (Fig. 4.1b). Accumulations drop off in western NYS, as well as in the Adirondack Mountains.

Figure 4.6 provides a summary of the observed and control forecast rain rate (mm hr$^{-1}$) frequency across all NYSM sites throughout the event. The number of sites with observed or forecast rain rates $\geq 2.54$ mm (grey solid line) as well as the start and end time of the precipitation event (vertical dashed lines) are both superimposed on Fig. 4.6. With the data presented in this way, a qualitative assessment of rainfall intensity changes and comparison of observations to the control simulation can ensue. Observations in Fig. 4.6a indicate that light precipitation ranging from 1–3 mm hr$^{-1}$ begins at a handful of sites around 1200 UTC 28 October, remaining light and localized until around 0600 UTC 29 October. At this point, precipitation becomes more widespread as sites with rain rate observations $>1$ mm hr$^{-1}$ increase in frequency. These rain rates increase to around 10 mm hr$^{-1}$ at some locations by 1800 UTC 29 October, which is followed by a time period when a majority of sites observe rain rates $>1$ mm hr$^{-1}$, with a few sites observing rain rates exceeding 25 mm hr$^{-1}$ between 1800 UTC 29 October and 0700 UTC 30 October. Thereafter, precipitation once again becomes localized and rain rates quickly taper off to <10 mm hr$^{-1}$, ending before 1800 UTC 30 October. The control simulation (Fig. 4.6b) almost mirrors the observations in terms of the time periods in which certain light (1–5 mm hr$^{-1}$), moderate (5–15 mm hr$^{-1}$), or heavy (>15 mm hr$^{-1}$) rain rates are forecast to occur. While the start and end times of the precipitation are both slightly too early, the simulated precipitation is more widespread with a greater number of mesonet sites experiencing precipitation from approximately 1300 UTC – 2200 UTC 29 October and also during the peak of precipitation as indicated by the number of sites with forecast rain rates $\geq 2.54$ mm (Fig. 4.6b). A combination of more widespread
rainfall during the beginning of the event, increased sites with > 25 mm hr\(^{-1}\) rain rates, and intensified heavy rainfall reaching almost 40 mm hr\(^{-1}\) at one site in the control forecast (Fig. 4.6b) may lead to an overzealous ensemble forecast.

### 4.5.1 Inter-comparison of Initial/Boundary Condition Uncertainty and Stochastic Perturbation Methods

As touched upon in Chapter 4.2, existing literature has demonstrated that the bulk of forecast uncertainty is derived from small but impactful changes to the initial and lateral boundary conditions of NWP. While the focus of this work is to assess the sensitivity of weather systems to microphysical perturbations and cascading effects, these results can be better put into context through comparisons to more traditional perturbation experiments, like those to the initial and boundary conditions. Supplementing the initial condition (IC) and boundary condition (BC) uncertainty with stochastic perturbations applied to tendencies output by parameterized schemes, such as the boundary layer, microphysics, and radiation (e.g., SPPT, [Palmer et al. 2009](#)) can better represent forecast uncertainty when compared to only involving IC/BC uncertainty. First, the representation of forecast uncertainty through differences in ICs and BCs is explored for the October event. To assess the forecast sensitivity to IC/BC, identify the degree of uncertainty that microphysical processes introduce to a precipitation forecast, and highlight any differences that exist between the two stochastic methods, the following experiments are run using the WRF setup outlined in Section 4.4.2:

- **IC/BC:** Members differ only by the GEFS member providing its respective ICs and BCs. No stochastic perturbations are applied, which allows for a baseline of expected forecast spread and will later provide an understanding of the potential benefits of adding stochastic perturbations to this ensemble.

- **IC/BC\(_{iSPPT_{MP}}\):** IC/BC plus the iSPPT\(_{MP}\) method.

- **IC/BC\(_{SPP_{IDEP}}\):** IC/BC plus the SPP method applied to IDEP.
Each of these ensembles consists of 15 members. Additionally, the spread and error derived from iSPPT$_{MP}$ is compared to SPP$_{IDEP}$, which is used to represent the SPP perturbation method. In the remainder of this section, each of these ensembles are intercompared through distribution means of forecasts and spread as well as probabilistic verification metrics, which consider NYSM observations to be ground truth at their specific point locations. This analysis will help to identify the degree of uncertainty that microphysical processes introduce to a precipitation forecast and highlight any differences that exist between the two stochastic methods.

Rank histograms, a measure of ensemble reliability, were created for all IC/BC and stochastic perturbation ensemble forecasts of hourly rain rate, 2-m temperature, and 10-m total wind speed (Fig. 4.7); related statistics for the hourly rain rate rank histogram (Fig. 4.7a) are available in Table 4.4. The interior bin edges are defined by the individual member forecasts, so that the first and last bins contain observations that fall below or above the lowest or highest member forecast, respectively. Therefore, the number of bins in a rank histogram are $N + 1$, where $N$ represents the total number of ensemble members. The rank histogram evaluates observations in relation to an ensemble forecast, to determine if they are predicted as equally probable members within each ensemble (Wilks 2011, p. 371). First, note that all ensembles have a U-shape, indicating that they are underdispersive as the observations are less likely to be represented by any of the ensemble members as they are to fall outside of the forecast range; this means that the ensemble members closely resemble each other and are therefore producing an overconfident forecast. Each of the rank histograms also skews too high (Fig. 4.7), meaning that when observations are outside of the forecast range, they most frequently fall below it. The IC/BC and IC/BC$_{iSPPT_{MP}}$ rank histograms for hourly rain rate are similar (Fig. 4.7a), with one exception: the addition of iSPPT$_{MP}$ reduces the number of observations above the forecast range from 7.7% to 4.0% and increases the observations within the range from 70.9% to 74.4% (Table 4.4). This signifies that the addition of iSPPT$_{MP}$ to IC/BC results in a broadening of forecast spread, improving the dispersion
of the ensemble. However, the rank histogram of IC/BC$_{SPP_{IDEP}}$ is barely distinguishable from IC/BC, with differences in the percentage of observations below, within, or above the forecast range on the order of $< 1\%$ (Table 4.4). Therefore, including or excluding SPP does not alter the reliability of an IC/BC ensemble. However, reliability does degrade with ensembles produced from only stochastic perturbations to microphysics tendencies; iSPPT$_{MP}$ narrows the forecast range relative to the IC/BC ensembles, as indicated by the increased frequency of observations both below and above that range. All four SPP ensembles produce relatively similar rank histograms, with the greatest differences among the percentage of observations within the forecast range (Table 4.4), ranging from 33.5\% (SPP$_{SMELT}$) to 37.8\% (SPP$_{IDEP}$). Similar to rain rate, the 2-m temperature (Fig. 4.7b) and 10-m total wind speed (Fig. 4.7c) rank histograms are both underdispersive and include similar differences among the IC/BC, iSPPT$_{MP}$, and SPP ensembles. However, these two rank histograms include even more observations falling below their forecast range, especially when considering the 10-m wind speed (Fig. 4.7c), which makes sense for the SPP ensembles specifically as perturbations to microphysics process rates would not be expected to appreciably affect forecasts of 2-m temperature or 10-m wind speed. It is evident that the inclusion of IC/BCs provides the most reliable ensembles (similarly observed by Clark et al. 2008), followed by iSPPT$_{MP}$ and SPP ensembles. These results are similar to those of Torn (2016), in which combinations of atmospheric and oceanic initial conditions with stochastic perturbations to drag and enthalpy exchange coefficients did not cause an additive increase in tropical cyclone intensity forecast spread, which would have resulted in rank histograms like those associated with IC/BC ensembles coupled with stochastic perturbations.

While useful in their own right, rank histograms do not provide any spatial details with regards to the ensemble spread. To fill that information gap, Fig. 4.8 shows the QPF spread at NYSM site locations. Locations where the site-predicted spread exceeds the state-predicted median QPF are denoted by circles, and squares where spread is less than the median. In addition to the spread magnitudes, one can compare and contrast the locations of the
upper-end of spread to determine if there is a location dependency on the type of uncertainty or stochastic perturbation method used. There are appreciable differences among each of the uncertainty techniques discussed in this section. With IC/BC\textsubscript{iSPPT\textsubscript{MP}} (Fig. 4.8a), not only do the spread magnitudes increase relative to IC/BC (Fig. 4.8a), but the locations of greatest spread also shift to the north and west. However, IC/BC\textsubscript{SPP\textsubscript{IDEP}} (Fig. 4.8c) barely adjusts the spread magnitude relative to IC/BC (Fig. 4.8a) and only causes a slight increase of mid-state sites. The most drastic shift occurs with iSPPT\textsubscript{MP} (Fig. 4.8d) and all SPP ensembles (Fig. 4.8e–h); iSPPT\textsubscript{MP} shifts the majority of the forecast uncertainty found in northern NYS to the west, while SPP ensembles also do so but to a lesser degree. Furthermore, the QPF spread magnitude is substantially reduced in the SPP ensembles as compared to the IC/BC and iSPPT\textsubscript{MP} ensembles. The QPF field itself is driving the aforementioned spatial differences: in each ensemble, the top 50% of locations with the greatest spread are also those with the greatest QPF. So, at least with the October 2017 case, the spread signature follows the QPF field, to varying degrees. Although tied to QPF itself, the method used to represent forecast uncertainty certainly matters as it alters the regions forecast to receive a considerable amount of precipitation as well as the amount of uncertainty surrounding that forecast.

Next, forecast error comparisons are addressed. A relative operating characteristics (ROC) curve can be used to assess ensemble skill, as it is effectively comparing the false alarm rate (FAR) to the probability of detection (POD). Ensemble skill can also be assessed from a quantity derived from the ROC curve: the area under the curve (AUC). While an area of 1 is deemed to be a highly skillful ensemble and 0.5 indicates an ensemble that performs similarly to climatology (i.e., no skill), an area of 0.7 has been used as the lower threshold for a useful ensemble (Buizza et al. 1999a). The AUC was calculated for each ensemble set rain rate threshold of 2.5, 5.0, and 7.5 mm hr\textsuperscript{-1} throughout the simulation (Table 4.5). The mean area under the ROC curve is compared among the various ensembles to understand the ability of each ensemble to discriminate between events, here defined by the rainfall thresholds. In
other words, the AUC analysis at these various thresholds indicates how well the ensemble forecasts the occurrence of low, moderate, and heavy rainfall. While reliable (as discussed above), the IC/BC ensembles (IC/BC, IC/BC_{iSPPT_{MP}}, and IC/BC_{SPP_{IDEP}}) do not provide more skillful forecasts than the stochastic methods. Actually, iSPPT_{MP} is the most skillful, with AUC scores of 0.78 (2.5 mm hr$^{-1}$), 0.75 (5.0 mm hr$^{-1}$), and 0.77 (7.5 mm hr$^{-1}$) which are the highest AUC among the ensembles for all three rain rate thresholds. Each of the AUC values for the remaining ensembles ranges from 0.66 (SPP\textsubscript{CRACCR}, 5 mm hr$^{-1}$) to 0.75 (IC/BC\textsubscript{iSPPT_{MP}}, 2.5 mm hr$^{-1}$) with the most common AUC within a few decimal points of 0.7 (Table 4.5), the cutoff value for a useful ensemble. AUC values in the range of 0.6–0.9 are common in other studies of convection-allowing ensembles (Romine et al. 2014; Clark 2019; Johnson et al. 2020; Roberts et al. 2020). Ensemble skill could potentially be increased by mitigating any factor that serves to inflate the FAR or suppress the POD, such as a time shift of precipitation in the forecast period. Additionally, applying postprocessing techniques such as smoothing filters could increase the AUC if undersampling is a concern, as seen in Clark (2019). The SPP ensembles are on par with the IC/BC ensembles, and therefore less skillful than iSPPT_{MP}, which indicates a lessened ability to correctly forecast the observed frequency of events at these thresholds with perturbations to microphysics process rates alone and when coupled with IC/BC uncertainty.

The QPF distribution of each ensemble affect the probabilistic verification metrics discussed in this section. Interestingly, a relationship may exist between the time-averaged (0000 UTC 29 October – 1800 UTC 30 October 2017) stochastic pattern value and QPF error at all NYSM sites (Fig. 4.9). While negative QPF errors occur most frequently with positive perturbations, Fig. 4.9a shows that positive QPF errors occur with both perturbation signs, but the most extreme errors (QPF error $\geq$ 100 mm) occur most frequently with negative perturbations. Moreover, the distribution of QPF error in iSPPT_{MP} is skewed positive (Fig. 4.9a) and has a long tail to 269 mm, almost quadruple the magnitude of the negative extrema of slightly less than $-69$ mm (Fig. 4.10a). While the distribution of pattern
values is identical for SPP\textsubscript{IDEP} (Fig. 4.9b), its relationship to QPF error does not mirror that of \(iSPPT\textsubscript{MP}\). Attention is only placed on SPP\textsubscript{IDEP} since the relationship between QPF error and the stochastic pattern are similar in the other SPP ensembles. The only differences between \(iSPPT\textsubscript{MP}\) and SPP methods are where the perturbations are applied in the model (i.e., outside or within the MP scheme, respectively) and what is being perturbed (i.e., tendency or process rate, respectively). This indicates that the method of stochastic perturbation to microphysics affects the distribution of QPF error, as can also be seen in Fig. 4.10a. SPP\textsubscript{IDEP} methods result in QPF errors with more of a normal distribution, albeit with a slight skew toward the positive. Furthermore, the three other SPP ensembles skew positive with bimodal peaks of QPF error at 0 mm and approximately 40 mm, but have a tighter error range from \(-57\) mm to 118 mm (Fig. 4.10a). When using SPP methods, a smaller total and absolute error tend to come at the expense of ensemble forecast spread (Fig. 4.10b). Again, since negative perturbations lead to large positive QPF errors and the applied stochastic patterns are identical between \(iSPPT\textsubscript{MP}\) and SPP ensembles, then the method chosen to perturb these tendencies (\(iSPPT\textsubscript{MP}\)) or physical process rates (SPP) determines the error magnitude. Also, \(iSPPT\textsubscript{MP}\) can spur non-normal behavior within the model since the saturation adjustment is not available to adjust perturbation-caused changes outside of the microphysics scheme, here inflating the high-end QPF. Therefore, applying stochastic perturbations to process rates provides a slight competitive edge over \(iSPPT\textsubscript{MP}\) in terms of reducing overall QPF forecast errors.

