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NUMERICAL MODELING STUDIES OF DEEP CONVECTION: 1-KM
ENSEMBLE FORECASTING, SECONDARY ICE PRODUCTION, AND
AEROSOL-CLOUD INTERACTIONS

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Abstract

This dissertation presents numerical modeling studies of deep convection triggered by sea breezes, which remains a challenge for operational numerical weather prediction (NWP) models due to the fine scale of sea breeze circulation, uncertainties in large-scale forcings, model uncertainties innate to physics parameterizations, and varying aerosol conditions. This research is organized into three parts.

Part I describes a 24-hour, 1-km, 48-member convection-allowing ensemble (CAE) produced with the Weather Research and Forecasting (WRF) Model during the Experiment of Sea Breeze Convection, Aerosols, Precipitation and Environment (ES-CAPE) field campaign near Houston, Texas, in June 2022. This CAE incorporates three initial/boundary conditions (ICs/BCs), four microphysics schemes, two planetary boundary layer (PBL) schemes, and two aerosol loadings. Ensemble precipitation forecasts are evaluated against observations for eight SBC cases. It is shown that ensemble diversity, especially through varied ICs/BCs, improves forecasts of light-to-moderate precipitation, though rare and extreme rainfall remains difficult to capture. An optimal single-physics configuration (Thompson microphysics with the Mellor–Yamada–Nakanishi–Niino PBL) achieves ensemble skill scores but retains precipitation biases, emphasizing the need for continued model physics parameterization development.

Part II expands the Thompson microphysics scheme to include three secondary ice production (SIP) mechanisms, which exert strong influences on convection and precipitation but have remain underrepresented in NWP models for decades. The three SIP mechanisms are: Hallett-Mossop (HM), ice–ice collisional breakup (IICOL), and fragmentation of freezing raindrops (FFD). Idealized simulations of a continental supercell and a tropical mesoscale convective system are performed to investigate the impacts of SIP on precipitation in deep convection. Results show that SIP systematically reduces precipitation by redistributing condensate from liquid to ice and from low to high levels, primarily suppressing the warm-rain pathway. Detailed analyses of SIP impacts

on cloud microphysics, thermodynamics, dynamics, and convection intensity, as well as interactions among different SIP mechanisms, are also presented.

Part III investigates the combined effects of SIP and aerosols on deep convection and precipitation using the SIP-included, aerosol-aware Thompson scheme in the WRF Model and a cloud tracking technique. An SBC case observed during ESCAPE is reproduced. Results show divergent, and even opposite outcomes when SIP is included, compared to previous studies. Overall, the findings highlight the dual importance of SIP and aerosols in shaping convective cloud microphysics, thermodynamics, and precipitation, underscoring the need to incorporate SIP and realistic aerosol treatments in NWP models to improve precipitation forecasts.

Chapter 1

Introduction

Accurate prediction of the location, timing, and intensity of precipitation by sea breeze convection (SBC) has remained challenging for numerical weather prediction (NWP) models in part due to the relatively fine scale of sea breeze circulation (Crosman and Horel 2010; Wang et al. 2018; Hock et al. 2022; Fonseca et al. 2025; Fu et al. 2021). SBC rainfall prediction is further limited by uncertainties in large-scale forcings (e.g., Park et al. 2020), model physics parameterizations (e.g., Yoon et al. 2021), and regional aerosol conditions (e.g., Fan et al. 2020). High-resolution convection-allowing ensembles (CAEs) address part of this challenge by sampling initial conditions/boundary conditions (ICs/BCs) and physics parametric uncertainties, and explicitly resolving convective storms (e.g., Xue et al. 2007; Kalina et al. 2021; Heinselman et al. 2024). While many studies have shown that multi-ICs/BCs and mixed-physics designs improve short-term and high-impact weather prediction (e.g., Schwartz et al. 2010; Johnson and Wang 2017; Alvarez Imaz et al. 2020), applications of CAEs to SBC precipitation forecast remain underexplored.

In Chapter 2, we present a 48-member, real-time, 24-hour, 1-km multi-ICs/BCs and mixed-physics ensemble performed with the Weather Research and Forecasting (WRF) Model, the first of its kind dedicated to SBC prediction along the Texas and Louisiana (TX/LA) coastline (Hu and Lebo 2025). This WRF CAE is conducted for the Experiment of Sea Breeze Convection, Aerosols, Precipitation and Environment (ESCAPE) field campaign in June, 2022 (Kollias et al. 2025; Dzambo et al. 2025), and

consists of 48 members, enveloping three ICc/BCs, four microphysics schemes each with two different aerosol loadings, and two planetary boundary layer (PBL) schemes. Specifically, precipitation forecasts are verified against observations for eight identified SBC cases. Detailed evaluation using both grid-scale and neighborhood verification methods and analyses of environmental controls are provided. Furthermore, we test the WRF CAE’s sensitivities to horizontal grid spacing (i.e., 1-km versus 3-km) and model physics parameterizations.

Results from Chapter 2 indicate that while ICs/BCs primarily account for the location and timing errors of SBC precipitation forecasts, the precipitation intensity biases are attributable to the cloud microphysics schemes, which directly act on precipitation formation pathways. Therefore, continued development of microphysics parameterization remains necessary. Yet, owing to expensive computational costs, limited observational and laboratory data constraints, cloud microphysical processes in bulk microphysics parameterizations are usually simplified and/or incomplete, such as secondary ice production (SIP) processes (Morrison et al. 2020), which have long been observed in clouds but overlooked in NWP models (Field et al. 2017).

SIP is a set of fundamental cloud microphysical processes that can rapidly produce additional ice particles in the presence of pre-existing ice, impacting cloud microphysics, dynamics, strength, lifetime, precipitation, and radiation (e.g., Field et al. 2017; Korolev and Leisner 2020; Korolev et al. 2020). For decades, NWP models consider only one SIP mechanism, the Hallett-Mossop (rime-splintering) process (HM; Hallett and Mossop 1974), even though there are many more SIP mechanisms observed and proposed (Korolev and Leisner 2020). This is because our physical understandings of SIP mechanisms are still limited due to a lack of in situ observations and laboratory studies (Morrison et al. 2020), thereby also a lack of appropriate incorporation of additional SIP mechanisms into NWP models.

Recently, more numerical parameterizations of SIP mechanisms such as ice-ice collisional breakup (IICOL), fragmentation of freezing rain drop (FFD), and sublimational breakup based on available observations and laboratory studies have been proposed (e.g., Sullivan et al. 2018a,b; Phillips et al. 2017, 2018; Deshmukh et al. 2022), which fueled numerous modeling studies incorporating these SIP mechanisms (Qu et al. 2022; Huang et al. 2022b; Sotiropoulou et al. 2020, 2021a,b; Zhao et al. 2021; Grzegorzcyk et al. 2025; Huang et al. 2025a). While the aforementioned studies generally demonstrate improved model performances with additional SIP mechanisms, a recent laboratory study reported no evidence of active HM mechanism (Seidel et al. 2024), which questions the fundamentalism of HM process and advocates for consideration of other SIP mechanisms in NWP models.

Clearly, it is of vital significance to include other SIP mechanisms in some fashion in NWP models, especially for simulation of deep convective clouds (DCCs) and prediction of convective precipitation. However, before the full promotion of SIP in research and even operational NWP models, a more in-depth understanding of how SIP mechanisms impact deep convective cloud properties and modulate precipitation is needed, which is the focus of Chapter 3.

In Chapter 3, we are the first to implement the IICOL (Phillips et al. 2017) and FFD (Phillips et al. 2018) mechanisms into the Thompson microphysics scheme (Thompson et al. 2008; Thompson and Eidhammer 2014; Jensen et al. 2023), which is the identified optimal microphysics scheme for SBC precipitation forecasts in Chapter 2 and also the microphysics scheme commonly adopted in scientific research and operational NWP models. Here, we perform idealized WRF simulations with the SIP-included Thompson scheme for two deep convection cases: one supercell and one tropical mesoscale convective system (MCS), which are initiated in distinctly different thermodynamical environments. Systematical examination and analyses of the impacts of SIP on

cloud microphysical hydrometeors, dynamics, thermodynamics, convection strength, and precipitation formation pathways for both cases are provided.

Aerosols, tiny particles in the atmosphere that can serve as cloud condensation nuclei (CCN) and ice nuclei (IN) in cloud formation and ice nucleation, are an important factor to be considered in weather prediction and climate projection. The effect of increased aerosol loadings on clouds has long been recognized (e.g., Twomey 1977). It is well established that an increase in aerosol loading in warm and shallow clouds leads to more numerous but smaller cloud droplets, which are less efficient at growing to precipitation-sized rain drops via collision-coalescence, thus an increase in cloud lifetime along a decrease in surface precipitation (e.g., Albrecht 1989). The effect of enhanced aerosol loadings in DCCs and resultant precipitation, however, remain a topic of debate and active research, with studies reporting divergent results and mechanisms (e.g., Koren et al. 2008; Rosenfeld et al. 2008; Li et al. 2011; Fan et al. 2013, 2025; Lebo et al. 2012; Lebo and Morrison 2014; Varble 2018; Varble et al. 2023).

ESCAPE took place in Houston, Texas, a region where isolated DCCs triggered by sea breezes are common and experiences a range of aerosol regimes spanning from urban and industrial pollution to significantly “cleaner” aerosol conditions over the Gulf of Mexico (Fridlind et al. 2019; Fan et al. 2020; Chao et al. 2025; Kollias et al. 2025; Jensen et al. 2025; Pehl et al. 2025; Al-Jabri et al. 2025). Hence, the Houston area offers an ideal testbed for studying the impacts of aerosol conditions on DCCs and precipitation. While Chapter 3 provides theoretical understanding of impacts of SIP on DCCs and precipitation, the idealized simulations do not capture the complexity of the real atmosphere. Furthermore, how aerosol loadings influence the ice production through SIP mechanisms remains unknown, especially in DCCs and in real case studies.

In Chapter 4, we present an SBC case study observed during ESCAPE to demonstrate the dual effects of SIP processes and aerosol loadings on DCCs and precipitation.

The selected SBC case is reproduced by the WRF Model using the aerosol-aware and SIP-included Thompson microphysics scheme (Thompson and Eidhammer 2014; Hu et al. 2025) under clean, semi-polluted, and polluted aerosol conditions. Cloud tracking techniques are applied to the observed and simulated cloud cells to investigate the impacts of SIP and aerosols on cloud properties through cloud lifetime. WRF simulations are further evaluated against airborne in situ data and surface precipitation observations.

Finally, in Chapter 5, a comprehensive summary of findings and future work that stem from the current dissertation are provided.

Chapter 2

A 1-km Multi-ICs/BCs and Mixed-physics WRF Ensemble for Sea Breeze Convection Prediction during ESCAPE: Precipitation Evaluation

*

*Accepted by *Wea. Forecasting*.

2.1 Introduction

A sea breeze is a cool marine air mass propagating inland when a cross-shore pressure gradient is created by daytime differential heating (Miller et al. 2003). Sea breezes play a key role in the initiation of deep convection, causing heavy precipitation (Chen et al. 2016; Zhang and Wang 2021; Huang et al. 2025b) and lightning (Chavez et al. 2022; Bruning et al. 2024) that can pose life-threatening risks to densely populated coastal communities. Moreover, sea breezes can redistribute near-surface aerosols, consequently impacting not only the local air quality (Banta et al. 2005; Caicedo et al. 2019; Chao et al. 2025) but also the subsequent convection and precipitation (Lebo 2018; Fan et al. 2020; Park and van den Heever 2022; Varble et al. 2023). Considering the wide-ranging impacts on human activities in coastal areas, it is important to provide accurate forecasts of sea breezes and their resulting convection.

Partly due to the fine scale of SBC, accurate prediction of SBC has remained a challenge for numerical weather prediction (NWP) models (Crosman and Horel 2010), even for convection-allowing (~ 4 km) models (Salvador et al. 2016; Wang et al. 2018; Chen et al. 2019; Hock et al. 2022; Fonseca et al. 2025) and large eddy simulations (LES, ~ 100 m) (Abulikemu et al. 2016; Chen et al. 2019; Fu et al. 2021). Another challenge faced by NWP models regarding the prediction of SBC is uncertainties associated with the environmental controls, such as large-scale meteorological forcings, surface parameters, aerosol conditions, and the urban heat island effect (Park et al. 2020; Park and van den Heever 2022; Fan et al. 2020; Zhang and Wang 2021; Fonseca et al. 2025). Uncertainties innate to the model physics parameterizations also add to the great difficulty of accurately simulating SBC. Several studies attempted to find the optimal combinations of physics parameterizations for deterministic SBC prediction (Yoon et al. 2021; McCabe and Freedman 2025), but the results are still inconclusive.

Instead of making a single deterministic forecast, ensemble forecasting is a method to produce multiple forecasts that encompass a range of possible outcomes. Advancements in computational capabilities in the past two decades have allowed the development of high-resolution convection-allowing ensembles (CAEs). In 2007, the Center for Analysis and Prediction of Storms began running an experimental 10-member, 33-hour ensemble with a 4-km horizontal grid spacing over the contiguous United States to improve severe weather prediction (Xue et al. 2007). Since then, considerable effort has been put into constructing CAE forecasting systems. Some examples include the High-Resolution Rapid Refresh Ensemble (HRRR-E; Kalina et al. 2021), the Warn-on-Forecast System (WoFS; Stensrud et al. 2013; Heinselman et al. 2024), the High Resolution Ensemble Forecast system version 2 (HREFv2; Roberts et al. 2019), and the UK Met Office Global and Regional Ensemble Prediction Systems (MOGREPS-UK; Hagelin et al. 2017). Other experimental high-resolution CAEs have also been established (e.g., Gao and Stensrud 2014; Luo and Chen 2015; Wang et al. 2019; Schwartz 2019; Wang et al. 2022; Kerr et al. 2023).

CAEs provide benefits over deterministic models not only by representing uncertainties in initial conditions/boundary conditions (ICs/BCs) (Peralta et al. 2012; Frogner et al. 2019; Manser and Ancell 2023) and in model physics (Bouttier et al. 2012; Wastl et al. 2019a,b) but also by explicitly simulating convective processes in each member. Nevertheless, the separate impacts of the ensemble approach and convection-allowing resolution on convective precipitation forecasts are inconclusive. Recent studies have found that by incorporating multiple ICs/BCs, microphysics schemes and planetary boundary layer (PBL) schemes, CAEs generally show improved forecast skill (e.g., Schwartz et al. 2010; Johnson and Wang 2017; Alvarez Imaz et al. 2020). However, Loken et al. (2019) found little difference in skill or reliability between mixed- and single-physics precipitation forecasts using 3-km CAEs. Furthermore, while increasing

from convection-parameterized ($>\sim 4$ km) to convection-allowing grid spacing leads to clear improvement in model forecasts of convection (e.g., Schwartz 2019), further increasing the horizontal grid spacing (e.g., to 1 km) has provided mixed results (Loken et al. 2017; Schwartz and Sobash 2019; Wang et al. 2022; Kerr et al. 2023). For example, Kerr et al. (2023) found that the 1-km WoFS outperforms the 3-km WoFS in predicting convection in terms of radar reflectivity, while Loken et al. (2017) suggested that adding more members to the ensemble, rather than simply refining the resolution below 4 km, is a more effective way to improve the accuracy of probabilistic weather forecasts, as they found no significant improvement of 1-km over 4-km forecasts.

Finally, although CAEs have shown improved short-term forecasts of high-impact weather events (e.g., Mittermaier and Csimas 2017; Woodhams et al. 2018; Roberts et al. 2020), their application to SBC remains limited. A few recent studies, though not mainly focused on SBC, point to clear benefits of CAEs for SBC forecasting. Cafaro et al. (2019) emphasized the added value in forecast skill by using the 2-km MOGREPS-UK CAE to predict sea breeze occurrence. Huang et al. (2022a) highlighted the benefit of using a 4-km CAE to forecast nocturnal convective precipitation of sea-land breezes over southern China compared to coarser-resolution global models. Motivated by these promising findings and the aforementioned ongoing challenges in simulating SBC, and to fill the gap where CAEs’ application to SBC is missing, we performed real-time 1-km simulations using the Weather Research and Forecasting (WRF) Model with different ICs/BCs and mixed-physics configurations, forming a 48-member CAE. This CAE was executed to assist the forecasting and nowcasting activities during the Experiment of Sea Breeze Convection, Aerosols, Precipitation and Environment (ESCAPE) field campaign, which occurred in June 2022, in Houston, Texas (TX) (Kollias et al. 2025; Dzambo et al. 2025).

The objective of this paper is to evaluate the 1-km WRF CAE’s performance in

predicting SBC along the coast of TX and Louisiana (LA), specifically the simulated precipitation and the environment in which SBC developed. More importantly, this work aims to answer the following questions. Q1: How does our 1-km 48-member WRF CAE compare to deterministic operational models in predicting SBC precipitation? Q2: Does adding varied ICs/BCs to a 1-km multi-physics ensemble lead to improvements in SBC precipitation forecasts? Q3: What is the benefit of using a higher resolution (1-km versus 3-km) ensemble in SBC precipitation forecasts? Q4: Is there an optimal physics configuration that can match the SBC precipitation forecast skill of a mixed-physics ensemble?

The paper is organized as follows. Section 2.2 details the 1-km WRF CAE configurations, as well as the observational datasets and verification methods used in this study. Sections 2.3 and 2.4 provide a thorough evaluation of precipitation and environmental parameters, respectively. Section 2.5 discusses the WRF ensemble’s sensitivity to horizontal grid spacing and model physics. Finally, a summary of the work is provided in Section 2.6.

2.2 Model configurations, data, and methodology

2.2.1 WRF model configurations

The Advanced Research WRF Model (Skamarock et al. 2019), Version 4.4, was used in this study. The forecasting area of the WRF Model is shown in Fig. 2.1. The WRF domain is rotated to make it parallel to the coastline, thus capturing more SBC and efficiently using computational resources. The WRF simulations were initialized twice daily at 06Z and 12Z (1AM and 7AM local time) during ESCAPE and run for a 24-hour forecasting period to capture the afternoon and overnight convection while allowing for sufficient model spin-up time. Little sensitivity to the different initiation

times was found during the analysis; hence, results from only the 06Z simulations are shown in this paper. Eight SBC days with research flight operations during ESCAPE were identified (Kollias et al. 2025). Results in this paper correspond to flight days only, specifically on June 2, 4, 8, 9, 10, 11, 16, and 17, 2022.

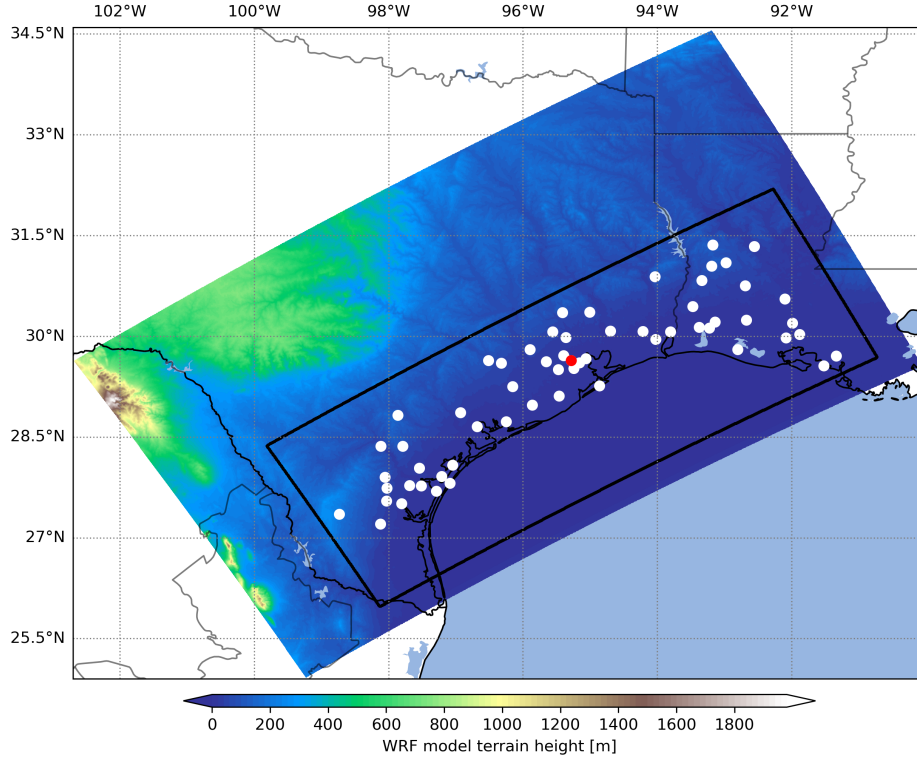


Figure 2.1: WRF forecasting domain with elevation shaded. The black box shows the verification region. White dots denote the location of ASOS sites within the verification region. The red dot indicates the ASOS Houston (HOU) site.

The WRF Model’s horizontal grid spacing was 1 km and vertical grid spacing ranged from 32 m to 408 m (81 vertical levels topped at 50 hPa). Adaptive time steps—ranging between 1 and 10 seconds with a target Courant–Friedrichs–Lewy criterion (Courant et al. 1967) of 0.8—was used. The model output was saved every 30 minutes. The Rapid Radiative Transfer Model for General Circulation Models (RRTMG) radiation scheme (Iacono et al. 2008) was utilized for longwave and shortwave radiation and the Noah multi-physics (Noah-MP) Land Surface Model (Niu et al. 2011) was used for the

land surface scheme. Model configurations listed above were employed for all WRF ensemble members. A summary of these configurations is provided in Table 2.1.

Model Parameter	Model Configuration	Reference
Initialization time	06Z, June 2, 4, 8, 9, 10, 11, 16, 17, 2022	-
Forecast duration	24 hours	-
Output frequency	30 minutes	-
Integration Time step	Adaptive (1~10 seconds)	-
Horizontal Grid Spacing	1 km	-
Grid Points	600×1000	-
Vertical Levels	81 (topped at 50 hPa)	-
Radiation	RRTMG	Iacono et al. (2008)
Land Surface	Noah-MP	Niu et al. (2011)

Table 2.1: Model configurations employed for all WRF ensemble members in this study.

The WRF ensemble consists of 48 members forced by three ICs/BCs, four micro-physics parameterizations each with two different cloud droplet number concentrations (N_d), and two PBL schemes. Table 2.2 summarizes the physics configurations used for the WRF ensemble, and the following provides a detailed description of the experimental design.

To account for uncertainty and variability in large-scale meteorological conditions, the WRF Model was forced by ICs/BCs from three verified operational model forecasts initialized at 06Z and 12Z. The three models are the 3-km and hourly High-Resolution Rapid Refresh (HRRR) model, the 12-km and hourly North American Mesoscale (NAM) model, and the $0.25^\circ \times 0.25^\circ$ and 3-hourly Global Forecast System (GFS) model. The HRRR model is convection-allowing and the NAM and GFS models are convection-parameterized.

Member	IC/BC	N_d	Microphysics	PBL
1	HRRR	200	P3	MYNN
2	HRRR	200	P3	YSU
3	HRRR	200	Morrison	MYNN
4	HRRR	200	Morrison	YSU
5	HRRR	200	Milbrandt	MYNN
6	HRRR	200	Milbrandt	YSU
7	HRRR	200	Thompson	MYNN
8	HRRR	200	Thompson	YSU
9	HRRR	1000	P3	MYNN
10	HRRR	1000	P3	YSU
11	HRRR	1000	Morrison	MYNN
12	HRRR	1000	Morrison	YSU
13	HRRR	1000	Milbrandt	MYNN
14	HRRR	1000	Milbrandt	YSU
15	HRRR	1000	Thompson	MYNN
16	HRRR	1000	Thompson	YSU
17-32	NAM	Same set of physics as members 1-16		
33-48	GFS	Same set of physics as members 1-16		

Note 1: The P3 scheme has double-moment rain water and ice hydrometeors. The Morrison scheme predicts double-moment rain water, cloud ice, snow, and graupel. The Milbrandt scheme predicts double-moment rain water, cloud ice, snow, graupel, and hail. The Thompson scheme has double-moment cloud ice and rain water and single-moment snow and graupel. The four microphysics schemes are configured to predict single-moment cloud droplets, as N_d is set as a constant of 200 or 1000 cm^{-3} for consistency among the schemes in this study.

Note 2: The MYNN EDMF PBL scheme is used in this study. But for simplicity, it is referred to as the MYNN scheme.

Table 2.2: ICs/BCs and physics configurations used for the WRF ensemble.

For simulations driven by the same IC/BC, a combination of physics options was applied, as summarized in Table 2.2. Specifically, four commonly used bulk microphysics schemes were employed due to their distinct representation of cloud and precipitation processes, including the Morrison scheme (Morrison et al. 2009), the Thompson scheme (Thompson et al. 2008), the Milbrandt scheme (Milbrandt and Yau 2005), and the Predicted Particle Property (P3) scheme with two ice species (Morrison and Milbrandt 2015; Milbrandt and Morrison 2016). Each microphysics scheme was used with two different N_d to represent varying aerosol conditions: a low concentration of 200 cm^{-3} (Nd200) and a high concentration of 1000 cm^{-3} (Nd1000). The observed aerosol number concentrations in the Houston area can range from $\sim 10 \text{ cm}^{-3}$ over the Gulf to $>2000 \text{ cm}^{-3}$ in the Houston urban area (Zhang et al. 2021; Kollias et al. 2025; Al-Jabri et al. 2025). Therefore, the selections of 200 cm^{-3} and 1000 cm^{-3} are deemed appropriate to represent a clean and a polluted environment, respectively, in our study. Furthermore, two PBL schemes were used in the ensemble: the Yonsei University (YSU) scheme (Hong et al. 2006) and the Mellor–Yamada–Nakanishi–Niino (MYNN) eddy-diffusivity mass-flux (EDMF) scheme (Nakanishi and Niino 2006; Olson et al. 2019).

The YSU scheme is a diagnostic “non-local” scheme that predicts vertical fluxes as a combination of the eddy diffusivity, mass flux, and entrainment flux. Conversely, the MYNN scheme uses EDMF equations (Olson et al. 2019) to account for “local” and “non-local” mixing, as well as entrainment between clouds and the environment. The differences in the representation of entrainment fluxes and mixing can affect the PBL structure (e.g., Juliano et al. 2019), in particular the vertical wind profile (Draxl et al. 2014), which is important for the organization of SBC clouds.

Finally, unless explicitly stated otherwise, the 48-member WRF ensemble is divided into three 16-member sub-ensembles by the IC/BC forcings. To differentiate the

WRF sub-ensembles from the operational deterministic models, the prefix “WRF_” is used in the rest of the paper. For example, “WRF_HRRR” represents the 16 WRF sub-ensemble members driven by the HRRR IC/BC, while “HRRR” represents the operational 3-km deterministic forecasts. The same terminology applies to the pairs of WRF_NAM and NAM, and WRF_GFS and GFS.

2.2.2 Observational data

To evaluate the precipitation forecasts, we considered the 1-km hourly Multi-sensor Quantitative Precipitation Estimate precipitation product (Martinaitis et al. 2020, 2021) from the Multi-Radar Multi-Sensor (MRMS) system as “truth”. In the interest of SBC, objective verification was performed along the coastal area as shown in Fig.2.1. As many verification methods require the model forecasts and observations share the same grid, we remapped the 1-km WRF simulated precipitation to the MRMS grid. The remapping procedure was done following Zhuang et al. (2023) using the “conservative” method.

Environmental conditions in which SBC developed during ESCAPE were also evaluated. Near-surface environmental parameters, such as 2-m temperature (T_{2m}), 2-m dew point temperature (TD_{2m}), and 10-m wind speed (WS_{10m}), were obtained from 60 Automated Surface Observing System (ASOS) sites within the verification domain shown in Fig.2.1. The simulated atmospheric vertical profiles were compared against the interpolated sonde data (Jensen et al. 2022a) collected near Houston during the Tracking Aerosol Convection interaction ExpeRiment (TRACER) campaign (Jensen et al. 2022b), which took place concurrently with ESCAPE. The planetary boundary layer height (PBLH) was obtained from the first Atmospheric Radiation Measurement Mobile Facilities (AMF1) (Morris 2022) collected during TRACER.

2.2.3 Verification methods

2.2.3.1 Grid scale

The 24-hour accumulated precipitation forecasts were evaluated at the grid scale with precipitation thresholds ranging from 1 mm day⁻¹ to 50 mm day⁻¹. A contingency table was constructed (Table 2.3) considering yes/no precipitation events. A *yes* event occurs when the precipitation is greater than or equal to a given threshold; otherwise, it is a *no* event. The four combinations of forecast events (yes/no) and observed events (yes/no) are as follows (see Table 2.3): *hit* - event forecast to occur and did occur; *miss* - event forecast not to occur but did occur; *false alarm* - event forecast to occur but did not occur; and *correct rejection* - event forecast not to occur and did not occur.

Precipitation (mm day ⁻¹)	Observed $\geq$ threshold	Observed $<$ threshold
Forecast $\geq$ threshold	A: Hit	B: False alarm
Forecast $<$ threshold	C: Miss	D: Correct rejection

Table 2.3: Binary contingency table for 24-hour accumulated precipitation forecast evaluation.

In this study, the probability of detection (POD), false alarm ratio (FAR), frequency bias (BIAS), and equitable threat score (ETS) were calculated as follows:

$$POD = \frac{A}{A + C} \quad (2.1)$$

$$FAR = \frac{C}{A + B} \quad (2.2)$$

$$BIAS = \frac{A + B}{A + C} \quad (2.3)$$

$$ETS = \frac{A - hits_{random}}{A + B + C - hits_{random}}, \quad (2.4)$$

where

$$hits_{random} = \frac{(A + B)(A + C)}{A + B + C + D}.$$

The POD and FAR range between 0 and 1. A perfect forecast has a POD of 1 and a FAR of 0, representing only hits and no false alarms. The BIAS ranges from 0 to infinity, with a perfect score of 1. BIAS indicates whether the forecast has a tendency to underforecast ($BIAS < 1$) or overforecast ($BIAS > 1$) precipitation events. The ETS ranges from $-\frac{1}{3}$ to 1, with 0 indicating no skill and 1 indicating a perfect forecast.

For each WRF ensemble member, the contingency table was constructed to evaluate 24-hour accumulated precipitation forecasts, with results aggregated over all flight days. These contingency table elements were then used to compute categorical statistics (e.g., POD) for individual members. Finally, the categorical statistics for the WRF ensemble were computed by averaging over all members.

2.2.3.2 Neighborhood probability analysis

As many studies have revealed (e.g., Theis et al. 2005; Roberts and Lean 2008; Schwartz et al. 2010; Duc et al. 2013; Mittermaier and Csima 2017), high-resolution model forecasts may not be accurate at the grid scale. This means that even small displacement errors get double penalized with the traditional grid-scale verification method—more false alarms and fewer hits—leading to poor categorical statistics even though the forecast may still be useful. Therefore, the neighborhood probabilistic approach with percentile thresholds following Schwartz and Sobash (2017) was used in this study to further evaluate the hourly precipitation forecasts.

First, a binary probability (BP) field for a given percentile threshold (p) was generated for every WRF member and the MRMS observations using Eq.(2.5). Percentile thresholds from the 95th to 99.9th were used to encompass a range of precipitation

events and were calculated separately for each WRF member and MRMS observations hourly on the MRMS grid for each flight day. This means that the physical values of the same percentile (e.g., the 95th) are time-dependent and can be different for model members and observations. This is desirable as it removes biases in the model forecasts (Schwartz and Sobash 2017). Additionally, if the physical threshold value of a given percentile was zero (i.e., no rain), then a minimum threshold of 0.01 mm hr^{-1} was applied. In doing so, we avoid introducing erroneous hits or reducing the sample size (i.e., excluding no-rain forecast hours).

$$BP(p) = \begin{cases} 1 & \text{if precipitation} \geq p, \\ 0 & \text{if precipitation} < p. \end{cases} \quad (2.5)$$

Second, temporal and spatial neighborhoods were applied to the grid-scale BP field to obtain the neighborhood probability (NP) for each WRF member and observations at a given percentile threshold p using

$$NP(p) = \frac{1}{N_a} \frac{1}{N_b} \sum_{t=1}^{N_a} \sum_{k=1}^{N_b} BP(p), \quad (2.6)$$

where N_a and N_b represent the temporal and spatial neighborhood sizes, respectively. In this study, we used a 3-hour temporal neighborhood ($t - 1, t, t + 1; N_a = 3$) and different square spatial neighborhood sizes, varying from $1 \text{ km} \times 1 \text{ km}$ (grid-scale, $N_b = 1$) to $151 \text{ km} \times 151 \text{ km}$ ($N_b = 151 \times 151 = 22801$). Essentially, the NP is the fractional coverage of precipitation event occurrence within temporal and spatial neighborhoods.

Next, the NP was averaged over the ensemble members (N_e) to produce the neighborhood ensemble probability (NEP) for precipitation forecasts at a given percentile

threshold p :

$$NEP(p) = \frac{1}{N_e} \sum_{j=1}^{N_e} NP(p). \quad (2.7)$$

For the whole WRF ensemble, N_e is 48; for a sub-ensemble, e.g., WRF_HRRR, however, N_e is 16.

Finally, to evaluate the NEPs, the fractions skill score (FSS) was calculated (Roberts and Lean 2008; Duc et al. 2013; Mittermaier 2021):

$$FSS(p) = 1 - \frac{\sum_{k=1}^{N_t} \left[\sum_{i=1}^N (NEP_i(p, t) - NPo_i(p, t))^2 \right]}{\sum_{k=1}^{N_t} \left[\sum_{i=1}^N (NEP_i(p, t)^2 + NPo_i(p, t)^2) \right]}, \quad (2.8)$$

where $NEP_i(p, t)$ represents the ensemble forecast and $NPo_i(p, t)$ the observed NP at the i th grid point for a given percentile p and as a function of time t . N is the number of total grid points in the verification domain, and N_t is the total number of forecasts. The FSS ranges from 0 (no skill) to 1 (perfect), and $FSS = 0.5$ is used as an approximation for a useful forecast (Roberts and Lean 2008; Mittermaier 2021).

2.2.3.3 Single site analysis

The WRF Model's prediction of environmental parameters were evaluated against observations at individual observation sites to shed light on model errors in precipitation forecasts. The mean bias (ε) was used for evaluation, and a perfect score is 0, i.e., no bias:

$$\varepsilon = \left(\frac{1}{N_e} \sum_{i=1}^{N_e} f_i \right) - o, \quad (2.9)$$

where o is the observed variable at an observation site, and f_i is the forecast from the i th WRF member averaged over a 5 km×5 km area centered on the nearest model grid point of the corresponding observation site.

2.2.4 Statistical significance test

Statistical significance of WRF precipitation time series was assessed using a bootstrap method with 10,000 paired resamples of hourly precipitation from two WRF sub-ensembles across all flight days. Unless otherwise noted, the difference between precipitation time series from two WRF sub-ensembles shown in the paper is significant at the 95% confidence level or higher. For biases between WRF ensemble forecasts and ASOS observations of environmental parameters, statistical significance was tested using a paired Student's t-test. All reported biases are significant at the 99% confidence level or higher unless otherwise noted.

2.3 Precipitation evaluation

2.3.1 Domain-averaged precipitation and areal coverage

The hourly precipitation forecasts and MRMS observations on native grids averaged over the verification domain and flight days are shown in Fig. 2.2. The observed precipitation generally starts around 18Z, peaks at 22Z, and continues through the night. This diurnal cycle is well aligned by the WRF ensemble mean, with only a small precipitation underprediction after 00Z. Compared to the WRF ensemble mean, the operational models, i.e., the HRRR, NAM, and GFS, show much poorer performances, with around 30% to 60% of precipitation underestimation compared to the observations. While the HRRR and GFS models can capture the diurnal cycle of the observed precipitation, the peak precipitation is delayed in the NAM model (03Z).

To answer Q2 in Section 2.1, further investigation of precipitation sensitivity to the ICs/BCs is explored. In Fig. 2.2, although the three operational models all underforecast precipitation, the WRF members driven by the three models present very different

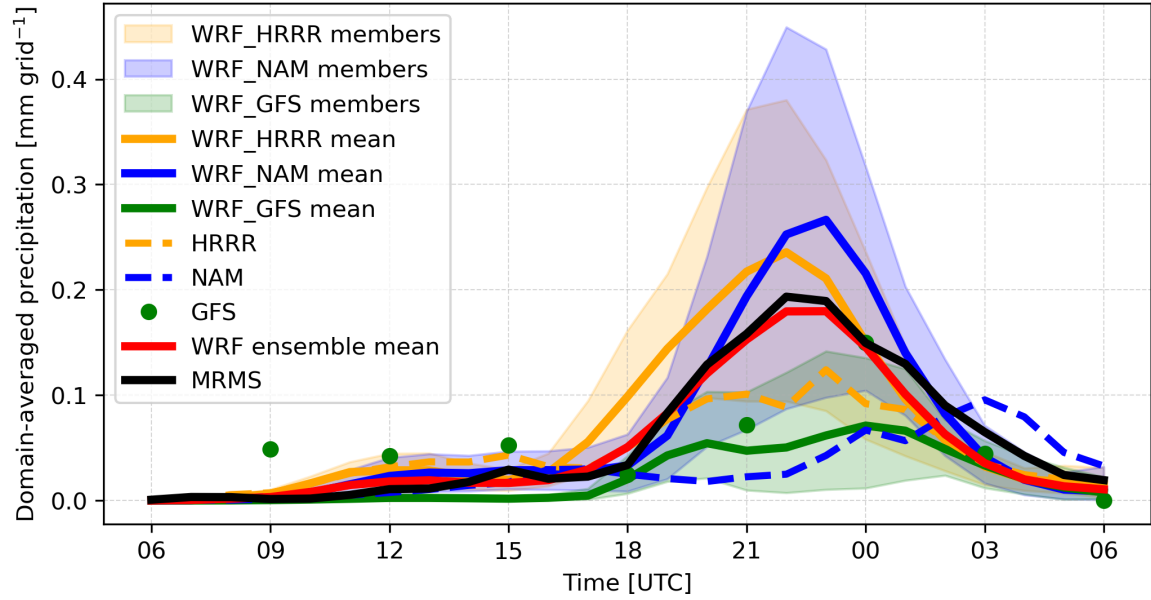


Figure 2.2: Time series of hourly precipitation (mm) averaged over the verification domain on native grids and flight days during ESCAPE. The orange, blue, and green shadings represent the 16-member minima and maxima comprising the WRF_HRRR, WRF_NAM, and WRF_GFS members, respectively, and the orange, blue, and green bold lines show the mean of WRF_HRRR, WRF_NAM, WRF_GFS sub-ensembles, respectively. The red line indicates the mean of the 48-member WRF ensemble. The orange and blue dashed lines depict the deterministic HRRR and NAM model forecasts and the green dots denote the deterministic GFS model forecasts. The black line shows the MRMS precipitation. The difference between the WRF ensemble mean and WRF sub-ensemble means is statistically significant at the 95% level from 08Z to 06Z of the next day.

results. While the WRF_HRRR and WRF_NAM sub-ensembles are able to encompass the observed precipitation, all WRF_GFS members underforecast precipitation, which is likely due to the aggressive downscaling from the coarse resolution (~ 30 km) of the GFS IC/BC to the 1-km WRF Model. It is clear in Fig. 2.2 that the 12-km NAM model shows the worst depiction of the diurnal cycle. Nevertheless, the WRF_NAM sub-ensemble captures the diurnal cycle the best, albeit with $\sim 40\%$ overestimation of precipitation amount between 20Z and 01Z. The WRF_HRRR sub-ensemble also shows an overestimation of precipitation and the precipitation started approximately two hours earlier.

Figure 2.3 shows the fractional areal coverage of the hourly precipitation (from 1 to 30 mm) forecasts and observations on native grids averaged over the verification domain and flight days. The WRF ensemble mean generally well represents the observed areal coverage of precipitation at all thresholds but with a slight underestimation after around 00Z for thresholds ≤ 20 mm hr $^{-1}$, which leads to the underestimation of the precipitation amount shown in Fig. 2.2. Notably, all WRF_GFS members underpredict the areal coverage. The WRF_NAM sub-ensemble mean overpredicts the observed areal coverage by $\sim 15\%$ at 1 mm hr $^{-1}$ to almost 100% at 30 mm hr $^{-1}$ during 18Z-03Z. The WRF_HRRR sub-ensemble mean overestimates the observations at thresholds ≤ 10 mm hr $^{-1}$ and the precipitation onset is about two hours early (16Z) compared to the MRMS (18Z). The early start and overestimation of light precipitation led to the precipitation timing shift by the WRF_HRRR sub-ensemble in Fig. 2.2. For precipitation heavier than ≥ 20 mm hr $^{-1}$, the WRF_HRRR sub-ensemble matches the observed precipitating area and diurnal cycle. Regarding the operational models, the HRRR model shows superior performance compared to the NAM and GFS models.

Figures 2.2 and 2.3 demonstrate the benefits of using a 1-km multi-ICs/BCs and mixed-physics ensemble for predicting SBC precipitation over the deterministic oper-

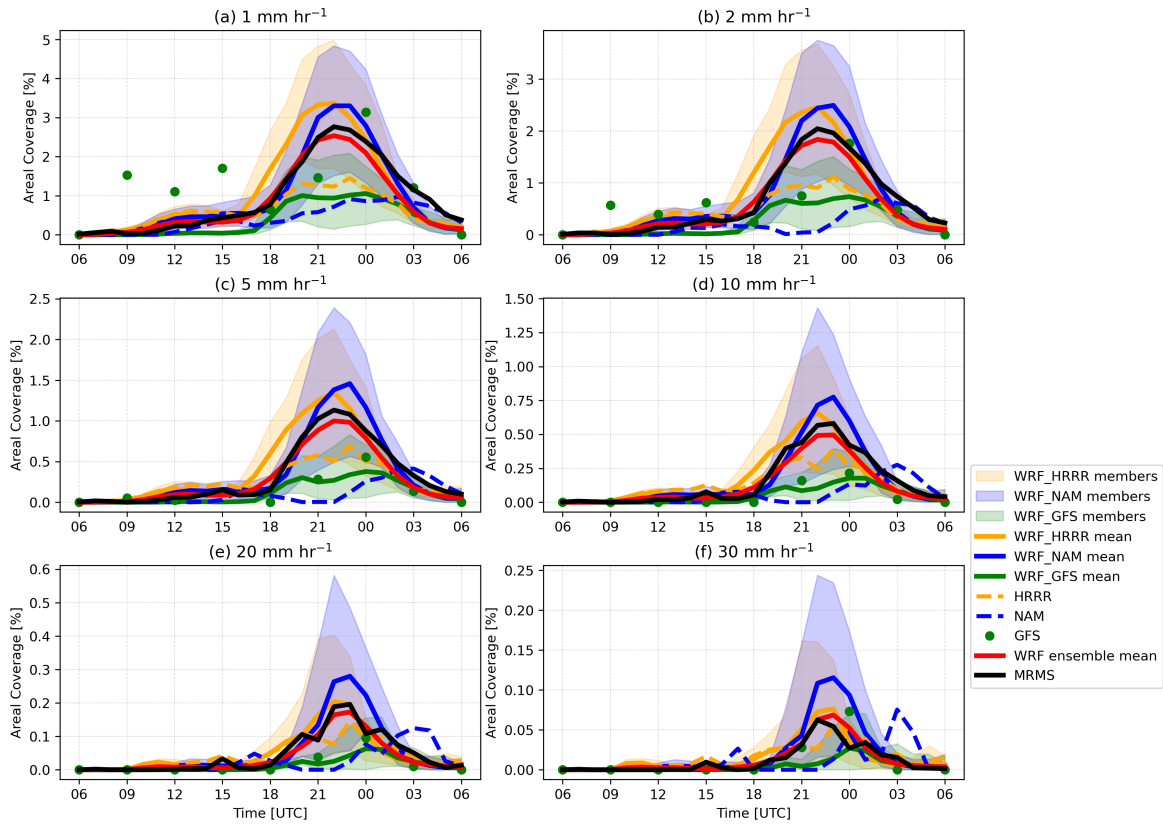


Figure 2.3: As in Fig. 2.2, but for areal coverage (%) of hourly precipitation $\geq$ (a) 1, (b) 2, (c) 5, (d) 10, (e) 20, (f) 30 mm hr⁻¹.

ational models. Furthermore, Figs. 2.2 and 2.3 illustrate the superior performance of the WRF_HRRR, WRF_NAM, and even WRF_GFS sub-ensembles, over the operational HRRR, NAM, and GFS models, respectively. These findings are consistent with previous studies demonstrating the added values of CAEs over deterministic models (e.g., Luo and Chen 2015; Mittermaier and Csima 2017; Woodhams et al. 2018; Roberts et al. 2020). More importantly, Figs. 2.2 and 2.3 also suggest that adding varied ICs/BCs to a 1-km mixed-physics ensemble shows the potential to improve SBC precipitation forecasts, as the 48-member WRF ensemble outperforms the 16-member WRF_HRRR, WRF_NAM, and WRF_GFS sub-ensembles in terms of forecasting precipitation amount, areal coverage and diurnal cycle.

2.3.2 Grid-scale verification

Hereafter, the verification of precipitation forecasts by the operational models is excluded. This is because (1) of their relatively poor performances shown above, and (2) verification methods hereafter require the forecast and observation to be on the same grid, which can induce errors when the grids differ greatly, as is the case for the GFS and NAM compared with the 1-km grid used in this study.

To evaluate the WRF ensemble’s 24-hour accumulated precipitation forecasts at the exact location, we calculated the POD, FAR, BIAS, and ETS at the grid scale for various precipitation thresholds (Fig. 2.4), ranging from 1 mm day⁻¹ (i.e., if there was precipitation at all) to 50 mm day⁻¹ (i.e., heavy rainfall). In general, the mean POD, FAR, and ETS for the WRF ensemble deteriorate rapidly with increasing rainfall rate, i.e., decreasing POD and ETS and increasing FAR with increasing thresholds (Fig. 2.4 (a,b,d)). At thresholds ≤ 3 mm day⁻¹, the WRF ensemble has a mean BIAS around 1 (Fig. 2.4 (c)), suggesting its good performance in predicting the coverage of light precipitation over the verification region. Overall, the WRF ensemble shows

an underprediction of precipitation weaker than 30 mm day^{-1} and overprediction for more intense precipitation.

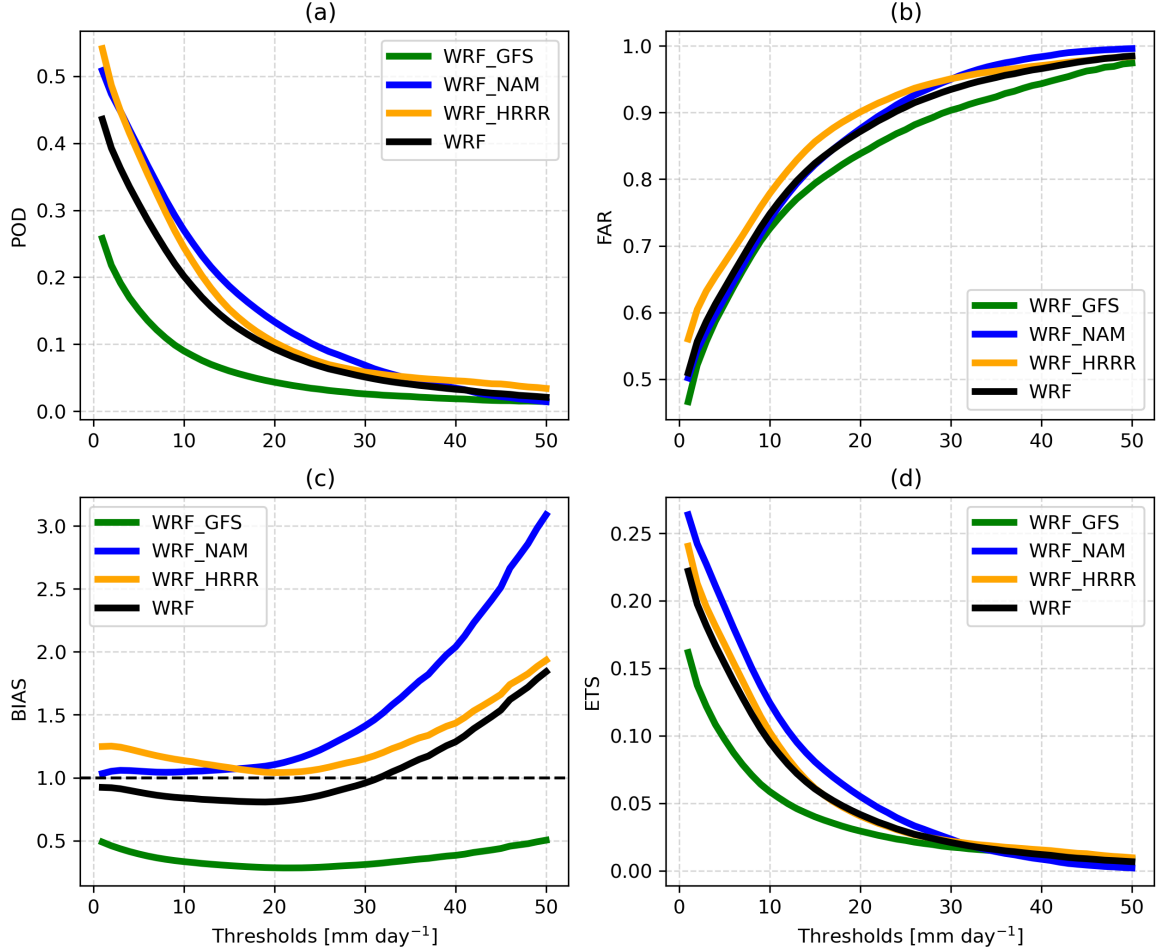


Figure 2.4: Mean (a) POD, (b) FAR, (c) BIAS, and (d) ETS for the WRF_HRRR (orange), WRF_NAM (blue), WRF_GFS (green) sub-ensembles and the WRF ensemble (black). The black dashed line in (c) indicates $BIAS = 1$ (perfect).

Compared to the WRF_HRRR sub-ensemble, the WRF_NAM sub-ensemble has a better mean ETS at thresholds $< 30 \text{ mm day}^{-1}$ (Fig. 2.4 (d)), as it has a higher mean POD and a lower mean FAR (Fig. 2.4 (a,b)). The WRF_NAM sub-ensemble also shows a mean BIAS around 1 at thresholds $\leq 20 \text{ mm day}^{-1}$, after which the mean BIAS increases rapidly (Fig. 2.4 (c)). The WRF_HRRR sub-ensemble generally shows the best mean BIAS, although it overpredicts precipitation occurrence at almost all

thresholds (Fig. 2.4 (c)), resulting in relatively high POD and FAR (Fig. 2.4 (a,b)). Meanwhile, the WRF_GFS sub-ensemble shows the worst scores, e.g., the lowest mean POD and the lowest mean ETS compared to WRF_HRRR and WRF_NAM (Fig. 2.4 (a,d)). Although WRF_GFS shows a lower mean FAR (Fig. 2.4 (b)), it is because it significantly underpredicts the precipitation frequency at all thresholds (Fig. 2.4 (c)) and thus has fewer false alarms.

Figure 2.4 suggests that the WRF ensemble struggles to predict 24-hour accumulated precipitation at the grid scale. Especially for heavy rainfall at 50 mm day^{-1} , the WRF ensemble shows a FAR near 1 (only false alarms) and POD and ETS of almost 0 (no hits). While it is possible that the convection’s intensity and structure are well predicted by the WRF model, Fig. 2.4 suggests clear displacement errors in the WRF ensemble. More importantly, results from Figs. 2.2-2.4 show obvious biases within the WRF_GFS and WRF_NAM sub-ensembles, and large spread within the WRF ensemble is also evident.

2.3.3 Neighborhood probabilistic verification

To focus on the spatial verification of precipitation, we used the percentile-based neighborhood approach to perform probabilistic verification (e.g., Theis et al. 2005; Roberts and Lean 2008; Schwartz and Sobash 2017), which is the focus of this section. Figure 2.5 shows the time series of percentile thresholds used in the neighborhood probabilistic verification process. As the percentiles increase, the difference between the WRF sub-ensembles and MRMS observations decreases. For example, the overprediction bias of the WRF_NAM sub-ensemble mean is gradually removed with increasing percentile thresholds.

To evaluate the forecasts of precipitation location, the FSS is calculated with a 3-hour temporal window and various spatial neighborhood lengths. Figure 2.6 shows

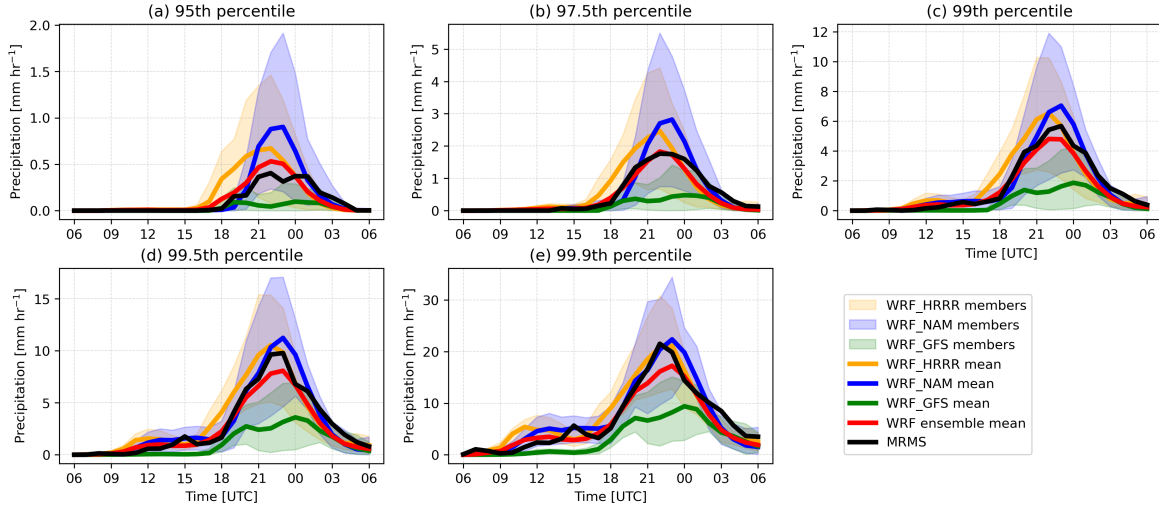


Figure 2.5: Time series of mean physical precipitation thresholds (mm hr^{-1}) corresponding to the (a) 95th, (b) 97.5th, (c) 99th, (d) 99.5th, and (e) 99.9th percentiles. The orange, blue, and green shadings represent the 16-member minima and maxima comprising the WRF_HRRR, WRF_NAM, and WRF_GFS members, respectively, and the orange, blue, and green lines show the mean of the WRF_HRRR, WRF_NAM, and WRF_GFS sub-ensembles, respectively. The red line indicates the mean of the 48-member WRF ensemble. The black line shows the MRMS observation mean. The percentiles were calculated for each WRF member and MRMS observations separately over the verification domain at every hour, then averaged on flight days to obtain the mean physical thresholds shown on the y axes.

that the FSS typically increases with larger neighborhood sizes and lower percentile thresholds, indicating less skillful forecasts for more localized and more intense precipitation. Specifically, the WRF ensemble forecasts has a useful neighborhood length of 31 km at the 95th percentile (Fig. 2.6 (a)). But to consider the WRF ensemble forecasts useful at the 99.9th percentile, a neighborhood length of ~ 120 km is needed (Fig. 2.6 (e)).

As for the sub-ensembles, WRF_HRRR and WRF_NAM show almost identical FSS across percentiles; only at percentiles between the 95th and 99th (Fig. 2.6 (a-c)) does WRF_NAM present a slightly higher FSS than WRF_HRRR at neighborhood lengths where useful skill exist (i.e., $FSS \geq 0.5$). This indicates that, similar to the WRF_HRRR sub-ensemble, the WRF_NAM sub-ensemble is capable of predicting precipitation in the vicinity of the observations, albeit that the WRF_NAM sub-ensemble overpredicts precipitation amount, areal coverage, and frequency (Figs. 2.2-2.4). Meanwhile, even though the bias is removed, the WRF_GFS sub-ensemble still shows the poorest performance with the lowest FSS and the largest minimum useful neighborhood length (Fig. 2.6), suggesting that it not only underestimates precipitation amount, areal coverage, and frequency (Figs. 2.2-2.4) but also suffers from large precipitation displacement errors.

Figure 2.7 shows the FSS calculated with a 31-km neighborhood length, which is the minimum useful neighborhood length at the 95th percentile for the WRF ensemble (Fig. 2.6 (a)). Note that the relatively high FSS values before 18Z in Fig. 2.7 are caused by the large number of correct rejections before convection initiation, i.e., no events in both observations and models, and do not necessarily mean good precipitation placement by the WRF ensemble and sub-ensembles. Nevertheless, the WRF ensemble is able to capture the diurnal variations and demonstrate usefulness in predicting precipitation placement during convective times, e.g., 18Z-00Z at the 95th percentile (Fig. 2.7 (a)),

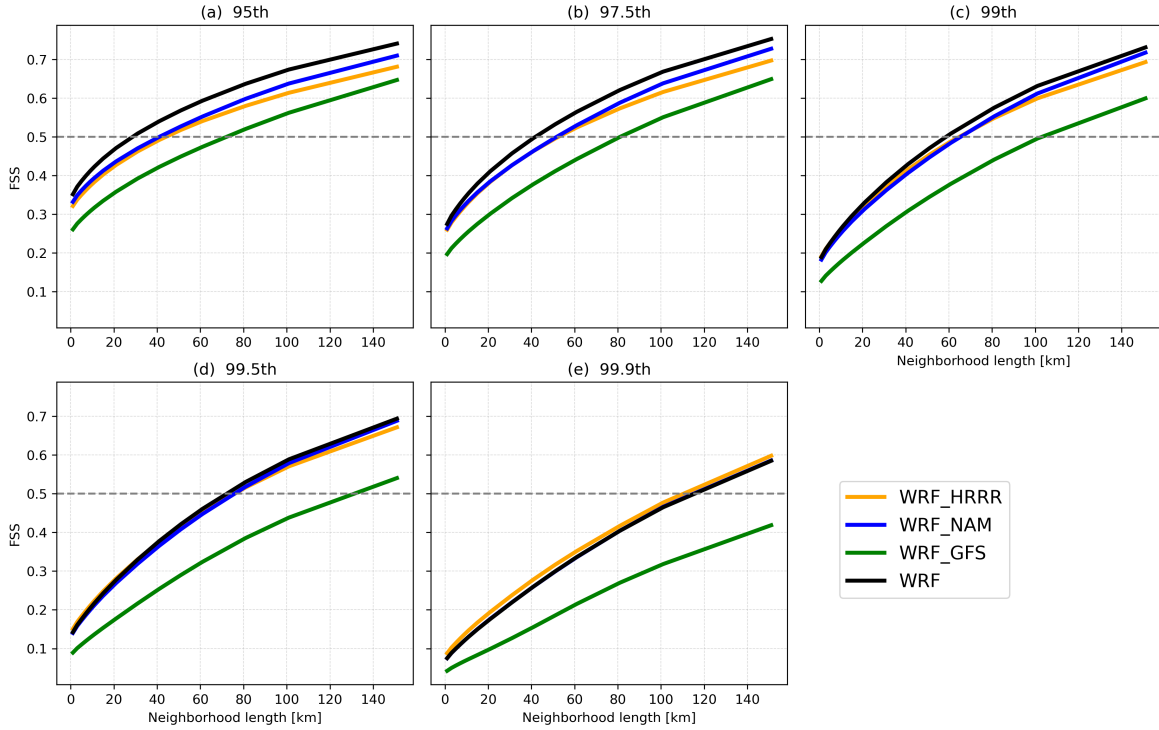


Figure 2.6: FSS as a function of neighborhood length (km) calculated from hourly precipitation aggregated between 18Z-03Z over flight days at the (a) 95th, (b) 97.5th, (c) 99th, (d) 99.5th, and (e) 99.9th percentiles. The black line represents the FSS calculated from the 48 WRF ensemble members. The orange, blue, and green lines show the FSS calculated from the 16 WRF_HRRR, 16 WRF_NAM, and 16 WRF_GFS members, respectively. The dashed line indicates a useful FSS of 0.5.

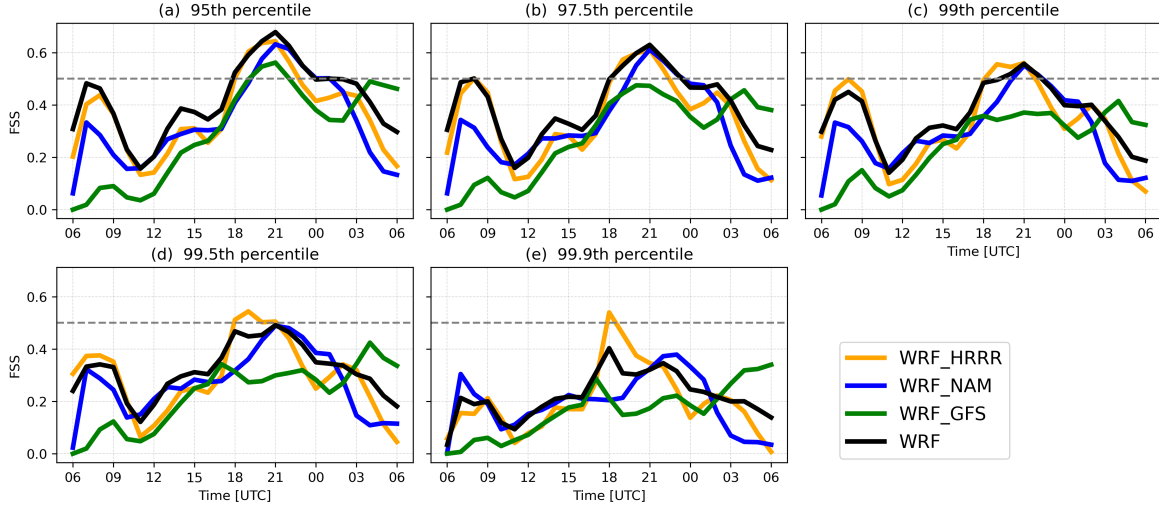


Figure 2.7: Time series of the FSS calculated from hourly precipitation aggregated over flight days with a 31-km spatial and 3-hour temporal neighborhood at the (a) 95th, (b) 97.5th, (c) 99th, (d) 99.5th, and (e) 99.9th percentiles. The black line represents the FSS calculated from the 48 WRF ensemble members. The orange, blue, and green lines show the FSS calculated from the 16 WRF_HRRR, 16 WRF_NAM, and 16 WRF_GFS members, respectively. The dashed line indicates a useful FSS of 0.5.

although the length of the useful time period decreases with increasing precipitation intensity. Compared to the WRF_NAM sub-ensemble, the WRF_HRRR sub-ensemble is more skillful during convection (18Z-21Z) at all percentiles. Again, although it also reproduces the diurnal signals, the WRF_GFS sub-ensemble is the least skillful at all thresholds compared to the WRF_HRRR and WRF_NAM sub-ensembles. The 48-member WRF ensemble is able to demonstrate matching skills to the WRF_HRRR and WRF_NAM sub-ensembles at the 95th to 99th percentiles but is less skillful than the WRF_HRRR sub-ensemble at higher percentiles, which is due to the worse skills by the WRF_NAM and especially the WRF_GFS sub-ensembles.

Analyses above suggest that, for light-to-moderate rain events (95th-99th percentiles), adding varied ICs/BCs improves the ensemble's spatial skill of SBC precipitation forecasts. But for more rare and intense precipitation events (99.5th and 99.9th percentiles) and during convective times, the benefits of using a multi-ICs/BCs

CAE over a single-IC/BC CAE is not retained.

2.4 Environmental parameters

The last section focused on the precipitation evaluation and answered Q1 and Q2 in Section 2.1. In this section, to explore the causes of the precipitation errors in the WRF ensemble, we evaluate the WRF Model’s performance in reproducing the environmental parameters at 18Z, which is the typical time for afternoon convection initiation in the study domain according to results shown above and from Fridlind et al. (2019) and Tuftedal et al. (2024).

2.4.1 Surface parameters

Figure 2.8 (a-c) displays the mean biases in T_{2m} , TD_{2m} , and WS_{10m} between the 48-member WRF ensemble and ASOS observations at 18Z. The WRF ensemble exhibits a mean bias of $-0.69\text{ }^{\circ}C$ for T_{2m} , a mean bias of $-0.76\text{ }^{\circ}C$ for TD_{2m} , and a near-zero bias for WS_{10m} (Fig. 2.8 (a-c)). This domain-wide cold and dry bias in the WRF ensemble is not conducive to convection initiation and producing precipitation. Thus not surprisingly, domain-wide underestimation of precipitation (mean: -9.08 mm) by the WRF ensemble in the following convective hours (18Z-03Z) is evident in Fig. 2.8 (d). The precipitation underestimation is attributed to the large negative bias in the wide area of LA and to the west of Houston, TX (Fig. 2.8 (d)), which mostly coincide with the ASOS sites indicating dry biases at 18Z (Fig. 2.8 (b)).

To identify the sources of the aforementioned biases in near-surface parameters, Fig. 2.9 presents the spatial distribution of biases at 18Z for the individual IC/BC sub-ensembles. The three 16-member sub-ensembles show similar spatial distribution of T_{2m} (Fig. 2.9 (a1-a3)) to the 48-member WRF ensemble (Fig. 2.8 (a)), with gen-

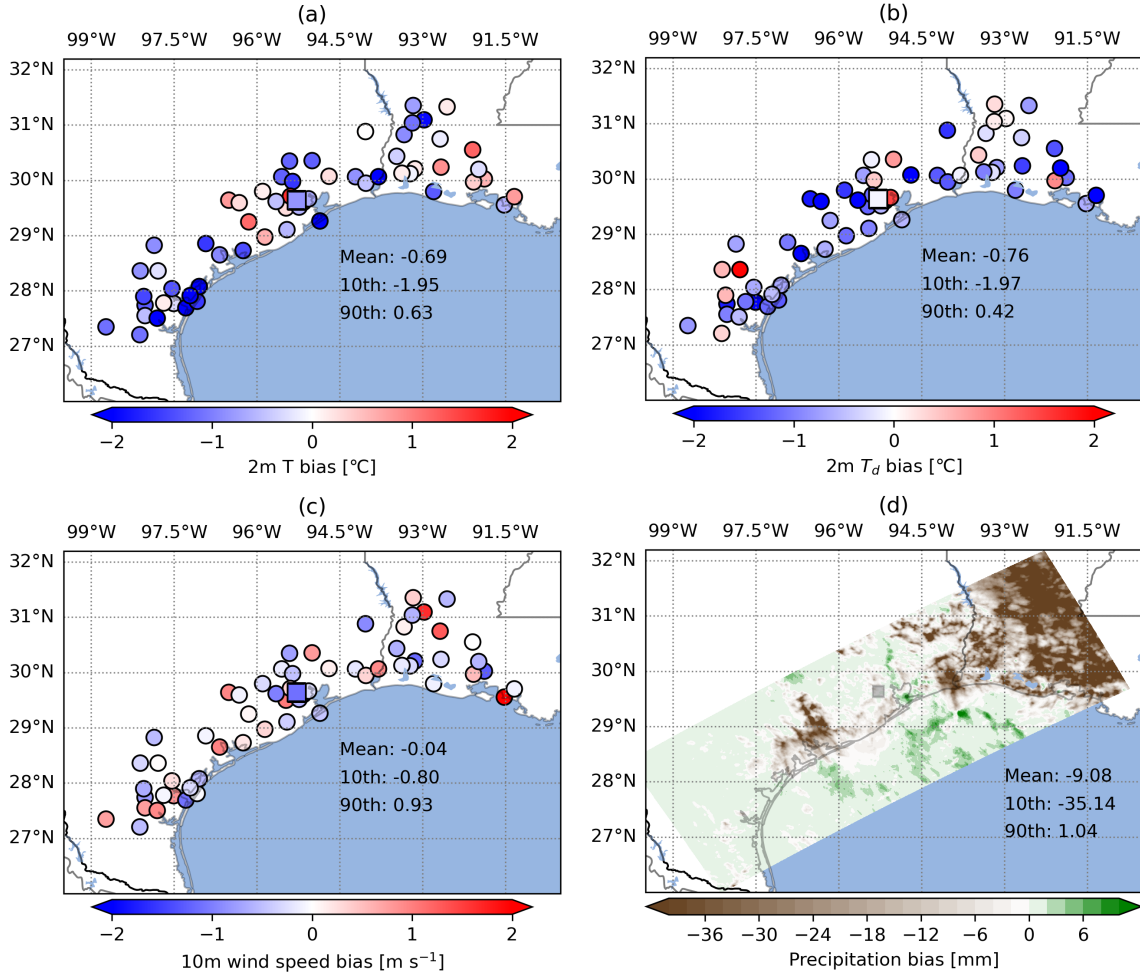


Figure 2.8: (a-c) Biases in T_{2m} ($^{\circ}\text{C}$), TD_{2m} ($^{\circ}\text{C}$), WS_{10m} (m s^{-1}) at 18Z and (d) total precipitation (mm) accumulated during 18Z-03Z. Biases were calculated between the mean of the 48-member WRF ensemble and ASOS sites (a-c) and the MRMS precipitation (d), averaged on flight days. The mean and the 10th and 90th percentiles of the biases are shown on each panel. Dots denote the ASOS sites and the square shows the ASOS HOU site.

erally warm biases in LA and west of Houston. But the WRF_GFS sub-ensemble also indicates a weak warm bias in southwest TX, leading to its smaller cold bias (mean: -0.42 °C) compared to the WRF_HRRR and WRF_NAM sub-ensembles (mean: -0.78 °C and -0.88 °C, respectively). However, the domain-wide dry bias in the WRF ensemble (Fig. 2.8 (b)) is mainly rooted in the WRF_GFS sub-ensemble, which has the largest mean TD_{2m} bias (-1.11 °C, Fig. 2.9 (b3)). Furthermore, the WRF_NAM sub-ensemble demonstrates the smallest TD_{2m} bias (mean: -0.33 °C, Fig. 2.9 (b2)) and largest WS_{10m} bias (mean: -0.24 m s $^{-1}$, Fig. 2.9 (c2)). Figure S1 suggests that the dry bias in the WRF ensemble can be attributed to the parent operational models, especially the HRRR and the GFS models. The dry surface conditions in the WRF_GFS sub-ensemble explains, at least in part, its large underprediction of precipitation as discussed previously. Relative to the other two sub-ensembles, the least dry bias in the WRF_NAM sub-ensemble is associated with more precipitation. Finally, the WRF_HRRR sub-ensemble exhibits a balanced performance relative to WRF_NAM and WRF_GFS in reproducing observed near-surface temperature, moisture, and wind speed fields (Fig. 2.9 (a1,b1,c1)). The intermediate and stable behavior of WRF_HRRR likely contributes to its relatively good performance in forecasting precipitation.

2.4.2 Vertical profiles and integrated parameters

In this section, the analysis of environmental parameters is extended to include the vertical structure of the atmosphere through a comparison with radiosonde observations collected during the TRACER campaign. However, the analysis is limited to the Houston (HOU) area, TX, owing to the much more limited data availability.

Figure 2.10 illustrates the mean biases in temperature (T), dew point temperature (TD), and wind speed (WS) between the WRF-simulated and TRACER-observed vertical profiles at HOU. In terms of T (Fig. 2.10 (a)), the WRF ensemble shows a warm

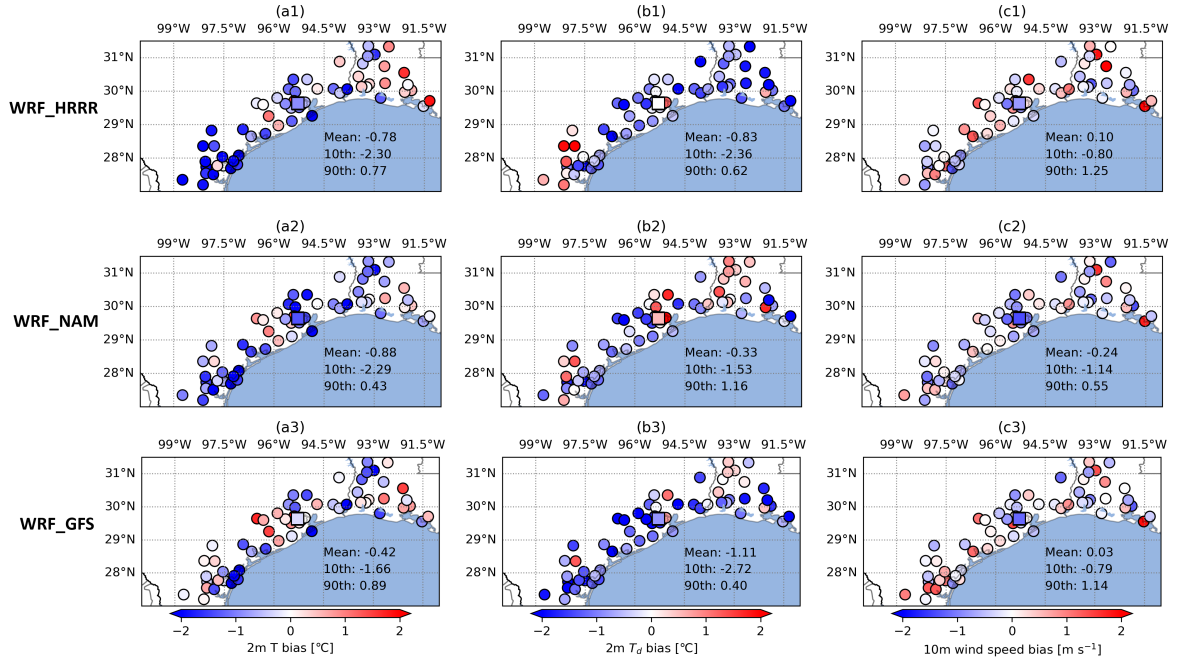


Figure 2.9: Biases in (a1-a3) T_{2m} (°C), (b1-b3) TD_{2m} (°C), and (c1-c3) WS_{10m} ($m s^{-1}$) at 18Z for the 16-member WRF_HRRR (top), WRF_NAM (middle), and WRF_GFS (bottom) sub-ensembles, respectively. Biases were calculated between the mean of the sub-ensembles and ASOS sites, averaged on flight days. The mean and the 10th and 90th percentiles of the biases computed from the 60 ASOS sites are shown on each panel. Dots denote the ASOS sites and the square shows the ASOS HOU site.

bias below ~ 800 hPa and a cold bias above. For moisture (Fig. 2.10 (b)), the WRF ensemble demonstrates a dry bias throughout the vertical layer, with a mean TD bias of -1.13 °C. Meanwhile, the WRF ensemble shows a slight overestimation (0.31 m s $^{-1}$) of WS from the surface to 800 hPa and a negative bias with a mean of -0.94 m s $^{-1}$ above 800 hPa (Fig. 2.10 (c)).

As for the different ICs/BCs, the WRF_NAM sub-ensemble shows a cold bias below 950 hPa and a warm bias between 950 hPa and 800 hPa, while the WRF_HRRR and WRF_GFS sub-ensembles both demonstrate a warm bias from the surface to 800 hPa (Fig. 2.10 (a)). Above 800 hPa, all model simulations suggest a cold bias. Regarding moisture (Fig. 2.10 (b)), the WRF_NAM sub-ensemble shows a weaker dry bias from the surface to 900 hPa but more intense dry bias between 900 hPa and 800 hPa, compared to the WRF_HRRR and WRF_GFS sub-ensembles. The resulting mean TD biases (surface–600 hPa) are -0.86 °C, -1.2 °C, and -1.34 °C for the WRF_NAM, WRF_HRRR, and WRF_GFS sub-ensembles, respectively.

The prior analysis outlines biases of the WRF ensemble at HOU in terms of the profiles of environmental variables. One question that remains is how do the aforementioned model–observation discrepancies affect other convection-related parameters, such as surface-based convective available potential energy (CAPE), wind speed shear (WSHR), and PBLH. Comparisons of these parameters are shown in Fig. 2.11, where WSHR is calculated as the bulk WS difference between the surface and 600 hPa.