To summarize, \(iSPPT\textsubscript{MP}\) and SPP ensembles have identical stochastic patterns but diverge in the manner in which perturbations affect microphysics. \(iSPPT\textsubscript{MP}\) applies the perturbation to the potential temperature (\(\theta\)) and water vapor (\(qv\)) tendencies after microphysics is called in WRF. As this occurs outside of the microphysics scheme, there is both artificial latent heating/cooling as well as artificial \(qv\) sinks and sources; mass and energy conservation are broken. In contrast, SPP applies perturbations to a specific process rate \textit{within} the microphysics scheme (e.g., AHM). These perturbations alter the process rate and
either increase or decrease the amount of mass transfer from one hydrometeor category to another (e.g., IDEP moves vapor to ice, or vice versa). If the perturbation inflates a process rate to the point in which it would move mass that surpasses the available mass, the process is scaled back to allow for mass conservation. This is followed by a saturation adjustment at the end of the model time step, so the environment is not sub- or super-saturated moving into the next timestep. Therefore, the SPP methodology does not lead to artificial mass sinks and sources like iSPPT\textsubscript{MP} does.

IC/BC\textsubscript{iSPPT\textsubscript{MP}} slightly alters the aforementioned relationship to the pattern values in that the distribution of error most frequently centers around zero (Fig. 4.10a), but with no considerable changes to the error extrema (Fig. 4.9c). There are slight differences in the error distribution with IC/BC\textsubscript{SPP\textsubscript{IDEP}} as compared to SPP\textsubscript{IDEP} (Fig. 4.9b), seen in Fig. 4.9d and Fig. 4.10a in a widening of the error distribution. Differences among the ensembles and uncertainty combinations also arise when considering QPF spread (Fig. 4.10b). The four SPP ensembles provide a relatively narrow range of solutions with little variation among the process rate perturbations, with the most frequent spread magnitude between 5.3–7.3 mm. Meanwhile, the iSPPT\textsubscript{MP} ensemble provides a much wider distribution of spread with frequencies peaking around 28 mm and extending to 72 mm. The IC/BC ensemble provides somewhat of a middle ground between SPP and iSPPT\textsubscript{MP}, in that the breadth of the distribution is less than iSPPT\textsubscript{MP} but larger than SPP and the peak is slightly above 20 mm. With IC/BC\textsubscript{iSPPT\textsubscript{MP}}, the spread distribution shifts to greater magnitudes, indicating a higher frequency of greater forecast spread. However, the same cannot be said for IC/BC\textsubscript{SPP\textsubscript{IDEP}}. The spread distribution shows very small changes, particularly in spread values below the most frequent magnitude of 20 mm. There is a lack of substantial spread differences for a few reasons: SPP ensembles include perturbations that are focused on micro-scale processes, which only affect areas with active microphysical processes (e.g., model grid cells with clouds present). iSPPT\textsubscript{MP} ensembles perturb the microphysical tendencies of $\theta$ and $qv$ after the saturation adjustment within the microphysics scheme, therefore creating
artificial sinks and sources of latent heating (cooling) and condensation (evaporation). This type of perturbation can have a runaway effect due to its independence from the microphysics saturation adjustment and interactions with other parameterized physical processes within WRF that affect/update $qv$ and $\theta$. Meanwhile, the IC/BC ensemble includes uncertainties only accounted for within the GEFS, which are born from initial condition uncertainty and model error (represented by stochastic forcing, [Zhu et al. 2018]), thereby honing in on synoptic scale uncertainties that are not only tied to precipitation processes. Therefore, the distribution of forecast spread is hypothesized to be attributed to differences in the representation of the synoptic storm itself, such as timing of precipitation, strength of the extratropical cyclone, duration of precipitation, and so on. These results suggest that for short-term forecasts, the ensemble already has a decent idea of the forecast mean. Overall, the stochastic methods analyzed here affect the forecast verification metrics inconsistently (e.g., reduced reliability, enhanced skill). It is necessary to note these differences between $iSPPT_{MP}$ and SPP methods due to the varied effects they spur within the forecast. Now, focus turns to understanding how the SPP methods alone lead to the forecast uncertainty presented in this section.

### 4.5.2 Ensemble Verification

A quantitative method to assess if the ensemble does actually forecast more rainfall than observed as suggested by Fig. 4.6 involves calculating a bias, which compares predicted and true (observed) values (see Appendix [A]). It would be helpful to know (1) the overall rainfall accumulation bias for each ensemble, (2) the QPF range where the greatest bias is found, and (3) the evolution of the rain rate bias. These quantities help to identify considerable deviations from observations that may fall outside of the ensemble spread at each NYSM site location and their timing. A comparison of the 99th percentile QPF (Table 4.6) to NYSM observations provides some of this information. There is not much variation among the ensemble sets; the 99th percentile QPF shows insensitivity to the microphysical perturbation, so similar conclusions can be drawn from each ensemble set. Generally, the comparison to
observations indicates that there is a wet-bias at 71.6–74.2% of NYSM sites (not shown), with a mean error of 24.3 mm and the greatest bias maximizing at a range of 90.5–98.6 mm at the Ballston Spa site in all ensembles (Table 4.6). The greatest bias in all ensembles is found within the QPF range of 25–100 mm (not shown).

Next, consider the hourly rain rate bias (mm hr\(^{-1}\)) throughout the forecast period, calculated separately at each NYSM site for the lower and upper quartiles of the rain rate and then averaged over those sites (Fig. 4.11). Focusing on the quartiles instead of the ensemble mean or median allows for a better understanding of the range of bias and how it varies temporally. After 1300 UTC 29 October, there is a positive bias for the 75th percentile rain rate that peaks at almost 3 mm hr\(^{-1}\) at 0200 UTC 30 October and then tapers off as the low pressure system moves from the area. The lower quartile follows a similar trend with a lesser magnitude of bias, but also with multiple bias reversals. This indicates that the higher-end forecast is almost always too high whereas the sign of the lower-end forecast bias varies with time. With this known, it is to be expected that rainfall errors will be largely positive for high-end rainfall whereas low-end rainfall may result in a mixture of negative and positive errors. Additionally, while the 25th and 75th percentile rain rate biases tend to parallel each other through each ensemble simulation and the biases from the various ensembles diverge during similar windows of time, the amount in which the 25th and 75th percentile biases differ is not always similar (Fig. 4.11). For example, during 1900–2100 UTC 29 October the 75th percentile bias had a larger inter-ensemble difference than the 25th percentile while the opposite was true during 0200–0600 UTC 30 October, suggesting that certain perturbations may impact lower (25th percentile) or higher (75th percentile) rainfall rates in an inconsistent manner (Fig. 4.11).

Inconsistent inter-ensemble differences also exist within the Brier score (BS), which was calculated for multiple quantiles of the QPF for each ensemble (Fig. 4.12a). The BS is used to assess the probabilistic forecast accuracy, which increases as BS → 0, as compared to NYSM observations. As seen in the previous analyses, the ensembles follow similar trajectories
across the quantiles and therefore only exhibit differences of $BS < 0.05$. However, those differences are nonexistent at quantiles 0.1–0.2 (23.8–39.3 mm), increase from quantiles 0.2–0.4 (39.3–62.7 mm) and 0.6–0.8 (75.2–88.8 mm), and decrease from quantiles 0.4–0.5 (62.7–69.3 mm) and 0.8–0.9 (88.8–98.3 mm). Again, as seen in the previous analysis, ensemble differences do not maximize as the amount of forecast precipitation increases. This means that perturbations to these process rates lead to varying precipitation forecasts not only at locations with the highest rain rates, but also anywhere the process rate is active within the precipitating cloud system. With increasing quantiles of QPF, the BS also increases although not at a constant rate. The BS increases quickly from 0.1 to approximately 0.28 at the 40th percentile (62.7 mm), then stays relatively steady until starting to increase again at the 60th percentile (75.2 mm), peaking above 0.3 at the 70–80th percentile in all but SPP$_{IDEP}$, and decreasing thereafter to $0.2 < BS < 0.25$. Therefore, forecast accuracy generally degrades as QPF increases in each ensemble as the BS ranges from 0.05 to 0.31. No specific ensemble outperforms the others.

To further investigate ensemble forecast skill relative to QPF magnitude, the AUC was calculated as in Section 4.5.1 for each SPP ensemble at each forecast hour for rain rates of 2.5, 5.0, and 7.5 mm hr$^{-1}$ (Fig. 4.12b). The AUC was not calculated for periods in which the rain rate was neither observed nor simulated, which indirectly allows for discrimination of when certain precipitation intensities are expected during the forecast period. With dips to magnitudes as low as 0.3, ensemble skill is especially poor from 1500 UTC to 1700 UTC 29 October. During this time period, the number of NYSM sites observing any of these rain rates was not changing, indicating that the storm was in a steady state (e.g., no intensity changes and no changes in areal coverage). However, the ensembles predicted an increase in the number of sites meeting or exceeding these rainfall thresholds during this time period, thereby increasing the FAR and plummeting the AUC. After this time period, AUC increases for all thresholds, with periodic variation depending on the forecast time. During the time period in which all thresholds provide AUC (1700 UTC 29 – 0800 UTC 30 October), each
threshold returns relatively similar values. The greatest AUC of 0.99 occurred at 1100 UTC 30 October among the ensembles at the 5 mm threshold, signifying nearly perfect skill for the SPP ensembles at low-moderate rain rates. AUC for all rain rates consistently remains above the minimum acceptable performance threshold of 0.7 after 0100 UTC 30 October until 1100 UTC 30 October, encapsulating the second half of the time period with the heaviest rainfall forecast (Fig. 4.6b). This may indicate that the ensemble forecasts perform better during widespread heavy rainfall, but tend to fail during transition periods where rainfall is more localized.

The predictability of a widespread heavy rainfall event with a clear wet-bias may be impacted by the ensemble’s ability to simulate the available moisture in the atmospheric column. To assess this, precipitable water (PWAT) calculated with the Python package MetPy [May et al. 2021] from the twice daily radiosonde launches in New York City, Albany, and Buffalo, NY are compared to the SPP ensembles at 0000 UTC and 1200 UTC on 29 and 30 October (Fig. 4.13). The PWAT observations peak at 0000 UTC 30 October in both New York City and Albany at 44.7 mm and 40.3 mm, respectively, but peak earlier in Buffalo at 0000 UTC 29 October at 21.7 mm. PWAT observations evolve similarly in New York City and Albany, increasing up until 0000 UTC 30 October, followed by a sharp decline at 1200 UTC 30 October. The observation in New York City is unknown at this time due to data issues. During the first three observations, the PWAT in Buffalo stays relatively consistent, ranging from 19.9 mm to 21.7 mm, decreasing to 10.3 mm at 1200 UTC 30 October. At various times in each location, all ensemble members are able to correctly simulate the amount and general evolution of PWAT, with the greatest forecast spread in both New York City and Albany. Note that PWAT spread generally scales with the amount of observed rainfall near each of these locations; event-total rainfall was 28.9 mm in Buffalo, 68.1 mm in Voorheesville, and an average of 69.4 mm between Southold and Wantagh, which are the NYSM sites closest to each radiosonde launch site. Since most PWAT observations fall within the range of ensemble forecasts during the event, the wet-bias in each ensemble
(Table 4.6) may be attributed to (1) precipitation processes affecting rain rate, duration, or both (Doswell et al. 1996), such as rate of vertical ascent or storm size and propagation speed, and (2) the point-to-point comparisons used within the verification metrics. If the simulated storm is more widespread than observed but the heavy rainfall is displaced, then QPF will increase and compare poorly to observations. The impact of using point-to-point comparisons when there are slight displacements of rainfall intensity could be mitigated by averaging the QPF in the grid points surrounding each NYSM site.