Presented in Fig. 2.11 (a), the dry biases of the WRF ensemble (Fig. 2.10) translates to an underestimation of CAPE. Compared to the WRF_HRRR and WRF_GFS sub-ensembles, the WRF_NAM sub-ensemble indicates the smallest underestimation of CAPE, which we attribute to the wet bias at the surface in WRF_NAM (Fig. 2.9 (b2)) and the overall less dry TD profiles (Fig. 2.10 (b)). The differing WS biases with height shown in Fig. 2.10 (c) lead to a small overestimation of WSHR for the WRF

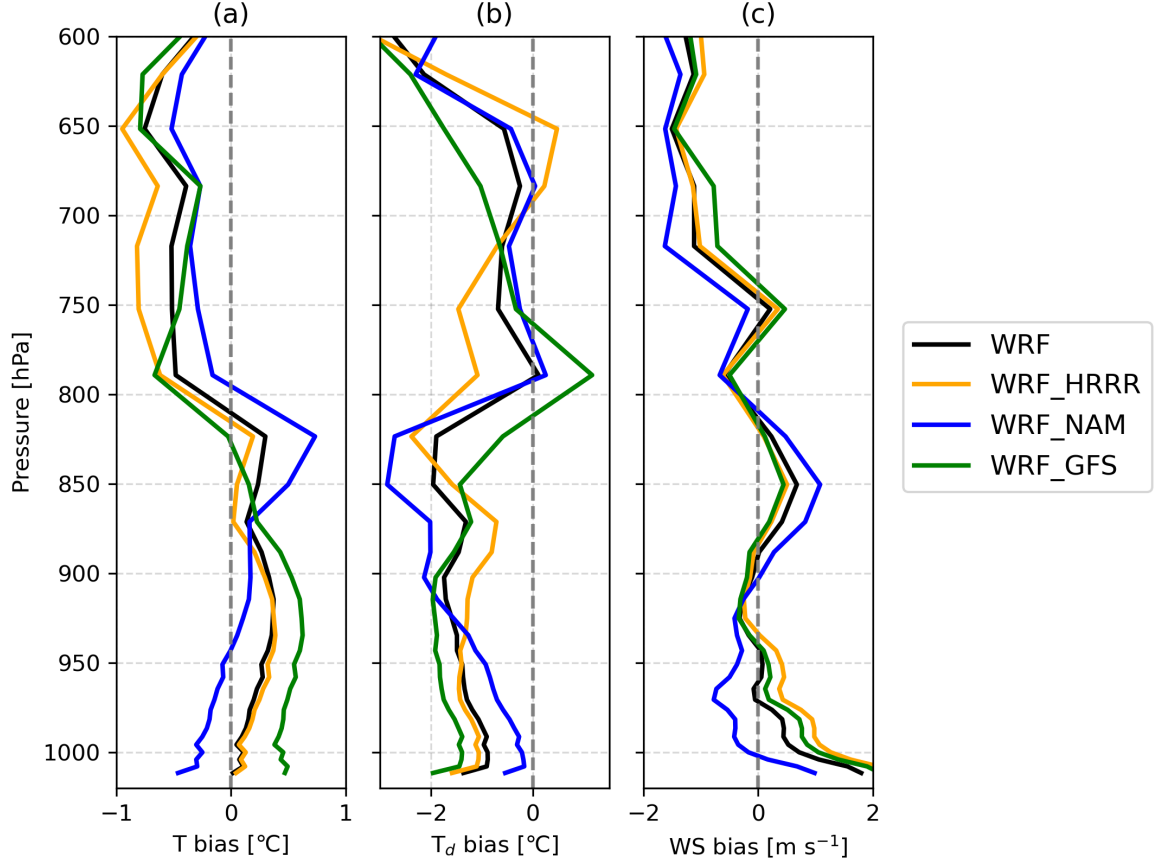


Figure 2.10: Bias profiles for (a) temperature (T , $^{\circ}C$), (b) dew point temperature (T_d , $^{\circ}C$), and (c) wind speed (WS , $m\ s^{-1}$) between the WRF ensemble forecasts and observations at 18Z. The black lines indicate the 48-member WRF ensemble, while the orange, blue, and green lines show the 16-member WRF_HRRR, WRF_NAM, and WRF_GFS sub-ensembles, respectively. Biases were calculated between the mean of the WRF ensembles and the TRACER AMF1 observations at HOU, then averaged on flight days. Dashed lines indicate zero bias.

ensemble (Fig. 2.11 (b)), but with generally no noticeable sensitivity to the different ICs/BCs. The WRF simulations underestimate the PBLH with large variations within the ensemble (Fig. 2.11 (c)), indicating that it is challenging for the WRF model to capture the PBLH in Houston for SBC. We argue that the underpredicted CAPE and PBLH contribute to the negative precipitation bias at HOU (Fig. 2.8 (d)).

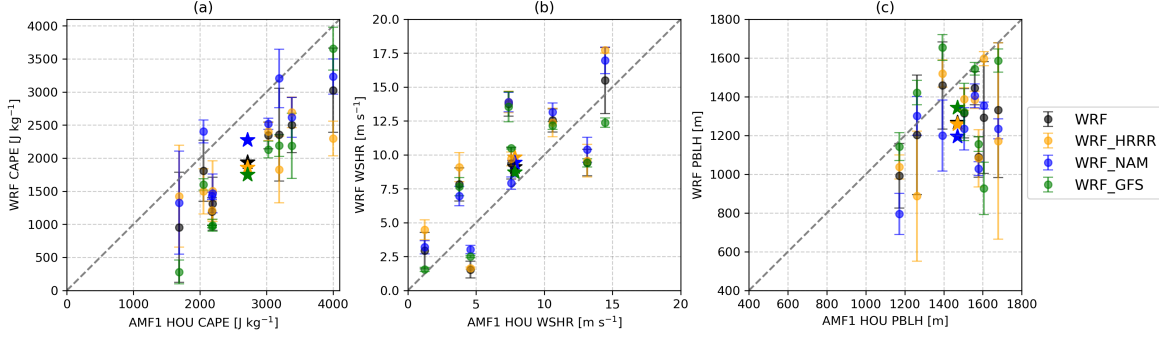


Figure 2.11: Comparison between the WRF-simulated and TRACER AMF1-observed (a) surface-based convective available potential energy (CAPE, J kg^{-1}), (b) wind speed shear (WSHR, m s^{-1}) between the surface and 600 hPa, and (c) planetary boundary layer height (PBLH, m) at 18Z, HOU. Dots indicate the means of the WRF ensembles and error bars show $\pm$ one standard deviation within each ensemble. Each dot represents one flight day. Stars denote the mean values averaged on all flight days. Black color indicates results from the 48-member WRF ensemble, while orange, blue, and green show results from the 16-member WRF_HRRR, WRF_NAM, and WRF_GFS sub-ensembles, respectively.

2.5 Grid spacing & model physics sensitivities

In the prior two sections, we assessed the overall skill of the 1-km WRF ensemble for SBC precipitation forecasts, analyzed the impact of adding varied ICs/BCs to the mixed-physics ensemble, and evaluated the environmental parameters that contribute to precipitation biases. However, Q3 and Q4 posed in Section 2.1 remain, which is the focus of this section.

2.5.1 Sensitivity to model physics

The sensitivity of SBC precipitation forecasts to differing model physics is explored in this section. Only the WRF_HRRR and WRF_NAM members are presented in this section as the WRF_GFS members showed substantial biases in previous analyses. The WRF_HRRR and WRF_NAM members are further grouped by model physics.

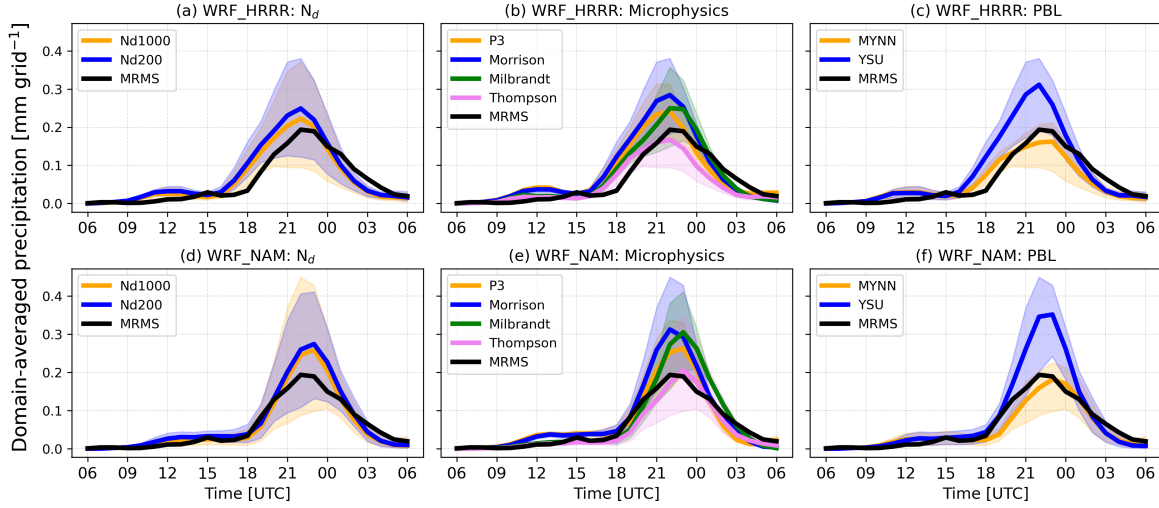


Figure 2.12: Time series of hourly precipitation (mm) averaged over the verification domain on native grids and flight days. WRF_HRRR members are shown in panels (a-c) and WRF_NAM members in panels (d-f). The black lines indicate the MRMS observations. Other labels in the legend of each panel indicates the physics option used in the WRF_HRRR (top) or the WRF_NAM (bottom) sub-ensembles. Shading shows the minima and maxima comprising the members in each grouping, and the solid line denotes the mean of those members. The difference among the means of each grouping is statistically significant at 95% level from 08Z to 06Z of the next day. In (a), Nd1000 means the eight WRF_HRRR members with $N_d = 1000 \text{ cm}^{-3}$, while Nd200 indicates the eight WRF_HRRR members with $N_d = 200 \text{ cm}^{-3}$. Similarly, P3, Morrison, Milbrandt, and Thompson in (b) represent the four WRF_HRRR members that used the P3, Morrison, Milbrandt, and Thompson microphysics schemes, respectively. MYNN and YSU in (c) represent the eight WRF_HRRR members that used the MYNN and YSU PBL schemes, respectively. The same legends apply to the WRF_NAM members in (d-f).

The ensemble forecasts in Fig. 2.12 (a, d) suggest that a higher aerosol loading ($N_d = 1000 \text{ cm}^{-3}$) leads to slightly less precipitation on average than a lower aerosol

loading ($N_d = 200 \text{ cm}^{-3}$), which is statistically significant and consistent across different ICs/BCs, i.e., WRF_HRRR and WRF_NAM. This finding that increased aerosol loading leads to less rain is consistent with recent studies (Park and van den Heever 2022; Pehl et al. 2025). Meanwhile, the WRF Model’s prediction of SBC precipitation shows more sensitivity to the microphysics schemes (Fig. 2.12 (b, e)). WRF members with the Thompson scheme tend to produce better SBC precipitation forecasts in terms of precipitation amplitude, while the other three microphysics scheme overforecast rainfall during 18Z-03Z. The largest sensitivity in precipitation arises from the PBL schemes (Fig. 2.12 (c, f)). The WRF members using the YSU scheme significantly overforecast precipitation, while the forecasts with the MYNN scheme generally agree better with the observations.

While we note that future work is needed to elucidate the causes of the differences in precipitation forecasts with different microphysics schemes and aerosol loadings, we briefly discuss the potential sources of precipitation forecast errors in the different PBL schemes by exploring the environmental parameters. At 18Z, the YSU members show a colder and less dry bias, with a mean bias of $-1.26 \text{ }^\circ\text{C}$ in T_{2m} , $-0.32 \text{ }^\circ\text{C}$ in TD_{2m} (Fig. 2.13 (d, e)), while the MYNN members indicate a mean bias of $-0.4 \text{ }^\circ\text{C}$ in T_{2m} and $-0.84 \text{ }^\circ\text{C}$ in TD_{2m} (Fig. 2.13 (a, b)). At HOU, the YSU members indicate a wetter bias than the MYNN members (Fig. 2.13 (b, e)), which extends into the upper atmosphere and lead to $\sim 500 \text{ J kg}^{-1}$ more CAPE on average (Fig. 2.14 (a)). As for WS, the MYNN members show a near-zero mean bias of WS_{10m} but a slightly higher WSHR at HOU than the YSU members. More notably, at 18Z, the MYNN members demonstrate a superior performance over the YSU members in depicting the PBLH (Fig. 2.14 (c)). Similar results have been shown in other studies. For instance, Yoon et al. (2021) found that the MYNN scheme is better than the YSU in representing the PBL structure and evolution for predicting sea breeze circulations along the east coast

of the Korean Peninsula. McCabe and Freedman (2025) also reported that the WRF Model with the MYNN scheme simulates the sea breeze conditions in the New York region better than the YSU scheme. Based on the results above, we attribute the better precipitation forecasts from the MYNN members to their overall better representation of the near-surface and vertical environmental parameters.

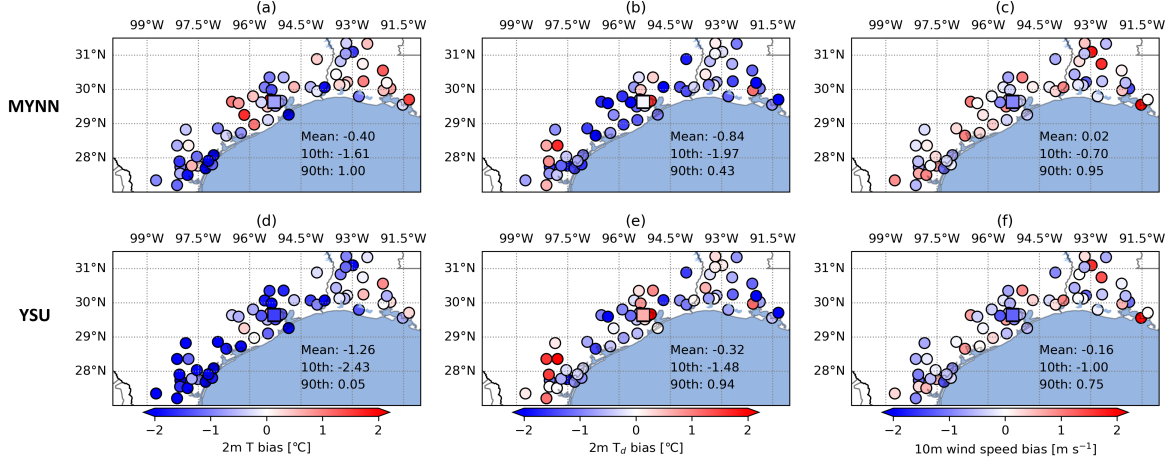


Figure 2.13: Biases in T_{2m} (°C, left), TD_{2m} (°C, middle), and WS_{10m} (m s⁻¹, right) between the WRF simulations and ASOS observations at 18Z, averaged on all flight days. Top row shows the biases for the 16 WRF members using the MYNN PBL scheme, and the bottom row shows the biases for 16 WRF members using the YSU PBL scheme. Dots show the ASOS sites, and the square indicates the ASOS HOU site. No WRF_GFS members are included in this comparison.

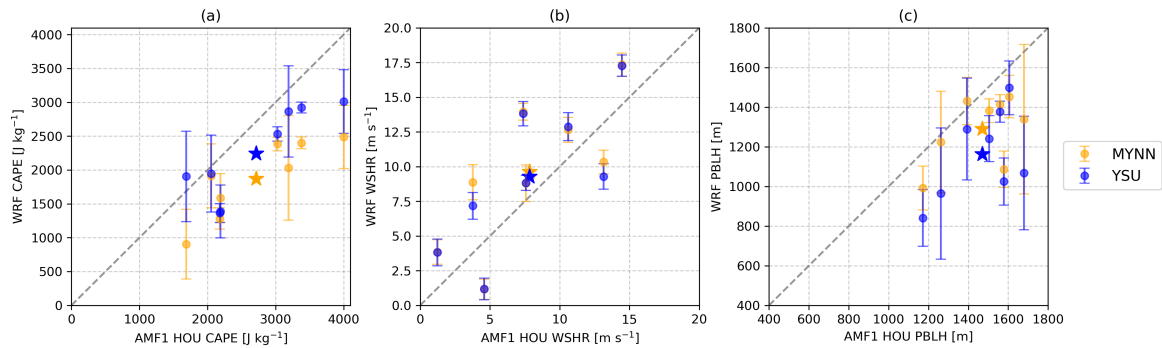


Figure 2.14: As in Fig. 2.11 but for WRF members with the MYNN (yellow) and the YSU (blue) PBL schemes. No WRF_GFS members are included in this comparison.

2.5.2 Sensitivity to horizontal grid spacing: 1-km versus 3-km

To answer Q3, additional WRF simulations at a 3-km horizontal grid spacing were conducted for all flight days. These WRF simulations were forced by the HRRR IC/BC at 06Z, used the MYNN PBL scheme, and applied four microphysics schemes each with two different N_d values. Hereafter, the 3-km 8-member WRF simulations are referred to as WRF_3km, and the same 8-member WRF simulations at 1 km are referred to as WRF_1km. Note that WRF_3km simulations were remapped to the 1-km MRMS grid to calculate verification statistics, such as POD, FAR, ETS, and FSS. All else equal, comparisons between WRF_1km and WRF_3km isolate the horizontal resolution effect on SBC precipitation forecasts.

Figure 2.15 (a) shows the domain-averaged hourly precipitation. Although the diurnal cycle is generally well captured between 18Z and 03Z, the precipitation onset is about two hours early in both WRF_1km and WRF_3km ensembles. We speculate that the early precipitation initiation is inherited from the HRRR IC/BC, as it is also evident in the HRRR forecasts and the WRF_HRRR sub-ensemble (Figs. 2.2, 2.3, and 2.5). Meanwhile, both WRF_1km and WRF_3km underforecast precipitation, but the WRF_3km ensemble mean indicates a larger underestimation of precipitation amplitude than WRF_1km, underscoring the benefit of increasing horizontal grid spacing from 3 km to 1 km.

Figure 2.15 (b) and (d) present the BIAS and ETS calculated from the 24-hour accumulated precipitation at varying thresholds. WRF_1km shows a higher BIAS but also a higher ETS for light precipitation ≤ 10 mm day⁻¹ than the WRF_3km. This implies that despite WRF_1km tending to overpredict light precipitation ($BIAS > 1$), it is better at predicting where light rains occur (higher ETS)—more hits and fewer false alarms—than WRF_3km. WRF_1km also tends to underforecast moderate precipitation (10-40 mm day⁻¹) but overforecast for heavier precipitation (> 40 mm

day⁻¹) (Fig. 2.15(b)). WRF_3km shows nearly unbiased forecasts ($BIAS \approx 1$) at thresholds ≤ 22 mm day⁻¹, but the BIAS then climbs monotonically to ≈ 2 at 50 mm day⁻¹ (Fig. 2.15(b)). As for the ETS (Fig. 2.15(d)), both the WRF_1km and WRF_3km forecasts show a monotonic decline of ETS as the threshold increases.

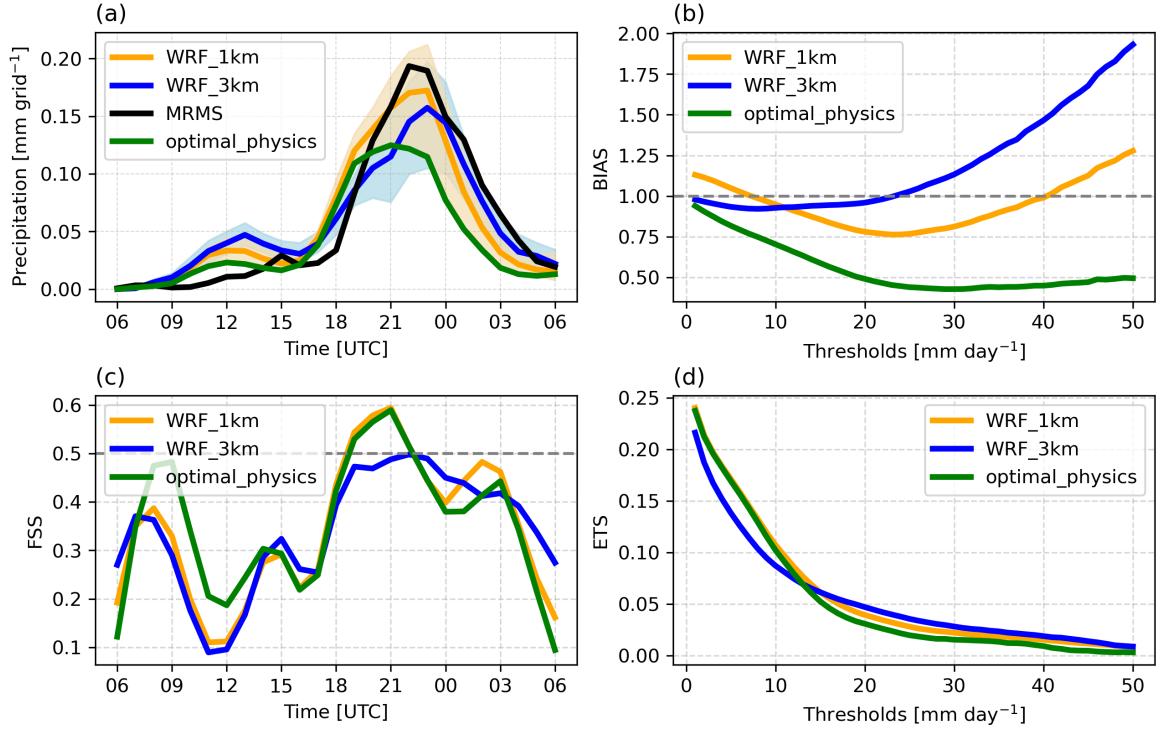


Figure 2.15: (a) Time series of hourly precipitation (mm) averaged over the verification domain on native grids and flight days. (b) BIAS as a function of precipitation thresholds. (c) Time series of the FSS calculated from hourly precipitation aggregated over flight days with a 41-km spatial and 3-hour temporal neighborhood at the 95th percentile. (d) ETS as a function of precipitation thresholds. The black line in (a) indicates the MRMS precipitation observations. Orange and blue lines show the mean of the 8-member WRF_1km and 8-member WRF_3km ensembles, respectively, while the orange and blue shadings in (a) represent the 8-member minima and maxima comprising the WRF_1km and WRF_3km members. Green lines show forecasts from the 1-km single WRF member with the optimal physics configuration (will be discussed in Section 2.52.5.3). The dashed lines in (b) and (c) indicate $BIAS = 1$ (perfect) and $FSS = 0.5$ (useful), respectively.

The benefit of using a 1-km ensemble over 3-km for forecasting SBC precipitation is further illustrated in Fig. 2.15 (c) and Fig. 2.16, which present the FSS calculated

from hourly precipitation with the percentile-based neighborhood verification method. During 18Z-22Z (Fig. 2.15 (c)), the WRF_1km forecasts indicate useful skills ($FSS > 0.5$), while at the same percentile threshold and neighborhood length, the WRF_3km forecasts can be barely considered useful ($FSS \approx 0.5$). WRF_1km also demonstrates more skillful forecasts at all percentiles than WRF_3km, and the difference between the two increases with percentiles and neighborhood lengths (Fig. 2.16). For example, to achieve a useful FSS (0.5) at the 95th percentile, a minimum neighborhood length of 40 km (55 km) for WRF_1km (WRF_3km) is required (Fig. 2.16 (a)). At the 99.9th percentile, WRF_1km can still achieve $FSS = 0.5$ at a neighborhood length of 95 km, while $FSS = 0.5$ is not reached by the WRF_3km forecasts at all neighborhood lengths shown in Fig. 2.16 (d).

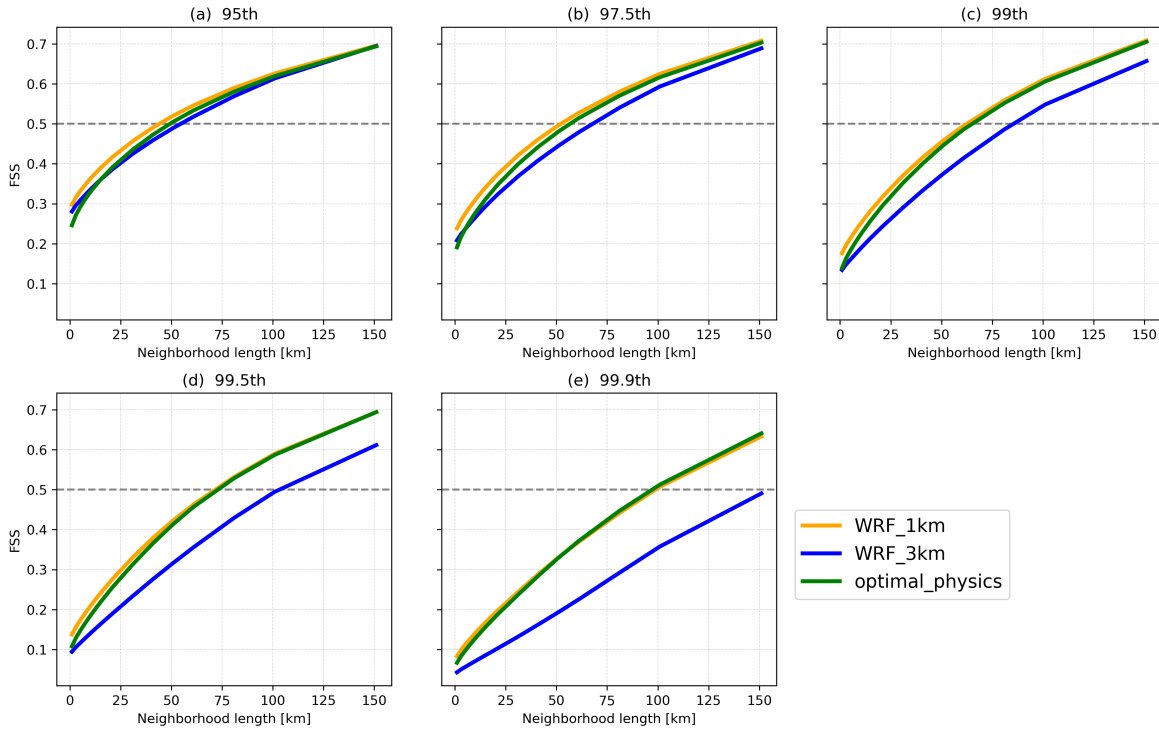


Figure 2.16: As in Fig. 2.6, but for the 8-member WRF_1km (orange) and 8-member WRF_3km (blue) ensembles, and the 1-km single WRF member with the optimal physics (green, will be discussed in Section 2.5.3).

Overall, Figs. 2.15 and 2.16 demonstrate the superior performance of WRF_1km compared to the WRF_3km ensemble, with reduced precipitation underestimation, and better categorical statistics (BIAS and ETS) for light-rain thresholds. Most notably, WRF_1km provides more skillful spatial precipitation forecasts than the WRF_3km. WRF_1km requires ~ 15 km shorter neighborhood lengths to reach a useful skill ($FSS = 0.5$) at the 95th percentile, and only WRF_1km achieves $FSS = 0.5$ for the rarest 99.9th-percentile precipitation events.

2.5.3 Single physics configuration

According to Fig. 2.12, the Thompson microphysics and MYNN PBL schemes show the most promise to produce accurate precipitation forecasts compared to other physic configurations. As for N_d , Nd200 was selected because the precipitation difference in Nd200 and Nd1000 is small and $N_d = 200 \text{ cm}^{-3}$ is closer to the default setting in the Thompson scheme. This configuration is referred to as optimal_physics in this study. With the same HRRR IC/BC, the optimal_physics member is compared to the mixed-physics WRF_1km ensemble (Figs. 2.15 and 2.16) to answer Q4 in Section 2.1.

Compared to the mean of the 8-member WRF_1km ensemble, the optimal_physics forecasts (i.e., a single-member deterministic run) largely underestimate the precipitation amplitude (Fig. 2.15 (a)), as it systematically underforecast grid-scale precipitation across all thresholds ($BIAS < 1$, Fig. 2.15 (b)). Especially for thresholds $\geq 20 \text{ mm day}^{-1}$, the optimal_physics forecasts show a nearly constant BIAS around 0.5. However, for light-rain events ($\leq 10 \text{ mm day}^{-1}$), the optimal_physics forecasts indicate identical ETS as the 8-member WRF_1km ensemble forecasts (Fig. 2.15 (d)). With the percentile-based neighborhood methods (i.e., bias-free), the optimal_physics shows comparable skill to WRF_1km during 18Z-00Z (Figs. 2.15 (c)). In fact, the optimal_physics forecasts match with the WRF_1km results for all percentiles at most

neighborhood lengths (Fig. 2.16). At smaller neighborhood lengths, WRF_1km outperforms the optimal_physics forecasts with a slightly higher FSS (though both < 0.5), but this difference in FSS generally decreases with increasing percentiles. It is noteworthy that the 1-km optimal_physics forecasts outperform the 8-member WRF_3km ensemble forecasts in terms of FSS at most percentiles (Fig. 2.16) and neighborhood lengths. Only at small neighborhood lengths (e.g., ≤ 20 km for the 95th percentile) or the grid scale does WRF_3km indicate a higher FSS (albeit not considered useful), which is the advantage of ensemble averaging over a single deterministic run.

The results in this section suggest that although the optimal_physics forecasts are greatly biased, i.e., underprediction of precipitation (Fig. 2.15 (a, b)), when the bias is removed, the optimal_physics can reproduce the forecast skills of the 8-member WRF_1km ensemble nearly identically across a wide range of precipitation events and neighborhood scales (Fig. 2.16). Only at small neighborhood lengths does the 8-member WRF_1km ensemble exhibit a marginally higher FSS - yet even in these length regimes neither forecast attains a useful FSS. Moreover, this slight ensemble advantage diminishes for rare (high-percentile) events. Our results indicate that careful physics tuning/choices alone shows the promise to capture almost all of the spatial-skill benefits afforded by an expensive high-resolution CAE.

2.6 Summary

This study describes a real-time 1-km WRF ensemble for predicting SBC, used in support of the ESCAPE campaign in Houston, TX, in June, 2022. The 48-member WRF ensemble consists of three ICs/BCs (HRRR, NAM, GFS), four microphysics schemes (P3, Morrison, Milbrandt, and Thompson) each with a low (Nd200) or high (Nd1000) aerosol loading, and two PBL schemes (MYNN and YSU). In this paper,

we present a comprehensive evaluation of the precipitation forecasts against the 1-km MRMS observations on eight SBC cases. The main findings are summarized below.

- **Ensemble evaluation:** The 48-member WRF ensemble mean well replicates the diurnal cycle and areal coverage of the observed SBC precipitation over the verification domain, but with a slight underestimation of magnitude after 00Z, which is due to precipitation underprediction in LA and west of Houston. The precipitation underestimation is associated with a cold and dry bias near the surface and an underestimation of CAPE and PBLH. At the grid scale, the WRF ensemble struggles to predict the correct amount of 24-hour accumulated precipitation with a tendency to overestimate precipitation heavier than 30 mm day^{-1} . Using the percentile-based neighborhood probabilistic verification method, the WRF ensemble is shown to provide skillful hourly precipitation forecasts of SBC at a minimum neighborhood length of 31 km.
- **Sensitivity to ICs/BCs:** The WRF_HRRR sub-ensemble exhibits the best performance in terms of precipitation amount, areal coverage, and spatial placement, especially during times of peak convection (18Z-00Z), which we attribute to its ability to reproduce the observed near-surface and vertical environmental parameters. While the WRF_NAM sub-ensemble can capture the precipitation diurnal cycle, it overforecasts precipitation amount, areal coverage, and frequency due to its less wet bias near surface and in the vertical column. However, the WRF_NAM sub-ensemble shows comparably skillful precipitation location forecasts as the WRF_HRRR, indicating that a wet-biased ensemble can score well with percentile-based verification, albeit failing to predict the actual hazardous precipitation amount. The WRF_GFS sub-ensemble demonstrates the worst precipitation forecasts with constant underestimation of precipitation amount, areal

coverage, and frequency and poor precipitation location predictions. This is related to its poor representation of the environmental parameters and the aggressive downscaling from the GFS model to the 1-km WRF Model.

- **Sensitivity to horizontal resolution:** All else equal, both the WRF_1km and WRF_3km ensembles replicate the observed precipitation diurnal cycle but underestimate the precipitation amplitude, although this underestimation is smaller in WRF_1km. Gird-scale categorical statistics suggest that despite a wetter light-rain bias ($BIAS > 1$ for threshold $\leq 10 \text{ mm day}^{-1}$), WRF_1km predicts light-rain events in the right locations more often (higher ETS) than WRF_3km. WRF_3km shows a much higher tendency to overforecast moderate-to-heavy precipitation ($\geq 22 \text{ mm day}^{-1}$). Spatial verification suggests that WRF_1km needs $\sim 15 \text{ km}$ shorter neighborhood lengths than WRF_3km to reach a useful FSS at the 95th percentile, and that only WRF_1km achieves useful FSSs at the 99.9th percentile.
- **Sensitivity to model physics:** With the same IC/BC, the WRF Model precipitation forecasts show the largest sensitivity to the PBL schemes, then microphysics schemes and finally aerosol loadings. WRF members with the MYNN scheme display more accurate precipitation forecasts than those employing the YSU scheme, as the YSU members show a relatively wetter bias and have a poorer PBLH depiction. The Thompson microphysics scheme presents the best precipitation alignment with the observations than the other three microphysics schemes, which all overforecast precipitation. The ensemble forecasts suggest that a higher aerosol loading leads to less precipitation and hence agrees better with the observations.

In Section 2.1, four questions were posed that the study aims to answer. From the results, we may conclude the following. (1) The 1-km 48-member WRF CAE

outperforms deterministic operational models in predicting SBC precipitation. This superior performance is due to both the increased horizontal grid spacing and the ensemble approach that accounts for model physics uncertainties. (2) In this study, adding varied ICs/BCs to a 1-km mixed-physics ensemble improves SBC forecasts of light-to-moderate precipitation. For more intense rainfall rates (≥ 99 th percentile), the benefits of using multiple ICs/BCs over a single IC/BC are not retained, especially when one IC/BC (e.g., GFS) already suggests poor performance. (3) Moving from 3-km to 1-km horizontal grid spacing delivers clear gains in SBC precipitation forecasts. At the grid scale, the 1-km CAE demonstrates better categorical statistics for thresholds $\leq 10 \text{ mm day}^{-1}$ than the 3-km CAE forecasts. Based on neighborhood verification, the 1-km CAE also demonstrates superior forecast skills over the 3-km CAE at all percentiles and neighborhood lengths. (4) The optimal physics configuration identified in this study is the Thompson microphysics scheme combined with the MYNN PBL scheme. With the same IC/BC, the 1-km WRF member configured with the optimal physics is able to match the forecast skills of a 1-km mixed-physics ensemble, but the mixed-physics ensemble demonstrates less-biased precipitation forecasts. Finally, we note that the results in this study should be interpreted cautiously because of the small number of SBC cases investigated, and future studies should work toward expanding the number of cases, potentially through new field campaigns.

While current computational resources still limit our ability to conduct LES-scale ensemble simulations, the 1-km grid spacing perhaps is the middle ground that compromises on the increased resolution but still allows for an ensemble approach in convective precipitation forecasts. Additionally, this work underscores the importance of model physics in SBC precipitation forecasts. It is critical to identify the key parameters and mechanisms within model physics parameterizations to enable process-based understanding of precipitation. Thus, we can contribute to model development and provide

more accurate precipitation forecasts even by deterministic models. Future work will scrutinize precipitation sensitivity to factors, such as aerosol conditions and ice production processes in clouds, which remain underrepresented in most NWP models today.

Chapter 3

How do secondary ice production processes impact precipitation formation in deep convection?

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*In preparation for submission.

3.1 Introduction

There are two microphysical pathways for precipitation formation, known as the warm-rain and the cold-rain processes, respectively (e.g., Gupta et al. 2023). In the warm-rain pathway, water vapor condenses onto cloud condensation nuclei to form tiny cloud droplets, which then collide and coalesce to form larger rain drops. These drops may (1) continue to grow by collision-coalescence until they become too heavy to remain suspended and fall as rain, or (2) freeze to form graupel. In the cold-rain pathway, tiny ice crystals form and grow, e.g., by vapor deposition through the Bergeron process (Bergeron 1935), then aggregate to form snow, and may further grow to form graupel/hail through riming. In reality, warm- and cold-rain pathways coexist and interact within clouds. However, the cold-rain process can be much faster than the warm-rain process to produce precipitation, since ice crystals can reach precipitation sizes more quickly than cloud droplets (McFarquhar et al. 2017a). Although the critical role of ice crystals in precipitation formation has long been recognized, our understanding remains limited due to the complexity of ice-phase particles (Gultepe et al. 2017; Morrison et al. 2020).

Ice crystals in clouds form through two sets of processes: primary ice production (PIP) and secondary ice production (SIP) processes (e.g., Kanji et al. 2017). PIP includes both homogeneous (HO) freezing and heterogeneous (HT) freezing. At temperatures below approximately -38°C , supercooled liquid drops in clouds can freeze spontaneously (homogeneously) to form ice particles. Between 0 and -38°C , ice nucleating particles (INPs) are required for supercooled liquid drops and water vapor to initiate the first ice crystal via HT freezing. Yet, airborne and in situ observations consistently show that ice particle number concentrations in clouds exceed INP concentrations by orders of magnitude, which cannot be explained by PIP processes (e.g.,

Murgatroyd and Garrod 1960; Hobbs et al. 1980; Harris-Hobbs and Cooper 1987; Field et al. 2001; Korolev et al. 2011; Ladino et al. 2017).

SIP processes, which generate additional ice from pre-existing ice particles, are widely believed to account for this discrepancy (Field et al. 2017; Korolev et al. 2022). Over the past several decades, multiple SIP mechanisms have been described. Korolev and Leisner (2020) reviewed laboratory studies of six: (1) fragmentation of freezing rain drop (FFD), (2) rime-splintering (Hallett-Mossop, HM), (3) ice-ice collisional break up (IICOL), (4) ice fragmentation under thermal shock, (5) fragmentation during sublimation, and (6) transient activation of INPs in supersaturation. More recently, two additional SIP processes have been proposed: (7) fragmentation of recirculated rain drops in the melting layer (Korolev et al. 2020) and (8) break-up of freezing water drops on impact with ice particles (James et al. 2021). Despite these advances, SIP representations in numerical models remain sparse due to limited understanding of their physical bases, large uncertainties in process rates, and a lack of in situ and laboratory constraints (Morrison et al. 2020).

FFD was the first SIP mechanism proposed and has been extensively studied in laboratory experiments (e.g., Langham and Mason 1958; Mason and Maybank 1960). As supercooled liquid drops freeze inward, internal pressure builds and may lead to cracking, shattering, and jetting of small ice particles (e.g., Lauber et al. 2018). Building on pooled laboratory evidence, Phillips et al. (2018) developed a numerical formulation for FFD implementation in models. HM refers to splinter production during riming, which occurs in a narrow temperature range of -3 to -8 °C and peaks at -5 °C (Hallett and Mossop 1974; Mossop and Hallett 1974). HM requires both small ($< 13 \mu\text{m}$) and large ($> 24 \mu\text{m}$) cloud droplets, as well as the presence of graupel. Among SIP mechanisms, HM is the most thoroughly studied and best quantified (see Table 2 in Korolev and Leisner (2020)), providing a basis for various formulations in models (e.g., Reisner

et al. 1998). IICOL describes the mechanical breakup of ice particles upon collision. Two laboratory studies (Vardiman 1978; Takahashi et al. 1995) investigated IICOL in different experimental setups and environmental conditions but reached different conclusions, though several parameterizations have been developed numerically based on these two studies (e.g., Phillips et al. 2017; Hoarau et al. 2018; Sullivan et al. 2018b). In addition, Deshmukh et al. (2022) proposed an empirical formulation for ice particle fragmentation during sublimation. However, aside from HM, FFD, and IICOL, little is known or has been observed about the other SIP mechanisms (Korolev and Leisner 2020).

For decades, HM was the only SIP mechanism incorporated into bin or bulk microphysics schemes (Field et al. 2017). Yet, HM alone cannot explain the large gap between INP and ice particle number concentrations (Stanford et al. 2017; Qu et al. 2018; Sullivan et al. 2018b; Huang et al. 2022b; Hu et al. 2023). Moreover, a recent laboratory study by Seidel et al. (2024) even reported no evidence of productive splinter formation by HM process, which fundamentally questions the importance of HM. Recently, efforts have expanded to include additional SIP processes into different bulk (Sullivan et al. 2018a; Huang et al. 2022a; Qu et al. 2022; Cholette et al. 2024; Zhao and Liu 2021; Sotiropoulou et al. 2021a,b; Georgakaki et al. 2022; Patnaude et al. 2025), bin (Grzegorzcyk et al. 2025; Yang et al. 2024) microphysics schemes, and Lagrangian parcel models (Sotiropoulou et al. 2020). Collectively, these studies show that incorporating SIP improves model performances and highlight SIP’s impacts on ice particle number concentrations, convective cloud development, precipitation, freezing rain forecasts, thunderstorm electrification, and global radiative forcing. Notably, some studies (e.g., Grzegorzcyk et al. 2025; Patade et al. 2025) report that SIP reduces surface precipitation, whereas Sullivan et al. (2018b) found the opposite—that SIP can systematically increase precipitation. Such divergent outcomes underscore the need for

further explicit investigations of how SIP processes interact and influence precipitation in different convective systems.

Building on recent efforts and addressing the contrasting precipitation results from previous studies, we aim to further examine the role of SIP in deep convection. Specifically, the objective of this work is to answer the question: how do SIP processes modulate precipitation formation pathways? Additionally, we investigate the complex interplay among different SIP processes and their impacts on the microphysical, dynamical, and thermodynamical properties of deep convection. To address these questions, we expand the representation of SIP processes in the Thompson microphysics scheme (Thompson et al. 2008; Thompson and Eidhammer 2014; Jensen et al. 2023) and perform two idealized simulations: a supercell and an oceanic mesoscale convective system (MCS), using the Weather Research and Forecasting (WRF) model.

The remainder of this Chapter is organized as follows. In Section 3.2, the Thompson scheme is briefly reviewed and the implementation of SIP is described. Section 3.3 details the design of the model experiments of the two idealized deep convection cases and methodologies used for calculations in this work. Section 3.4 analyzes the impacts of SIP on cloud and precipitation properties for the supercell case. Section 3.5 presents results for the tropical MCS case, as well as comparisons of simulated ice properties with field campaign observations. Finally, Section 3.6 summarizes the main findings.

3.2 SIP implementation in the Thompson scheme

3.2.1 The Thompson microphysics scheme

The Thompson microphysics scheme is distinguished by its coupling to aerosol properties and has been widely adopted in numerical models for scientific research and operational weather forecasting purposes. Three versions of the Thompson microphysics

scheme are currently available: the default Thompson scheme (Th08; Thompson et al. 2008), the aerosol-aware Thompson scheme (TE14; Thompson and Eidhammer 2014), and the hail-aware Thompson scheme (TJ23; Jensen et al. 2023), respectively. The hydrometeor properties predicted by these three schemes are summarized in Table 3.1. Note that the TJ23 scheme does not explicitly predict a hail hydrometeor category; rather, it represents both graupel and hail through variable graupel densities (Jensen et al. 2023).

Scheme	Mass mixing ratio (Q; kg kg ⁻¹)	Number concentration (N; kg ⁻¹)
Th08	Qc, Qr, Qi, Qs, Qg	Nr, Ni
TE14	Qc, Qr, Qi, Qs, Qg	Nc, Ni, Nr, Nn, Nni
TJ23	Qc, Qr, Qi, Qs, Qg	Nc, Ni, Nr, Nn, Nni, Ng

Note 1: c-cloud water, r-rain water, i-cloud ice, s-snow, g-graupel, n-cloud condensation nuclei, ni-ice nuclei.

Note 2: TJ23 also predicts the volume mixing ratio of graupel.

Table 3.1: Hydrometeor properties predicted by the three Thompson microphysics schemes.

Ice production processes in the Thompson schemes consist of multiple PIP processes and one SIP process. PIP processes include homogeneous freezing below -38 °C (Koop et al. 2000) and several heterogeneous freezing: immersion freezing (Bigg 1953) and a combination of deposition/condensation freezing (Cooper 1986; Phillips et al. 2008; DeMott et al. 2010). While additional SIP processes have been tested in many different microphysics schemes, SIP within the Thompson bulk microphysics scheme remains underrepresented. The only SIP process parameterized in the Thompson schemes is the HM process (Hallett and Mossop 1974; Reisner et al. 1998), and graupel must be present in the proper temperature range.

In this work, two additional SIP processes: IICOL and FFD, are implemented in the

three Thompson schemes using an explicit bin-emulating approach. That is, a system of bins is used to discretize the size distribution of each type of hydrometeor (e.g., cloud ice), with the number concentrations, mass mixing ratios, and fall speeds represented in each bin. The SIP process rates are stored as lookup tables for consistency and accessibility.

3.2.2 IICOL implementation

IICOL is implemented into the Thompson schemes following Phillips et al. (2017), which is developed based on the conservation of collisional kinetic energy. The theoretical consideration of collisional fragmentation in Phillips et al. (2017) is based on the ice production rate from Takahashi et al. (1995) and the process rate depends on ice particle size, temperature, collisional kinetic energy, and degree of prior riming. The colliding ice particles can belong to any categories, such as cloud ice crystals, snow, graupel, and hail.

The Thompson schemes consider three ice categories: cloud ice, snow and graupel (Table 3.1). Specifically, ice-ice collision is allowed between cloud ice-snow, cloud ice-graupel, snow-snow, snow-graupel, and graupel-graupel. Additionally, graupel-hail and hail-hail collisions were considered for the TJ23 scheme. No collision between cloud ice and cloud ice is permitted. A minimum size of 100 μm (300 μm) is required for cloud ice (snow) to undergo collisions with other ice particles. It is assumed that the smaller particle will break up. Fragments from collisions between graupel and hail are assigned to the snow category if the mass of fragments are larger than the mass of the smallest snow particle. Otherwise, fragments are assigned to the cloud ice category.

While Phillips et al. (2017) provided detailed description of the IICOL scheme, two parameters need to be adjusted in our implementation. The first parameter is the rimed fraction Ψ for cloud ice and snow. A rimed fraction of $\Psi < 0.5$ is required

in Phillips et al. (2017) concerning collisions of either cloud ice or snow with any ice category. However, like many other bulk microphysics schemes, the Thompson schemes do not explicitly predict Ψ for cloud ice or snow. Therefore, a constant $\Psi = 0.4$ is used in this study. We note that it is unrealistic to assume a constant Ψ as it depends both on particle size and temperature. Yet Sotiropoulou et al. (2021a) reported that ice multiplication by IICOL is not sensitive to the rimed fraction and $\Psi = 0.4$ can be used as long as cloud-ice-to-snow autoconversion is considered in the microphysics scheme, which is true for the Thompson schemes.

The second parameter is the collision efficiency E_c between ice particles. The collision efficiency can be expressed as $E_c = 1 - E_a$, where E_a is the aggregation efficiency between ice particles. The Thompson schemes assume $E_a = 0.05$ for snow aggregating cloud ice and no aggregation between other ice particles. Previous studies have assumed $E_a = 0.1$ for ice-ice collections (aggregation) (e.g., Morrison and Grabowski 2010; Sotiropoulou et al. 2021b). Huang et al. (2022b) found that the main conclusions and results did not change in their sensitivity experiments with E_a ranging between 0.02 and 0.21 at different temperatures and a final $E_a = 0.1$ was applied in their study. Therefore, we assume $E_c = 0.95$ ($E_a = 0.05$) for cloud ice-snow collision and $E_c = 0.9$ ($E_a = 0.1$) for other types of ice-ice collisions in the IICOL implementation.

3.2.3 FFD implementation

The FFD scheme proposed by Phillips et al. (2018) include two modes, both of which were implemented in the Thompson schemes. Mode 1 is the fragmentation of spherical rain drops during heterogeneous freezing. The number of fragments generated per drop depends on the drop size and ambient temperature, and the fragments were assigned to different ice categories (graupel/snow/cloud ice) per their size and mass. Mode 2 represents the collisions of supercooled rain drops with more massive ice particles. In

the Thompson schemes, we considered collisions of rain drop with snow and graupel (and with hail for the TJ23 scheme). The Thompson schemes assume accretion efficiencies of 0.95 and 0.75 for rain-snow and rain-graupel. Therefore, a collision efficiency of $E_c = 0.05$ ($E_c = 0.25$) was used for collisions of rain drops with snow (graupel). All fragments produced by mode 2 were assigned to the cloud ice category.

3.3 WRF Model and methodology

The WRF Model version 4.6 (Skamarock et al. 2019) is used to perform idealized simulations of two deep convection cases. Essential information about the WRF Model configurations are summarized in Table 3.2 and applied to all experiments in this work. Shortwave and longwave radiation, surface layer physics, cumulus scheme are neglected. The hail- and aerosol-aware Thompson microphysics scheme (Jensen et al. 2023) is used for all simulations in this study. Finally, a 1.5-order turbulent kinetic energy 3D clousure is used for subgrid-scale mixing instead of a planetary boundary layer scheme. More detailed configurations for each case is revealed below.

Model Parameter	Model Configuration
Duration	3 hours
Output frequency	5 minutes
Spin-up time	30 minutes
Integration time step	1 second
Horizontal grid spacing	200 m
Grid points	751×751
Microphysics	Hail- and aerosol-aware Thompson scheme (TJ23)
Planetary boundary layer	1.5-order turbulent kinetic energy 3D closure

Table 3.2: Model configurations employed for all experiments in this work.

3.3.1 Continental supercell

A supercell that produced the 24 May 2011, EF5 tornado near El Reno, Oklahoma (French et al. 2015) is simulated with 100 vertical levels topped at 20 km. The warm bubble method with a temperature perturbation of 3 K is used to initiate convection. Figure 3.1 (a) shows the thermodynamic profile used for the idealized simulation. This profile is based on the sounding derived from a Rapid Update Cycle forecast near the observed supercell as in Orf et al. (2017) but with a modified wind profile as in Kacan and Lebo (2019). Large amount of surface-based convective available potential energy (CAPE; 4878 J kg^{-1}) and wind shear (31.8 m s^{-1} between 0-6 km) are present in the sounding.

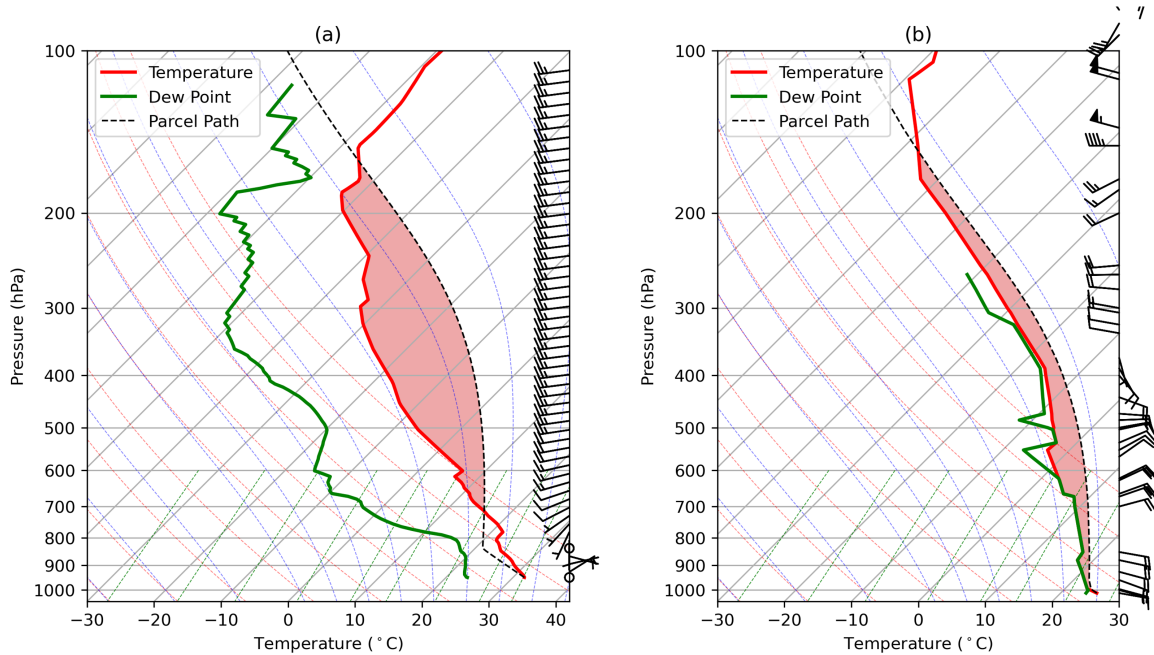


Figure 3.1: Input soundings used to initialize the idealized simulations of (a) continental supercell and (b) tropical oceanic deep convection; temperature (red), dew point temperature (green), and wind barbs (black) are also shown in the diagrams. The red shading area indicates the surface-based convective available potential energy.

3.3.2 Tropical MCS

An MCS was observed on 26 May 2015 in the tropics during the High Altitude Ice Crystals and High Ice Water Content (HAIC-HIWC) field campaign (Strapp et al. 2021). Eighty vertical levels topped at 18 km is used in this case. The input sounding for model initialization is taken from a radiosonde released at Cayenne at 00Z on 26 May 2025 (Fig. 3.1 (b)). The sounding has an absolutely unstable layer and is saturated below ~ 600 hPa, with 1397 J kg^{-1} of surface-based CAPE and wind shear of 6.7 m s^{-1} between 0-6 km. Easterly winds prevail below ~ 350 hPa and westerly winds prevail above.

Convection is initiated by nudging the vertical velocity tendency in the boundary layer (Ziegler et al. 2010). The updraft tendency ($\frac{dw}{dt}$) is determined by:

$$\frac{dw}{dt} = \alpha \times \mu \times \gamma \times \cos^2\left(\frac{\pi}{2} \times \beta\right), \quad (3.1)$$

where μ is vertical mass perturbation. The nudging function (Eq. 3.1) is contained within a spheroidal volume with horizontal and vertical radii of 10 and 2.5 km ($x_r = y_r = 10$, $z_r = 2.5$), respectively, a central elevation of 2.5 km above ground level ($z_c = 2.5$), and an amplitude of 0.1 m s^{-2} ($\alpha = 0.1$). The coefficients γ and β are calculated as follows:

$$\gamma = \begin{cases} 1, & \text{if } t < 55 \text{ min,} \\ 1 - \frac{t - 55}{5}, & \text{if } 55 \leq t < 60 \text{ min,} \\ 0, & \text{if } t \geq 60 \text{ min.} \end{cases} \quad (3.2)$$

$$\beta = \sqrt{\left(\frac{x - x_c}{x_r}\right)^2 + \left(\frac{y - y_c}{y_r}\right)^2 + \left(\frac{z - z_c}{z_r}\right)^2}, \quad (3.3)$$

where x_c and y_c are the horizontal locations of the domain center.

During the HAIC-HIWC field campaign, airborne in situ measurements of cloud properties were taken from the NRC Convair 580, operated by the National Research Council Canada. In this research, we used the ice number concentration and IWC measurements calculated from particle size distributions from the 2D-Stereo probe and the Precipitation Imaging Probe (Korolev and Heckman 2017).

3.3.3 Sensitivity experiments

Model Experiment	PIP processes	SIP processes
noSIP (baseline)	HO, HT	None
3SIP	HO, HT	HM, IICOL, FFD
HMonly	HO, HT	HM
IICOLonly	HO, HT	IICOL
FFDonly	HO, HT	FFD
HM+IICOL	HO, HT	HM, IICOL
HM+FFD	HO, HT	HM, FFD
FFD+IICOL	HO, HT	FFD, IICOL

Table 3.3: WRF Model experiments designed for both idealized cases in this work.

To examine the impacts of SIP processes on deep convection, eight simulations were conducted using the configurations summarized in Table 3.2. The baseline simulation considering no SIP processes is referred to as noSIP hereafter, and the simulation including all three SIP processes is referred to as 3SIP. Experiments isolating individual SIP processes—HM or IICOL or FFD—are denoted HMonly, IICOLonly and FFDonly, respectively, while experiments investigate combinational effects of two SIP processes are denoted as HM+IICOL, HM+FFD, and FFD+IICOL, respectively. All

experiments include both HO and HT freezing processes. The eight experiments are summarized in Table 3.3 and the same design is applied to both the supercell case and the tropical MCS case.

3.3.4 Temporal and vertical analyses

Besides direct model output, other variables analyzed in this work include water content (WC), water path (WP), and latent heat power density ($\dot{Q}$). Calculations of these variables are summarized in Table 3.4. Specifically, temporal analyses of the volume-weighted domain average of a field $r(t)$ are calculated using Eq. 3.4.

$$r(t) = \frac{\sum_{k,i,j} r(t, k, i, j) dz(t, k, i, j)}{\sum_{k,i,j} dz(t, k, i, j)}, \quad (3.4)$$

where dz is the vertical resolution as a function of time (t) and space (k, i, j).

Symbol	Description	Unit	Equation
WC	Water content	$kg\ m^{-3}$	$WC = Q\rho_a$
WP	Water path	$kg\ m^{-2}$	$WP = \int_0^z WC dz$
$\dot{Q}$	Latent heat power density	$J\ m^{-3}s^{-1}$	$\dot{Q} = \rho_a c_p (\frac{\partial T}{\partial t})$

Note: ρ_a is air density and $c_p = 1005\ J\ kg^{-1}K^{-1}$ is specific heat of air.

Table 3.4: Descriptions and equations for variables analyzed in this research.

Considering the sensitivity of SIP processes to temperature, vertical profiles are presented as a function of temperature binned at 2 °C intervals (0.5 °C for HM). For each temperature bin m and time t , the volume-weighted mean of a field $r_m(t)$ over all grid cells whose temperature falls in bin m is first computed using Eq. 3.4, then averaged on time. Finally, as noSIP is the baseline run, differences between SIP-including runs and noSIP are calculated as $\Delta = SIP - noSIP$ (if not otherwise stated), while relative changes are calculated as $change = \frac{SIP - noSIP}{noSIP}$.

3.4 Results: Supercell

In the following sections, we first demonstrate the impact of SIP on surface precipitation, then explore the underlying mechanisms by analyzing its effects on cloud microphysical, dynamical, and thermodynamical properties for the supercell case.

3.4.1 Precipitation

Figure 3.2 shows the time series of domain-averaged cumulative precipitation and relative precipitation amount change. All runs indicate precipitation onset after 30 minutes spinup time. But clearly, SIP runs lead to persistent and substantial reductions (up to 30%) in surface precipitation compared to noSIP (Fig. 3.2 (b)). One exception is the IICOLonly run, which initially increases precipitation up to 5%, but also reduces precipitation after 45 minutes.

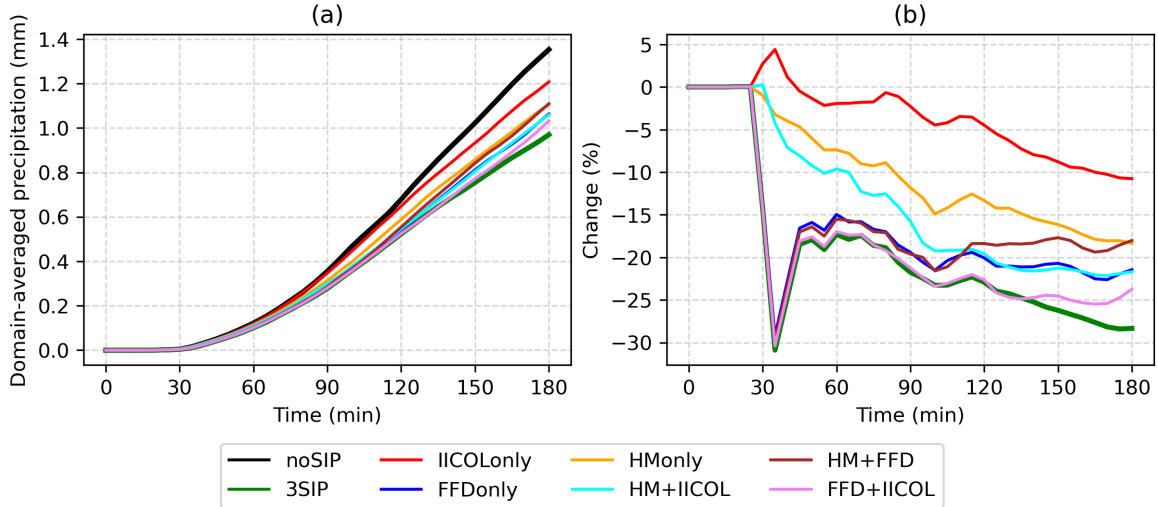


Figure 3.2: (a) Domain-averaged cumulative precipitation (mm) from each run. (b) Domain-total precipitation change (%) from SIP-including runs relative to noSIP.

Additionally, Table 3.5 presents the changes of SIP-including runs relative to noSIP in domain-averaged total, liquid, and ice water paths (TWP, LWP, and IWP), respec-

tively, as well as surface precipitation reductions at 180 minutes. Even though all SIP runs substantially reduce surface precipitation, the changes in TWP, however, are relatively small, ranging from -8.65% to +3.63%. It is also noteworthy that 3SIP results in a greater reduction in total precipitation compared to single-SIP and two-SIP runs but nonlinear modifications in WPs. These results raise two questions: (1) How SIP modifies the microphysical pathways to suppress rainfall? (2) What are the interactions and feedback between SIP processes that influence convective precipitation?

Experiments	TWP (%)	LWP (%)	IWP (%)	Precipitation (%)
3SIP	-3.05	-32.65	6.58	-28.33
IICOLonly	-3.29	-11.21	-0.71	-10.76
FFDonly	-0.97	-28.23	7.90	-21.45
HMonly	-8.65	-19.55	-5.11	-18.35
HM+IICOL	-4.92	-22.55	0.81	-21.70
HM+FFD	3.63	-23.53	12.46	-18.02
FFD+IICOL	1.84	-28.52	11.71	-23.74

Table 3.5: Changes in domain-averaged TWP, LWP, IWP, and surface precipitation of SIP-including runs relative to noSIP. Changes in WPs are calculated for the 30-180 minutes, while changes in precipitation are calculated at 180 minutes.

3.4.2 Microphysical properties

To investigate how SIP suppresses surface precipitation, we examine the microphysical hydrometeor properties that directly impact precipitation formation. We start with single-SIP experiments, and move on to multiple-SIP runs to identify which SIP process dominates rainfall reduction and through which pathway, and whether these processes act to amplify or offset each other.

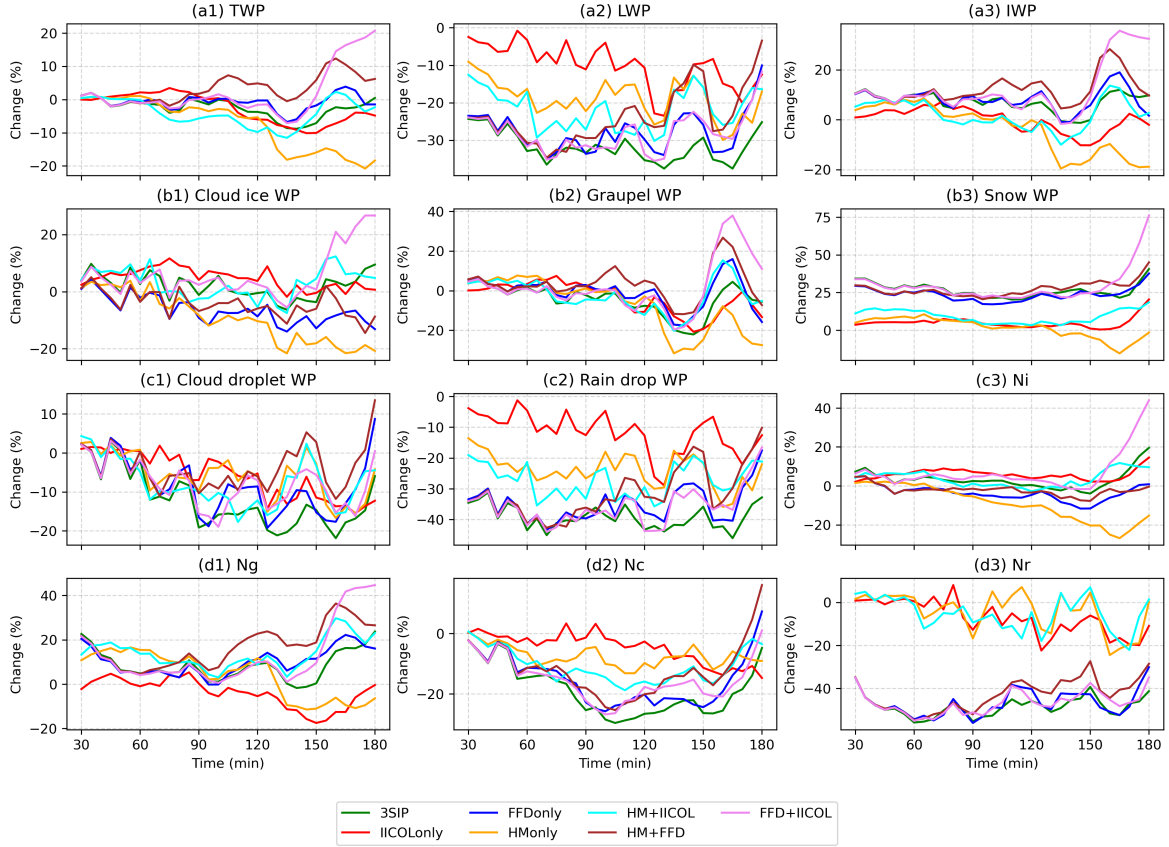


Figure 3.3: Time series of changes (%) of SIP-including runs relative to noSIP in (a1-c2) domain-averaged total, liquid, ice, cloud ice, graupel, snow, cloud droplet, and rain drop WPs, and (c3-d3) volume-weighted domain average of cloud ice, graupel, cloud droplet, and rain drop number concentrations.

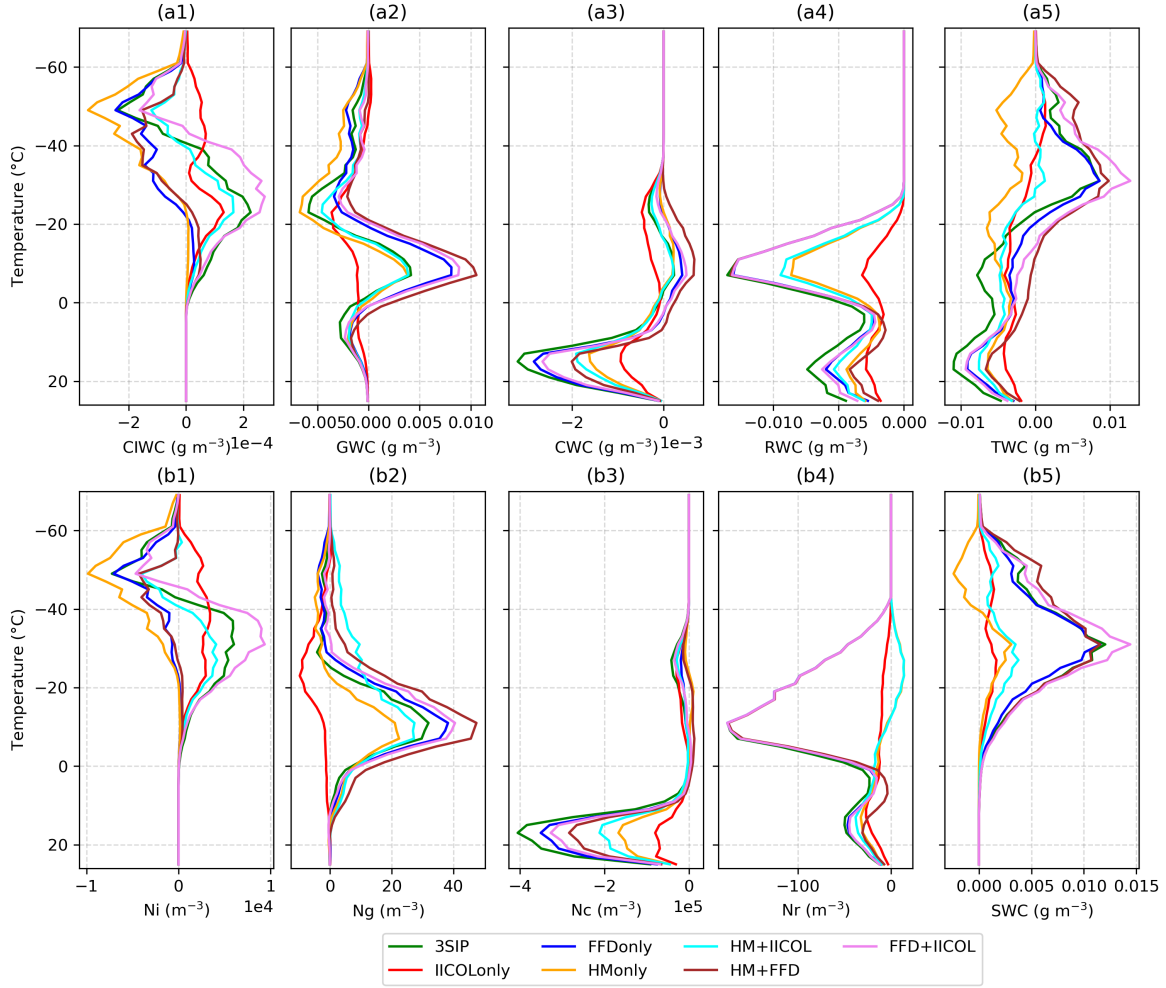


Figure 3.4: Vertical profile of differences in (a1-a5, b5) cloud ice, graupel, cloud droplet, rain drop, total, and snow WCs (g m^{-3}), and (b1-b4) cloud ice, graupel, cloud droplet, and rain drop number concentrations (m^{-3}). For each run, vertical profiles are volume-weighted in each temperature bin (2°C interval), then averaged on time between 30-180 minutes. Differences are calculated between SIP-including and noSIP profiles.

3.4.2.1 IICOLonly

Compared to other SIP-including runs, IICOLonly produces the smallest reduction in surface precipitation (-10.76%), consistent with the smallest reductions in both LWP (-11.21%) and IWP (-0.71%), and a modest decrease in TWP (-3.29%; Table 3.5 and Fig. 3.2). In terms of time evolution of water condensates, LWP is consistently reduced in IICOLonly over time, whereas IWP is enhanced prior to 100 minutes and decreased afterwards (Fig. 3.3 (a2,a3)). For liquid hydrometeors, IICOLonly gradually reduces both cloud and rain water masses and numbers, and to smaller magnitudes compared to other SIP runs (Fig. 3.3 (c1,c2,d2,d3)). Vertically, IICOLonly shows the weakest cloud water mass reductions below 0 °C but induces the strongest cloud water mass reduction above (Fig. 3.4 (a3,b3)), while it generally reduces rain water mass and number the least across the entire column (Fig. 3.4 (a4,b4)). For ice particles, IICOLonly persistently enhances cloud ice mass and number, as well as snow mass over time, while graupel mass and number decreases after 90 minutes (Fig. 3.3 (b1-b3,c3,d1)). These features are also evident in the vertical profiles: enhanced cloud ice and snow at sub-freezing levels, paired with graupel reductions through most of the column and slight graupel increases only at the lowest temperatures (< -50 °C; Fig. 3.4 (a1,a2,b1,b2,b5)).

In general, the impact of IICOLonly on liquid hydrometeors is relatively small, especially during the developing stage, when liquid hydrometeors remain nearly unaffected and surface precipitation is temporarily enhanced (Fig. 3.2 (b)). In this stage, when liquid is still abundant, the additional ice particles formed by IICOL act as targets for riming and aggregation, briefly strengthening the cold-rain pathway and yielding the transient enhancement in surface precipitation. This indicates that IICOL alone does not substantially inhibit condensational growth or collision-coalescence early on. Instead, its influence emerges more strongly during the mature and decaying stages, when enhanced vapor competition weakens the warm-rain pathway. Overall, the main

effect of IICOL is to redistribute ice mass from graupel to smaller ice particles such as cloud ice and snow, particularly in the high levels and from the mature to decaying stages of the supercell. These changes reduce the riming efficiency of graupel and weakens snow-to-graupel driven cold-rain formation, eventually leading to less surface precipitation.

3.4.2.2 FFDonly

Among the one-SIP runs, FFDonly produces the largest reduction in surface precipitation (-21.45%) despite only a minimal change in TWP (-0.97%; Table 3.5). LWP decreases substantially (-28.23%), with cloud water mass and number decreasing by up to 20% and rain water mass and number dropping by up to 50% (Fig. 3.3 (a2,c1,c2,d2,d3)). Liquid hydrometeor masses and numbers are also heavily reduced in the vertical column (Fig. 3.4 (a3,a4,b3,b4)). In contrast, IWP is enhanced by 7.9%, consistent with large increases over time (Table 3.5, Fig. 3.3 (a3)). The IWP enhancement stems primarily from a constant increase ($\sim 25\%$) in snow mass over time, as cloud ice mass and number are consistently reduced, and graupel mass declines between 90-150 minutes but with increased graupel number (Fig. 3.3 (b1-b3,c3,d1)). Vertically, fewer but larger cloud ice crystals are present between 0 and -20 °C, while cloud ice mass and number are strongly reduced at lower temperatures (Fig. 3.4 (a1,b1)). Snow mass is substantially enhanced throughout the column (Fig. 3.4 (b5)). Graupel mass and number are greatly increased between 0 and -20 °C, coinciding with the strongest rain water depletion; above this layer, graupel mass and number are reduced (Fig. 3.4 (a2,b2,a4,b4)).

These results suggest that FFD efficiently redistributes condensate mass from liquid to ice, directly suppressing the warm-rain pathway by reducing rain water. Meanwhile, relatively large ice particles produced by FFD can collect cloud water by riming while

small ice particles can compete with cloud water for vapor. Both processes limit the formation of rain drops and indirectly suppress the warm-rain pathway further. Additionally, the increase of snow, with concurrent decreases of cloud ice and graupel at high levels suggests enhanced aggregation of cloud ice into snow but reduced conversion of snow to graupel. This redistribution constrains the cold-rain pathway by weakening graupel growth aloft and favoring snow mass retention, ultimately reducing the efficiency of cold-rain precipitation formation. Therefore, by suppressing both the warm-rain and the cold-rain pathways, FFDonly causes the largest precipitation reduction compared to IICOLonly and HMonly.

3.4.2.3 HMonly

HMonly produces the largest reduction in TWP(-8.65%) with substantial decreases in LWP (-19.55%) and the largest reduction in IWP (-5.11%), resulting in 18.35% less surface precipitation at the end of simulation (Table 3.5 and Fig. 3.2). In terms of LWP, HMonly exhibits persistent 10-30% reductions throughout time (Fig. 3.3 (a2)), attributable to decreases in both cloud and rain water masses (Figs. 3.3 (c1,c2) and 3.4 (a3,a4)). Although rain mass decreased overall, the number of rain drops is enhanced at temperatures lower than -10 °C (Fig. 3.4 (b4)) and from 90-150 minutes (Fig. 3.3 (d3)), suggesting the formation of smaller but more numerous supercooled rain drops aloft during this time period.

For ice, HMonly initially increases IWP before 120 minutes but transitions to a 10-20% reduction thereafter (Fig. 3.3 (a3)). This change results from a decline in cloud ice mass starting near 80 minutes, followed by reductions in graupel and snow masses (Fig. 3.3 (b1-b3)). Cloud ice number also decreases in HMonly after 80 minutes (Fig. 3.3 (c3)). Graupel number is up to 20% higher in HMonly despite little difference in mass before 120 minutes, implying more but smaller graupel particles during the

developing to mature stages in HMonly (Fig. 3.3 (b2,d1)). Although HM is only active between -3 and -8 °C, its impact extends beyond this narrow layer. Graupel mass and numbers are increased between 0 and -15 °C but decreased above this layer (Fig. 3.4 (a2,b2)), while snow mass is increased between 0 and -40 °C but decreased above (Fig. 3.4 (b5)). Meanwhile, cloud ice mass and numbers are largely reduced at temperatures < -25 °C (Fig. 3.4 (a1,b1)). These patterns potentially imply that HMonly produces less cloud ice via heterogeneous and homogeneous freezing aloft, therefore weaker snow growth by aggregation and reduced conversion of snow to graupel compared to noSIP.

The localized activation of HM between -3 and -8 °C cascades both upward and downward, ultimately suppressing precipitation production through both the warm-rain and the cold-rain pathways. The many small ice splinters produced by HM dilute riming efficiency, which slows down new secondary ice particle formation and graupel growth. Therefore, after 90 minutes, there are decreases in ice masses and numbers and a rebound in liquid. The smaller, more numerous particles (supercooled rain drops and graupel at subfreezing temperatures) in HMonly are less effective at contributing to warm-rain formation. Meanwhile, diminished cloud ice and snow aloft limit the conversion of snow to graupel, further reducing the efficiency of cold-rain processes.