4.5.3 Impact of Perturbations on Precipitation

Armed with an understanding of the rainfall event and performance of the SPP ensembles, it is now time to delve into how these perturbations affect surface rainfall forecasts. Curious if the relative importance of a process rate scales with the QPF spread its perturbation produces, Fig. 4.14 provides a comparison of process rate sums and QPF spread for each SPP ensemble. To determine how active each process rate is in the system, a temporal and column sum of each process is averaged over all NYSM site locations in the control simulation. The QPF spread is calculated by taking the standard deviation of the NYSM-mean QPF across all ensemble members for each ensemble (see Appendix A). The melting of snow (SPPSMELT) is found to be the dominant process rate out of the four that are perturbed, but only leads to the second greatest amount of QPF spread when averaging total QPF across all NYSM sites (Fig. 4.14). IDEP is the lowest relative contributing process rate, but when perturbed within SPPIDEP it does not lead to the lowest relative amount of QPF spread (Fig. 4.14). This suggests that additional active processes were consequential in the creation of QPF spread although they were not directly perturbed and that perturbations to a relatively active process rate (e.g., CRACCR) do not necessarily lead to a relatively larger QPF spread.

As seen in Fig. 4.14, QPF spread varied among the ensembles, but it is unclear how that spread varied across NYS. To identify differences in spread across the NYSM sites within each ensemble, kernel density smoothing (see Appendix A) was applied to distributions of
storm-aggregate QPF spread at each NYSM site for all SPP ensembles (Fig. 4.15). The peak in QPF spread of each ensemble varies between 4–7 mm and the greatest spread values extend to 22.3 mm in SPP$_{IDEP}$, 17.9 mm in SPP$_{SDEP}$, 18.4 mm in SPP$_{CRACCR}$, and 17.9 mm in SPP$_{SMELT}$. Interestingly, SPP$_{IDEP}$ results in sites that experience more frequent high spread (>13 mm) ensemble forecasts. These spread magnitudes are not present at this frequency in the three other ensembles, which signifies that perturbations to IDEP are a source of slightly greater uncertainty at certain locations within NYS. Perturbations to IDEP may lead to greater forecast uncertainty because any changes to ice deposition impact water vapor mass and ice size, which can change rates of autoconversion to snow and thus snow mass and size within the same model time step. In other words, it is possible to alter water vapor, ice, and snow quantities within a single time step when perturbing IDEP, in contrast to perturbing the remaining process rates that directly impact only two mass quantities in one time step. Also, SPP$_{CRACCR}$ has a marginally different distribution structure, as between 2 mm and 10 mm it is shifted about 2 mm to the right of the other SPP ensemble distributions. This indicates that perturbations to CRACCR more frequently lead to moderate spread in place of low-end spread, likely due to the impact on rain fall speed through changes to the rain mass, which alter rain size distribution parameters.

As the spread distributions differ slightly among the SPP ensembles, it is helpful to identify what kind of relationship exists between the amount of QPF and the spread observed at each NYSM site and if that relationship is sensitive to the perturbed process rate. To do so, the percentage of the ensemble mean QPF that is QPF spread \(\frac{\text{stddev}(QPF)}{QPF} \times 100\%\) is calculated and compared to the ensemble mean QPF for each ensemble. Fig. 4.16 highlights that spread scales with total QPF for all ensembles, as to be expected with a multiplicative perturbation method such as SPP. Forecast spread is smaller relative to QPF when QPF is low. For example, when QPF is low (0–50 mm), spread can be expected to be 1–7.5% of that QPF but when QPF is high (>75 mm), spread can be expected to be 2.5–17.5% of the total QPF. That means the QPF range forecast by an SPP ensemble will increase
with higher expected rainfall. This relationship is not unique to SPP; iSPPT$_{MP}$ and IC/BC ensembles exhibit a similar relationship, but with spread at higher percentages of the ensemble mean QPF (not shown). Therefore, in this case, the SPP method is not introducing any new relationship between spread and QPF. Instead, it is dialing down the effect of the relationship. Additionally, SPP$_{IDEP}$ has elevated spread for QPF ranging from 0–50 mm relative to the other SPP ensembles, meaning that perturbations to IDEP may be beneficial when there is uncertainty associated with low-end precipitation (Fig. 4.16a). Interestingly, this spread increase at the low-end QPF range does not translate to a spread enhancement at all other ranges, instead matching the maximum 10% spread of the other ensemble medians (Fig. 4.16b–d). Rather, the IQR of SPP$_{IDEP}$ spread percentage broadens with increasing QPF which results in an increased forecast uncertainty range at higher QPFs.

To help understand why there is a greater amount of uncertainty within SPP$_{IDEP}$, the spread of several microphysics process rates are analyzed relative to SPP$_{IDEP}$. All process rates considered and discussed within are listed in Table 4.9. For each process rate and ensemble, the total spread is found and the percent change of the spread is computed between SPP$_{IDEP}$ and the remaining three ensembles. When the percent change is negative in a certain ensemble, the process rate spread has decreased relative to the spread of the same process rate in SPP$_{IDEP}$. Therefore, the greatest process rate spread is associated with SPP$_{IDEP}$ when the percent change is negative in SPP$_{SDEP}$, SPP$_{CRACC}$, and SPP$_{SMELT}$. Furthermore, the greater QPF spread percentage in Fig. 4.16a likely emanates from the processes that produce the greatest spread relative to the other SPP ensembles. Figure 4.17 is critical in narrowing in on these processes, as stars indicate the following processes with the greatest spread in SPP$_{IDEP}$: RFRZ, IMELT, IDEP, ISUB, IRRCOLLECT, INUC, IRISCOLLIS, GDEP, IRICOLLECT, GEVAP, CSACCGRIME, CGSPLINT, and RGCOLLECT-BF. Note that all ice-related processes are included in that list except for AGG, ISACCR, and IRRSCOLLIS. The connections between IDEP perturbations and RFRZ, GDEP, GEVAP, CSACCGRIME, CGSPLINT, and RGCOLLECT-BF are
less clear. However, IDEP affects ice and vapor mass, which in turn impact supersaturation with respect to liquid water and ice, and indirectly impacts the saturation adjustment thereby affecting the available vapor and cloud droplet mass. These seemingly unrelated processes listed above have connections to the impacted quantities; GDEP and GEVAP are dependent on the altered water vapor, RGCOLLECT-BF depends on graupel fall speed which can be impacted by changes to graupel mass through the previous two processes, and CSACCRGRIME and CGSPLINT depend on cloud droplet mass, which is controlled through the saturation adjustment. RFRZ seems to have a less natural connection to IDEP, but likely depends on cloud to rain autoconversion which could be affected if the saturation adjustment leads to greater cloud droplet mass, affecting the rain mass available for homogeneous freezing. The combination of spread spurred from perturbations to IDEP from most ice-related processes and the other tangentially related processes likely leads to the enhanced spread percentage seen in Fig. 4.16a. The response of these and other process rates to perturbation is discussed in further detail in the following section.

4.5.4 Impact of Perturbations on Other Cloud Processes

The perturbed process rate naturally affects the other cloud processes in the system due to the immediate change in available ice, liquid, or vapor mass. It is of interest to understand the degree to which these processes are affected, and if one process, such as SMELT, has a stronger hold over the remaining process rate responses or not. This ultimately aids in gaining an understanding of how perturbing one process rate leads to uncertainty in other parts of the storm system, culminating in QPF spread. The ensemble standard deviation of each process rate can be compared within and among the SPP ensembles to understand how perturbing one rate affects the remaining process rate uncertainty. The spread of each process rate is computed by taking the standard deviation of a temporal and column sum averaged over NYSM site locations for each ensemble (see Appendix A). Each process rate spread is then ranked within each ensemble to reveal the spread generators within the storm.
system and how those differ among the ensembles (Fig. 4.18). Interestingly, the perturbed process rates do not provide the highest ranked spread in each ensemble; IDEP is ranked 3rd in SPP$_{IDEP}$, SDEP is 2nd in SPP$_{SDEP}$, CRACCR is 4th in SPP$_{CRACCR}$, and SMELT is 5th in SPP$_{SMELT}$. While still highly ranked, the perturbed process may not be expected to return the greatest forecast spread as it is only one component of the system, which has continuous feedbacks during each model time step. For example, if a perturbation reduces IDEP (as in SPP$_{IDEP}$), then more vapor is available for subsequent processes. Enhancing subsequent vapor-dependent processes will affect the rest of the system and ultimately the QPF. This effect may also propagate through time and compound as IDEP continues to be perturbed throughout the simulation.

The change in mass due to rain-snow collection (RSCOLLECT-AF) returns the greatest spread in all ensembles, meaning that it is both impactful to in-cloud spread generation and rank-insensitive to the perturbed process rate (e.g., IDEP, DEP, CRACCR, or SMELT). Cloud condensation/evaporation (CCOND) is ranked either second or third relative to the other process rate spreads in all ensembles. The process rates ranked below RSCOLLECT-AF and CCOND truly paint a picture as to the effect of the perturbations on the other process rates in the cloud system. When perturbing deposition processes such as IDEP or SDEP, the spread of these quantities is highly ranked in each respective ensemble (e.g., SPP$_{IDEP}$ and SPP$_{SDEP}$), ranging between 2nd–4th. However, in the SPP$_{CRACCR}$ and SPP$_{SMELT}$ ensembles, the spread of IDEP and SDEP have ranks anywhere between 6th–9th, meaning that without direct perturbations their significance in spread generation fades, but also that they are highly responsive to direct perturbation. The rank swapping of CRACCR and SMELT in SPP$_{CRACCR}$ and SPP$_{SMELT}$ is less dramatic, which may be tied to their lower magnitude relative to the other perturbed rates (Fig. 4.14). Also of note within the SPP$_{IDEP}$ and SPP$_{SDEP}$ ensembles are other related processes, such as the melting of ice (IMELT) and accretion of ice by snow (ISACCR); IMELT jumps to a rank of 8 in SPP$_{IDEP}$, compared to ranks of 13th–15th while ISACCR leaps to ranks of 8th–9th
compared to a rank of 14th in the other ensembles. By using an ensemble framework, the direct effect of perturbations to ice deposition on processes like the melting of that perturbed ice mass and its autoconversion to snow mitigate the full effects of chaos seeding, which occurs when perturbations quickly and unrealistically impact the full model state ([Ancell et al. 2018](#)). This issue in perturbation experiments was discussed by [Ancell et al. (2018)](#), where they note that small perturbations within initial conditions, boundary conditions, or physics parameterizations in numerical weather prediction can be contaminated by chaos seeding, at times resulting in faulty conclusions if these effects are assumed to be caused only by physical processes. While the results herein may have contributions from numerical ripple effects especially in the lower ranking process rates where connections between some rates are not overtly apparent, they also exhibit coherence as the expected spread generators are consistent across each ensemble. The connection between the perturbed rate and other related rates is obvious in all of these ensembles. Slightly less obvious are the differences in spread magnitude for process rates that have similar ranks among ensembles, such as \textit{RSCOLLECT-AF}. These differences are less noticeable in the ensemble-relative rankings, but may matter when considering how process rate spread changes with different process rate perturbations.

Another factor to consider when analyzing process rate spread and its impacts is where the perturbed process rate resides within the process rate hierarchy. For example, is spread generation the greatest when perturbing a process rate that directly affects surface rainfall with limited subsequent processes, such as accretion or melting processes? The answer is complex, as it is difficult to tease out such relationships in an instantaneously evolving system. However, looking back at Fig. 4.14 may help to provide some insight. There appear to be two factors controlling spread generation in each ensemble: (1) the magnitude of the process rate and (2) the possibility for mass transfer during perturbation to be redistributed throughout the cloud system. For example, if a melting process is perturbed, there are far fewer processes for it to affect and therefore the likelihood those perturbations directly impact
surface rainfall increases. Conversely, if ice deposition is perturbed, the mass gained or lost is quickly dispersed throughout the cloud system meaning that many cloud processes are also affected, but the likelihood those small adjustments affect surface precipitation are small. However, the relatively large magnitude of IDEP counteracts this, meaning that the changes due to the mass gain/loss are more likely to affect the QPF field.

Only focusing on the perturbed process rate magnitude does not provide information about the relative impact of those perturbations on other cloud processes. At this point, it is illuminating to compare the ensemble spread of the process rates that occur the most frequently among all SPP ensembles (Fig. 4.19). By doing this, the process rates that have the greatest change in spread, and therefore the greatest sensitivity, when perturbing different process rates can be identified. It may be expected that perturbations to IDEP, SDEP, CRACCR, or SMELT would lead to the greatest relative change in spread among themselves, but this is not the case. RSCOLLECT-AF is the most affected by the perturbation choice, particularly when perturbing SMELT. Note that while RSCOLLECT-AF has the greatest spread among all process rates, this process is neither one of the four perturbed rates nor does it occur the most frequently within this storm system (i.e., ~600 count vs. >1000 count for IDEP). It is hypothesized that this response is due to nonlinear microphysical relationships; some of the perturbed rates impact RSCOLLECT-AF more than others, leading to a wide range of variability in this process (and others) that may extend to surface rainfall spread.

As mentioned in the previous paragraph, there are a handful of process rates (e.g., RSCOLLECT-AF, RGCOLLECT-AF, CCOND) that exhibit greater spread than those that are directly perturbed (Fig. 4.18, Fig. 4.19). There are physically plausible explanations for each of these that tie into the processes that are perturbed in each ensemble. RSCOLLECT-AF and RGCOLLECT-AF are both dependent on the fall speed of rain, as well as the fall speed of snow and graupel, respectively. Thus, any perturbation-led impacts to those fall speeds will directly alter RSCOLLECT-AF and RGCOLLECT-AF.

\[ \text{Process rate frequency is considered to be the grid point count where a process } > 10^{-8} \text{ g kg}^{-1} \text{ s}^{-1}. \]
It is seen from Fig. 4.19 that SPP$_{SMELT}$ leads to the greatest spread in $RSCOLLECT$-$AF$. Perturbations to $SMELT$ impact both snow and rain mass mixing ratios and number concentrations, thereby also altering both size distributions and ultimately both snow and rain fall speeds. With variability in both snow and rain, the impacts to the forecast spread of $RSCOLLECT$-$AF$ are appreciable. The remaining ensembles lead to a cluster of lesser $RSCOLLECT$-$AF$ spread, with impacts to snow from SPP$_{SDEP}$, rain from SPP$_{CRACCR}$, and ice from SPP$_{IDEP}$ (later impacting snow through autoconversion, snow-ice collection, etc.). Since each of these ensembles involves perturbations that only impact one hydrometeor class that $RSCOLLECT$-$AF$ is dependent upon, they return less spread. $RGCOLLECT$-$AF$ is very similar to $RSCOLLECT$-$AF$, but is instead dependent on rain and graupel fall speeds. $RGCOLLECT$-$AF$ has slightly lower rank than $RSCOLLECT$-$AF$ (Fig. 4.18) in all ensembles because graupel is forecast less frequently than snow (Fig. 4.20) and is not directly impacted by any of the four perturbed processes. Finally, $CCOND$ ranks highly across all ensembles due to the saturation adjustment, which occurs at the end of the microphysics calculations. The saturation adjustment depends on the saturation vapor pressure, which is a function of the ambient temperature, and available vapor to determine if cloud droplet evaporation or condensation is necessary to keep the environment in a balanced saturation state. Each perturbation explored herein directly impacts vapor mass ($IDEP$, $SDEP$) or latent heat release ($IDEP$, $SDEP$, $SMELT$), or instead indirectly impacts mass quantities that through subsequent processes cascade into changes to vapor mass or latent heat release ($CRACCR$). Also, since $CCOND$ spread is one of the greatest spread generators among all other process rates considered, it indicates the importance of the saturation adjustment when using stochastic perturbation methods, as there is considerable resultant variability that impacts vapor/cloud mass and phase-change induced temperature fluctuations. This highlights a physical advantage of using SPP instead of iSPPT$_{MP}$.

These natural relationships continue to clarify when analyzing the process rates in Fig. 4.19 with respect to the perturbed rate. In addition to $RSCOLLECT$-$AF$, $SEVAP$
is also strongly impacted by $SMELT$ perturbations, since the evaporation of melted snow ($SEVAP$) undergoes an increase in spread in $SPP_{SMELT}$ as $SMELT$ directly impacts the amount of melted snow available for evaporation. Other changes in process rate spread follow this line of reasoning, including the impacts of perturbing $IDEP$ on the sublimation of ice ($ISUB$) due to the change in available ice mass and vapor (Fig. 4.20) affecting ice supersaturation, and also on the change in rain mass due to ice-rain collection ($IRRCOLLECT$) through a change in ice mass available for that collection process. The relationships between the perturbed processes and remaining related process rates not yet touched upon can be reasoned out, but are not done so here for the sake of brevity. Finally, perturbations of a single process rate do not affect all other process rates equally. Even though a singular process may be incredibly active within a cloud system, it may not lead to considerable spread within the system due to a lack of related and cascading processes. Therefore, the web of relationships among these processes and their impacts on surface precipitation should be considered if perturbations to specific processes are to be made.

### 4.5.5 Differing Perturbation Impacts on Regions with Low- and High-End QPF

A byproduct of the low-pressure system tracking through NYS is the partitioning of roughly the western and eastern regions of NYS into the cold and warm sectors of the storm, respectively. One proxy for determining which sector each NYSM site resides is the altitude above ground level at which the time-averaged $0^\circ C$ isotherm is located (Fig. 4.21). NYSM site locations with forecasts that exceed the event-total QPF median (i.e., 86.5 mm in $SPP_{IDEP}$, 86.9 mm in $SPP_{SDEP}$, 86.3 mm in $SPP_{CRACCR}$, and 85.8 mm in $SPP_{SMELT}$) in each ensemble only occur where the freezing level is found above an altitude of approximately 2.4 km (Fig. 4.21). In contrast, forecasts below the QPF median have a wider distribution of freezing levels in each ensemble. Fig. 4.21 indicates that forecasts exceeding the median QPF more frequently occur in environments where the freezing level is at a higher altitude and thus are comprised of a relatively warm and vertically extended lower atmospheric layer. The deeper
layer where melting processes can occur can also support warm-rain processes, including increased rates of collision-coalescence. Unsurprisingly, sites with the lowest QPF spread are located in western NYS within the cold sector and those with the greatest are located in the Catskill Mountains and the southwestern Hudson Valley region (see Fig. 4.1b), within the warm sector (Fig. 4.8e–f). This warrants a closer look and comparison among such sites, to further elucidate the responses of the storm system to the specific microphysics perturbation. When it comes to QPF spread generation, the relationship between the perturbed process and other microphysics processes may become as important as the perturbed process itself, as touched upon in the previous section.

High-end QPF, and therefore QPF spread (based on the direct relationship seen in Fig. 4.16), only occurs in warmer regions of the synoptic storm whereas low-end amounts occur throughout the spectrum of environmental conditions within the low-pressure system. Due to these differences, it is of interest to identify if and how responses to the perturbed process rates change at sites with low-end and high-end QPF. Low-end QPF is defined as NYSM site locations that are forecast to receive < the NYSM site ensemble median QPF ($N_{sites} = 60$), and high-end QPF includes locations forecast to receive > the NYSM site median QPF ($N_{sites} = 60$). In each ensemble, the sites with low- and high-end QPF are shown using square and circle markers in Fig. 4.8e–h, respectively.

There is particular interest in answering the following question: do perturbations to certain process rates lead to a relatively enhanced forecast response (e.g., enhanced spread) in either the low- or high-end forecast group? To address this question, Fig. 4.22 compares the distribution of QPF spread in the low- and high-end forecast groups for all four ensembles normalized by the total number of counts and the bin-width of 2 mm, which allows for both comparison between groups and among ensembles. The low-end QPF group includes spread frequency maxima between 0 and 6 mm, with varied breadths of spread distribution. SPP$_{IDEP}$ and SPP$_{CRACCR}$ both provide the greatest median spread in the low-end QPF group, indicating that perturbations to $IDEP$ and $CRACCR$ return the greatest QPF.
spread where low-end precipitation occurs. As \textit{SPP}_{DEP} has an extended tail of low-end group QPF spread to 18 mm, it is the only ensemble that matches the extrema of its high-end QPF group. Spread distributions associated with high-end QPF are fairly similar in terms of the range and most frequent spread values, but the extension of the low-end QPF spread distribution in \textit{SPP}_{DEP} signals the sensitivity of precipitation processes in those regions to the ice deposition process. In contrast, the majority of the low-end QPF spread occur at lower magnitudes in \textit{SPP}_{SMELT} as indicated by the lower median, which suggests a relative insensitivity to the melting of snow near the included sites. The associated decrease in spread in the low-end group and spread in the high-end group that is similar to the other ensembles results in an inflated difference between the two groups. Without comparing the low- and high-end spread distributions, a greater difference between the medians would lead to a faulty conclusion that the QPF spread distribution is more sensitive to perturbation of \textit{SMELT} in the high-end group. In reality, this is not true since the larger change is driven by the decrease in spread in the low-end group. This is why it is necessary to not only assess the spread differences between these two QPF groups, but also carefully analyze the differences in these distributions so proper conclusions are drawn. Perturbations to \textit{SDEP} lead to the greatest increase in spread relative to the low-end group simply due to suppressed spread in the low-end group.

To elucidate why these two groups respond differently to the perturbation of specific process rates, attention is focused on process rate spread in four groups: creation, growth, decay, and melting. Creation includes ice nucleation, cloud condensation, rime splintering, and ice-ice aggregation. Growth includes accretion, deposition, condensation, and collection processes. Decay includes evaporation and sublimation processes. Finally, melting includes ice, snow, and graupel melting processes. Fig. 4.23 shows the total spread (e.g., the sum of all process rate spreads in each respective group) in each of these major processes broken down into the low- and high-end QPF groups for each individual ensemble. Each ensemble demonstrates an overall increase in spread moving from the low- to high-end group in creation,
growth, decay, and melting processes. This increase in growth process spread is to be expected as the multiplicative perturbation is applied to the relatively greater hydrometeor growth processes within the high-end QPF group (Fig. 4.24). As mentioned previously, the theme continues where a linear relationship exists between QPF and QPF spread. This is clear here as well in two ways: (1) high-end QPF results in a higher spread for each ensemble relative to its low-end counterpart; (2) the frequency at which growth occurs is greater than creation, decay, and melting processes, and thus a larger spread occurs for growth processes (not shown). There are slight spread increases in the decay process group due to a thicker sub-cloud layer supporting evaporation and sublimation (not shown); also, negative perturbations are applied to negative processes, enhancing decay in subsaturated regions. Some ensembles involve larger changes between the QPF groups than others. For example, within the melting process the difference is larger in $\text{SPP}_{\text{SDEP}}$ than it is in $\text{SPP}_{\text{SMELT}}$. This suggests that even when directly perturbing $\text{SMELT}$, a similar spread response in the melting process group is seen throughout all NYSM sites.

Finally, specific rates leading to these process rate group differences can be identified by comparing the change in process rate magnitude and the change in its associated spread between the low- and high-end QPF groups. If a relationship is identified, then the perturbed process rate will affect the forecasts of the two groups unevenly. However, if no relationship is found then the perturbed process rate will affect the forecast of both groups to a similar degree. To clarify, we want to identify if an increase in any process rate magnitude leads to an increase in the forecast spread of that process rate, as has been the general observed trend throughout. Figure 4.25 directly compares the change in the ensemble mean temporal and column sum of a process rate to the change in its associated forecast spread for each process rate and ensemble included in the grouped analysis in Figures 4.23 and 4.24. The figure is divided into four sections, including an increase in both process rate sum and spread (Quadrant 1), a decrease in sum and an increase in spread (Quadrant 2), a decrease in both sum and spread (Quadrant 3), and an increase in sum and decrease in spread (Quadrant 4).
4). When a process rate is in Quadrant 1 or 4, its overall magnitude increases within the high-end QPF group and increases or decreases in spread (e.g., uncertainty), respectively. A process rate in Quadrant 4 indicates that although the process rate has increased in the high-end group, the uncertainty of that process has diminished. This could potentially lead to a lessened impact on the overall QPF uncertainty. Process rates in Quadrants 2 or 3 indicate a decreased magnitude in the high-end QPF group, with increased or decreased uncertainty, respectively. A decrease in process rate magnitude coupled with an increase in uncertainty suggests that such a process rate can still be an important spread generator in the high-end QPF group even though it experienced a magnitude reduction. A process rate in Quadrants 1 or 3 indicates that its change in uncertainty is related to its change in magnitude. Finally, a process rate in one SPP ensemble may not be clustered into a single quadrant, as seen with SSUB (Fig. 4.25, Quadrants 2 & 3). When this occurs, it indicates that such a process is particularly sensitive to the microphysics process rate perturbed in each ensemble, resulting in a change of magnitude, sign, or both.

All process rates except IMELT, SSUB, ISUB, and RSRIME (but only for SPP\textsubscript{IDEF}) noticeably increase in magnitude within the high-end QPF group (Fig. 4.25, Quadrants 1 and 4). The decrease in magnitude of SSUB and ISUB in Fig. 4.25 (Quadrant 2) likely drives the decrease in magnitude of overall decay processes as seen in Fig. 4.24. Melting process magnitudes increase slightly in the high-end group (Fig. 4.24); the increase is driven by the melting of graupel (GMELT) and SMELT (Quadrant 1) and is only marginally suppressed by the decrease in IMELT (Quadrant 2). While the greatest process rate sums are within the melting group (Fig. 4.24) as all precipitating frozen hydrometeors melt before reaching the surface as rain, the greatest spread is within the growth group (Fig. 4.23) due to numerous growth processes happening more frequently than a handful of melting processes (not shown). The general increase among the remaining process rates (Quadrant 1) in Fig. 4.25 conceptually makes sense, as the increased precipitation forecasts comprising the high-end group need to physically emanate from enhanced process rates. Relating these magnitude changes to spread
changes becomes complex as the four ensembles and their associated perturbations lead to varied differences. The spread change is most frequently found to be positive, but this is not the case in some ensembles, such as SPP$_{IDEP}$ and SPP$_{CRACCR}$ (Fig. 4.25, Quadrant 3). For specific processes, the spread from each ensemble is incredibly sensitive to the perturbed process rate. At times, there is a difference between the sign of the spread change, where SPP$_{SMELT}$ exclusively results in an increase in spread for all process rates regardless of the change in magnitude whereas the other ensembles lead to mostly increased but sometimes varying amounts of decreased spread. Again, this type of response points to the process rate magnitude and/or spread sensitivity to the perturbed rate. Overall, perturbations to IDEP, SDEP, CRACCR, or SMELT lead to increased spread in a majority of process rates, especially when perturbing SMELT. Even though the other ensembles (SPP$_{IDEP}$, SPP$_{SDEP}$, SPP$_{CRACCR}$) do not always lead to increased process rate spread in the high-end group as some processes in those ensembles (e.g., SSUB, CFRZ, CEVAP, SMELT, etc.) are in Quadrants 3 and/or 4 (Fig. 4.25), their total resultant in-cloud process rate spread may exceed that of SPP$_{SMELT}$ as the decreases in spread are isolated to a handful of processes and are small ($< -10^{-3}$) relative to the spread increases. As has been the major takeaway from this analysis of the October 2017 case, perturbing a leading process rate does not result in maximum spread in the cloud system or at the surface due to complex relationships that may compound over time.