3.4.2.4 HM+IICOL

Although individually HMonly and IICOLonly reduce total IWP, their combined effect results in a slight overall increase in IWP (0.81%) and a stronger reduction in LWP (-22.55%). This combination yields a modest reduction in TWP (-4.92%) but a substantial surface precipitation suppression (-21.7%; Table 3.5 and Fig. 3.2). Compared with either process alone, HM+IICOL depletes liquid water more extensively (Fig. 3.3 (a2)), driven by a pronounced reduction in cloud water mass and number and rain water mass, though rain number is less strongly affected (Figs. 3.3 (c1,c2,d2,d3) and

3.4 (a3,a4,b3,b4)). In contrast, the ice hydrometeors are enhanced. IWP is enhanced prior to 90 minutes and again after 150 minutes (Fig. 3.3 (a3)), reflecting increases in cloud ice, graupel, and snow (Fig. 3.3 (b1-b3)). Vertically, cloud ice mass and number are increased (decreased) at temperatures higher (lower) than -40°C , graupel mass is increased between 0 and -20°C but decreased above, while graupel number and snow mass are increased throughout the vertical column (Fig. 3.4 (a1,a2,b1,b2,b5)).

These results suggest a positive feedback between HM and IICOL, i.e., combining HM and IICOL amplifies ice-ice interactions and redirect liquid condensate more aggressively into the ice phase. Similar to HMonly, HM+IICOL produces smaller rain drops but with a larger magnitude of reduction in rain mass, since additional ice particles generated by IICOL not only deplete cloud water by riming but may also compete for vapor through depositional growth. At temperatures $< -40^{\circ}\text{C}$, snow mass remains nearly unchanged in HM+IICOL compared to IICOLonly, paired with reduced cloud ice number and increased graupel number, indicating balanced cloud ice aggregation to snow and snow conversion to small graupel. Meanwhile, larger graupel from riming growth at lower levels is fragmented into smaller ice particles through IICOL. These redistribution processes suppress the warm-rain pathway by depleting liquid condensates and vapor, while at the same time weakening the cold-rain pathway by limiting the buildup of snow mass and fragmenting graupel into smaller, less precipitation-efficient particles. Together, these processes reduce the efficiency of both precipitation pathways and contribute to the stronger rainfall suppression seen in the combined run.

3.4.2.5 HM+FFD

When HM is combined with FFD, TWP is increased (3.63%) owing to a strong enhancement in IWP (12.46%), despite a substantial reduction in LWP (-23.53%) and a pronounced suppression of surface precipitation (-18.02%; Table 3.5 and Fig. 3.2).

Over time, reductions in LWP by HM+FFD broadly overlays with FFDonly before 90 minutes (Figs. 3.3 (a2)). Afterward, however, HM+FFD exhibits a weaker reduction in liquid properties, and even a temporary increase in cloud water mass from 130-160 minutes (Figs. 3.3 (c1,c2,d2,d3)). Vertically, this is reflected in the relatively small reduction in rain water mass and number below the freezing level and an increase in cloud water mass above freezing (Fig. 3.4 (a3,a4,b4)). For the ice phase, IWP enhancement by HM+FFD also largely overlaps with FFDonly before 90 minutes, but the enhancement becomes more strongly thereafter (Fig. 3.3 (a3)). This increase is primarily due to large and persistent snow mass gain both in time and vertically (Figs. 3.3 (b3) and 3.4 (b5)). By contrast, cloud ice mass is consistently reduced over time and at temperatures lower than -25°C , while cloud ice number remains relatively unchanged over time but still decreases at these high levels (Figs. 3.3 (b1,c1) and 3.4 (a1,b1)). While graupel number is increased persistently across time and vertical column, graupel mass is decreased during 120-150 minutes followed by a large increase after 150 minutes; graupel mass is also decreased vertically at temperatures $< -20^{\circ}\text{C}$ and $> \sim 5^{\circ}\text{C}$ (Fig. 3.3 (b2,d1) and 3.4 (a2,b2)).

HM+FFD (-18.02%) reduces precipitation less than either HMonly (-18.35%) or FFDonly (-21.45%), because the feedback between HM and FFD is mixed and time dependent. During the developing stage (before 90 minutes), FFD dominates by aggressively breaking up frozen rain drops into ice particles, which supplies HM to produce more smaller ice splinters, which then may (1) trigger additional rain drop freezing and possible fragmentation and (2) compete with cloud water for vapor. Either way accelerates liquid depletion and suppresses the warm-rain process. During the mature stage (90-150 minutes), the cloud is already heavily glaciated, and with fewer rain drops available, FFD weakens but still supplies graupel fragments to HM. However, because graupel is more numerous and smaller, riming efficiency is diluted. While ice

particles continue to compete for water vapor, less cloud water gets collected by riming. As a result, liquid depletion is slowed down during this stage and cloud water mass is even increased temporarily, yielding a brief recovery of the warm-rain pathway. During the decaying stage (after 150 minutes), sufficient liquid builds up again, and FFD reasserts its influence by converting rain drops into ice fragments. Meanwhile, snow persistently aggregates cloud ice (especially at higher levels) and some converts to small graupel, enhancing the cold-rain pathway. Ultimately, HM+FFD produces more, smaller graupel that survive to melt, resulting in weaker surface precipitation suppression.

3.4.2.6 FFD+IICOL

Besides 3SIP, the FFD+IICOL run produces the largest precipitation reduction (-23.74%), despite an enhancement in TWP (1.84%) relative to noSIP. This net increase arises from a substantial LWP reduction (-28.52%) and a notable LWP increase (11.71%; Table 3.5 and Fig. 3.2). The reduction in LWP closely resembles that in FFDonly, with nearly identical decreases in cloud water and rain water over time and throughout the vertical column (Figs. 3.3 (c1,c2,d2,d3) and 3.4 (a3,a4,b3,b4)). IWP enhancement is also broadly similar to FFDonly, but FFD+IICOL exhibits a distinct increase after 150 minutes (Fig. 3.3 (a3)), associated with strong increases in all ice categories during this time period (Fig. 3.3 (b1-b3)) and through most of the vertical column (Fig. 3.4 (a1,a2,b1,b2,b5)). Snow mass also increases at temperatures lower than -40 °C, accompanied by decreases in cloud ice and graupel (Fig. 3.4 (a1,a2,b1,b2,b5)).

Clearly, there is a synergy between FFD and IICOL, whereby the two processes amplify each other's effects. FFD fragments provide abundant collision-able ice particles for IICOL. In turn, IICOL generates additional small cloud ice crystals and snow

particles, which further enhance the possibility of rain drop freezing and fragmentation. Compared to FFDonly, this coupled process intensifies the redistribution of liquid condensate into numerous smaller ice particles, that are more efficient at competing for water vapor, limiting the condensation formation of cloud water and thus limiting the warm-rain pathway. Meanwhile, the cold-rain pathway is also further suppressed in FFD+IICOL, as larger ice particles such as graupel and snow continue to fragment into smaller ice particles, while riming growth is inhibited by the limited availability of cloud water.

3.4.2.7 3SIP

When all three SIP processes are combined, surface precipitation is perhaps unsurprisingly reduced the most (-28.33%; Table 3.5). To more clearly demonstrate the combined effects of 3SIP on precipitation formation relative to noSIP, we present the time series (Fig. 3.5) and vertical profiles (Fig. 3.6) of microphysical properties for noSIP, 3SIP, and their differences.

In both 3SIP and noSIP runs, TWP increases rapidly after spinup, peaks near 90 minutes, and then gradually declines (Fig. 3.5 (a1)). While the overall evolution is similar, 3SIP maintains lower TWP after ~ 60 minutes, with relative changes reaching $\sim -8\%$ during the mature and decaying stages. Vertical profiles reveal that TWC reduction is concentrated at temperatures higher than $\sim -25^\circ\text{C}$, while TWC is slightly higher in 3SIP at lower temperatures (Fig. 3.6 (a5)). From ~ 30 minutes onward, 3SIP exhibits a 25-38% reduction in LWP (Fig. 3.5 (a2)), while IWP is constantly higher in 3SIP, with relative increases up to 10% (Fig. 3.5 (a3)). In terms of total change, 3SIP substantially reduces LWP by -32.65% but only increases IWP by 6.58%, resulting in a small net reduction of TWP by -3.05% (Table 3.5).

As for individual hydrometeors, 3SIP enhances cloud ice mass and number (5-10%)

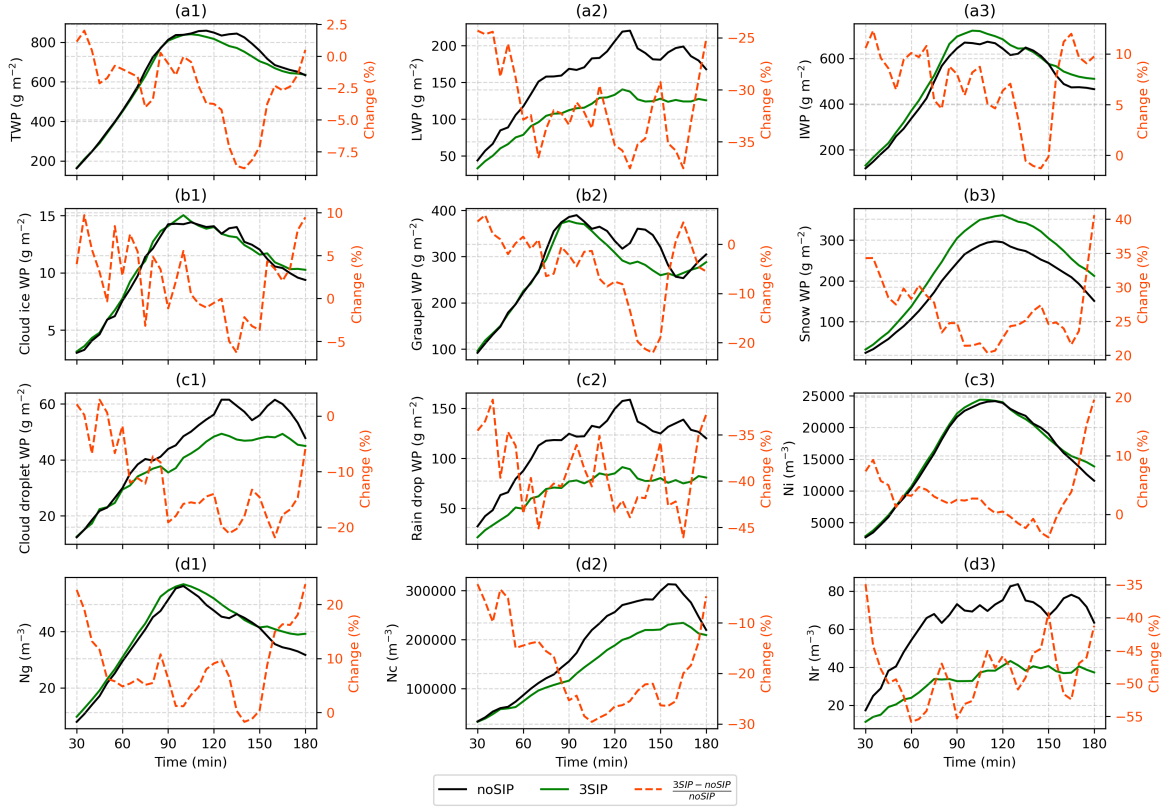


Figure 3.5: Time series of (a1-c2) domain-averaged total, liquid, ice, cloud ice, graupel, snow, cloud droplet, and rain drop WPs ($g m^{-2}$), and (c3-d3) volume-weighted domain averages of cloud ice, graupel, cloud droplet, and rain drop number concentrations (m^{-3}) from 3SIP and noSIP. Orange dashed lines show the relative changes (%) of 3SIP to noSIP.

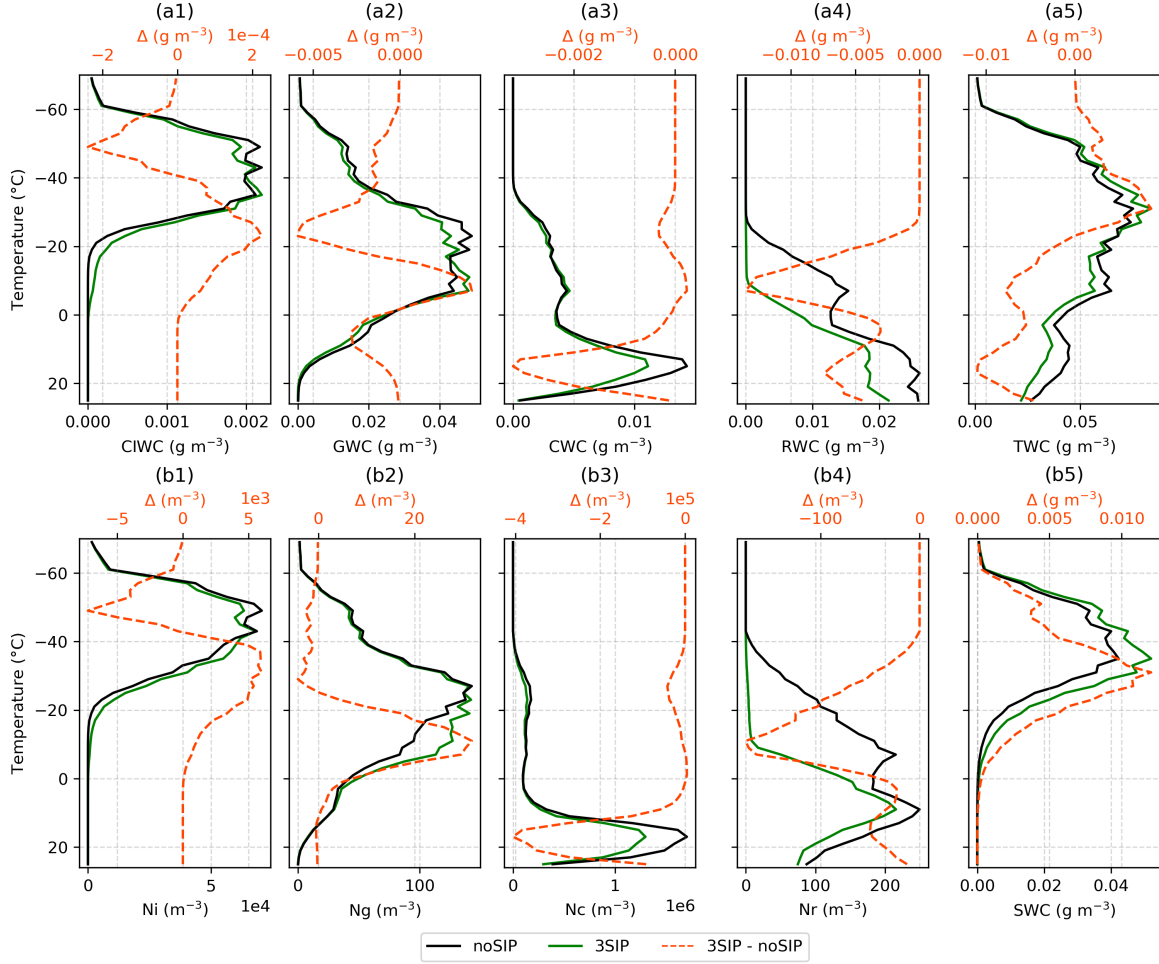


Figure 3.6: Vertical profiles of (a1-a5,b5) cloud ice, graupel, cloud droplet, rain drop, total, and snow WCs (g m^{-3}), and (b1-b4) cloud ice, graupel, cloud droplet, and rain drop number concentrations (m^{-3}). Vertical profiles are volume-weighted in each temperature bin (2°C interval), then averaged on time between 30-180 minutes. Orange dashed lines show the differences between 3SIP and noSIP.

during 30-100 minutes and after 150 minutes, but produces less cloud ice crystals during 100-150 minutes (Fig. 3.5 (b1,c3)). Vertical profiles indicate that these increases are located between 0 and -40 °C, with particularly sharp increases between -3 and -20 °C, whereas the decreases occur at temperatures lower than -40 °C (Fig. 3.6 (a1,b1)). The IWP enhancement by 3SIP stems from the consistently higher snow mass in both time and height, with increases of 20-30% over time (Fig. 3.5 (b3)) and a maximum increase near -35 °C (Fig. 3.6 (b5)). Graupel mass is slightly lower in 3SIP during the developing stage, followed by larger reductions (up to 20%) during mature (Fig. 3.5 (b2)), leading to an overall $\sim 6\%$ decrease in the vertical column (Fig. 3.6 (a2)). In contrast, graupel number is higher over time (Figs. 3.5 (d1)) and at temperatures > -20 °C (Fig. 3.6 (b2)), indicating a shift toward more numerous but smaller graupel particles in subfreezing levels in 3SIP. The LWP reduction in 3SIP is reflected by consistent deficits of cloud water and liquid water, with reductions of up to 20% and 50% in cloud water and rain water, respectively (Fig. 3.5 (c1,c2,d2,d3)). Vertically, the largest reduction of cloud water in 3SIP occurs near 20 and -30 °C (Fig. 3.6 (a3,b3)), while the rain water is mostly reduced near 20 and -10 °C (Fig. 3.6 (a4,b4)).

Overall, the impact of 3SIP on precipitation formation is broadly comparable to that of HM+FFD, with IICOL in 3SIP further amplifies the suppression of the warm-rain pathway. By continuously generating additional small ice particles, IICOL enhances competition for water vapor, thereby intensifying liquid depletion and constraining the transient warm-rain rebound as discussed previously in HM+FFD during the mature stage. At the same time, IICOL persistently fragments larger graupel and snow particles, which limits the accumulation of snow mass and snow-to-graupel conversion as well as graupel growth (as riming efficiency is also diluted by the many more small ice particles), and weakens the cold-rain pathway.

In summary, the precipitation reduction in 3SIP arises from a dual suppression

of both warm-rain and cold-rain processes: warm-rain formation is reduced by direct rain water loss from FFD and indirect liquid loss by riming collection of cloud water and enhanced vapor competition from abundant small ice crystals, while cold-rain production is curtailed by inhibited snow-to-graupel conversion from IICOL. Finally, even though 3SIP substantially reduces surface precipitation, it does not drastically remove water from the cloud system, as shown by the minor TWP reduction (-3.05%). Instead, 3SIP reduces precipitation by redistributing water from liquid to ice and from lower to higher levels that are less efficient at producing rain.

3.4.3 Cloud ice crystal production

To better understand how SIP processes modulate the precipitation formation pathways discussed above, it is necessary to examine the sources of cloud ice crystals, as they are the seed for subsequent growth into snow and graupel. Therefore, we next analyze the cloud ice number budget as a function of temperature to identify where SIP is most active and how it compares with PIP (Fig. 3.7). Moreover, we examine the temporal evolution and vertical distribution of secondary cloud ice crystal production rates by each SIP mechanism to provide a more in-depth understanding of interactions among different SIP processes (Fig. 3.8).

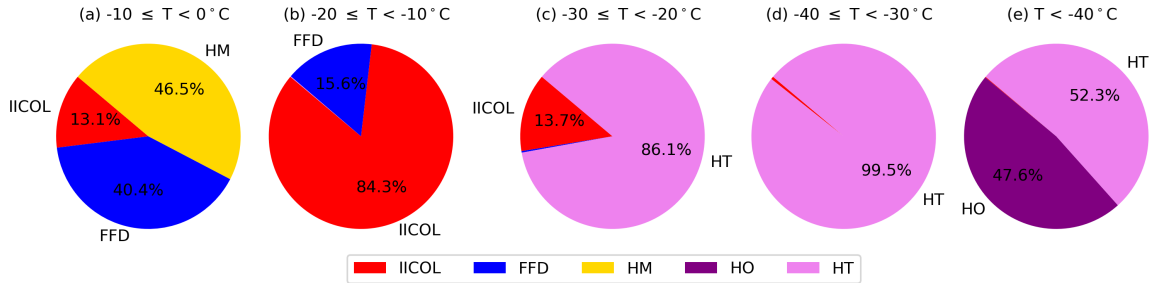


Figure 3.7: Total cloud ice number budget in different temperature ranges through the entire cloud lifetime. Ice production processes include IICOL, FFD, HM, heterogeneous freezing (HT), and homogeneous freezing (HO). Results are from the 3SIP simulation.

The relative contributions of different ice production processes to total cloud ice number over the supercell’s lifetime are highly temperature-dependent (Fig. 3.7). Between -10 and 0 °C, HM (46.5%) and FFD (40.4%) dominate, with IICOL contributing 13.1%, highlighting the importance of HM and FFD for ice initiation in the warm mixed-phase layers. While between -20 and -10 °C, IICOL overwhelmingly dominates (84.3%), consistent with efficient collisional breakup among snow and graupel in this colder mixed-phase layer. At $-30 \leq T < -20$ °C, HT becomes the primary source (86.1%) of cloud ice, while IICOL remains a minor contributor (13.7%). At lower temperatures, ice production is almost exclusively primary: HT accounts for 99.5% between -40 and -30 °C, while at $T < -40$ °C, HT (52.3%) and HO (47.6%) both contribute substantially. Clearly, SIP processes are most influential within the mixed-phase region ($-20 \leq T < 0$ °C), where they efficiently redistribute liquid condensate into abundant small ice particles and thereby regulate the warm-rain pathway. At higher levels, ice initiation is governed predominantly by PIP processes.

Results from the previous section suggested synergistic interactions among different SIP processes. This is confirmed by the temporal evolution and vertical distributions of secondary ice particle production rates shown in Fig. 3.8. IICOL rate increases fast during the developing stage, peaks during the mature stage, and remains effective throughout the supercell’s lifetime (Fig. 3.8 (a1)). Vertically, IICOL is active in a broad layer spanning from -5 to -40 °C and peaks at -30 °C (Fig. 3.8 (a2)). Since fragmentation produces more graupel and snow available for collisions, IICOL rate is greatly enhanced when combined with FFD (FFD+IICOL). However, although HM shows small enhancements of IICOL rates (HM+IICOL), the addition of HM in 3SIP yields lower IICOL rates than FFD+IICOL.

FFD rates increase sharply during the developing stage, peak around 90 minutes then gradually decline as the availability of rain drops for freezing decreases (Fig.

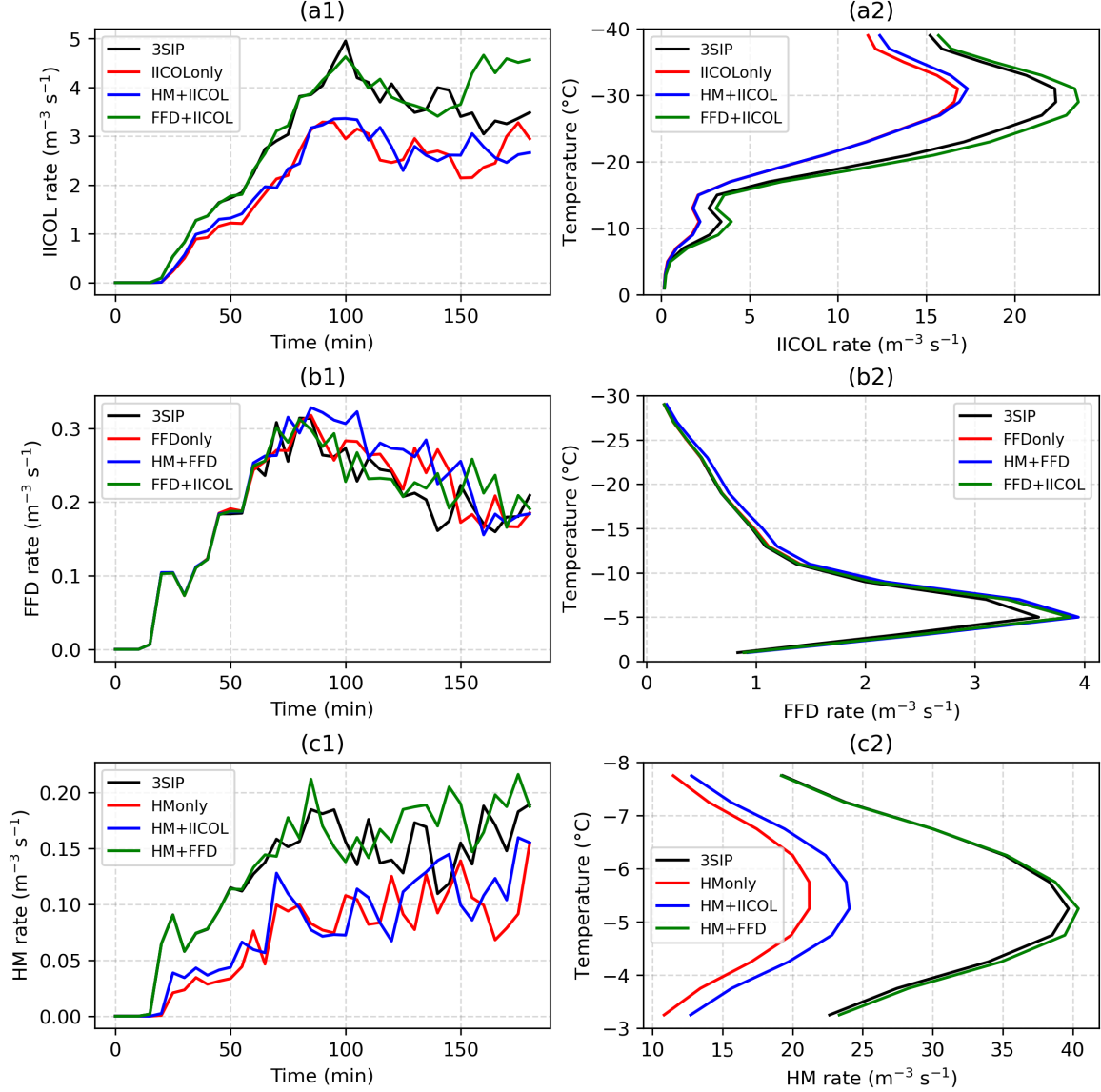


Figure 3.8: Time series and vertical profiles of SIP rate by (a1, a2) IICOL, (b1, b2) FFD, and (c1, c2) HM processes, respectively. For time series, SIP rates are volume-weighted domain averages. Vertical profiles are volume-weighted in each temperature bin (0.5°C interval for HM), then averaged on time between 30-180 minutes.

3.8 (b1)). Vertically, FFD is also active in a broad temperature range but with a maximum around -5°C (Fig. 3.8 (b2)). IICOL and HM show no impacts on FFD rates during the developing stage and only minor effects on FFD rates during the mature and decaying stages. HM slightly enhances FFD, owing to the warm-rain rebound during the mature stage as discussed previously. IICOL also amplifies FFD locally near its peak temperature (-5°C) by fragmenting colliding ice particles and potentially promoting additional freezing. But temporally, including IICOL shows mixed effects on FFD, with alternating periods of enhancement and suppression. Overall, 3SIP exhibits weaker FFD rates than FFDonly or two-SIP runs.

HM rates generally increase over time and, as expected, is confined to the narrow -8 to -3°C range with a peak near -5°C (Fig. 3.8 (c1,c2)). Both IICOL and FFD enhance HM in time and throughout the active temperature range; however, FFD has a much stronger effect. Again, HM rates are weaker in 3SIP than in HM+FFD.

These results highlight that the three SIP processes are not simply additive but strongly interactive. FFD substantially amplifies both HM and IICOL by supplying relatively large ice fragments for collision and riming. However, HM and IICOL exert only minor influences on FFD, even though HM and IICOL have much higher cloud ice production rates. We speculate that this is because HM and IICOL do not directly act on rain water but by vapor competition and cloud water depletion that indirectly slow rain water formation. The interaction between HM and IICOL is more subtle. HM produces small ice splinters that can grow or aggregate to snow, which may subsequently feed into IICOL. In turn, IICOL can produce more graupel fragments which continue riming, thereby creating more opportunities for HM to act. This feedback allows HM and IICOL to amplify one another. At the same time, however, both processes compete for graupel: if IICOL fragments graupel too aggressively, HM riming efficiency diminishes. Consequently, 3SIP shows a balance between mutual amplifica-

tion and competition, yielding higher ice crystal production rates than one-SIP runs but showing more complex, sometimes compensating effects compared to two-SIP runs. This dynamic and complex interplay explains why precipitation reductions in 3SIP are nonlinear.

3.4.4 Thermodynamical and dynamical properties

As demonstrated in the previous sections, SIP substantially redistributes water condensates in the supercell. Such redistribution will inevitably impact the thermodynamical and dynamical properties of the cloud. To investigate how SIP-driven modifications in hydrometeors feed back onto buoyancy generation and convective strength, which ultimately impact precipitation, we next examine the latent heat release and vertical velocities from noSIP and 3SIP.

The volume-weighted net latent heat power density ($\dot{Q}_{\text{net}}$) in 3SIP is lower than in noSIP most of the time (Fig. 3.9 (a1)), primarily due to 10-20% reductions in heating rates (Fig. 3.9 (a2)), consistent with the substantial liquid reductions in 3SIP, thereby less heating from condensation. In noSIP, $\dot{Q}_{\text{net}}$ peaks around 75 minutes (i.e., when liquid condensates in noSIP reach their first maximum (Fig. 3.5 (a2))), but this peak is slightly lower and delayed in 3SIP (Fig. 3.9 (a1)). Between 120-150 minutes, noSIP exhibits a pronounced increase in heating (Fig. 3.9 (a2)), coinciding with its enhancements in cloud ice, graupel, cloud water, and rain water (Fig. 3.5), indicating stronger heating from condensation, freezing and riming in noSIP. Meanwhile, noSIP also shows slightly stronger cooling over time (Fig. 3.9 (a3)), particularly around 150 minutes, which results from more graupel melting.

Vertically, 3SIP shows a pronounced and narrow heating spike just above the freezing level, whereas the heating range is more broad and at higher levels ($\sim 20^\circ\text{C}$) in noSIP (Fig. 3.10 (a1,a2)). In 3SIP, secondary ice particles are formed just above the

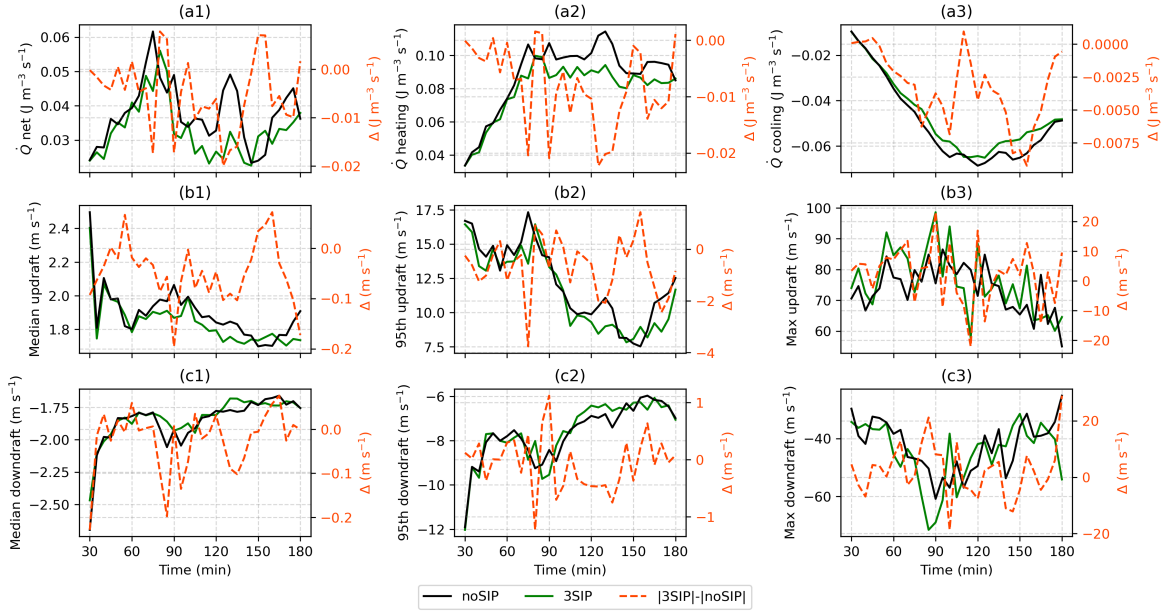


Figure 3.9: Time series of (a1-a3) volume-weighted domain average $\dot{Q}_{\text{net}}$, $\dot{Q}_{\text{heating}}$, and $\dot{Q}_{\text{cooling}}$ ($\text{J m}^{-3} \text{s}^{-1}$), (b1-b3) median, 95th-percentile, and maximum updrafts (m s^{-1}), and (c1-c3) median, 95th-percentile, and maximum downdrafts (m s^{-1}), respectively. Updrafts and downdrafts are defined as vertical velocity $W > 1 \text{ m s}^{-1}$ and $W < -1 \text{ m s}^{-1}$, respectively. Orange dashed lines indicate the absolute differences between 3SIP and noSIP. For $\dot{Q}_{\text{cooling}}$ and downdrafts, positive (negative) differences mean stronger (weaker) cooling and downdraft in 3SIP.

freezing level by FFD and HM (Fig. 3.8 (b2,c2)), leading to the latent heat release near the freezing level. But the more numerous but smaller graupel in 3SIP is less riming efficient, especially in this liquid-poor environment, thus, less latent heat release due to riming at higher levels compared to noSIP. Between -5 and -40 °C, 3SIP also shows enhanced cooling (Fig. 3.10 (a3)), which we attribute to sublimation of increased snow and cloud ice. Below the freezing level, 3SIP exhibits both reduced heating and reduced cooling (Fig. 3.10 (a2,a3)), consistent with its lower cloud water, rain water and graupel masses (Fig. 3.6 (a2-a4))—less condensational heating and less melting cooling.

The nearly persistent reductions in both heating and cooling in 3SIP (Fig. 3.9 (a2,a3)) leads to its weaker median updrafts and downdrafts in time and space (Figs. 3.9 (b1,c1) and 3.10 (b1,c1)). For stronger updrafts, the 95th percentile is also weaker in 3SIP most of the time and vertical profile differences are mostly negative, with small positive bands between -30 and -40 °C (Figs. 3.9 (b2) and 3.10 (b2)). For the maximum updrafts, the time series shows alternating periods of increases and decreases (Fig. 3.9 (b3)), but the vertical profiles indicate a slight enhancement (up to 3 m s^{-1}) at temperatures higher than -40 °C (Fig. 3.10 (b3)). Notably, 3SIP experiences a brief convection-strengthening episode that is absent in noSIP around 150 minutes, with coincident increases in median, 95th-percentile, and maximum updrafts (Fig. 3.9 (b1-b3)) alongside increased latent heat warming and reduced cooling (Fig. 3.9 (a2,a3)). The 95th and maximum downdrafts are stronger in 3SIP mainly during the developing stage but weaker during the mature stage and then stronger again (Fig. 3.9 (c2,c3)). Vertically, the 95th downdrafts are slightly enhanced in 3SIP from -15 to -50 °C but weakened at higher temperatures ($\pm 0.5 \text{ m s}^{-1}$, Fig. 3.10 (c2)). For the maximum downdrafts, this pattern shifts downward and amplifies: 3SIP shows enhancement at temperatures $< -10 \text{ °C}$ (up to 2.5 m s^{-1}), is slightly weaker ($\sim 0.5 \text{ m s}^{-1}$) at higher

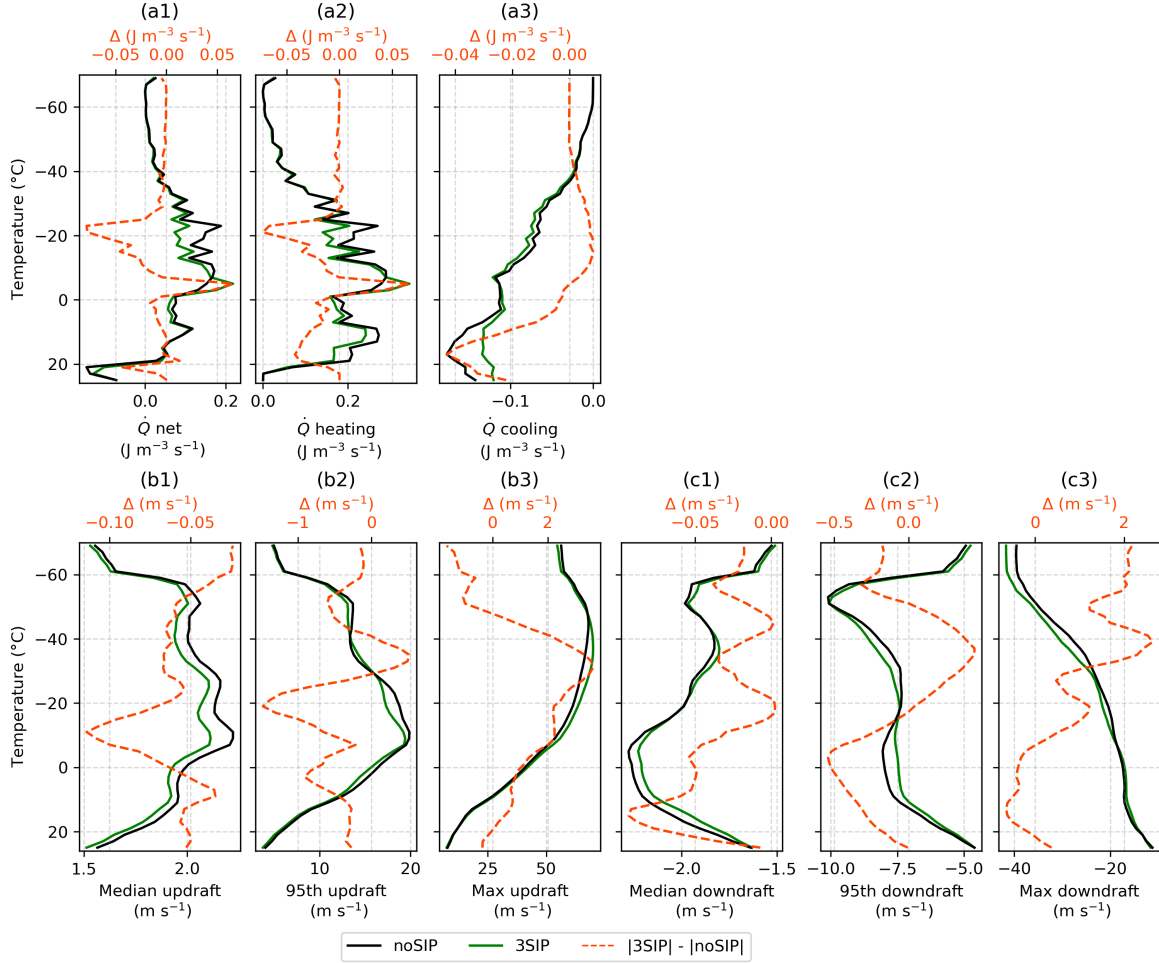


Figure 3.10: Vertical profiles of (a1-a3) volume-weighted mean $\dot{Q}$ net, $\dot{Q}$ heating, and $\dot{Q}$ cooling ($\text{J m}^{-3} \text{s}^{-1}$), (b1-b3) median, 95th percentile, and maximum updrafts (m s^{-1}), and (c1-c3) median, 95th percentile, and maximum downrafts (m s^{-1}), respectively. Updrafts and downrafts are defined as vertical velocity $W > 1 \text{ m s}^{-1}$ and $W < -1 \text{ m s}^{-1}$, respectively. Orange dashed lines indicate the absolute differences between 3SIP and noSIP. For $\dot{Q}$ cooling and downrafts, positive (negative) differences mean stronger (weaker) cooling and downraft in 3SIP.

temperatures, but enhances again below 20 °C.