### 4.6 Additional Case Studies

The findings from the October 2017 case are likely to change for other weather events and even similar cases due to the dependence on the thermodynamic profile and spatial scale of the precipitating system. Furthermore, the differences in the role of microphysics between synoptic and mesoscale (e.g., a lake-effect storm) storms need to be determined. The ensemble investigations and microphysical analyses are applied to two additional cases that are both lake-effect storms. The first is the 15–16 December 2013 case, and extends the in-depth
The methodology used in each lake-effect case is identical to that in section 4.5, with the exception of ensemble verification of the December 2013 case since the NYSM was not yet installed during the OWLeS field campaign. As such, comparative analyses to these data are not possible and therefore are not included. However, there is still value in keeping the non-verification analysis methods introduced in section 4.5 as these simply use the locations of the NYSM sites. The stochastic pattern tuning experiments were not repeated for either of the lake-effect cases, which is standard practice given the computational resources required for tuning experiments (Lupo et al. 2020).

Analogous to OWLeS IOP4, lake-effect precipitation was observed downwind of Lakes Ontario and Erie on 15–16 December 2017. A shortwave trough north of Lakes Ontario and Erie reoriented the southwesterly near-surface winds to westerly and parallel to the long fetch of the lake, providing one of the necessary ingredients for spurring organized lake-effect convection. In the 2017 case, the LES lifetime was about 36 hours long, exceeding the 2013 case by approximately 12 hours. Atmospheric profiles from radiosondes launched at the Buffalo, NY weather forecasting office are provided for this event in Fig. 4.26d–f for the sake of analysis and comparison to the December 2013 case (Fig. 4.26a–c). The capping inversion lifted from roughly 700 hPa at 0000 UTC to 600 hPa at 1200 UTC in the 2017 case (Fig. 4.26d, f), potentially allowing for thicker LES clouds, which likely supported increased in-cloud
microphysics processes. Even with higher cloud tops, the temperatures near cloud-top ranged similarly between $-25$ to $-20^\circ C$ (Fig. 4.26b,c,e,f), thereby likely supporting similar rates of cold-cloud processes, such as heterogeneous ice nucleation. Finally, near-surface winds veer with height during 1200 UTC 15 December and 0000 UTC 16 December, but eventually become uniformly westerly with height by 1200 UTC 16 December.

Without the hyper-focus downwind of Lake Ontario, as was the case in Chapters 2 and 3, it is now evident that widespread precipitation was forecast downwind of both Lake Ontario and Lake Erie during the December 2013 event (Fig. 4.27). Splitting up the NYSM site location forecasts into the low- (< median, squares) and high-end (> median, circles) groups allows for a refined focus on precipitation that is most likely related to lake-effect processes and not other lingering synoptic or mesoscale precipitating features. Within the December 2013 case, almost all of the locations with negligible (0–1 mm) QPF are within the low-end group (Fig. 4.27a–d). However, in the December 2017 case, this no longer holds; low-end precipitation involves QPF values up to approximately 3 mm (Fig. 4.27e–h). The > QPF median group within this case includes QPF that more frequently surpasses that of December 2013 (Fig. 4.27, 4.28). There is extension of the precipitation forecast in the Hudson Valley and Long Island in the 2017 case that was associated with an offshore low-pressure system tracking along the eastern seaboard. While the QPF at these locations is not associated with the lake-effect systems, they are minimal compared to the site locations forecasting lake-effect precipitation (2–4 mm, Fig. 4.27e–h) and the associated precipitation occurs for a much shorter duration, on the order of a few hours (not shown). As such, these site locations will continue to be included in the forthcoming analysis that compares and contrasts the perturbation response in the low- and high-end QPF groups.

The QPF distributions in the control simulation of both cases indicate that precipitation is highly concentrated in the low-end, ranging from 0–3 mm in December 2013 and 0–5 mm in December 2017 (Fig. 4.28). High-end QPFs extend to a maximum of no more than 13 (Fig. 4.28a) and 15 mm (Fig. 4.28b). The median QPF in both cases is a strong indicator
of the high frequency of low-end QPF, as it is 0.78 mm in December 2013 and 2.09 mm in December 2017. As indicated by Fig. 4.27, separating these distributions into the low- and high-end QPF groups allows for a rough distinction between non lake-effect and lake-effect precipitation, respectively. This allows for better isolation of which process perturbations truly lead to forecast uncertainty in lake-effect precipitation later in this section.

The top four most active process rates in both December cases were identified to be ice deposition (IDEP), snow deposition (SDEP), cloud condensation (CCOND), and accretion of cloud droplets by snow (CSSRIME). For reference, each of these is listed in Table 4.7. 15-member ensembles were run with SPP applied to IDEP, SDEP, CCOND, and CSSRIME resulting in a total of 4 ensembles for each December case. Table 4.8 provides a snapshot of the ensemble performance for the December 2017 storm, as compared to the NYSM total precipitation observations. Installation of the NYSM began in 2014, and so the 2013 event was excluded from this analysis. On average, the ensembles now exhibit a slight dry bias ranging from $-1.37$ to $-0.97$ mm, in contrast to the wet bias in the October case. However, the ensembles do still include a range of biases, with minimum and maximum absolute biases of $-17.1$ to $-16.1$ mm and $11.0-13.9$ mm, respectively. Overall, the error statistics for this lake-effect case are reduced, on average, compared to those for the October case likely due to lessened overall precipitation amounts.

QPF spread in both of the lake-effect events (Fig. 4.29) is drastically reduced compared to the October 2017 event (Fig. 4.8e–f). In both December cases, SPP$_{IDEP}$ forecasts the greatest spread of 1 mm in 2013 and up to 2 mm in 2017 at site locations close to Lake Ontario and Lake Erie (Fig. 4.29a,e), where the remaining ensembles also forecast spread, but to a lesser degree. This indicates that perturbing IDEP is once again the most optimal method to spur QPF uncertainty, even more-so in these lake-effect cases. The remaining ensembles involve lesser spread that is confined downwind of the lakes and at the site locations within QPF $>\text{median}$. While spread magnitude is an important quantity, the location where the most considerable spread is in the forecast domain is also of importance. While sites
with the greatest spread are directly downwind of the aforementioned lakes and common to all ensembles, some site locations with the greatest uncertainty shift to southeastern NYS, including Long Island. The Long Island sites are associated with precipitation from a synoptic system exiting eastern NY coinciding with the onset of the lake-effect systems and so are disregarded as unaffiliated with the case study. In the December 2017 case, there is less forecast uncertainty dependence on the perturbed rate downwind of Lake Ontario whereas the opposite is true downwind of Lake Erie. Even when minimal, the location of the spread remains forecast where lake-effect precipitation is expected downwind of Lakes Ontario and Erie.

The QPF spread emanating from each ensemble in the December cases is also shown in Fig. 4.30. Once again immediately evident is how the lake-effect systems respond to IDEP perturbations; this is in stark contrast to the very similar forecast spread responses of the October 2017 case to all process rate perturbations. Clearly, SPP\textsubscript{IDEP} leads to more frequent spread that is in the right-most tails of the other ensemble spread distributions. This indicates that IDEP is an important process in both cases, due to its magnitude, indirect impacts on other process rates, or a combination of both. Meanwhile, the other process rate perturbations lead to spread that is highly concentrated in the 0–0.1 mm (Fig. 4.30a) and 0–0.25 mm range (Fig. 4.30b) in December 2013 and December 2017, respectively. In both cases, SPP\textsubscript{SDEP} and SPP\textsubscript{CSSRIME} lead to the highest relative frequency in this range, while SPP\textsubscript{CCOND} has a lower frequency, with increasing instances of larger spread, particularly when QPF spread > 0.2 mm. Overall, perturbations to IDEP lead to greater QPF spread magnitudes that elicit a considerably different response from the LES cloud system.

When relating process rate magnitude to its associated QPF spread in Fig. 4.31 for both lake-effect cases, a greater sum is related to a greater relative average QPF spread in SPP\textsubscript{IDEP} and SPP\textsubscript{SDEP}, but not SPP\textsubscript{CCOND} and SPP\textsubscript{CSSRIME}. This suggests that although CSSRIME is the fourth most active process within both lake-effect systems, other cascading processes lead to greater forecast spread than perturbing CCOND, which is approximately
three (one) orders of magnitude greater than CSSRIME in December 2013 (2017). It is interesting that this response is consistent for both cases, especially since the difference between the CCOND and CSSRIME magnitudes between the cases are considerable. Recall that this result of process rate magnitude not directly corresponding to QPF spread was also found in the October 2017 case (Fig. 4.14). Additional insight into why perturbing a relatively less active process rate would lead to more QPF spread may be found when investigating the relationships between these and other process rates in the cloud system.

Fig. 4.32 shows process rate spreads for both lake-effect cases and their fluctuation when perturbing different process rates. There are only minimal changes in the top spread rankings, with deposition of ice and snow (IDEP, SDEP) remaining within the top four spread-producing process rates regardless of the perturbed rate, somewhat similar to how RSCOLLECT-AF and CCOND remained as the top ranking spread sources in October 2017 (Fig. 4.18). Unlike the October case, SPP_{IDEP} led to IDEP producing the greatest amount of spread in both lake-effect cases, and in the December 2017 case SPP_{SDEP} produces the top ranking spread from SDEP. This shift in spread importance suggests that these lake-effect cloud systems are more sensitive to changes in ice and snow deposition. This is not a surprise, due to the considerable body of research on the effect of nonspherical ice growth on ice deposition rates, which in turn impacts cloud lifetime, radiative effects, and precipitation (as in Ervens et al. 2011; Harrington et al. 2013b; Sulia et al. 2013, 2014; Gaudet et al. 2019; Sterzinger and Igel 2021). Due to this, attention should continue to be paid to ice-phase hydrometeor growth through vapor deposition in numerical simulations of cold clouds.

As may be garnered from Fig. 4.30, SPP_{IDEP} also leads to greater spread percentages (Fig. 4.33). Additionally, the relationship between total QPF and the associated spread (represented as a percentage of the QPF in Fig. 4.33) no longer increases with QPF, as was the response in the October 2017 case. Rather, the spread percentage is the greatest in low-end QPF (<4 mm), signaling that perturbations to all of the tested process rates lead to the greatest relative change in low-end QPF. There is particular interest in the inflation of
spread percentage for SPP_{IDEP}, compared to the remaining ensemble; the spread percentages are roughly double those in the other ensembles across the QPF range. This increase is indicative that perturbations to IDEP spur QPF uncertainty unseen when perturbing SDEP, CCOND, or CSSRIME. This is likely directly related to the relationship drawn from Fig. 4.31 for the December cases: the greatest QPF spread is produced when perturbing the cloud process with the greatest overall magnitude, IDEP.

Similar to the October case analysis, it is of interest to understand how perturbations affect areas with low- and high-end QPF, with each group defined using the median QPF in each ensemble. These groupings result in different QPF distributions due to varying spatial coverage of the LES precipitation in the December 2013 and 2017 cases, as was touched upon earlier in this section. Similar to the October 2017 analysis, processes are grouped into creation, growth, decay, and melting so that they can be easily compared between the low- and high-end groups (Fig. 4.34). The spread associated with the growth of hydrometeors in both cases is greater within the high-end group in all SPP ensembles, but especially when perturbing IDEP in both December 2013 and 2017 and SDEP in December 2017 (Fig. 4.34). As lake-effect processes tend to be dominated by cold-cloud processes, it is not a coincidence that perturbations to deposition onto ice-phase hydrometeors have a strong impact on forecast spread as compared to perturbations to CCOND or CSSRIME in December 2013 (Fig. 4.34a). There are more considerable spread increases in the high-end group when perturbing CCOND and CSSRIME in the December 2017 case, but they are still lesser than perturbing the deposition processes (Fig. 4.34b). Spread within decay processes is not markedly notable in the December 2013 case, which indicates that decay processes may not occur often or at a large magnitude within either group. Differences in decay processes are more pronounced in December 2017, with spread increasing for all perturbations. Finally, creation and melting spread does not exist at the magnitudes analyzed in Fig. 4.34 in either group for the December 2013 case and melting is only barely visible for the high-end group in December 2017, while creation differences are similar to those in the
decay group in December 2013. Even though the creation and melting group spread do not appear for either or both December cases, the spread from melting processes may still exist at a lesser magnitude than the spread generated from growth or decay.

Lastly, it is illuminating to compare how the magnitude and spread of each process rate changes when moving from the low- to high-end group (Fig. 4.35). Similar to October 2017 (Fig. 4.25), the majority of the process rates increase in both magnitude and spread in the December 2013 case (Fig. 4.35a). In this case, IMELT, REVAP, IRRSCOLLIS, ISUB (except for in SPP_CCOND), and IDEP (only in SPP_CSSRIME) undergo a decrease in spread within the high-end group while also generally experiencing a decrease in magnitude (except for ISUB and IDEP). In contrast, the process rates that underwent the greatest increase in magnitude and spread were IDEP (all ensembles except SPP_IDEP) and SDEP (Fig. 4.25a), which is not surprising considering these are within the top four sources of spread as was seen in Fig. 4.32a. Once again, perturbations to a specific process rate within the high-end group do not consistently lead to an increased amount of spread. In December 2017, the relationship between the change in process rate magnitude and spread within the high-end group shifts closer to what would be expected of a multiplicative perturbation: an increase in process rate magnitude is associated with an increase in process rate spread (Fig. 4.25b). Now, CFRZ experiences a decrease in both magnitude and spread in Quadrant 3 while INUC (in SPP_CCOND and SPP_CSSRIME) and ISUB (SPP_IDEP) increase in magnitude but decrease in spread within Quadrant 4. The most appreciable change in both magnitude and spread comes from IDEP and SDEP, which again is not unanticipated when recalling that these process rates are in the top three spread producers for the December 2017 case (Fig. 4.32b). Both December cases differ from the October 2017 case in that there are no process rates that noticeably reside in Quadrant 2, meaning that when the SPP ensemble methods are applied to lake-effect cases, a decrease in process rate magnitude where high-end precipitation is expected will not be associated with an increase in its uncertainty. However, both December cases have a similar response to the October 2017 case in that some processes
show sensitivity (demonstrated through a change in quadrant) to the ensemble perturbation used (e.g., ISUB of SPP$_{DEP}$ in Quadrant 4 compared to ISUB of SPP$_{COND}$ in Quadrant 1, Fig. 4.35a,b). In summary, this analysis exemplifies that changes in process rate magnitude and its spread are not always directly related and perturbations to specific process rates may lead to indirect relationships (e.g., when processes are in quadrant 2 or 4).

4.7 Summary

The impact of microphysics on forecast uncertainty is explored through stochastic perturbations to microphysics process rates. The aim of this research is to identify sensitivities (informing on future work) for various weather events that affect NYS, thereby elucidating the predictability of such high-impact weather due to microphysics. To do so, the following methodology was employed: SPP was introduced into the AHM (and WRFv3.7.1), a 3-moment microphysics scheme that tracks the non-spherical growth and evolution of ice crystals, to allow for stochastic perturbations to individual microphysics process rates, such as deposition of vapor onto ice crystals. The major focus of this work was placed on a synoptic rainstorm affecting NYS from 29–30 October 2017. SPP was applied to the microphysics process rates that were identified to be the most actively affecting the cloud system. The most active process rates in the October 2017 storm were deposition of vapor onto ice (IDEP) and snow (SDEP), accretion of droplets by rain (CRACCR), and the melting of snow (SMELT).

Nine tuning experiments involving five ensemble members each were conducted to determine the stochastic pattern parameter combinations that produce the greatest amount of physical forecast spread. Through these experiments, decreasing the length scale along with increasing the amplitude and time scale led to the greatest spread. As such, SPP ensembles with 15 members each were created by perturbing each of these four process rates using this specific parameter set. To understand how the characteristics of these ensembles differed from more common techniques accounting for forecast uncertainty, these ensembles were then compared to those accounting for initial and boundary condition uncertainty (IC/BC),
independent stochastic perturbed parameterization tendencies (iSPPT), and a combination of IC/BC with iSPPT and SPP_{IDEP}. Through metrics derived from rank histograms and relative operating characteristic (ROC) curves, it was found that forecast spread and reliability are hindered when applying SPP to microphysics process rates as the sole method of uncertainty. Overall, SPP ensemble forecasts were found to be skillful but underdispersive.

While building ensembles with the greatest forecast skill, reliability, and precision is certainly necessary for operational activities, the work presented herein more-so applies the SPP methodology to microphysical processes that contribute most substantially to heavy precipitation events in order to assess (1) the impacts on individual microphysical processes and (2) the associated sensitivity to those perturbations. However, there is value in including a suite of verification metrics to build a high-level understanding of ensemble performance. As such, an in-depth verification of the SPP ensembles followed using observational data from the NYSM. An analysis of rain rate bias found that high-end precipitation almost always resulted in a wet-bias whereas low-end precipitation varied between a wet and dry bias. When comparing event-total observations of rainfall to the 99th percentile QPF, the wet bias was evident at a majority of NYSM sites. A similar comparison between observations and ensemble mean forecasts of 2-m temperature indicated a pervasive warm-bias. The accuracy of each SPP ensemble as assessed by the Brier score generally declined at increasing QPF thresholds. The area under the ROC curve (AUC) was applied using specified rain rate thresholds and indicated less than desirable skill (AUC<0.7) during the beginning of the event, but increasing skill at all tested thresholds as the event continued. Finally, observations and ensemble member forecasts of precipitable water (PWAT) were compared at the three radiosonde launch sites in NYS, indicating the ability of the ensembles to capture the magnitude and evolution of available moisture during the simulation.

The impact of applying SPP to microphysics process rates on the precipitation forecast was then explored. Distributions of QPF spread for each SPP ensemble showed relatively similar distributions, with a longer tail to greater spread from SPP_{IDEP}. Furthermore, spread
generally increased as QPF increased, although at greater magnitudes in the 0-50 mm range within SPP\textsubscript{IDEP}, when compared to the other ensembles. The importance of the perturbed process rate in the cloud system was approximated through its magnitude throughout the event and was compared to the QPF spread generated in each ensemble. Interestingly, when comparing process rate magnitudes to each other, the associated QPF spread does not fall in the same sequential order due to complex relationships among the process rates in the cloud system. As such, perturbations to the most active process may not consistently lead to the greatest QPF spread, implying that these more active processes are not necessarily as sensitive to perturbation as processes that contribute less significantly to the system.

The response of the other microphysics processes to these SPP perturbations was investigated through comparison of process rate spread among the SPP ensembles and the different responses and relationships that exist between the perturbed process rates and the remaining process rates. All perturbations led to spread among the other process rates, but the greatest source of spread was never associated with the process rate that was directly perturbed; instead, the unperturbed \textit{RSCOLLECT-AF} was consistently the greatest source of spread. Despite this, clear and different spread relationships among the process rates developed from perturbing \textit{IDEP}, \textit{SDEP}, \textit{CRACCR}, and \textit{SMELT}. No clear trend emerged in the perturbed process rate and the resulting spread among all microphysical processes, indicating the complexities in microphysics and the compounding interactions among processes.

While no predictable trends emerged among perturbed processes, investigations continue to determine any trends in the resultant QPF due to process perturbations. Inspired by the clustering of the greatest QPF at locations with the highest freezing level, the dependence of process rate perturbation response to QPF amount and thereby also spatial location was explored through grouped analyses of process rates. The greatest difference in process rate spread between the low- and high-end QPF groups was associated with hydrometeor growth processes, specifically when perturbing \textit{IDEP}. However, regardless of which process was
perturbed, IDEP returned the greatest change in magnitude and spread when moving from the low- to high-end QPF group. This signifies that regardless of the four process rates that are perturbed, IDEP is affected similarly and as such remains as the most sensitive rate in the high-end group.

Curious if the responses and relationships identified and explored in the October 2017 rainstorm would hold true in other weather events, the SPP methodology and analysis was applied to lake-effect storms that impacted areas downwind of Lakes Erie and Ontario during 15–16 December 2013 and 15–16 December 2017. Each had similar QPF, albeit slightly greater in December 2017. As the environmental and thermodynamic conditions within which these storms formed were similar, they shared the same four most active process rates: IDEP, SDEP, CCOND, and CSACCR. The spread of each ensemble forecast was focused downwind of both lakes and was greatest in SPP_{IDEP} for both cases. Diverging from the October case, IDEP returned the greatest spread when it was directly perturbed in both cases, a more predictable trend. SDEP similarly returned the greatest spread when directly perturbed, but only in the December 2017 case. These results indicate not only the significance of vapor deposition to LES (in contrast to the October 2017 case) but also the considerable uncertainty that exists in the prediction of vapor deposition, as has been previously shown by the literature.

The LES simulations similarly divert from the October 2017 case in the trend in QPF spread relative to QPF magnitude. The greatest QPF spread was attributed to magnitude ranges 0–2.5 mm in December 2013 and 0–5 mm in December 2017, decreasing as QPF magnitudes increase. This is contradictory to the relationship between spread and QPF identified in October 2017, in which the percentage of spread increased along with QPF, meaning that the uncertainty range of QPF increased along with QPF. Beyond QPF, when performing analyses on microphysical processes clustered into low- and high-end QPF groups, growth and decay processes generally had greater spread in the high-end group. The change in the process magnitude and spread differed between the two December cases; while there
was a general increase in spread with magnitude, December 2013 included a number of
decreases in both magnitude and spread within the high-end group. These decreases were
related to ice melt and rain processes that were less prevalent where the LES precipitation
was occurring. Irrespective of the perturbed process rate, IDEP generally saw the greatest
change in magnitude and spread in both cases.

Within this work, it was found that stochastic perturbations to microphysics processes
inject a considerably minor amount of uncertainty in an ensemble precipitation forecast, as
compared to IC/BC ensembles. This is due to many factors, the most dominant including
the small magnitude of the process rates and the perturbation only affecting these quantities
when they are nonzero. The resultant forecast spread emanates from cascading impacts of
the original perturbation to directly and indirectly related process rates. These relationships
were muddled at times, but through analysis of process rate spread and how that changed
among the ensembles, clear impacts were identified, such as those of ice deposition in all
three cases. This final research has demonstrated the ever complex microphysical interactions
within and among both synoptic and mesoscale weather events, once again shining a light on
the importance of ice microphysical processes to forecast uncertainty.
### 4.8 Tables

<table>
<thead>
<tr>
<th>Physical Process</th>
<th>Scheme</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Longwave Radiation</td>
<td>RRTMG</td>
<td>Iacono et al. (2008)</td>
</tr>
<tr>
<td>Shortwave Radiation</td>
<td>Dudhia</td>
<td>Dudhia (1989)</td>
</tr>
<tr>
<td>Boundary Layer</td>
<td>YSU</td>
<td>Hong and Noh (2006a)</td>
</tr>
<tr>
<td>Cumulus (Only D01)</td>
<td>Kain-Fritsch</td>
<td>Kain (2003)</td>
</tr>
</tbody>
</table>

Table 4.1: Reference table of the physical scheme setup for WRF simulations.
<table>
<thead>
<tr>
<th>Rate</th>
<th>Description</th>
<th>Affected Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>IDEP</td>
<td>Ice deposition</td>
<td>ice/vapor</td>
</tr>
<tr>
<td>SDEP</td>
<td>Snow deposition</td>
<td>snow/vapor</td>
</tr>
<tr>
<td>CRACCR</td>
<td>Accretion of droplets by rain</td>
<td>rain/cloud</td>
</tr>
<tr>
<td>SMELT</td>
<td>Melting of snow</td>
<td>snow/rain</td>
</tr>
</tbody>
</table>

Table 4.2: Table of the process rates perturbed individually in the AHM along with the hydrometeor categories they directly add to and detract from.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Label</th>
<th>Amplitude</th>
<th>Lengthscale (km)</th>
<th>Timescale (s)</th>
<th>% of observations in forecast bounds</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>REF</td>
<td>0.35</td>
<td>150</td>
<td>3600</td>
<td>24.6</td>
</tr>
<tr>
<td>2</td>
<td>A0.3</td>
<td>0.3</td>
<td>150</td>
<td>3600</td>
<td>24.1</td>
</tr>
<tr>
<td>3</td>
<td>A0.4</td>
<td>0.4</td>
<td>150</td>
<td>3600</td>
<td>25.8</td>
</tr>
<tr>
<td>4</td>
<td>L45km</td>
<td>0.35</td>
<td>45</td>
<td>3600</td>
<td>24.9</td>
</tr>
<tr>
<td>5</td>
<td>L500km</td>
<td>0.35</td>
<td>500</td>
<td>3600</td>
<td>24.0</td>
</tr>
<tr>
<td>6</td>
<td>T900s</td>
<td>0.35</td>
<td>150</td>
<td>900</td>
<td>23.4</td>
</tr>
<tr>
<td>7</td>
<td>T21600s</td>
<td>0.35</td>
<td>150</td>
<td>21600</td>
<td>24.9</td>
</tr>
<tr>
<td>8</td>
<td>IAT</td>
<td>0.4</td>
<td>150</td>
<td>21600</td>
<td>25.4</td>
</tr>
<tr>
<td>9</td>
<td>IATDL</td>
<td>0.4</td>
<td>45</td>
<td>21600</td>
<td>26.5</td>
</tr>
</tbody>
</table>

Table 4.3: Table of all tuning experiments run for SPP\textsubscript{IDEP}. The combinations of amplitude, lengthscale (km), and timescale (s) autocorrelation parameters are provided for each experiment along with the percentage of observations that are within the forecast bounds, as assessed by a rank histogram.
### Rank Histogram

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Percentage of observations in forecast range</th>
<th>Percentage of observations below forecast range</th>
<th>Percentage of observations above forecast range</th>
</tr>
</thead>
<tbody>
<tr>
<td>IC/BC</td>
<td>70.9</td>
<td>21.4</td>
<td>7.7</td>
</tr>
<tr>
<td>IC/BC_{iSPPT_{MP}}</td>
<td>74.4</td>
<td>21.6</td>
<td>4.0</td>
</tr>
<tr>
<td>IC/BC_{SPP_{IDEP}}</td>
<td>70.7</td>
<td>21.3</td>
<td>8.0</td>
</tr>
<tr>
<td>iSPPT_{MP}</td>
<td>52.9</td>
<td>35.6</td>
<td>11.5</td>
</tr>
<tr>
<td>SPP_{IDEAEP}</td>
<td>37.8</td>
<td>39.8</td>
<td>22.4</td>
</tr>
<tr>
<td>SPP_{SDEP}</td>
<td>34.7</td>
<td>42.0</td>
<td>23.3</td>
</tr>
<tr>
<td>SPP_{CRACCR}</td>
<td>35.4</td>
<td>41.9</td>
<td>22.8</td>
</tr>
<tr>
<td>SPP_{SMELT}</td>
<td>33.5</td>
<td>42.6</td>
<td>23.9</td>
</tr>
</tbody>
</table>

Table 4.4: Statistics derived from a rank histogram of hourly QPF forecasts created for each ensemble experiment.