Overall, SIP reduces domain average latent heating and cooling, and systematically weakens the median updrafts and downdrafts. This is consistent with the water redistribution of SIP: less liquid condensate and more smaller graupel and snow, therefore the associated loss of condensation- and riming-driven buoyancy. These reductions are most pronounced during the mature stage, when noSIP produces stronger heating, cooling, and vertical motions tied to heavier liquid and graupel masses. However, despite weaker bulk buoyancy, 3SIP occasionally exhibits localized enhancements in maximum updrafts and a burst around 150 minutes. These episodes coincide with temporary liquid water recovery and momentary increases in latent heating, suggesting that SIP does not simply damp convection uniformly. Instead, by redistributing water condensate, SIP also redistributes convective vigor in space and time, producing intermittent pockets of stronger ascent even as the storm as a whole weakens.

3.4.5 Reflectivity and cloud top height

To further investigate how SIP impacts the storm’s convective strength, we next analyze the contoured frequency by altitude diagrams (CFADs), vertical profiles of reflectivities (Fig. 3.11), and probability density functions (PDFs) of cloud top heights (CTHs; Fig. 3.12) between noSIP and 3SIP.

For all grid points with reflectivity > -10 dBZ, the noSIP CFAD exhibits a slanted mode of moderate-to-weak echoes that increase in height, with maximum frequencies near 14 km (-60 °C), while moderate-to-strong echoes occur mainly below 7 km (-20 °C, Fig. 3.11 (a)). Differences in CFADs indicate that 3SIP produces weak-to-moderate echoes (< 40 dBZ) more frequently across most altitudes and strong echoes (> 40 dBZ) less frequently (Fig. 3.11 (b)). This pattern is mirrored in the profile differences (Fig. 3.11 (c)), with 3SIP showing negative reflectivity differences in mean

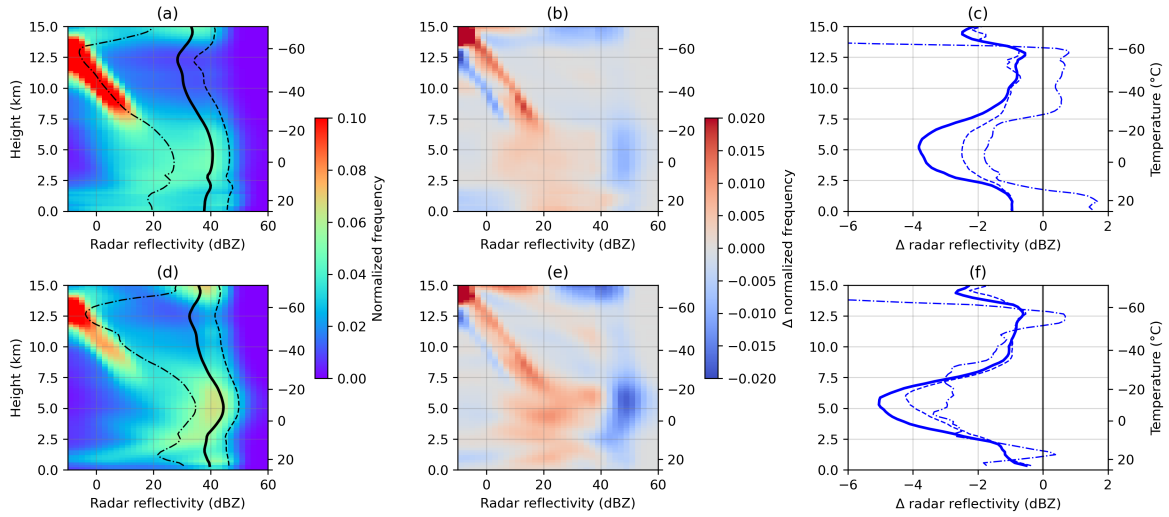


Figure 3.11: (a) Contoured frequency by altitude diagram (CFAD) of reflectivity (dBZ) from the noSIP simulation, overlaid with the median (dot dashed), mean (solid) and the 95th percentile (dashed) of reflectivity profiles. (b) Differences in reflectivity CFADs between the 3SIP and noSIP simulations ($3SIP - noSIP$), red (blue) color is positive (negative). (c) Differences in the median (dot dashed), mean (solid) and the 95th percentile (dashed) reflectivity profiles between 3SIP and noSIP ($3SIP - noSIP$). Results shown in (a-c) are calculated for reflectivity values > -10 dBZ over the entire domain and 30-180 minutes, while results shown in (d-f) are similar to (a-c) but are conditioned to the updraft regions ($W > 1 \text{ m s}^{-1}$). Reference temperature levels are labeled on the right ordinate of each panel.

and 95th-percentile profiles throughout the column. These results are consistent with reduced rain water in mid-to-low levels in 3SIP (Fig. 3.6 (a4,b4)). The differences between the median profiles are positive between approximately 8-14 km (-30 to -60 °C, Fig. 3.11 (c)) due to the enhanced snow mass in 3SIP (Fig. 3.6 (b5)), which increases the frequency of weak echoes (< 20 dBZ) in this layer (Fig. 3.11 (b)). The positive difference of median profiles below around 2 km (15 °C) can be explained by graupel completely melting to rain drops at this level (Fig. 3.6 (a2,b2,a4,b4)). These slightly more numerous but smaller graupel particles in 3SIP melt to smaller rain drops, leading to its increased frequency of weak-moderate echoes (20-40 dBZ) near surface, even though strong echoes (> 40 dBZ) remain less frequent (Fig. 3.11 (b)). In updraft regions ($W > 1 \text{ m s}^{-1}$), the same patterns intensify. 3SIP predominantly simulates more echoes < 40 dBZ and fewer strong echoes > 40 dBZ, especially at temperatures higher than -20 °C (Fig. 3.11 (e)), leading to even larger reductions in the median, mean, and 95th-percentile profiles throughout the column (Fig. 3.11 (f)).

For all cloudy grid points (total condensate mass $> 10^{-6} \text{ kg kg}^{-1}$, Fig. 3.12 (a)), 3SIP shows slightly more shallow and mid-level cloud tops (2 and 10 km) and less deep cloud tops around 13 km. In updrafts (Fig. 3.12 (b)), noSIP again has more frequent deep cloud tops near 13.5km, whereas 3SIP suggests slightly higher frequencies beyond the 95th percentiles, though the median profiles remain identical for both runs. These differences in CTHs are consistent with vertical velocity changes. While 3SIP simulates overall weaker median updrafts compared to noSIP, the 95th-percentile and especially the maximum updrafts are enhanced to some extent (Fig. 3.10 (b1-b3)). These results suggest that, by redistributing water condensate away from rain/graupel at low-to-mid levels to ice/snow at high levels, 3SIP reduces warm-rain- and riming-driven strong echoes, enhances weak-moderate echoes, and modestly lower typical CTHs but occasionally increases extreme CTHs.

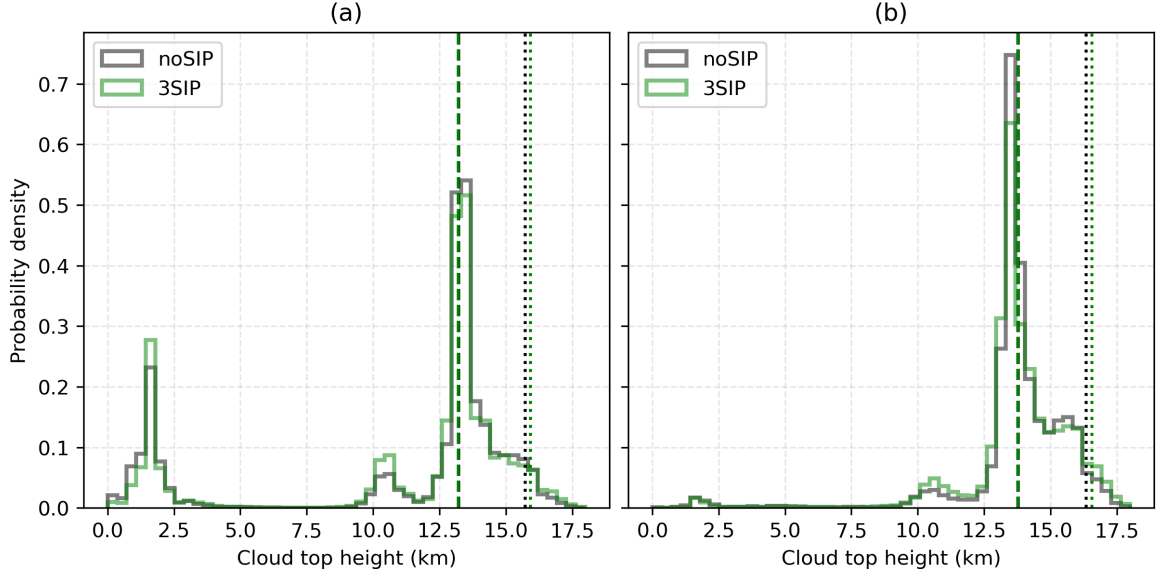


Figure 3.12: Probability density functions (PDFs) of cloud top heights (CTHs; km). CTHs in (a) are calculated for all cloudy grid points (total condensate mass $> 10^{-6} \text{ kg kg}^{-1}$) over the entire domain and 30-180 minutes, while CTHs in (b) are similar to (a) but are conditioned to the updraft regions ($W > 1 \text{ m s}^{-1}$). Dashed lines indicate the medians and the dotted lines the 95th percentiles.

3.5 Results: Tropical MCS

3.5.1 Precipitation

In the tropical MCS case, 3SIP again reduces precipitation (-3.37%, Table 3.6), but to a much smaller degree compared to the supercell case (-28.33%, Table 3.5). Time series of precipitation change suggests that all SIP runs increase precipitation relative to noSIP before 30 minutes (Fig. 3.13 (b)), suggesting earlier precipitation onsets in SIP runs. But this may also be a model spinup issue. After 30 minutes, SIP runs reduce precipitation sharply and with a similar pattern as in the supercell case: FFD-containing runs substantially reduce precipitation, HM-containing runs suggest modest decreases, and IICOLonly shows minor suppression. After around 60 minutes, precipitation reductions in SIP runs all exhibit a less-more-less-reduction pattern. Especially

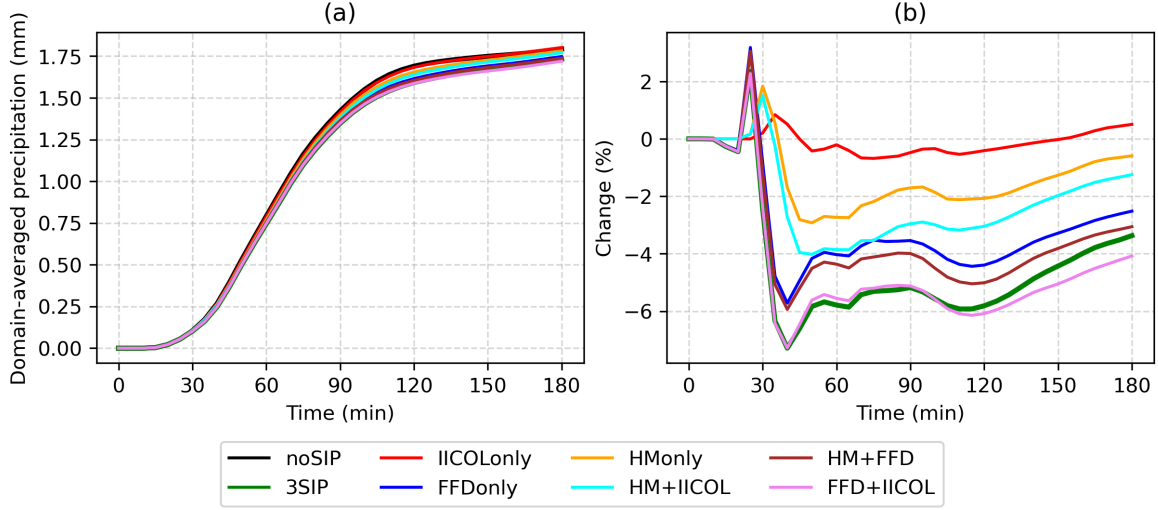


Figure 3.13: Similar to Fig. 3.2 but for the tropical MCS.

after 120 minutes, all SIP runs show persistent surface precipitation increases (Fig. 3.13 (b) and Table 3.6), suggesting potential secondary convection initiation in SIP runs. Compared to the supercell case, the tropical MCS highlights how SIP mechanisms operate differently in a warm and moist environment. While the overall trend of rainfall suppression by SIP persists, the magnitude and timing of impacts vary. This emphasizes that the role of SIP in precipitation formation depends not only on microphysical pathways, but also on the thermodynamic structure of the environment.

3.5.2 Cloud properties

The relatively modest precipitation reduction in 3SIP aligns with the small change in LWP (-3.38%, Table 3.6). Before 60 minutes, 3SIP simulates $\sim 8\%$ less LWP than noSIP (Fig. 3.14 (a2)), driven by $\sim 20\%$ reductions in rain water mass and number (Fig. 3.14 (c2,d3)). However, cloud water remains nearly unaffected (Fig. 3.14 (c1,d2)), since the boundary layer is saturated and water vapor is abundant. IWP in 3SIP is substantially increased due to large enhancements across all ice categories (Fig. 3.14

Experiments	TWP (%)	LWP (%)	IWP (%)	Precipitation (%)
3SIP	13.03 (12.59)	-3.38 (-7.03)	33.56 (46.74)	-3.37 (-5.65)
IICOLonly	4.38 (3.88)	0.43 (-1.15)	9.32 (12.65)	0.50 (-0.35)
FFDonly	8.72 (9.38)	-3.44 (-6.47)	23.94 (36.97)	-2.52 (-4.26)
HMonly	6.42 (6.14)	-2.10 (-4.36)	17.09 (24.43)	-0.59 (-2.01)
HM+IICOL	9.50 (8.63)	-1.77 (-4.49)	23.60 (31.47)	-1.25 (-2.90)
HM+FFD	9.64 (9.94)	-3.76 (-6.98)	26.41 (39.40)	-3.06 (-4.88)
FFD+IICOL	11.27 (11.43)	-4.07 (-7.29)	30.47 (44.03)	-4.08 (-5.95)

Table 3.6: Similar to Table 3.5 but for the tropical MCS case. Relative changes of SIP-including runs to noSIP at 120 minutes are shown in parentheses.

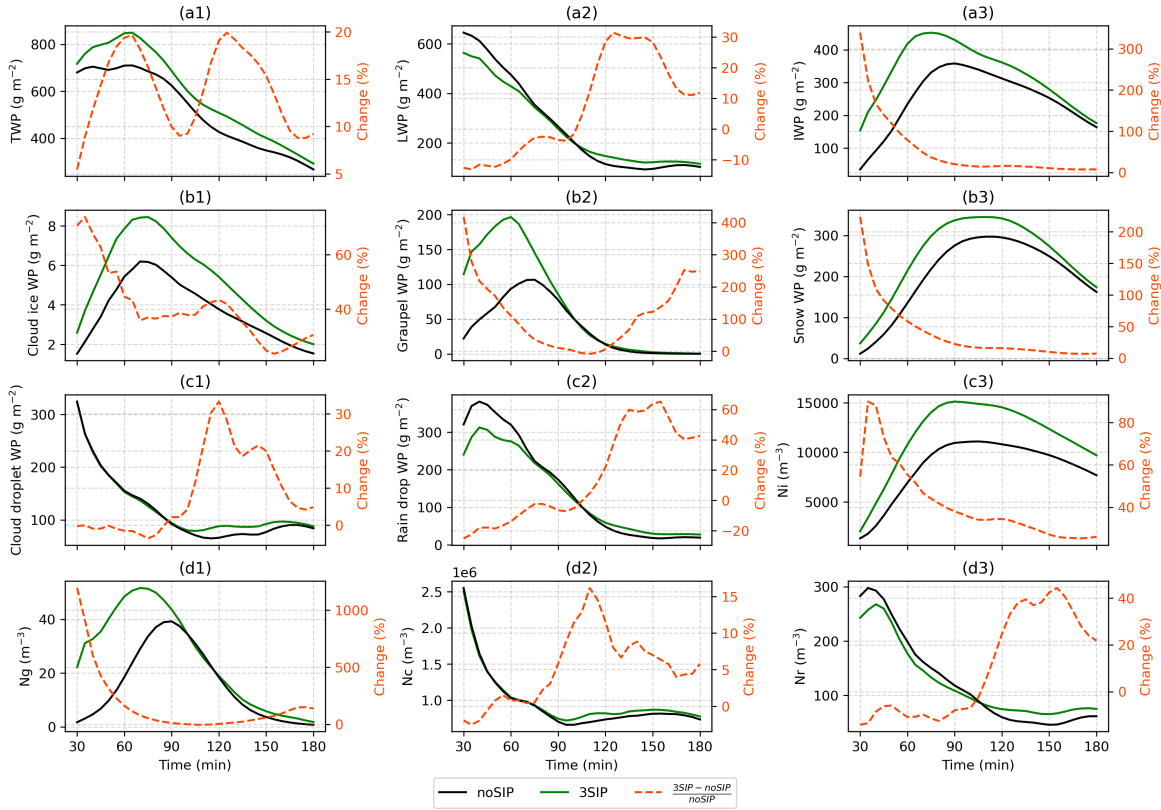


Figure 3.14: Similar to Fig. 3.5 but for the tropical MCS case.

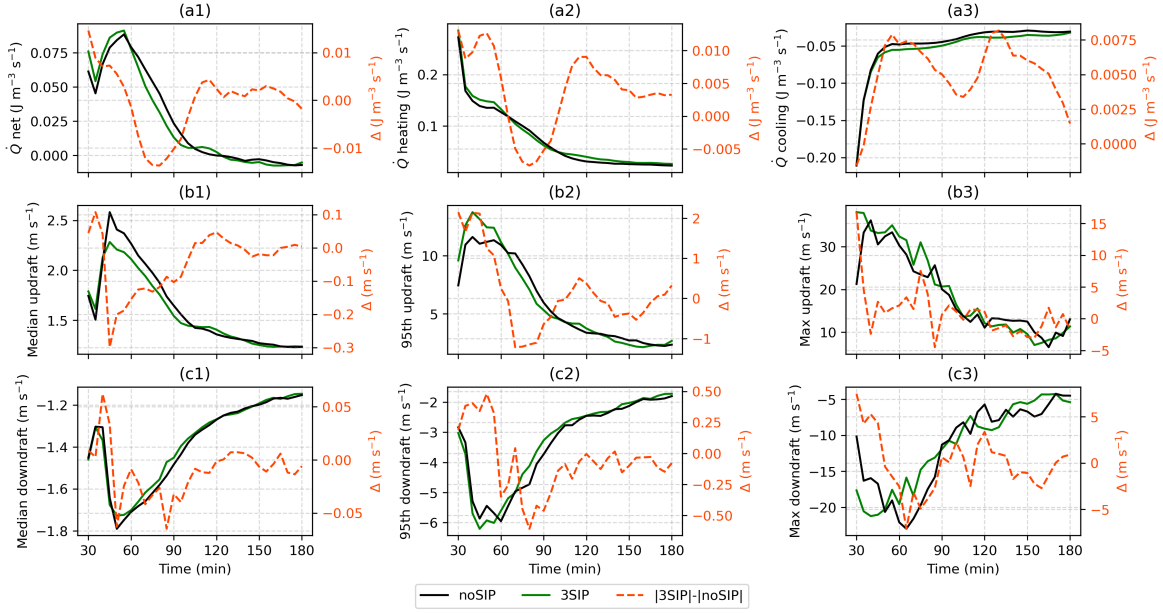


Figure 3.15: Similar to Fig. 3.9 but for the tropical MCS case.

(a3-b3)). The additional SIP-generated ice particles are able to grow rapidly by riming, as suggested by strong increases in graupel mass (Fig. 3.14 (b2)). The condensation, deposition, freezing, and riming collectively enhance latent heat release in 3SIP (Fig. 3.15 (a1,a2)), which strengthens the strong updrafts (Fig. 3.15 (b2,b3)). Meanwhile, the larger population of ice particles in 3SIP contributes to melting, producing stronger cooling and downdrafts (Fig. 3.15 (a3,c1-c3)).

Around 60-100 minutes, 3SIP shows increases in cloud water mass and number, and smaller reductions in rain water mass and number (Fig. 3.14 (c1,c2,d2,d3)), resulting in a weaker suppression of LWP (Fig. 3.14 (a2)). This period coincides with declining IWP and decreases in ice particle masses, particularly graupel, suggesting that copious ice particles from aloft are now falling out and melting, feeding back into cloud and rain water (Fig. 3.14 (a3-b3)). Notably, IWP peaks about 30 minutes earlier in 3SIP than in noSIP (Fig. 3.14 (a3)), which aligns with the graupel curves (Fig. 3.14 (b2,d1)). This indicates that graupel grows and peaks more quickly in 3SIP, while noSIP sustains

riming longer into the mature stage. Thus, 3SIP enters a glaciation/melting phase earlier, while noSIP still experiences vigorous graupel growth and strong latent heating. As a result, 3SIP exhibits weaker net latent heating (Fig. 3.15 (a1-a3)) and generally weaker updrafts, and the median, 95th, and maximum downdrafts are also weaker in 3SIP (Fig. 3.15 (b1-c3)).

After 100 minutes, 3SIP exhibits a TWP rebound due to increases in both LWP and IWP (Fig. 3.14(a1-a3)). Graupel masses decline identically in both runs, but 3SIP maintains higher graupel number, implying more numerous but smaller graupel particles (Fig. 3.14 (b2,d1)). Cloud ice mass and number, along with snow mass, are consistently higher in 3SIP, indicating enhanced aggregation and depositional growth (Fig. 3.14 (b1,b3,c3)). Cloud and rain water also recover in 3SIP (Fig. 3.14 (c1,c2,d2,d3)). Latent heat warming and cooling remain stronger in 3SIP, leading to slightly stronger net heating in 3SIP (Fig. 3.15 (a1-a3)). Dynamically, median and 95th updrafts and downdrafts are broadly similar between runs, though 3SIP shows alternating periods of increases and decreases in maximum updrafts and downdrafts (Fig. 3.15 (b1-c3)).

Time-averaged vertical profiles show that 3SIP maintains higher TWC throughout the column, mainly due to the large graupel and snow contributions (Fig. 3.16 (a2,b2,a5,b5)). Notably, at temperatures $< -25^{\circ}\text{C}$, graupel in 3SIP experiences a second enhancement, coinciding with slower increases of snow and suggesting a potential snow-to-graupel conversion at this level (Fig. 3.16 (a2,b2,b5)). Cloud ice is increased in 3SIP between 0 and -30°C but reduced at lower temperatures (Fig. 3.16 (a1,b1)), due to weaker PIP efficiency in 3SIP than in noSIP (not shown). Cloud water is higher below the melting level but lower above (Fig. 3.16 (a3,b3)), since it is collected by graupel riming growth above and replenished by ice melting below. Rain water mass and number are both strongly reduced between 0 and -20°C , especially near -5°C , but enhanced below the melting level, with more but smaller rain drops (Fig. 3.16 (a4,b4)).

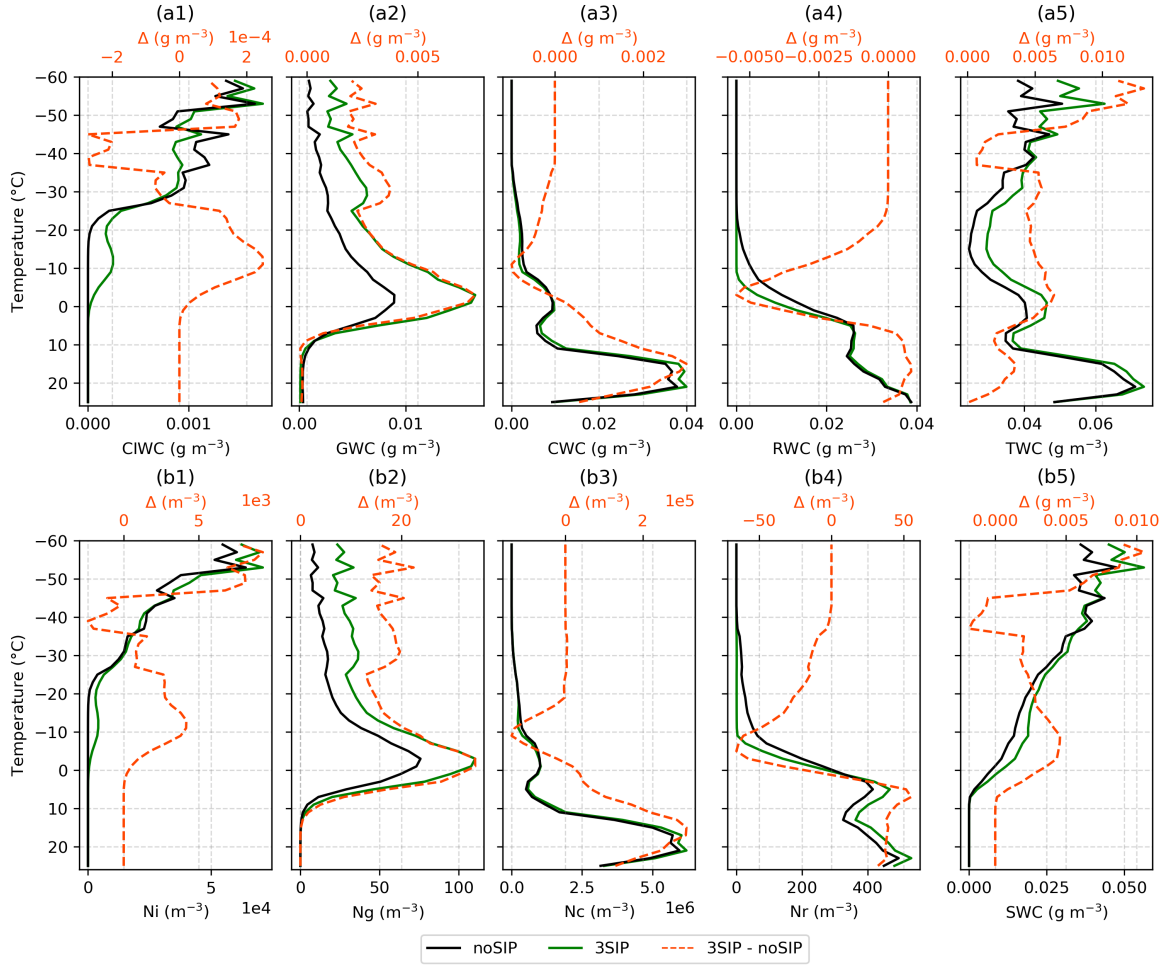


Figure 3.16: Similar to Fig. 3.6 but for the tropical MCS case.

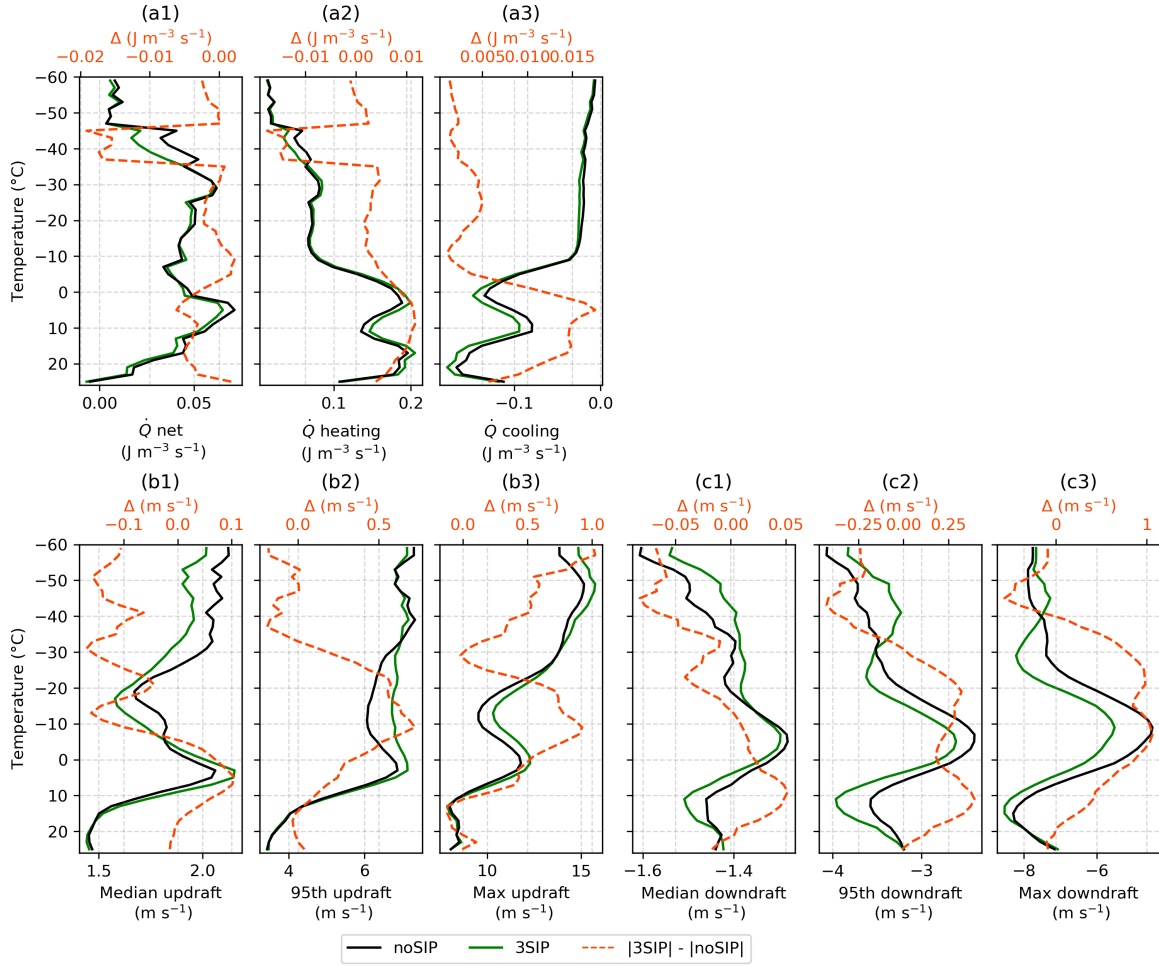


Figure 3.17: Similar to Fig. 3.10 but for the tropical MCS case.

Latent heating is stronger in 3SIP through much of the vertical column, particularly below freezing, with only weaker heating between -35 and -45 °C due to reduced ice nucleation (Fig. 3.17 (a2)). Latent cooling is also stronger throughout the column, especially below the freezing level (Fig. 3.17 (a3)). However, net latent heating remains weaker overall in 3SIP vertically (Fig. 3.17 (a1)). In terms of vertical motion, 3SIP suggests stronger (weaker) median updrafts at temperatures higher (lower) than -5 °C, and stronger 95th and maximum updrafts through much of the column (Fig. 3.17 (b1-b3)). Similarly, 3SIP shows enhanced downdrafts that broadcast from low levels to higher levels from the median to the maximum downdrafts (Fig. 3.17 (b1-b3)).

In summary, SIP drastically alters the tropical MCS evolution, redistributes liquid condensate vertically from liquid to ice, yet with only limited impacts on surface precipitation. In the developing stage, SIP rapidly converts cloud and rain water to ice, producing abundant new ice particles but without strongly depleting total liquid due to the saturated environment and plentiful vapor supply. This sustains condensation, deposition, and riming, enhances latent heat release, and invigorates early updrafts. Between 60-100 minutes, the early glaciation in 3SIP leads to enhanced graupel fallout and melting, which temporarily replenishes liquid water and slows rain depletion. After 100 minutes, the recovery of liquid condensate suggests a secondary convection initiation, triggered by graupel melting and reduced riming efficiency that allow liquid to persist longer. Dynamically, median updrafts are stronger in 3SIP at warmer mixed-phase layers but weaker at colder layers, indicating buoyancy from riming and condensation near freezing versus reduced riming aloft. Meanwhile, consistently stronger 95th and maximum updrafts in 3SIP suggest that SIP invigorates localized intense convective cores.

From a pathway perspective, these results suggest that warm-rain suppression by SIP is relatively weak and temporary in the moist tropical environment. The abundant

moisture also sustains rapid depositional growth of secondary ice particles into snow, but the conversion of snow to graupel appears limited, as almost no graupel mass exists in both runs after 120 minutes. In other words, cold-rain pathway is inefficient in this environment. Together, these effects explain why precipitation reductions are relatively small in this case: while SIP effectively redistributes mass from liquid to ice and from lower to higher levels, the saturated environment buffers against large rainfall suppression.

3.5.3 Cloud ice crystal production

Similar to the supercell case, SIP processes are the predominant sources of cloud ice crystals at temperatures higher than -20°C , while PIP dominates the ice production at lower temperatures (Fig. 3.18). However, in the MCS case, HM (61.2%) is the major contributor to ice crystals at temperatures between -10 and 0°C , followed by IICOL (25.5%) and then FFD (13.3%). Between -20 and -10°C , IICOL (96.5%) dominates ice production with minor contribution from FFD (3.3%). Between -30 and -20°C , IICOL (90.1%) dominates ice production with minor contribution from HT (9.8%). Between -40 and -30°C , HT (99.4%) dominates ice production with minor contribution from HO (0.6%). Between $T < -40^{\circ}\text{C}$, HT (91.6%) dominates ice production with minor contribution from HO (8.3%).

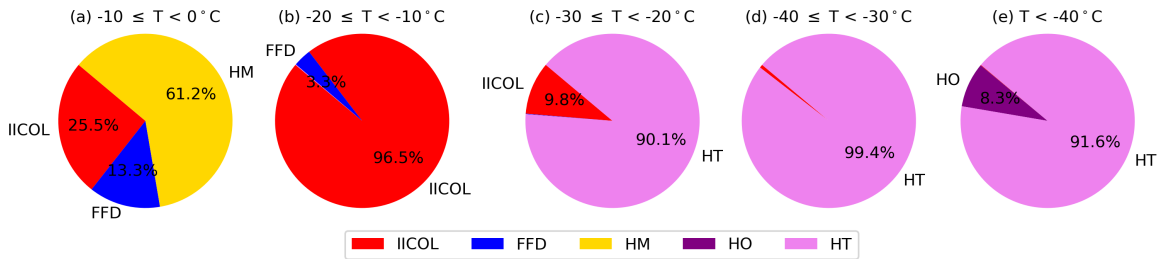


Figure 3.18: Similar to Fig. 3.7 but for the tropical MCS case.

The time evolution and vertical structure highlight the synergistic yet non-additive SIP interactions again in the MCS case. IICOL is strongly amplified and peaks earlier in multi-SIP runs, especially when combined with FFD (Fig. 3.19 (a1,a2)). A similar amplification effect is also evident for HM (Fig. 3.19 (c1,c2)). However, IICOL and HM

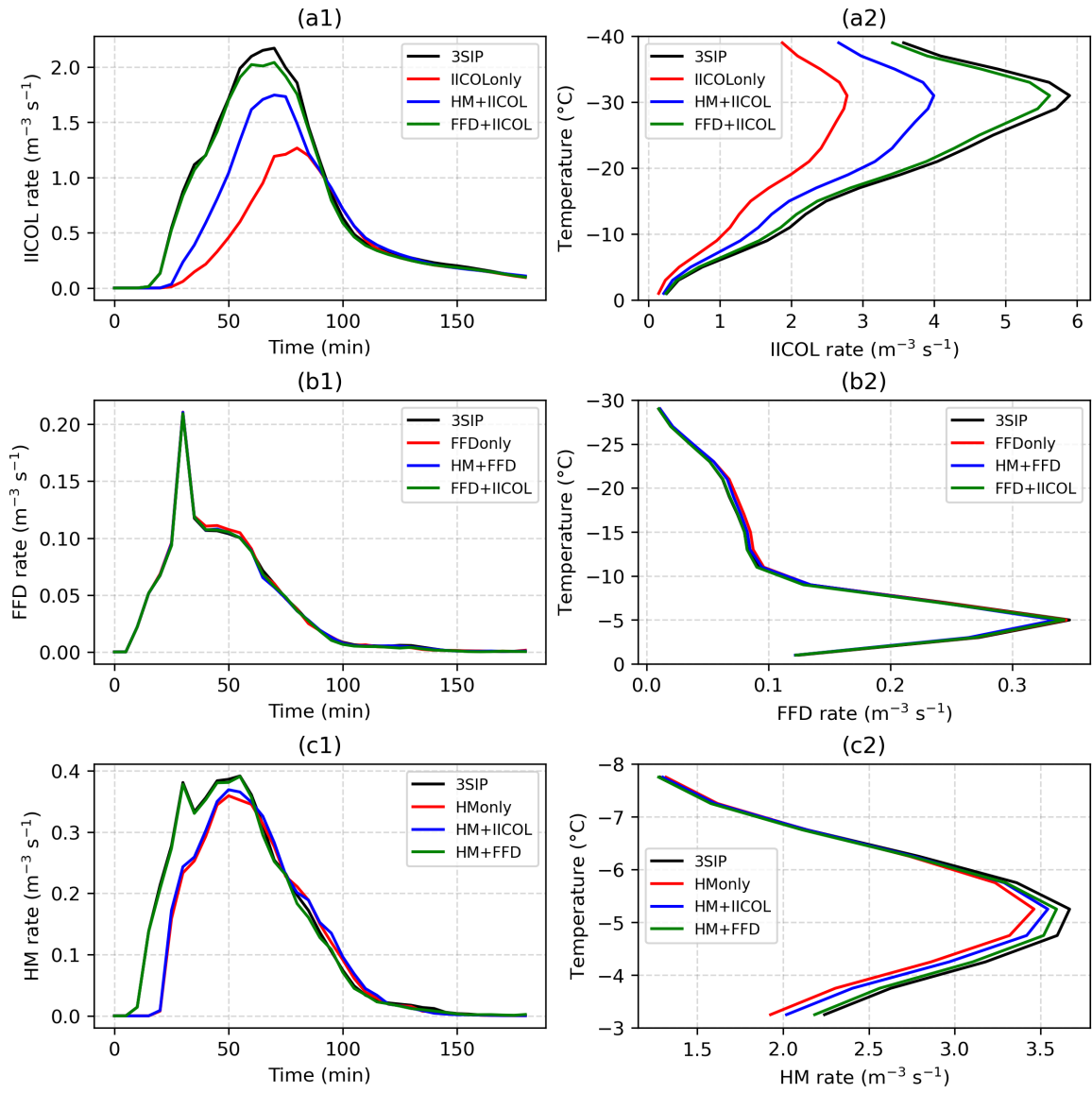


Figure 3.19: Similar to Fig. 3.8 but for the tropical MCS case.

again exert little influence on FFD rates. FFD-containing runs exhibit a sharp, narrow peak around 40 minutes and $-5\text{ }^{\circ}\text{C}$ (Fig. 3.19 (b1,b2)), which is consistent with the substantial reductions in rain water (Figs. 3.14 (c2,d3) and 3.16 (a4,b4)). This suggests that FFD is primarily governed by rain availability and temperature conditions, rather than by interactions with other SIP processes in this case. Furthermore, SIP process rates are much weaker in the MCS case compared to supercell case (Fig. 3.8), which also explains the weaker precipitation suppression by SIP in the MCS case as SIP processes are generally less efficient.