### Area Under the ROC Curve

<table>
<thead>
<tr>
<th>Experiment</th>
<th>2.5 mm hr^{-1}</th>
<th>5.0 mm hr^{-1}</th>
<th>7.5 mm hr^{-1}</th>
</tr>
</thead>
<tbody>
<tr>
<td>IC/BC</td>
<td>0.72</td>
<td>0.68</td>
<td>0.71</td>
</tr>
<tr>
<td>IC/BC_{iSPPT_{MP}}</td>
<td>0.75</td>
<td>0.69</td>
<td>0.72</td>
</tr>
<tr>
<td>IC/BC_{SPP_{IDEP}}</td>
<td>0.70</td>
<td>0.70</td>
<td>0.69</td>
</tr>
<tr>
<td>iSPPT_{MP}</td>
<td>0.78</td>
<td>0.75</td>
<td>0.77</td>
</tr>
<tr>
<td>SPP_{IDEAEP}</td>
<td>0.72</td>
<td>0.68</td>
<td>0.71</td>
</tr>
<tr>
<td>SPP_{SDEP}</td>
<td>0.72</td>
<td>0.67</td>
<td>0.69</td>
</tr>
<tr>
<td>SPP_{CRACCR}</td>
<td>0.72</td>
<td>0.66</td>
<td>0.70</td>
</tr>
<tr>
<td>SPP_{SMELT}</td>
<td>0.72</td>
<td>0.67</td>
<td>0.71</td>
</tr>
</tbody>
</table>

Table 4.5: Area under the ROC curve averaged during the time period of 00 UTC 29 October – 18 UTC 30 October 2017 for multiple rain rate thresholds.

### October 2017

<table>
<thead>
<tr>
<th>Perturbed Process Rate</th>
<th>Average Bias (mm)</th>
<th>Min/Max Bias (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IDEP</td>
<td>24.0</td>
<td>-38.2/90.5</td>
</tr>
<tr>
<td>SDEP</td>
<td>24.6</td>
<td>-34.4/98.7</td>
</tr>
<tr>
<td>CRACCR</td>
<td>25.3</td>
<td>-36.5/96.3</td>
</tr>
<tr>
<td>SMELT</td>
<td>23.4</td>
<td>-35.7/93.8</td>
</tr>
</tbody>
</table>

Table 4.6: Average bias of the event-total 99th percentile QPF, relative to NYSM observations, and averaged over the 120 NYSM sites. The minimum and maximum biases within each ensemble are also included.
<table>
<thead>
<tr>
<th>Rate</th>
<th>Description</th>
<th>Affected Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>IDEP</td>
<td>Ice deposition</td>
<td>ice/vapor</td>
</tr>
<tr>
<td>SDEP</td>
<td>Snow deposition</td>
<td>snow/vapor</td>
</tr>
<tr>
<td>CCOND</td>
<td>Condensation of cloud droplets</td>
<td>cloud/vapor</td>
</tr>
<tr>
<td>CSSRIME</td>
<td>Accretion of droplets by snow</td>
<td>snow/cloud</td>
</tr>
</tbody>
</table>

Table 4.7: As in Table 4.2, but for the December 2013 and 2017 cases.

<table>
<thead>
<tr>
<th>Perturbed Process Rate</th>
<th>December 2017</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average Bias (mm)</td>
</tr>
<tr>
<td>IDEP</td>
<td>-0.97</td>
</tr>
<tr>
<td>SDEP</td>
<td>-1.34</td>
</tr>
<tr>
<td>CCOND</td>
<td>-1.37</td>
</tr>
<tr>
<td>CSSRIME</td>
<td>-1.37</td>
</tr>
</tbody>
</table>

Table 4.8: As in Table 4.6, but for the December 2017 case. The December 2013 case is excluded from this table due to the lack of NYSM observations.
<table>
<thead>
<tr>
<th>Process Rate</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CCOND</strong></td>
<td>Cloud condensation</td>
</tr>
<tr>
<td><strong>IDEP</strong></td>
<td>Vapor Deposition onto Cloud Ice</td>
</tr>
<tr>
<td><strong>SDEP</strong></td>
<td>Snow deposition</td>
</tr>
<tr>
<td><strong>GDEP</strong></td>
<td>Graupel deposition</td>
</tr>
<tr>
<td><strong>ISUB</strong></td>
<td>Ice sublimation</td>
</tr>
<tr>
<td><strong>SSUB</strong></td>
<td>Snow sublimation</td>
</tr>
<tr>
<td><strong>GSUB</strong></td>
<td>Graupel sublimation</td>
</tr>
<tr>
<td><strong>CEVAP</strong></td>
<td>Cloud droplet evaporation</td>
</tr>
<tr>
<td><strong>REVAP</strong></td>
<td>Rain evaporation</td>
</tr>
<tr>
<td><strong>SEVAP</strong></td>
<td>Melting then evaporation of snow</td>
</tr>
<tr>
<td><strong>GEVAP</strong></td>
<td>Graupel evaporation</td>
</tr>
<tr>
<td><strong>CSGRIME</strong></td>
<td>Riming of cloud droplets on snow, added to graupel</td>
</tr>
<tr>
<td><strong>CRACCR</strong></td>
<td>Accretion cloud droplets by rain</td>
</tr>
<tr>
<td><strong>ISACCCR</strong></td>
<td>Accretion of cloud ice by snow</td>
</tr>
<tr>
<td><strong>IMELT</strong></td>
<td>Ice melting</td>
</tr>
<tr>
<td><strong>SMELT</strong></td>
<td>Snow melting</td>
</tr>
<tr>
<td><strong>GMELT</strong></td>
<td>Graupel melting</td>
</tr>
<tr>
<td><strong>CSSRIME</strong></td>
<td>Riming cloud droplets onto snow, added to snow</td>
</tr>
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<td><strong>RSRIME</strong></td>
<td>Riming of rain on snow</td>
</tr>
<tr>
<td><strong>CSACCRGRIME</strong></td>
<td>Riming onto graupel from cloud droplet accretion by snow that did not undergo splintering</td>
</tr>
<tr>
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<td>Change in rain mass due to ice-rain collection, added to graupel</td>
</tr>
<tr>
<td><strong>RSCOLLECT-AF</strong></td>
<td>Rain-snow collection, T &gt; 0°C</td>
</tr>
<tr>
<td><strong>RSCOLLECT-BF</strong></td>
<td>Rain-snow collection, T &lt; 0°C</td>
</tr>
<tr>
<td><strong>RGCOLLECT-AF</strong></td>
<td>Collection of rain by graupel, T &gt; 0°C</td>
</tr>
<tr>
<td><strong>RGCOLLECT-BF</strong></td>
<td>Collection of rain by graupel, T &lt; 0°C</td>
</tr>
<tr>
<td><strong>IRICOLLECT</strong></td>
<td>Change in ice mass due to ice-rain collection, added to graupel</td>
</tr>
<tr>
<td><strong>SRGCOLLECT</strong></td>
<td>Conversion to graupel due to rain-snow collection</td>
</tr>
<tr>
<td><strong>IRRSCOLLIS</strong></td>
<td>Change in rain mass due to ice-rain collision, added to snow</td>
</tr>
<tr>
<td><strong>IRISCOLLIS</strong></td>
<td>Change in ice mass due to ice-rain collision, added to snow</td>
</tr>
<tr>
<td><strong>CFRZ</strong></td>
<td>Freezing of cloud droplets</td>
</tr>
<tr>
<td><strong>RFRZ</strong></td>
<td>Freezing of rain</td>
</tr>
<tr>
<td><strong>INU</strong></td>
<td>Heterogeneous ice nucleation</td>
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<td>Splintering cloud droplets accreted onto graupel</td>
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<tr>
<td><strong>RGSPLINT</strong></td>
<td>Splintering rain accreted onto graupel</td>
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<tr>
<td><strong>CRAUTO</strong></td>
<td>Autoconversion cloud droplets to rain</td>
</tr>
<tr>
<td><strong>AGG</strong></td>
<td>Ice-ice aggregation</td>
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Table 4.9: Microphysics processes that are discussed herein. All units are g kg\(^{-1}\) s\(^{-1}\)
4.9 Figures

Figure 4.1: (a) Domain configuration for all WRF ensemble simulations. The stochastic pattern is shown from a random ensemble member and forecast time. (b) Rainfall accumulation (mm) at each of the NYSM sites (circles) reporting data during the 29–30 October 2017 event. Lake Ontario, Lake Erie, the NYSM Tannersville site, and the NYC region are annotated for reference.
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Figure 4.30: As in Fig. 4.15, except for the a) 15–16 December 2013 and b) 15–16 December 2017 cases.
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Figure 4.32: As in Fig. 4.18 except for the a) 15–16 December 2013 and b) 15–16 December 2017 cases.
Figure 4.33: As in Fig. 4.16 except for the a–d) 15–16 December 2013 and e–h) 15–16 December 2017 cases. Here, the bin size is 0.15 mm for panels a–d and 0.5 mm for panels e–h.
Figure 4.34: As in Fig. 4.23, where hatching is again unique to each ensemble: horizontal lines are for SPP_{DEP}, horizontal and vertical lines are for SPP_{SDEP}, stars are for SPP_{CCOND}, and dots are for SPP_{CSSRIME}.
Figure 4.35: As in Fig. 4.25, but for SPP$_{\text{IDEP}}$, SPP$_{\text{SDEP}}$, SPP$_{\text{CCOND}}$, and SPP$_{\text{CSSRIME}}$. 
5. Summary, conclusions, and recommendations

The role of microphysics in the uncertainty associated with numerical weather prediction forecasts of high-impact weather, such as lake-effect snow or synoptic rainstorms, is explored in this work through ensemble sensitivity tests. Each of these investigations is summarized in the following sections, followed by the major conclusions from the dissertation as a whole. Finally, recommendations for related future work explore how the methods and findings within this dissertation can be used to continue this line of research.

5.1 Summary and Conclusions

5.1.1 Impacts of Ice Crystal Nucleation and Growth on a Lake-effect Storm

The improvement of microphysical representation within weather research and forecasting models has been an increasing focus in the research community over the past several decades. This is a result of computational innovation, allowing for more resolved simulations of cloud physics. As investigations into the microphysical nature of many mesoscale and synoptic systems increase, it has become evident that the processes associated with microphysics are highly complex, and the sensitivities of these systems to the microphysical processes within remains largely unknown. To that end, a breadth of work has emerged to develop new, physically based parameterizations for the representation of many microphysical processes, aiming to reduce model uncertainties. Hence, this work performs investigations on the most commonly parameterized microphysical processes within numerical models, with a focus on the representation of ice crystals.

Ice crystals are typically assumed to grow spherically in microphysics schemes due to the complexity of numerically representing their natural growth. However, this assumption is not representative of the actual method of growth, which occurs nonspherically due to the myriads of structures the crystals can form, including plate-like, columnar, and polycrystal formations. While not perfect, several studies have demonstrated that moving toward a more proper
A representation of these crystal shapes and growth mechanisms involves making a spheroidal shape assumption to approximate nonspherical growth. The impacts of nonspherical ice growth have been shown to control cloud lifetime as well as the timing and amount of precipitation in both cold and mixed-phase clouds. In Chapter 2, the impacts of ice crystal mode of growth in a lake-effect snowstorm are investigated using the Adaptive Habit Model (AHM). In addition, the parameterization chosen to represent heterogeneous ice crystal nucleation has direct impacts on the number and mass mixing ratio of pristine ice crystals. The impacts of choosing different nucleation parameterizations on the lake-effect storm forecast were also explored in this research.