3.5.4 Reflectivity and cloud top height

In the MCS case, most reflectivity echoes cluster below $\sim 30\text{ dBZ}$, with decreasing frequency as reflectivity increases, and frequency maxima occurring above 7.5 km (Fig. 3.20 (a)). Vertical profiles peak near the melting level, with the 95th and mean values reaching 40 dBZ, while the median is around 10 dBZ. Below 5 km (near $0\text{ }^{\circ}\text{C}$), the mean exceeds the 95th percentile, suggesting that a small fraction of strong echoes dominate in the lower levels, while most of the distribution is much weaker. In the updrafts (Fig. 3.20 (d)), the reflectivity distribution shifts toward higher values, with frequent occurrences above 20 dBZ extending into temperatures below $-20\text{ }^{\circ}\text{C}$. The mean and 95th percentiles are around 40-50 dBZ, indicating the presence of large rimed particles lofted within updrafts.

CFAD differences indicate that 3SIP produces more frequent moderate reflectivities (20-40 dBZ) but fewer weak echoes ($< 20\text{ dBZ}$) above the freezing level (Fig. 3.20 (b)). Notably, the strong -10 dBZ mode at 7.5 km in noSIP is less pronounced in 3SIP (Fig. 3.20 (a,b)), consistent with the reduced cloud water near $-10\text{ }^{\circ}\text{C}$ (Fig. 3.16 (a3, b3)). Profile differences show that 3SIP increases the median reflectivity ($\sim +3\text{ dBZ}$) between 0 and $-20\text{ }^{\circ}\text{C}$, but decreases the 95th percentile ($\sim -3\text{ dBZ}$) in the

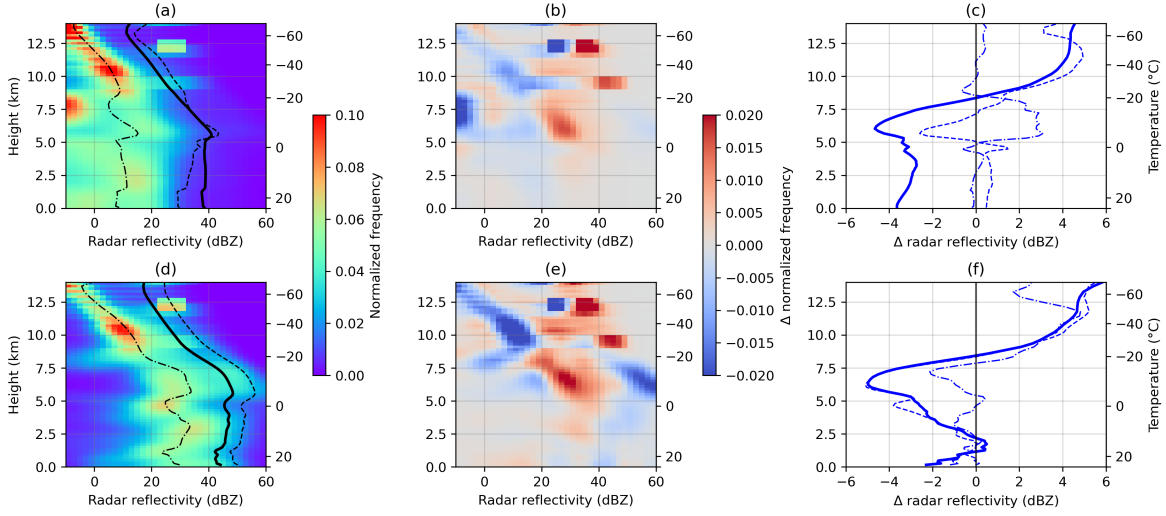


Figure 3.20: Similar to Fig. 3.11 but for the tropical MCS case.

same layer, while slightly enhancing it above and below (Fig. 3.20 (c)). Similarly, the mean reflectivity is reduced at warmer levels (> -20 °C) but enhanced aloft. When conditioned to updraft regions, these patterns become more pronounced (Fig. 3.20 (e,f)). 3SIP generates more frequent moderate echoes (20-40 dBZ) throughout the column, but fewer weak (< 20 dBZ) and strong (> 40 dBZ) echoes. Consequently, the median, mean, and 95th percentile reflectivities are smaller in 3SIP at temperatures > -20 °C but larger at lower temperatures (Fig. 3.20 (f)).

Figures 3.14 (b2,d1) and 3.16 (a2,b2) show that both graupel number and mass are substantially increased in 3SIP, yet the results above suggest that 3SIP generates fewer strong echoes than noSIP, especially in the updrafts and in the warm layer (> -20 °C). This means that riming growth in 3SIP is still suppressed, even in the moist environment where cloud water is not efficiently depleted. Instead, there are more numerous but smaller graupel particles in 3SIP that sustains moderate echoes. In the upper layer (< -20 °C), SIP enhances reflectivity through more snow particles, shifting precipitation growth toward deposition and aggregation aloft (cold-rain) rather than riming (warm-rain) in mid-levels.

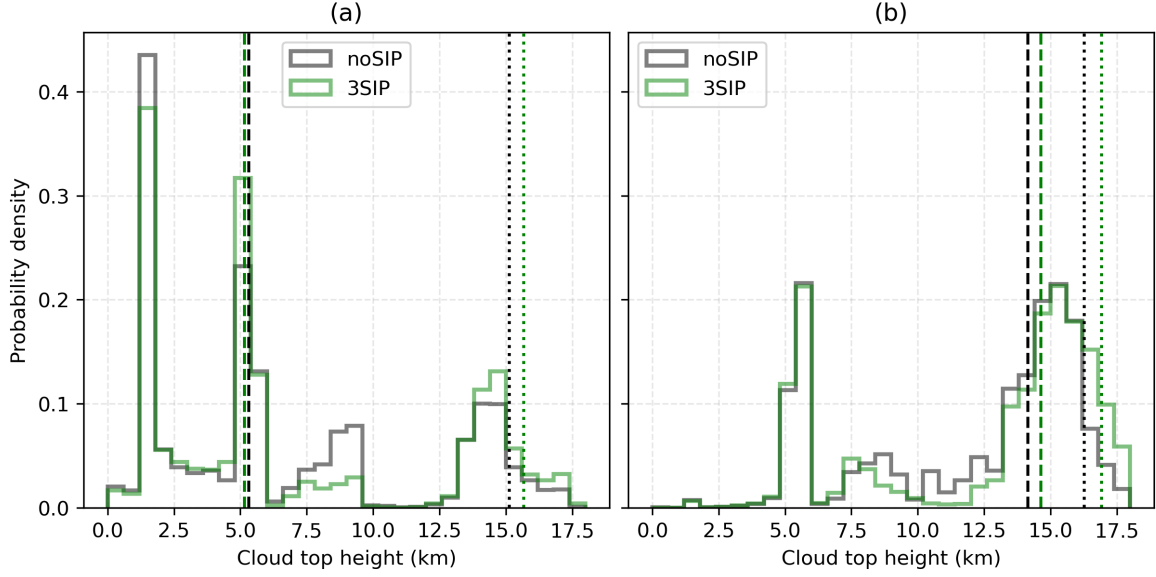


Figure 3.21: Similar to Fig. 3.12 but for the tropical MCS case.

For all cloudy pixels, 3SIP and noSIP exhibit broadly similar CTH distributions (Fig. 3.21 (a)). However, 3SIP shows more frequent CTHs near 5 km and 14 km, while noSIP favors shallower and mid-level tops around 2 km and 9 km. The median CTHs are nearly identical between noSIP and 3SIP, but the 95th percentile is higher in 3SIP, indicating that SIP promotes more extreme cloud tops. This distinction becomes more clear in the updraft regions (Fig. 3.21 (b)), where 3SIP produces a higher occurrence of CTHs exceeding 16 km, while noSIP favors moderate tops between 8-12 km. Furthermore, both the median and 95th percentile CTHs are elevated and higher in 3SIP. These results suggest that by redistributing water condensate from liquid to ice upward, SIP promotes the vertical extent of tropical deep convective clouds, especially in active updraft regions.

3.5.5 Comparison to observations

Consistent with previous research (e.g., Qu et al. 2022; Huang et al. 2022b), SIP is crucial for matching observed high ice particle number concentrations. Figure 3.22 (a) shows that compared to observations, noSIP severely underestimates ice number concentrations, with a steep cutoff below $\sim 10^5 \text{ m}^{-3}$, while all SIP runs dramatically increase simulated ice number concentrations. In terms of individual SIP runs, FF-Donly produces the largest concentrations at values less than $\sim 10^4 \text{ m}^{-3}$ but drops off steeply soon after. HMonly and HM+FFD produce broader tail into higher concentrations, but still heavily underestimate the observed concentrations. When IICOL is included, the simulated ice number concentrations are largely enhanced and closer to observed distributions. As for IWC (Fig. 3.22 (b)), noSIP again shows substantial underestimations, especially for higher values ($> 2 \text{ g m}^{-3}$). But interestingly, all SIP runs converge to similar distributions, which largely remain below the observed frequencies for values between $0.25\text{-}3.0 \text{ g m}^{-3}$. This suggests that SIP improves particle numbers but does not substantially increase IWC compared to observations. This reflects a shift towards more numerous, smaller ice particles rather than fewer, more massive ones in the simulated clouds.

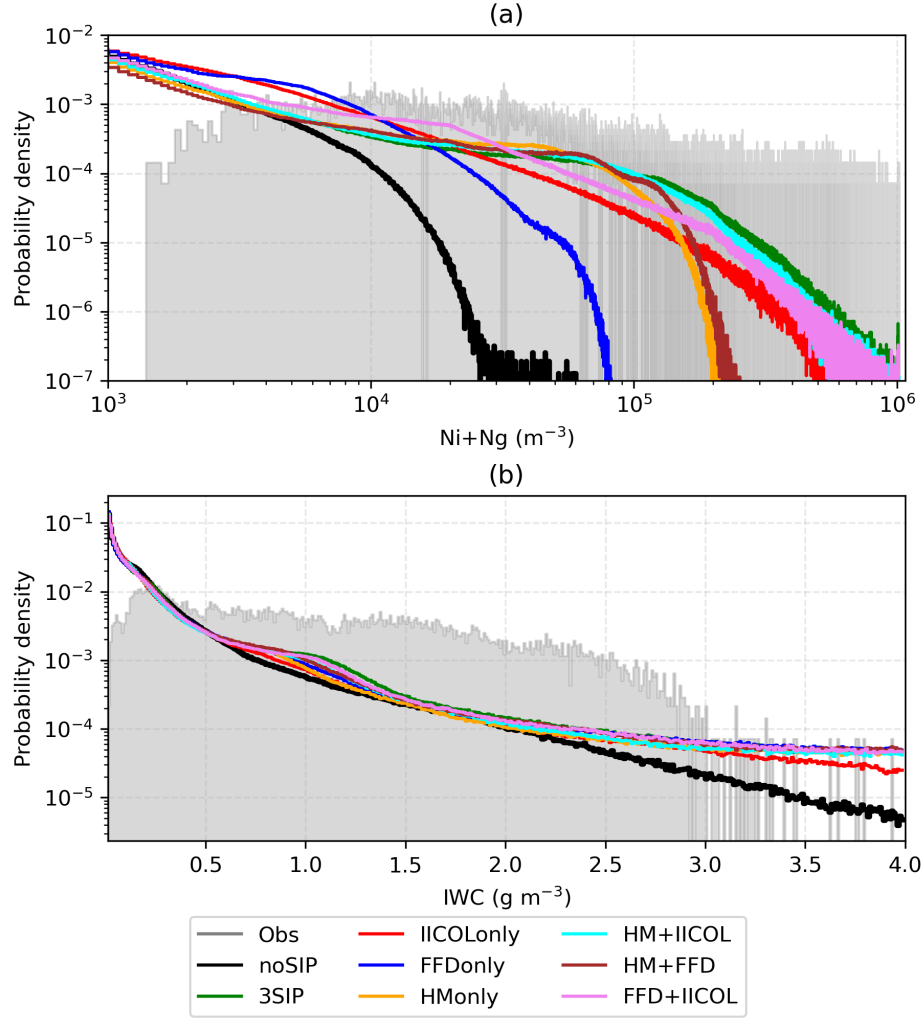


Figure 3.22: PDF comparisons of (a) ice number concentration (m^{-3}) and (b) IWC (g m^{-3}) between WRF model simulations and HAIC-HIWC airborne in situ observations collected on May 26, 2015. WRF-simulated ice number concentrations in (a) are calculated from cloud ice and graupel number concentrations. Comparisons are performed within the temperature range $[-12.72, -5.57]$ ($^{\circ}\text{C}$) and ice particle size range $[77.1, 3523.5]$ (μm).

3.6 Summary

In this study, besides HM, we implemented two additional SIP mechanisms: IICOL and FFD, in the Thompson microphysics scheme and performed two idealized simulations to investigate the impacts of SIP on precipitation formation in deep convection. The two cases were represented by different thermodynamic soundings: a continental supercell and a tropical MCS. The main findings of this research are summarized below.

- **Precipitation and water redistribution** In both cases, SIP reduces surface precipitation without drastically removing water condensate from the cloud system. Rather, SIP redistributes water condensate from liquid to ice and from low to high levels, yielding a dual suppression of warm- and cold-rain pathways. FFD fragments rain drops into ice particles above the freezing level, directly reducing warm-rain production. Abundant secondary ice splinters and particles from HM and IICOL intensify vapor competition and dilute riming efficiency, indirectly further suppressing the warm-rain pathway. Continuous breakup by IICOL limits snow-to-graupel conversion, weakening the cold-rain pathway. Precipitation reductions are much stronger in the supercell (-10~-28%) than in the tropical MCS (-0.5~-3%) because the moist tropical conditions resupplies liquid that buffers against large rainfall suppression.
- **SIP interactions** SIP mechanisms are synergistic but non-additive. FFD substantially amplifies HM and IICOL by supplying targets for riming and collision, but HM and IICOL exert only limited influences on FFD, as FFD is primarily governed by rain water availability. Interactions between HM and IICOL can be either synergistic or competitive: HM splinters can aggregate into snow that feeds IICOL, while IICOL produces graupel fragments that create more HM opportunities; however, they both compete for graupel and excessive fragmentation

by IICOL can limit HM efficiency. Overall, a mutual amplification between HM and IICOL is evident vertically.

- **Dynamics and thermodynamics** In the supercell case, SIP reduces both latent heating and cooling by depleting liquid and producing many smaller graupel that are less riming efficient. Heating with SIP is shifted downward near the freezing level (HM/FFD activity) rather than broadly aloft. Median updrafts and downdrafts are weakened with SIP, but vertically localized enhancements in maximum updrafts are evident. In the tropical MCS case, SIP modifies buoyancy by enhancing early heating and cooling through rapid glaciation and subsequent melting, which invigorates both updrafts and downdrafts. Vertical profiles confirm stronger heating and cooling below freezing in SIP, yielding stronger warm-layer median updrafts and downdrafts. Again, stronger 95th and maximum updrafts and downdrafts with SIP are evident through most of the vertical column.
- **Convective signatures** In both cases, with SIP, reflectivity CFADs show fewer strong echoes (> 40 dBZ) and more frequent moderate echoes (20-40 dBZ), owing to reduced rain and more numerous but smaller graupel at low-mid levels and enhanced snow aloft. CTH PDFs have similar medians but higher 95th percentiles, especially in active updraft regions, indicating more frequent extreme tops in SIP as condensate is shifted upward into ice.
- **Comparison to observations** SIP is crucial to approaching the observed high ice number concentrations and noSIP severely underestimates ice number concentration. However, all runs (with or without SIP) still underpredict IWC.

Finally, while this study provides insights into how SIP processes alter precipitation pathways and convection evolution, limitations should be noted. First, the analysis is based on idealized WRF simulations with prescribed environmental soundings, which

do not capture the complexity and variability of real atmospheric conditions. Second, SIP numerical representations are still highly uncertain due to a lack of in situ observations and laboratory studies. A different choice of SIP scheme might greatly impact the conclusions of this study. Therefore, while the qualitative insights into precipitation pathways and SIP interactions are more robust, the quantitative results should be interpreted with caution.

Nevertheless, this study underscores the importance of SIP in deep convection and precipitation formation, thereby the potential to incorporate them in atmospheric numerical models. However, the current study is conducted at a 200-m horizontal grid spacing, which is far too fine for general research and operational models. Therefore, future work will focus on the application of SIP in real case studies with coarser (e.g., 1-km) grid spacing and under different aerosol conditions, which have profound impacts on cloud condensation, ice nucleation, convection evolution, and consequent precipitation.

Chapter 4

Dual effects of secondary ice production processes
and aerosol conditions on deep convection: A sea
breeze convection case study during
ESCAPE/TRACER

4.1 Introduction

Aerosols, clouds, and precipitation are tightly coupled components of the Earth’s climate system, and their interactions remain among the largest sources of uncertainty in weather and climate prediction (Gordon et al. 2023). Aerosols, through their role as cloud condensation nuclei (CCN) and ice nuclei (IN), influence cloud microphysical properties, lifetime, and precipitation (e.g., Tao et al. 2012). An increase in aerosol concentration leads to higher cloud droplet number concentration and smaller cloud droplet sizes (Twomey 1977), which are less efficient in collision-coalescence and thereby delay or suppress the warm-rain formation and lengthen cloud lifetime (Albrecht 1989; Lohmann and Feichter 2005). These aerosol-cloud-precipitation interactions are robust in shallow warm-phase clouds (e.g., Tao et al. 2012).

In contrast, aerosol-cloud-precipitation interactions in the context of deep convective clouds (DCCs) remain uncertain and often debated, particularly regarding aerosol effects on updrafts and precipitation (e.g., Khain et al. 2005; van den Heever et al. 2006; Tao et al. 2007; Koren et al. 2008; Rosenfeld et al. 2008; Khain 2009; Fan et al. 2013, 2018, 2025; Seifert et al. 2012; Seigel et al. 2013; Grabowski 2006, 2015; Lebo et al. 2012; Lebo and Morrison 2014; Lebo 2014, 2018; Miltenberger et al. 2018; Igel and van den Heever 2021; Varble 2018; Varble et al. 2023). Two widely-hypothesized pathways by which aerosol loadings can affect updrafts and precipitation in DCCs are: (1) the mixed-phase invigoration (or cold-phase invigoration or freezing-induced invigoration) (e.g., Khain et al. 2005; Rosenfeld et al. 2008; Fan et al. 2013), whereby increased aerosol loading leads to more numerous but smaller cloud droplets, greater lofting of cloud condensate mass into the mixed-phase region and more latent heating due to freezing, enhancing in-cloud buoyancy, updraft velocities, and surface precipitation; and (2) the warm-phase invigoration (or condensational invigoration) (e.g., Lebo et al.

2012; Fan et al. 2018; Igel and van den Heever 2021), where high aerosol number concentrations accelerate droplet activation and reduce supersaturation, enhancing latent heat release through additional condensation of water vapor and invigorating updraft velocities.

Numerical models have been essential for studying aerosol-DCC interactions, yet simulating aerosol impacts on DCCs remains challenging in part due to uncertainties in microphysics parameterizations, especially for ice-phase processes relevant to the cold-phase invigoration (Varble et al. 2023). In particular, the representation of ice formation in most numerical models is insufficient (Morrison et al. 2020). This includes secondary ice production (SIP), a group of microphysical processes that can rapidly generate additional ice crystals in the presence of preexisting ice particles within convective clouds (Korolev and Leisner 2020). Although field observations and laboratory studies have long documented multiple SIP mechanisms (e.g., Hobbs et al. 1980; Harris-Hobbs and Cooper 1987; Field et al. 2017; Korolev and Leisner 2020; Korolev et al. 2022), SIP has been largely overlooked in many atmospheric models owing to limited process-level understanding, large uncertainties in process rates, and still scarce in situ and laboratory studies (Morrison et al. 2020). Recently, substantial progress has been made toward expanding the representation of SIP processes in numerical models (Sullivan et al. 2018a,b; Huang et al. 2022b; Qu et al. 2022; Cholette et al. 2024; Patnaude et al. 2025; Grzegorzcyk et al. 2025; Yang et al. 2024; Sotiropoulou et al. 2020, 2021a,b; Georgakaki et al. 2022; Hu et al. 2025; Zhao et al. 2021; Zhao and Liu 2021). These studies have collectively demonstrated the significance of SIP in cloud microphysics, dynamics, convection evolution, precipitation formation, thunderstorm electrification, and even global radiative forcing.

Using an idealized configuration for a tropical mesoscale convective system, Qu et al. (2022) showed that SIP can strengthen existing convective updrafts and initiate

new updrafts above the melting layer. For a similar case, Hu et al. (2025) found that SIP primarily redistributes condensate vertically, invigorating early updrafts through enhanced freezing and riming, followed by accelerated graupel fallout and melting that temporarily replenishes liquid water and trigger potential secondary convection. However, Hu et al. (2025) also reported that while stronger 95th-percentile and maximum updrafts with SIP are evident through much of the vertical column, median updrafts are weakened within the subfreezing layer, and SIP systematically reduces surface precipitation through dual suppression of warm- and cold-rain pathways.

Despite these advances, how SIP manifests in real cases, especially under varying aerosol conditions, remain underexplored. Huang et al. (2025a) examined the joint impacts of SIP and aerosols in real-world deep convection, but with a primary focus on thunderstorm electrification. The current study is among the first to investigate the dual effects of SIP and aerosol conditions on cloud and precipitation characteristics in deep convection. Because the lifecycle of convective clouds, from initiation to maturity and eventual dissipation, is driven by a combination of dynamical, thermodynamical, and microphysical processes that are strongly coupled and vary spatially and temporally (e.g., Lebo 2018; Varble 2018; Varble et al. 2023), we apply a cloud tracking technique to individual convective cells to diagnose their life-cycle responses to aerosol conditions and SIP mechanisms.

This study aims to address three questions: (1) How do SIP and aerosols impact convection microphysically, thermodynamically, and dynamically? (2) How do different aerosol conditions influence cloud ice production? (3) What are the individual and combined effects of SIP and aerosols on surface precipitation? To answer these questions, a set of simulations was conducted for a sea breeze convection (SBC) case using the Weather Research and Forecasting (WRF) Model with the aerosol-aware Thompson microphysics scheme (Thompson and Eidhammer 2014) and three SIP mechanisms.

The remainder of this manuscript is organized as follows. Section 4.2 describes the SBC case, observational datasets used for model evaluation, the WRF model experimental design, and the tracking methodology applied to both observations and simulations. Section 4.3 presents results specific to the three research questions posed in Section 4.1. Finally, Section 4.4 summarizes the main findings of this research.

4.2 Data and methods

4.2.1 Case description

The SBC case studied in this research was observed on 17 June 2022 in the Houston area during the Experiment of Sea Breeze Convection, Aerosols, Precipitation and Environment (ESCAPE; Kollias et al. 2025; Dzambo et al. 2025; Hu and Lebo 2025) and the TRacking Aerosol Convection interactions ExpeRiment (TRACER; Jensen et al. 2022b, 2025) field campaigns. Figure 4.1 shows the time evolution of the SBC case obtained from the Geostationary Operational Environmental Satellites (GOES16) Channel 1 and Channel 13. Clear conditions were observed along the Texas coastline at 12Z. Later in the morning, with daytime heating, shallow convective clouds initiated by sea breeze were observed off the southeastern Texas and western Louisiana coastline (Fig. 4.1 (a)). Aided by the onshore sea breeze flow, the shallow convection moved inland (Fig. 4.1(b)) and soon developed into DCCs near the TX/LA border with scattered convection near the Houston area (Fig.4.1(c)). These DCCs persisted for a few hours around the state border line (Fig. 4.1 (d)) and decayed around 03Z, 18 June 2022.

Two research aircrafts were deployed during ESCAPE, including the National Research Council of Canada Convair-580 and the Stratton Park Engineering Company Learjet. On 17 June 2022, three research flights (RFs), two by the Learjet and

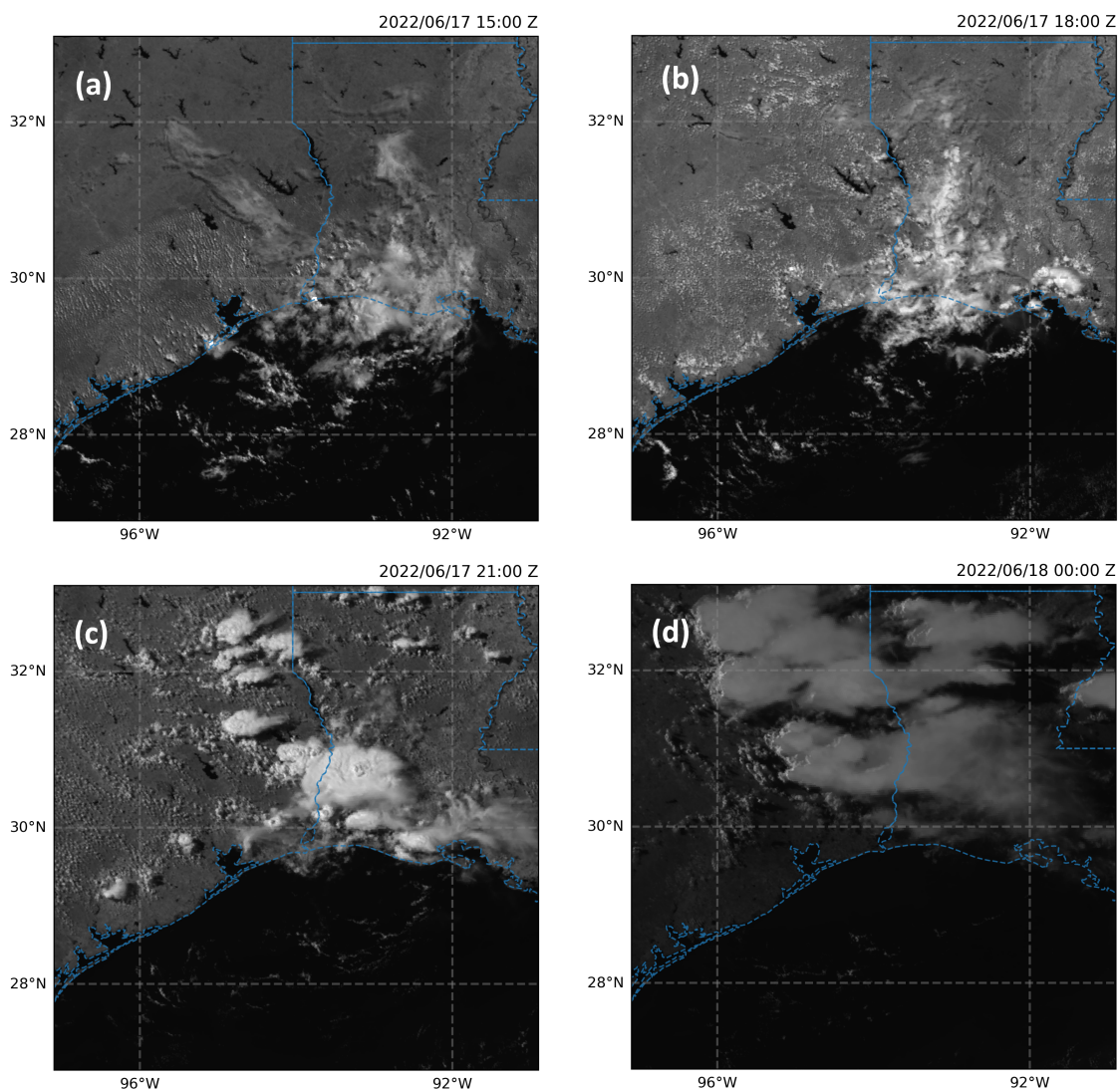


Figure 4.1: Composite satellite images from GOES16 Channel 1 and Channel 13 at (a) 15Z, (b) 18Z, (c) 21Z, 17 June 2022 and (d) 00Z, 18 June 2022.

one by the Convair-580, were conducted (Fig. 4.2 (a)). The Learjet first took off around 12Z (LRF10) to sample developing land breeze convection off the coast of the Texas/Louisiana (TX/LA) border. Around 16Z, both Convair-580 (CRF13) and Learjet (LRF11) took off to sample isolated SBC off the eastern Texas coast and around the Houston area.

4.2.2 Observational datasets

Observational datasets used to evaluate the WRF model’s performance include the quality-controlled radar reflectivity and precipitation from the Multi-Radar/Multi-Sensor System (MRMS). The Convair-580 was equipped with Cloud Droplet Probe (CDP). The Learjet was equipped with the Fast Cloud Droplet Probe (FCDP). The liquid water content (LWC) was derived from droplet size distributions measured by the CDP and FCDP (McFarquhar et al. 2017b; Patil 2025). Unfortunately, due to data quality concerns, ice water content (IWC) data collected during ESCAPE is not considered for model evaluation in this work.

4.2.3 Experimental designs

4.2.3.1 WRF Model configurations

This study is conducted with the Advanced Research WRF Model (Skamarock et al. 2019), Version 4.6, by applying the same model setup as in Hu and Lebo (2025). A single domain with a horizontal grid spacing of 1 km is used, as shown in Fig. 4.2 (a). The model has 81 vertical levels topped at 50 hPa with varying grid spacing ranging from 32 m to 408 m. The WRF simulations are initialized at 06Z on 17 June 2022, ran for 24 hours till 06Z on 18 June 2022, and the output is saved every 4 minutes. The model uses adaptive time steps ranging between 1 and 10 seconds. The Rapid Radiative Trans-

fer Model for General Circulation Models (RRTMG) radiation scheme (Iacono et al. 2008) is utilized for longwave and shortwave radiation, and the Noah multi-physics (Noah-MP) Land Surface Model (Niu et al. 2011) for the land surface scheme. With a 48-member multi-physics ensemble, Hu and Lebo (2025) identified the optimal physics configurations for predicting SBC, including the initial conditions/boundary conditions (ICs/BCs) from the 3-km and hourly-updated High-Resolution Rapid Refresh (HRRR) model forecasts, the Mellor-Yamada-Nakanishi-Niino (MYNN) eddy-diffusivity mass-flux (EDMF) scheme (Nakanishi and Niino 2006; Olson et al. 2019) for the planetary boundary layer (PBL) scheme, and the Thompson microphysics scheme (Thompson et al. 2008). Therefore, this set of model configurations is employed in this study. For microphysics scheme specifically, we utilize the aerosol-aware Thompson scheme (Thompson and Eidhammer 2014) to account for different aerosol conditions. A summary of the model configurations is provided in Table 4.1.

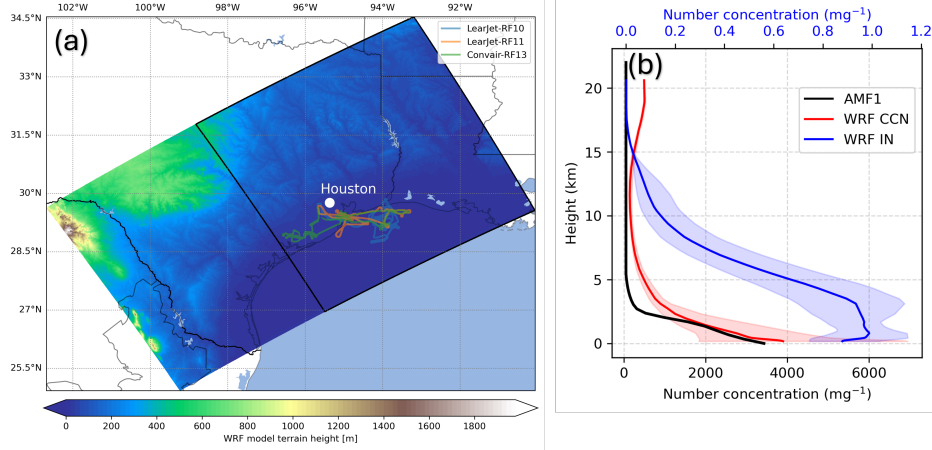


Figure 4.2: (a) WRF simulation domain with elevation shaded. The black box shows the analysis region. The white dot indicates the location of Houston, Texas. Colored lines show the research flight (RF) tracks conducted by the Convair and the Learjet. (b) Vertical profiles of aerosol number concentration (mg^{-1}). The red and blue lines and shadings indicate the median and the 5th-95th percentiles of semi-polluted CCN and IN, respectively, in the analysis region. The black line is the aerosol profile derived from AMF1 observations near Houston during the pre-convective periods on 17 June 2022 from TRACER.

Model Parameter	Configuration	Reference
Initiation time	06Z, June 17, 2022	-
Simulation period	24 hours	-
Output frequency	4 minutes	-
Time step	Adaptive (1~10 seconds)	-
Grid Spacing	1 km	-
Grid Points	600×1000	-
Vertical Levels	81 (topped at 50 hPa)	-
Radiation	RRTMG	Iacono et al. (2008)
Land Surface	Noah-MP	Niu et al. (2011)
IC/BC	HRRR	-
PBL	MYNN-EDMF	Nakanishi and Niino (2006)
		Olson et al. (2019)
Microphysics	Aerosol-aware Thompson	Thompson et al. (2008)
		Thompson and Eidhammer (2014)

Table 4.1: WRF Model configurations employed for all simulations in this study.

4.2.3.2 Sensitivity experiments

Several sensitivity experiments are performed to investigate the dual impacts of SIP and aerosol conditions on SBC. Specifically, we consider three SIP mechanisms: Hallett-Mossop process (HM, also known as the rime spinterling process), fragmentation of freezing rain drop (FFD), and ice-ice collisional breakup (IICOL), and three aerosol conditions: clean, semi-polluted (WRF default), and polluted. Implementation of SIP mechanisms into the Thompson scheme is described in Hu et al. (2025). The default aerosol input is monthly-averaged model data taken from multi-year (2001-2007) global model simulations. The aerosol-aware Thompson scheme considers water-friendly and ice-friendly aerosols, i.e., CCN and IN, respectively. Figure 4.2 (b) presents the vertical profiles of default CCN and IN from WRF input, overlaid with an observation-derived aerosol vertical profile (Chen et al. 2024) at the AMF1 (the first Atmospheric Radiation Measurement Mobile Facility) site LaPorte, Texas, from the TRACER field campaign on 17 June 2022. The WRF CCN and the AMF1 profiles align well below ~ 2 km but diverge above, with WRF input overestimating the aerosol number concentrations. However, it is worth noting that the AMF1 profile is site-specific, while the WRF curves present domain statistics. Therefore, the default WRF input aerosol conditions are deemed representative for the research domain.

To isolate the influences of SIP mechanisms on SBC, five WRF simulations are performed with no SIP, one SIP, and three SIP processes under the semi-polluted aerosol conditions, which are referred to as noSIP, HMonly, IICOLonly, FFDonly, and 3SIP, respectively. The noSIP run is considered as the baseline run in this research. The semi-polluted aerosol conditions (both IN and CCN) are then scaled by 0.1 and 10 to represent a clean and a polluted environment, respectively. The clean and polluted aerosol conditions with both no SIP and three SIP are performed, referred to as noSIP_c, noSIP_p, 3SIP_c, and 3SIP_p, respectively. Additionally, to separate the

Model run	SIP	Aerosol conditions
noSIP (baseline)	None	Semi-polluted (Default)
3SIP	HM, IICOL, FFD	Semi-polluted
HMonly	HM	Semi-polluted
IICOLonly	IICOL	Semi-polluted
FFDonly	FFD	Semi-polluted
noSIP_c	None	Clean (Default $\times 0.1$)
noSIP_p	None	Polluted (Default $\times 10$)
3SIP_c	HM, IICOL, FFD	Clean
3SIP_p	HM, IICOL, FFD	Polluted
3SIP_pi	HM, IICOL, FFD	Clean (Default IN $\times 10$)
3SIP_pw	HM, IICOL, FFD	Polluted (Default CCN $\times 10$)

Table 4.2: Description of WRF Model experiments in this study.

impacts of IN and CCN, two more experiments are performed with 3SIP and polluted IN and CCN, referred to as 3SIP_pi and 3SIP_pw, respectively. A summary of model experiments is provided in Table 4.2.

4.2.4 Tobac cloud tracking

We used the Tracking and object-based analysis of clouds (tobac), version 1.5 (Heikenfeld et al. 2019; Sokolowsky et al. 2024) to identify and track convective cells triggered by sea breeze. The observed cells were tracked with the MRMS composite radar reflectivity, while the WRF-simulated cells were tracked with the column maxima of radar reflectivity. Both MRMS observations and WRF simulations were tracked at every 4 minutes.

Tobac tracks clouds through three steps: feature detection, segmentation, and linking (Sokolowsky et al. 2024). Specifically in this study, individual features were first

detected at each time step as local maxima in the 2D composite radar reflectivity fields with multiple thresholds (5, 10, 20, 30, and 40 dBZ). Then watershed segmentation with a single threshold of 5 dBZ was performed to obtain the associated surface area of the detected features at each time step. Finally, the identified features with their associated surface area at each time step were linked into consistent trajectories through time to represent the tracked clouds over their life cycles. In this study, tracked clouds that were initiated and dissipated within the analysis region (Fig. 4.2 (a)) and at least 20 km away from the WRF domain boundary were selected for analysis.

4.2.5 Temporal and vertical analyses

For each cell, temporal analyses of the volume-weighted mean of a field $r(t, k)$ are calculated as below:

$$r(t, k) = \frac{\sum_{i,j} r(t, k, i, j) dz(t, k, i, j) A(t, i, j)}{\sum_{i,j} dz(t, k, i, j) A(t, i, j)}, \quad (4.1)$$

where dz is the vertical resolution and A is the area of the given cloud cell. To ensure comparability, the lifetime of each selected cell is normalized to a 0-to-1 scale. Considering the sensitivity of SIP processes to temperature, vertical profiles are presented as a function of temperature binned at 2 °C intervals (0.5 °C interval for HM rates). Finally, if not otherwise stated, temporal and vertical analyses presented in this work are shown for the 95th percentile of selected cloud cells.