Heterogeneous ice nucleation is represented within the AHM by either immersion-condensation freezing nucleation as parameterized by DeMott et al. (2015) and deposition-condensation freezing by Meyers et al. (1992), as these are considered to be some of the most important forms of heterogeneous nucleation (Kanji et al. 2017). DeMott et al. (2015) ingests information about the dust present in the environment, which is provided by the Advanced Particle Microphysics model (Yu and Luo 2009). Relative to DeMott et al. (2015), Meyers et al. (1992) was found to produce a relatively increased concentration of pristine ice crystals. The increased number of ice crystals elevated the competition effect for vapor deposition growth, which was enhanced even more when nonspherical growth allowed for increased vapor fluxes. For this reason, simulations allowing for nonspherical growth coupled with the Meyers et al. (1992) parameterization led to a slightly lower precipitation forecast as compared to DeMott et al. (2015). Therefore, changing the method of ice growth does impact the lake-effect precipitation forecast, as was pondered in research question #2: Do changes in method of ice crystal growth (i.e., spherical or nonspherical) alter the forecast of a winter storm?

More interestingly, the change in nucleation parameterization led to different hydrometeor partitioning within the lake-effect storm, ultimately changing the precipitation type at the surface. This finding answers research question #1: Does representing pristine ice
nucleation with different parameterizations have impacts on a winter storm forecast? The identified response occurs because the Meyers et al. (1992) parameterization nucleates a number concentration of ice crystals high enough to allow for vapor depositional growth at the expense of cloud droplets. Therefore, cloud glaciation occurs at a faster rate and there is a reduction in cloud liquid water content, which reduces/completely eliminates autoconversion to rain droplets. Therefore, the primary precipitation type at the surface includes both ice and snow when using the Meyers et al. (1992) parameterization. With a lessened nucleation rate when using DeMott et al. (2015), depositional growth serving to reduce cloud liquid water content does not occur at the same rate, so cloud to rain autoconversion takes place and graupel production occurs due to riming processes from the now available liquid. As such, mixed-precipitation falls to the surface, including ice, snow, graupel, and rain. Hence, it is found that choice of nucleation parameterization cascades into the forecast of precipitation type.

5.1.2 Impacts of Uncertainty in Microphysics Parameters, Parameterizations, and Schemes on a Lake-effect Storm

To build upon Chapter 2 and widen the breadth of the microphysics processes that may lead to forecast uncertainty, ice nucleation, mode of ice crystal growth, aerosol concentration, potential IN concentration, fall speeds, and spectral indices were isolated and changed within the AHM and National Taiwan University (NTU, also an AHM) microphysics schemes to build a microphysical ensemble. This 24-member ensemble also included members that differed in terms of the microphysics scheme itself rather than isolating changes within the scheme. Through this work, it was found that the changes in microphysics schemes dominated changes in the precipitation forecast, but differences among parameterizations of graupel formation and growth had the strongest hold on the precipitation type forecast. This makes the answer to research question #3 complex; the parameter and parameterization differences impact the forecast type the most, but the changes in microphysics scheme alter
the overall forecast magnitude while also encapsulating the aforementioned differences in graupel processes. Therefore, the impacts of each type of microphysics change depends on if the end-user is more interested in precipitation type or precipitation magnitude. This interest would likely be a function of thermodynamic conditions within the storm that may or may not support precipitation type uncertainty.

5.1.3 Stochastic Representation of Forecast Uncertainty and Applications to Microphysics

The fourth and final research question was addressed through applying stochastic perturbations to the four most active microphysics process rates within a synoptic rainstorm affecting the entirety of NYS in October 2017: What degree of uncertainty do microphysical processes introduce to a forecast and how does that uncertainty propagate through a cloud system? The four process rates included ice and snow deposition, accretion of cloud droplets by rain, and the melting of snow. Focus was placed on the rainfall forecast, and specifically the forecast spread in each of the four stochastic perturbation ensembles. Each of these ensembles were compared to other ensembles that included initial and boundary condition uncertainty, iSPPT to microphysics, or various combinations of all three techniques. The IC/BC ensembles elicited the greatest forecast spread and the SPP ensembles had comparable forecast skill.

The cloud system did not respond equally to the perturbations of differing process rates, nor did these perturbations become the largest source of spread in the cloud system. The relationships between the perturbed and remaining process rates indicate that perturbations were indeed propagating correctly throughout the system. In an effort to understand if parallels exist to other weather events that affect NYS, attention was turned to applying this same methodology to lake-effect storms.

As these lake-effect storms occurred in the cold-season, the top four most active process rates in both cases still included ice and snow deposition, but shifted away from the top
October 2017 rates to include cloud condensation and evaporation and droplet accretion by snow. When these rates were stochastically perturbed within the AHM, ice deposition elicited a larger spread response both within the QPF distribution and among the process rates, relative to the other perturbed rates. Similar relationships were found among the process rate spread in both cases as compared to the October 2017 case, suggesting that using the SPP method within the AHM provides reasonable and reliable results within the studied weather event types.

5.1.4 Major Conclusions

Through the first two projects outlined in Chapters 2 and 3, it was discovered that precipitation type in forecasts of a lake-effect storm is not only directly controlled by the pristine ice nucleation parameterization, but also indirectly altered by parameterizations representing graupel formation and growth. This clearly has important consequences on predictions of snowfall and the impacts on infrastructure and society due to the uncertainty that is injected by these seemingly trivial parameterization choices within microphysics schemes. These findings shed light on the importance of considering the cloud microphysics processes that could play an important role in the forecast of an event that could result in mixed-precipitation. Historically, these types of winter season events have left forecasters, decision-makers, and the general public frustrated when all-snow forecasts turn into mixed-phase events, and vice versa, due to the different impacts for which to be prepared and considered during and after the weather event. Furthermore, end-users of forecasts such as winter recreationalists indicate that the decision to participate in activities such as skiing, snowboarding, and snowmobiling are strongly affected by precipitation types that would degrade snow conditions, like rain and freezing rain (Rutty and Andrey 2014).

While forecast uncertainty stemming from ice nucleation, mode of ice growth, and graupel creation and growth processes were not specifically investigated in the stochastic perturbation work in Chapter 4, other processes were investigated as these were found to
be the most active within the October 2017 synoptic rainstorm. Since precipitation type is not of concern in the environmental conditions within which this storm took place, it was of most interest to understand how these perturbations bred forecast uncertainty at the surface, namely in changes to the intra-ensemble rainfall forecast spread. When different microphysics process rates are stochastically perturbed, the relationship between that rate and the remaining process rates change resulting in spread generation that is not derived from the same source. The same methods were applied to two lake-effect events, including OWLeS IOP4, which was also studied extensively in Chapters 2 and 3, and 15–16 December 2017. Interestingly, perturbations to ice deposition rates led to the greatest spread generation both within the cloud system and in the QPF field. These results narrow in on one of the foci of Chapters 2 and 3, where the sensitivity to mode of ice growth, and indirectly ice deposition rates, was explored. Although only minimal impact was found as a result to altering the ice growth mode within IOP4, stochastic perturbations to this quantity provide a different and larger spread response than perturbations to other processes. This further suggests that ice deposition is considerably sensitive relative to the other process rates within lake-effect cloud systems, which should encourage continued work toward including nonspherical growth within NWP for both research and operational applications.

5.2 Recommendations for Future Work

Future work could build upon the research results herein to continue strengthening the understanding of the influence of microphysics on forecast uncertainty. Focus was placed on both mesoscale and synoptic phenomena affecting NYS. These methods could both be extended to additional weather events of the same type as well as other weather types such as summertime convection and synoptic winter storms. It would be illuminating to compare and contrast the relationships between microphysics and precipitation highlighted in LES to a synoptic snowstorm, where dynamics may have more of a control over the forecast. If computational resources were readily available, it would be further enlightening to perturb
each active microphysics process rate for multiple weather types and events, so that broader conclusions could be drawn across the multiple potential microphysics relationships/influences. There may be unanticipated indirect affects that are uncovered by choosing to perturb all microphysics process rates in their own individual ensembles. In this way, results would be considerably more robust and conclusions strengthened.

Inspired by the discussion of Palmer (2012) to make use of stochastic framework where there is uncertainty about which deterministic parameterization to use, it is suggested to use stochastic methods to determine the ice nucleation parameterization at a given time step and model grid point. As the various heterogeneous nucleation modes do not happen in isolation in nature, some combination of the different parameterized modes could be used if integrated with stochastic methods. In a purely deterministic simulation using the AHM, one would need to choose between the Meyers et al. (1992) or DeMott et al. (2015) ice nucleation parameterizations. However, this could be altered so that a stochastic choice is made as to which parameterization is used at a certain grid point and time step depending on the sign of the stochastic pattern. For example, if the pattern value were positive, then Meyers et al. (1992) would be used and if it were negative, then DeMott et al. (2015) would be used instead. Since the pattern is autocorrelated in space and time and invariant in the vertical dimension, the nucleated ice concentrations would not be disjointed between most grid spaces. This could be a potential issue where the pattern values are close to 0 and frequent switches between nucleation parameterization may occur. These sudden jumps or falls in concentrations would be most drastic in regions with relatively warm temperatures (e.g., $T > -20^\circ C$), as this is where the differences between the Meyers et al. (1992) and DeMott et al. (2015) parameterizations are maximized (Fig. 2.1).
APPENDIX A
Definitions of Commonly Used Terms

A handful of terms used throughout Chapter 4 are defined below, with equations and explanations of how and why they are used.

1. Ensemble Spread

   Spread is discussed in terms of rainfall rate and QPF, as well as individual process rates. To compute the spread for each ensemble, the standard deviation is taken of the specific variable (e.g., rainfall rate, QPF, process rate) across the ensemble members, leaving a standard deviation value (i.e., spread) for each NYSM site location,

   \[ \text{spread} = \text{standard\_deviation}(\text{variable}). \]

   Spread is used to assess the ensemble forecast distribution for the variable of interest at each NYSM site location. This variable is important within the Chapter 4 analysis to understand how the forecast range and dispersion are impacted by the perturbations used in each ensemble.

   When calculating the spread of the process rates, an additional step needs to be completed as the time dimension and NYSM site location dimensions are collapsed as only a summary value is desired instead of a value at each time and location. First, each process rate (dimensions = [time, vertical levels, locations]) is averaged across all NYSM sites for each ensemble member:

   \[ \text{process\_rate\_mean} = \text{mean}(\text{process\_rate}, \text{dimension} = \text{locations}). \]
Then, those values are summed through time and all vertical levels:

\[ \text{process\_rate\_sum} = \text{sum}(\text{process\_rate\_mean}, \text{dimension} = (\text{time, vertical\_levels})). \]

Once those steps are completed for each ensemble member, the standard deviation is taken to determine the spread for that specific process rate:

\[ \text{process\_rate\_spread} = \text{standard\_deviation}(\text{process\_rate\_sum}). \]

2. Error

Error is defined herein in two different ways. The first is a term used to describe the limitations associated with models within physical parameterizations and approximations. The second is a statistical measure of the difference between the forecast and observed value. Error is specifically used within the root mean square error (RMSE) and ensemble-mean error, where

\[ \text{RMSE} = \sqrt{\text{MSE}}, \]

\[ \text{MSE} = \frac{1}{n_{\text{locations}}} \sum_{i=0}^{n_{\text{locations}}-1} (\text{forecast} - \text{observation})^2, \]

and

\[ \text{ensemble\_mean\_error} = \text{mean}(\text{forecast} - \text{observation}, \text{dimension} = (\text{ensemble\_members, locations, time})). \]

3. Bias

Bias can have particularly vague definitions, but is generally used to express systematic
error. Bias can also be used to describe ensemble-mean error, as it can also be averaged over the temporal and spatial dimensions. Note that errors inherently include any existing bias(es), but the opposite is not true. Bias is used to understand existing errors that permeate and affect ensemble forecasts and ultimately performance.

4. **Kernel Density Smoothing**

Kernel density smoothing can be applied to a dataset to smooth its distribution, producing a kernel density estimate. This allows for easier comparison among various datasets than histograms offer; for example, they are used to compare QPF spread distributions in Fig. 4.15. To construct a kernel density estimate, kernels (e.g., Quartic, Triangular, Guassian; p. 35–36, Wilks 2011) are used to smooth the data. The chosen kernel shape is centered at each represented data value, scaled in width by a smoothing parameter, and stacked; the heights of all the kernel shapes are then added at each given value to produce the kernel density estimate.
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Senior Peer Review Support Associate
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617-226-3926

On Mon, Jan 11, 2021 at 9:18 AM Gaudet, Lauriana C <lgaudet@albany.edu> wrote:

Hello,

I am in the process of putting together my dissertation and want to include all of the material from a publication that I am the first-author of [https://doi.org/10.1175/JAS-D-19-0603.1] within the Journal of the Atmospheric Sciences. I am writing to ask for permission to use these materials in my dissertation, as required by the University at Albany, SUNY Graduate School. My dissertation is titled "Identifying the Microphysical Sensitivities of Mesoscale and Synoptic Precipitation Using an Ensemble Framework."

Thank you.

Lauriana Gaudet
Ph.D. Candidate
Dept. of Atmospheric and Environmental Sciences
University at Albany, SUNY

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Thank you,

Lauriana Gaudet

_________________________________________________________________
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