4.3 Results

4.3.1 Statistics of tracked cloud cells

Compared to the observations, WRF model runs indicate more numerous but smaller, slower, and longer-lived cloud cells (Fig. 4.3). In terms of SIP sensitivity, SIP-including runs generally show more cloud cells than their no-SIP counterparts, e.g., 2656 and 2471 total cells for 3SIP and noSIP, respectively (Fig. 4.3 (g)). Cloud cells from 3SIP indicate shorter lifetime, similar propagation speed, and larger area than noSIP, but the differences between their 95th lifetime and propagation speed percentiles are not statistically significant (Fig. 4.3(a-c)). Meanwhile, no substantial sensitivity is seen among the HMonly, IICOLonly, and FFDonly runs (Fig. 4.3 (g)). Furthermore, increasing aerosol loadings tend to produce less cloud cells, (e.g., 3395, 2656, 2199 total cells for 3SIP_c, 3SIP, and 3SIP_p, respectively), lengthen cloud lifetime, slow down cells' propagation speed, and enlarge cloud area (Fig. 4.3 (d-g)). But again, the 95th percentile differences between 3SIP and 3SIP_p are not statistically significant ($p > 0.05$). Finally, 3SIP_pi simulates more cloud cells than 3SIP_pw (Fig. 4.3 (g)) and statistics for 3SIP_pw are highly identical to those for 3SIP_p (not illustrated).

4.3.2 SIP effects on cloud properties

Figure 4.4 compares LWC and IWC between noSIP and SIP-including runs under semi-polluted aerosol conditions, while Figure 4.5 presents individual hydrometeor components. In noSIP, LWC is present between 30 and -20 °C, peaking in early lifetime and gradually diminishing, whereas IWC appears at subfreezing temperatures, mainly confined to the -20~-40 °C layer (Fig. 4.4 (a1, c1)). Lifetime-averaged vertical profiles show that SIP-including runs reduce LWC and increase IWC relative to noSIP, with

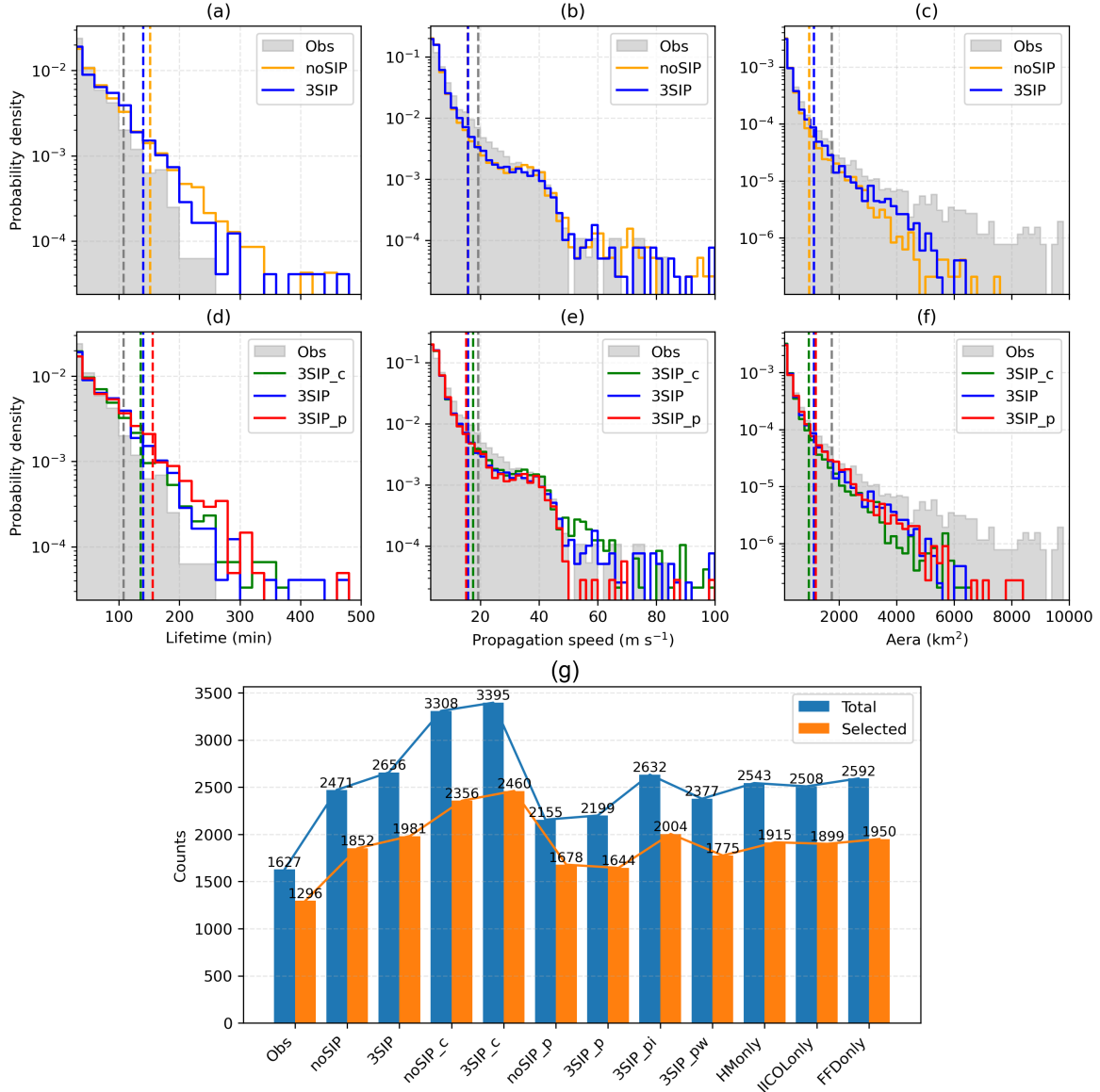


Figure 4.3: Probability density functions (PDFs) of (a, d) lifetime (min), (b, e) propagation speed (m s^{-1}), and (c, f) area (km^2) of selected cells for observations and WRF model runs. Dashed lines represent the 95th percentiles. The differences of 95th percentiles between noSIP and 3SIP in (a, b), between 3SIP and 3SIP_c in (d), and between 3SIP and 3SIP_p in (d-f) are not statistically significant ($p > 0.05$). (g) Number of total and selected cells for observations and WRF model runs.

increasing magnitudes in the order of IICOLonly, HMonly, FFDonly, and 3SIP (Fig. 4.4 (b1,d1)). Among these, 3SIP, HMonly, and FFDonly substantially reduce LWC throughout the mixed-phase and low layers (Fig. 4.4 (a2,a3,b3)), primarily through reduced rainwater mass (Fig. 4.5 (b3)), partially offset by enhanced supercooled cloud water (Fig. 4.5 (b2)), especially in the early lifetime (not shown). The modest net LWC reduction in IICOLonly arises from increased LWC in the low levels during the first half of the lifetime, followed by reductions later in lifetime and higher up vertically (Fig. 4.4 (b2)). Overall, WRF-simulated LWCs, with or without SIP, remain within observed ranges (Fig. 4.4 (b1)).

IWC enhancements occur in 3SIP, HMonly, and FFDonly throughout cloud lifetime and across all subfreezing temperatures (Fig. 4.4 (c2,c3,d3)), driven by substantial snow mass increases at all subfreezing temperatures and graupel mass increases between 0 and -10 °C (Fig. 4.5 (a3,a4)). However, cloud ice mass and number are reduced at very low temperatures in 3SIP, HMonly, and FFDonly (Fig. 4.5 (a1,a2)), suggesting enhanced ice growth and snow aggregation in these SIP runs. IICOLonly shows IWC distributions similar to noSIP, with slight decreases between -20 and -40 °C (Fig. 4.4), caused by reduced snow mass throughout cell lifetime in this layer (not shown), and increases at higher temperatures resulting from enhancements in all ice categories (Fig. 4.5 (a2-a4)).

Latent heat power density Q results from 3SIP show stronger warming and cooling at temperatures lower than 0 °C and weaker warming and cooling at higher temperatures relative to noSIP (Fig. 4.6 (a2,c2)), which is predominantly governed by FFD (Fig. 4.6 (b3,d3)), with contributions also from HM (Fig. 4.6 (a3,c3)). The enhanced warming effect in the subfreezing layer is most pronounced during the early lifetime, whereas the reduced warming in the low level persists through most of the lifetime. An exception is IICOLonly, showing enhanced warming and cooling in low levels during

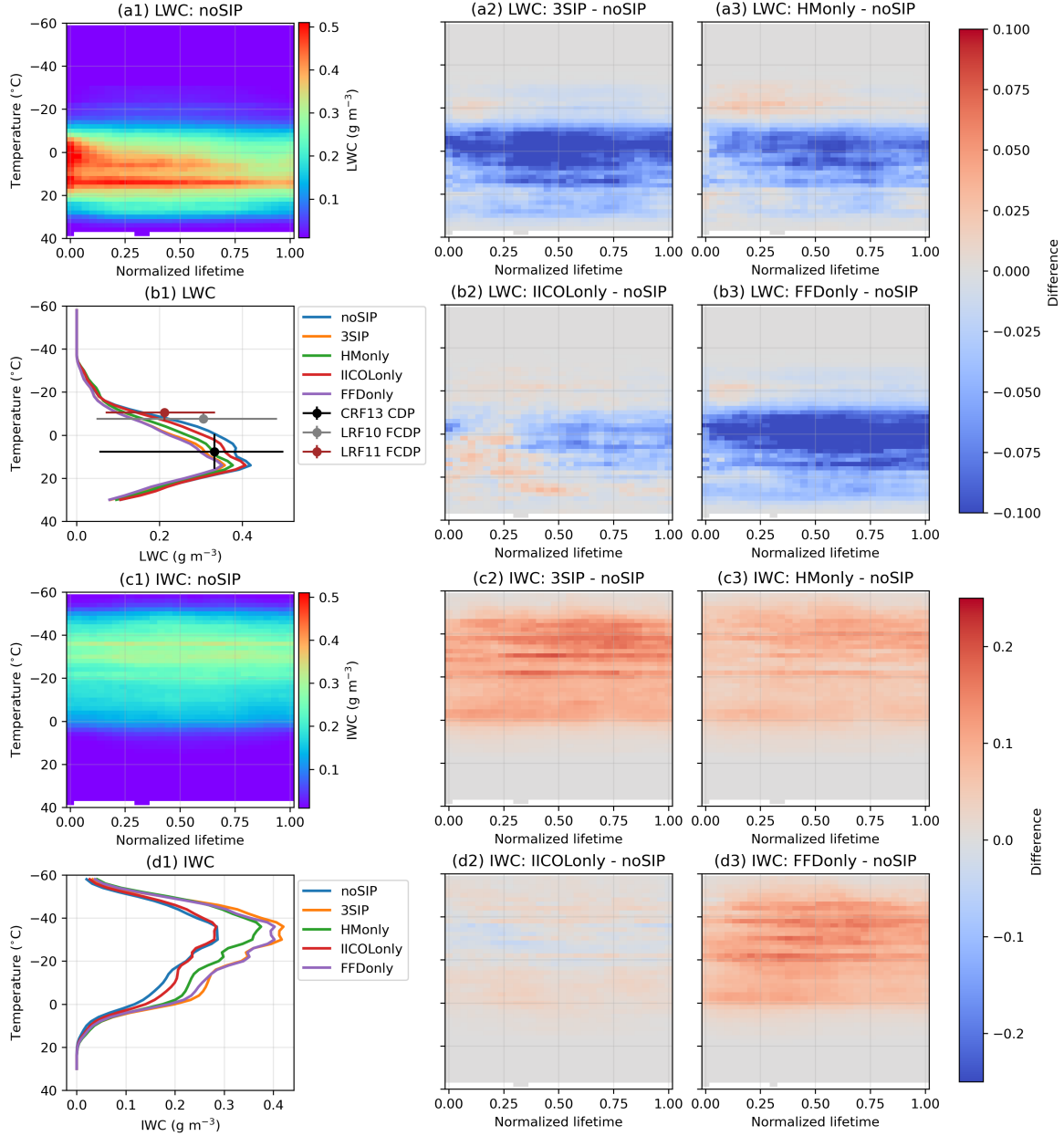


Figure 4.4: (a1) Liquid and (c1) ice water contents (LWC and IWC; g m^{-3}) from noSIP simulation as a function of normalized cell lifetime and temperature. (b1) and (d1) show lifetime-averaged vertical profiles of LWC and IWC, respectively, from noSIP, 3SIP, HMonly, IICOLonly, and FFDonly simulations. Airborne CDP and FCDP measurements of LWC from CRF13, LRF10, LRF11 are overlaid in (b1), with dots indicating the lifetime means of LWC from observed cells and lines indicating the 25th-75th percentiles ranges of temperature and LWC. (a2,a3,b2,b3) show LWC differences between SIP-including runs and noSIP, while (c2,c3,d2,d3) show IWC differences.

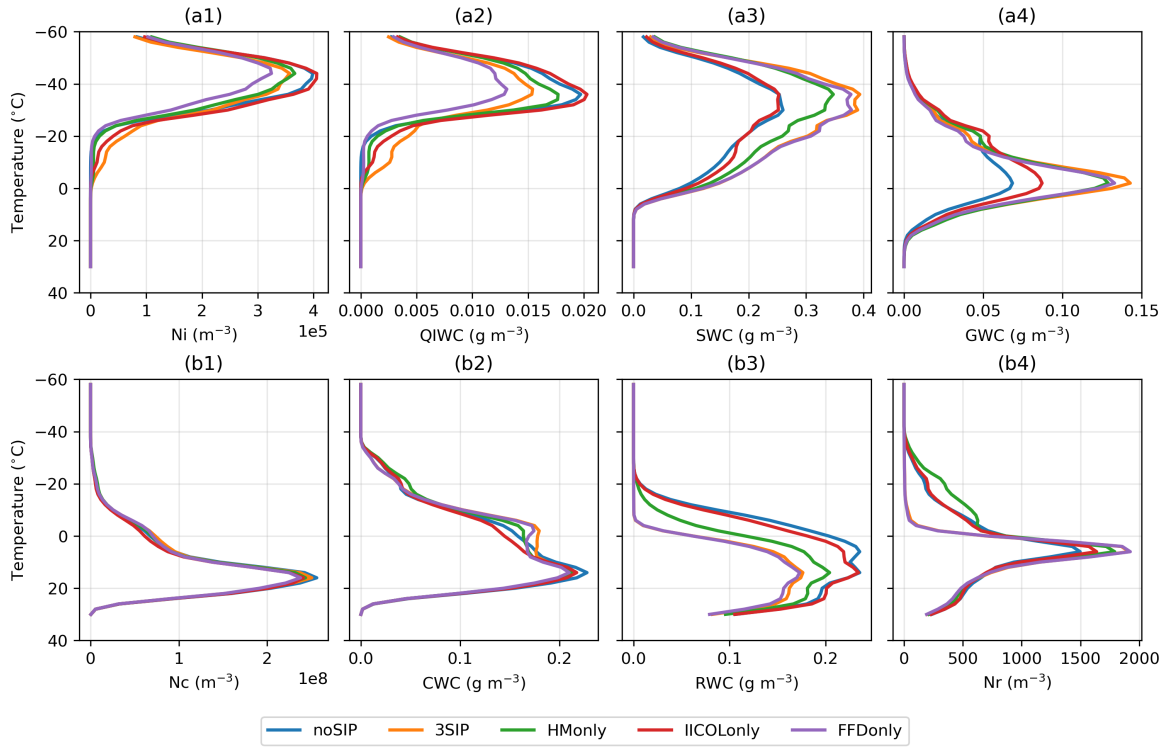


Figure 4.5: Lifetime-averaged vertical profiles of (a1) cloud ice number concentration, (a2) cloud ice water content, (a3) snow water content, (a4) graupel water content, (b1) cloud water number concentration, (b2) cloud water content, (b3) rainwater content, and (b4) rainwater number concentration, from noSIP and SIP-including runs. Number concentrations are in m^{-3} and water contents are in g m^{-3} .

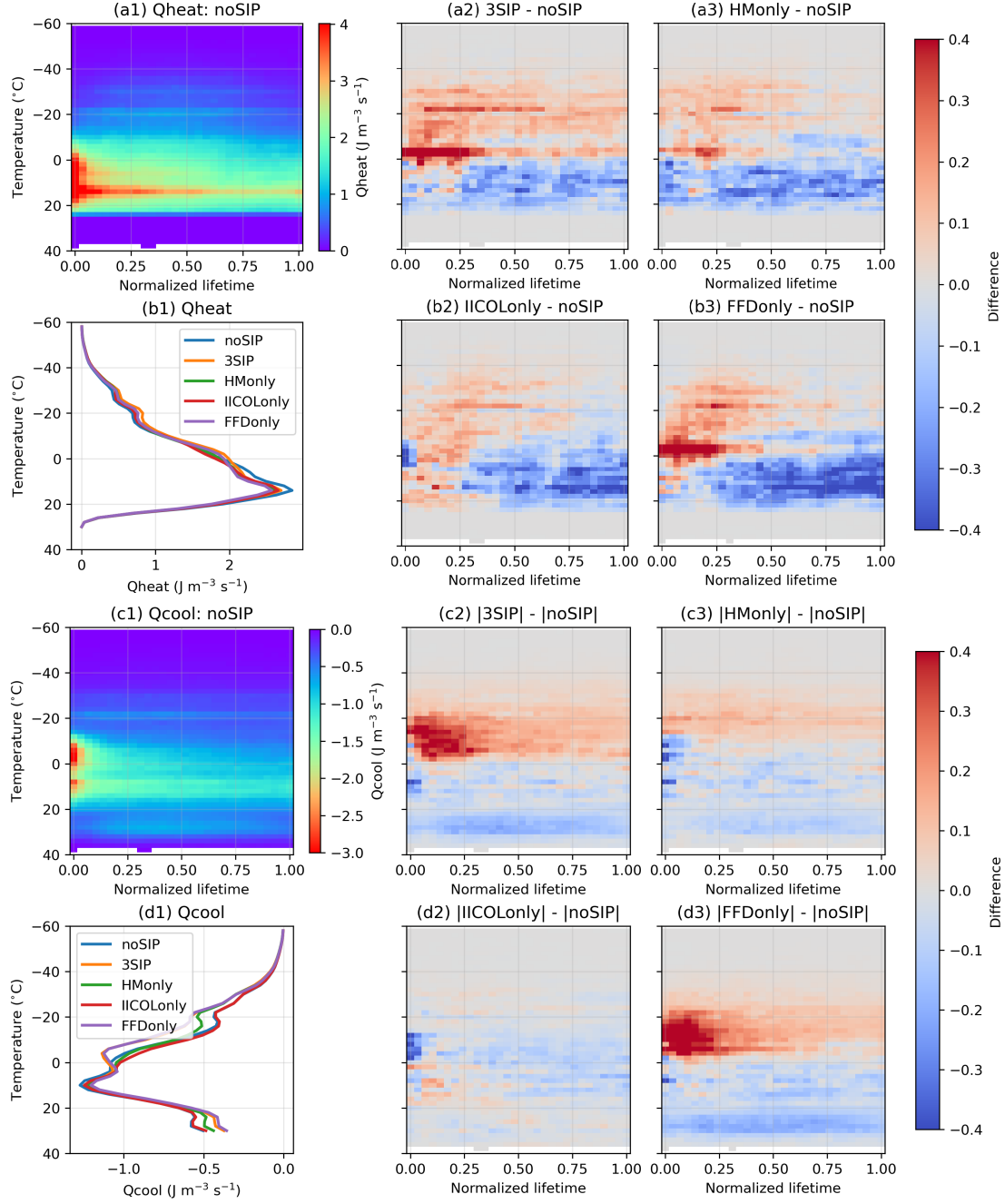


Figure 4.6: Latent heat (a1) warming and (c1) cooling (Q_{heat} and Q_{cool} ; $\text{J m}^{-3} \text{s}^{-1}$) from noSIP simulation as a function of normalized cell lifetime and temperature. (b1) and (d1) show lifetime-averaged vertical profiles of Q_{heat} and Q_{cool} , respectively, from noSIP, 3SIP, HMonly, IICOLonly, and FFDonly simulations. (a2,a3,b2,b3) show Q_{heat} differences between SIP-including runs and noSIP while (c2,c3,d2,d3) show Q_{cool} differences. Red (blue) colors indicate stronger (weaker) warming and cooling.

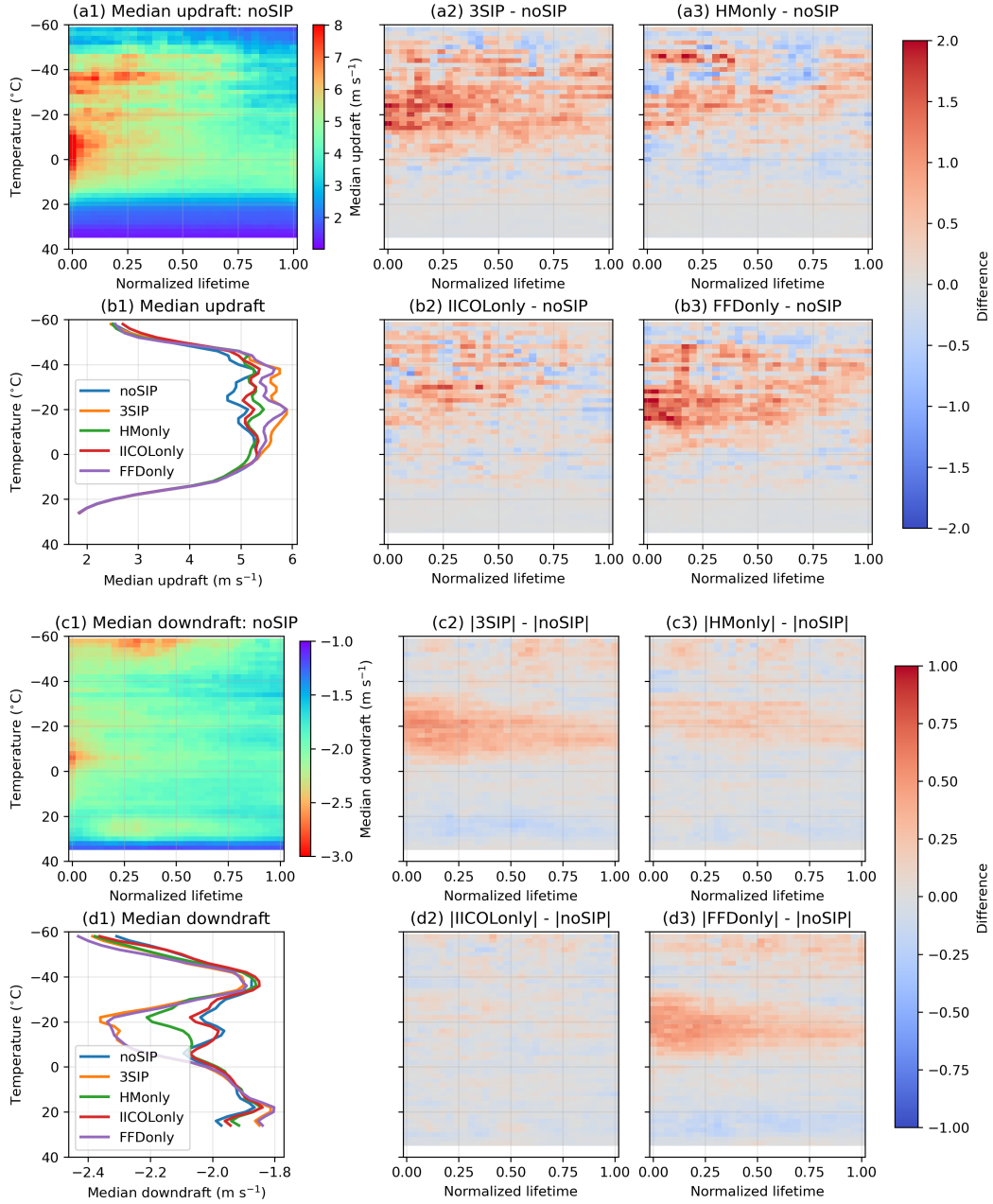


Figure 4.7: (a1,c1) Median updrafts and downdrafts ($m s^{-1}$) from noSIP as a function of normalized cell lifetime and temperature. (b1,d1) Lifetime-averaged vertical profiles of median updrafts and downdrafts from noSIP, 3SIP, HMonly, IICOLonly, and FFDonly. (a2,a3,b2,b3) show median updraft differences between SIP-including runs and noSIP, and (c2,c3,d2,d3) show median downdraft differences. Updraft and downdraft are defined as $W > 1 m s^{-1}$ and $W < -1 m s^{-1}$, respectively. Red (blue) colors indicate stronger updrafts and downdrafts.

early lifetime (Fig. 4.6 (b2,d2)), which is linked more cloud water in the low level and less higher up (not shown), thereby stronger associated condensation heating and evaporative cooling. Lifetime-averaged vertical profiles of latent heating show only small differences between SIP-including and noSIP runs, with slightly stronger low-level heating in noSIP, while the overall weaker cooling effect in noSIP is more clear in the subfreezing layers (Fig. 4.6 (b1,d1)).

Enhanced heating in the subfreezing layers leads to stronger updrafts in SIP-including runs compared to noSIP throughout most of the cloud lifetime (Fig. 4.7 (a1-b3)). Similarly, strengthened (weakened) median downdrafts are evident in subfreezing (lower) layers, especially in 3SIP, FFDonly, and HMonly, while IICOLonly show largely similar distributions to noSIP (Fig. 4.7 (c1-d3)). The 95th-percentile and maximum updrafts and downdrafts are likewise enhanced in SIP-including runs within the subfreezing layers (not shown).

In summary, SIP acts to redistribute condensate from liquid (especially rainwater) to ice (snow and graupel) and from warm to cold layers, leading to both enhanced latent heating and cooling, and stronger updrafts and downdrafts in cold layers.

4.3.3 Aerosol effects on cloud properties

Without SIP, increasing aerosol loading from clean (noSIP_c) to semi-polluted (noSIP) substantially modifies cloud condensate. LWC increases between 20 and -10 °C but decreases at higher temperatures (Fig. 4.8 (a1)). The increases are mainly due to enhanced cloud water mass and numbers, whereas decreases are driven by reduced rainwater, particularly rainwater numbers in the low level (Fig. 4.9 (b1-b4)). IWC increases consistently across temperatures, cloud lifetime, and all ice categories (Figs. 4.8 (b1,b3) and 4.9 (a1-a4)).

These condensate changes indicate stronger condensation, freezing, deposition, and

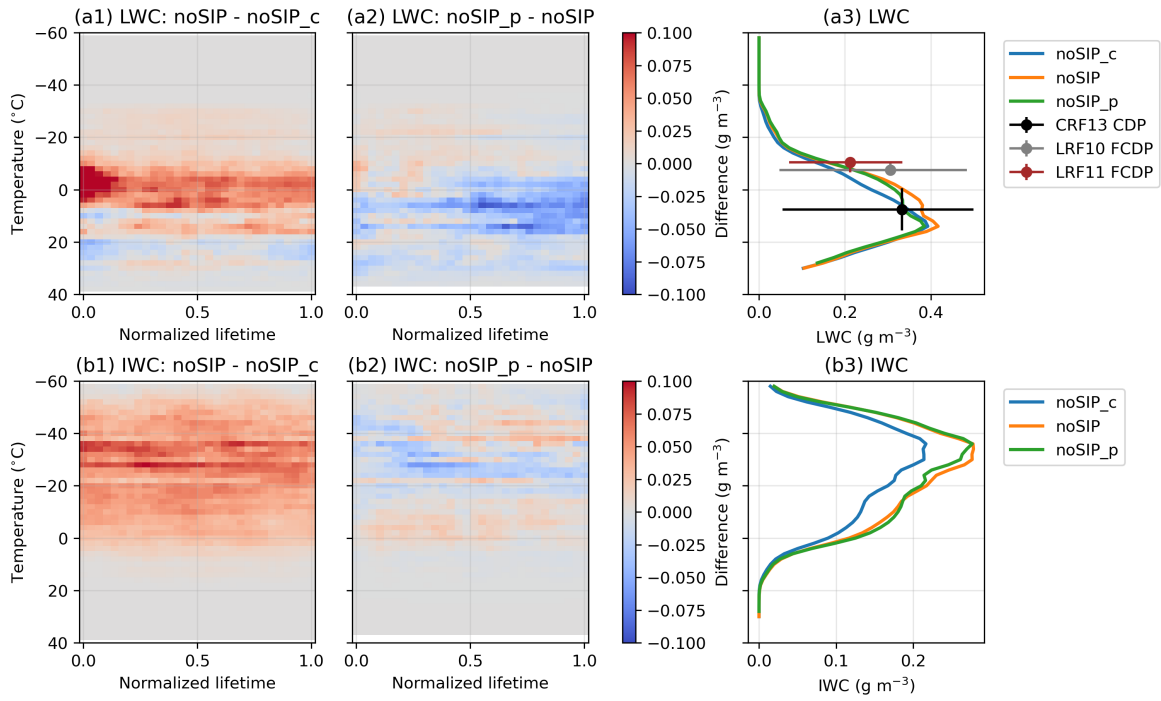


Figure 4.8: (a1,a2) LWC and (b1,b2) IWC differences of noSIP_c and noSIP_p relative to noSIP. (a3) and (b3) show the lifetime-averaged vertical profiles of LWC and IWC, respectively from noSIP_c, noSIP, and noSIP_p.

riming in noSIP compared to noSIP.c. This is confirmed by the enhanced latent heating throughout cloud lifetime and all vertical levels in noSIP (Fig. 4.10 (a1,a3)), which further translate to generally stronger updrafts, although weakened updrafts occur at temperatures lower than -20°C during early and late lifetime (Fig. 4.11 (a1,a3,b1,b3)). Latent cooling is strongly enhanced at temperatures lower than $\sim 15^{\circ}\text{C}$, while slightly reduced at higher temperatures (Fig. 4.10). Downdrafts show similar patterns: enhanced at temperatures lower than $\sim 15^{\circ}\text{C}$, with stronger magnitude during early lifetime, and weakened at higher temperatures (Fig. 4.11 (c1,c3,d1,d3)).

Further increasing aerosol loading from semi-polluted (noSIP) to polluted (noSIP_p) reduces LWC through most of cloud lifetime and vertical levels (Fig. 4.8 (a2)). This reduction arises primarily from decreased rainwater mass (Fig. 4.9 (b3)), and from $\sim 25\%$ reduced cloud water mass in the low level during late stages (not shown), despite persistently higher cloud water numbers (Fig. 4.9 (b1)). Lifetime-averaged vertical profiles of IWC and individual ice-phase components between noSIP and noSIP_p are similar (Figs. 4.8 (b3) and 4.9 (a1-a4)). Temporal analyses, however, reveal IWC increases in noSIP_p between 0 and -20°C throughout cloud lifetime and at temperatures $< -40^{\circ}\text{C}$ during mature and late lifetime (Fig. 4.8 (b2)), which are controlled by enhanced snow mass and early graupel mass increases (not shown).

Latent heating in noSIP_p is enhanced near 20°C throughout cloud lifetime and in subfreezing layers during early lifetime, then reduced elsewhere (Fig. 4.10 (a2)). Enhanced heating near 20°C is associated with substantially increased cloud droplet numbers in noSIP_p (Fig. 4.9 (b1)), thereby increased condensational heating, while enhanced heating in the mixed-phase during early lifetime is linked to increased freezing of small cloud droplets, and snow and graupel mass enhancements (not shown). Reduced latent heating at later stages (Fig. 4.10 (a2)) corresponds to decreased warm-layer cloud water and graupel mass in subfreezing layers (not shown). Updrafts in

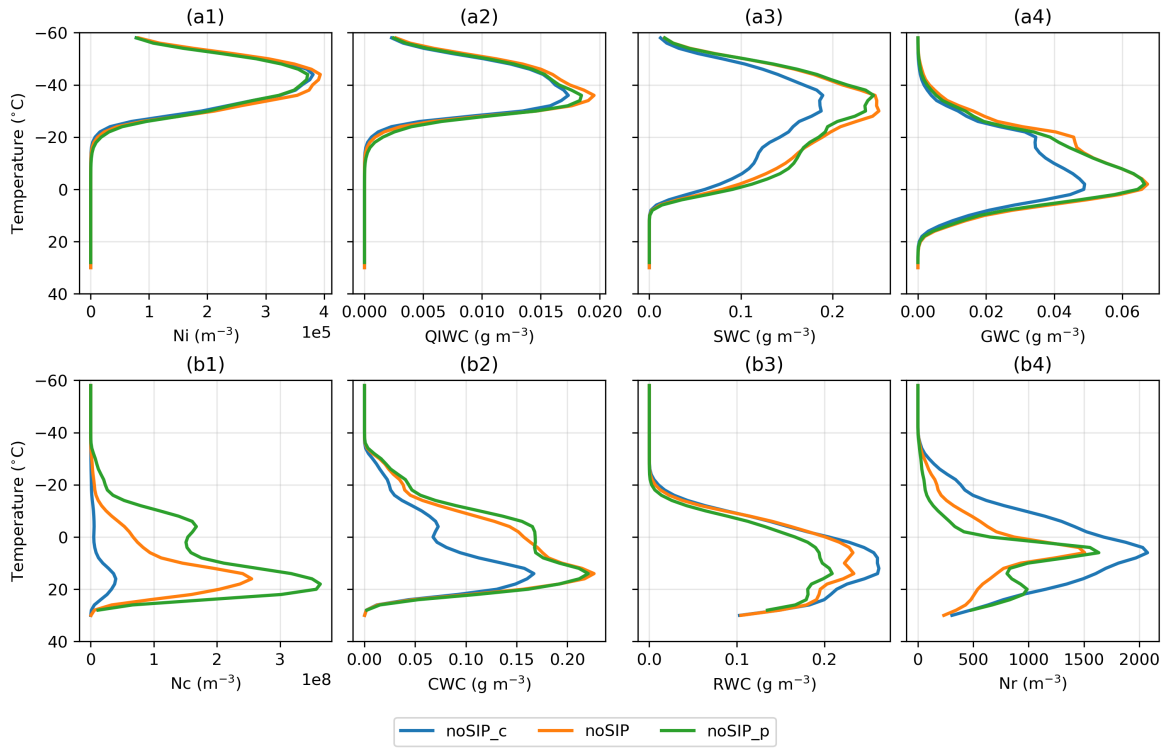


Figure 4.9: Similar to Fig. 4.5 but for noSIP runs under different aerosol conditions.

noSIP_p are generally stronger, especially during early lifetime, but weakening episodes still occur (Fig. 4.11 (a2,a3,b2,b3)).

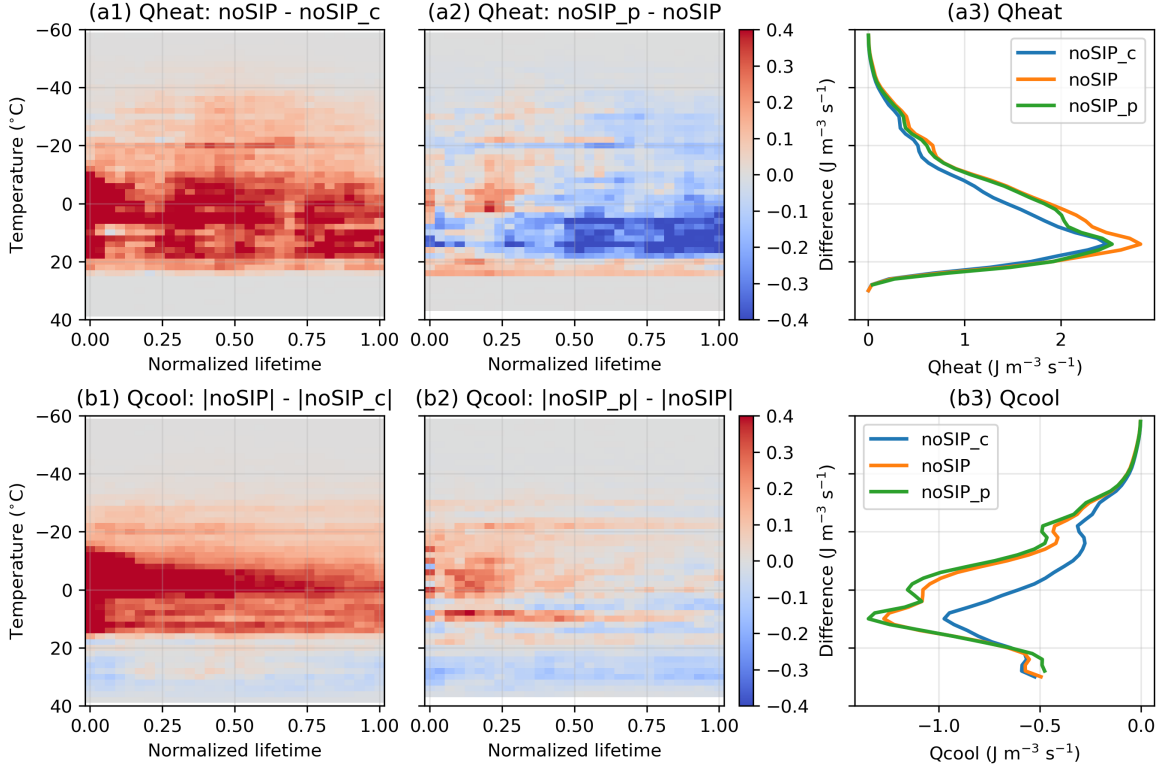


Figure 4.10: Differences in latent heat (a1,a2) warming and (b1,b2) cooling (Q_{heat} and Q_{cool}) of noSIP_c and noSIP_p relative to noSIP. Red (blue) colors indicate stronger (weaker) warming and cooling. (a3) and (b3) show lifetime-averaged vertical profiles of Q_{heat} and Q_{cool} from noSIP_c, noSIP, and noSIP_p, respectively.

Latent cooling shows similar response as in the clean-to-semi-polluted transition: enhanced at temperatures lower than ~ 20 °C but reduced at higher temperatures (Fig. 4.10 (b2,b3)), with downdrafts responding accordingly (Fig. 4.11 (c2,c3,d2,d3)). However, Fig. 4.9 (b3,b4) shows higher rain drop numbers and smaller rainwater contents in noSIP_p relative to noSIP at temperatures higher than 15 °C, implying more numerous but smaller rain drops in noSIP_p, which favor evaporation and stronger cooling. Additionally, graupel mass is slightly reduced in noSIP_p compared to noSIP (Figure 4.9 (a4)). It is possible that there are more numerous but smaller graupel

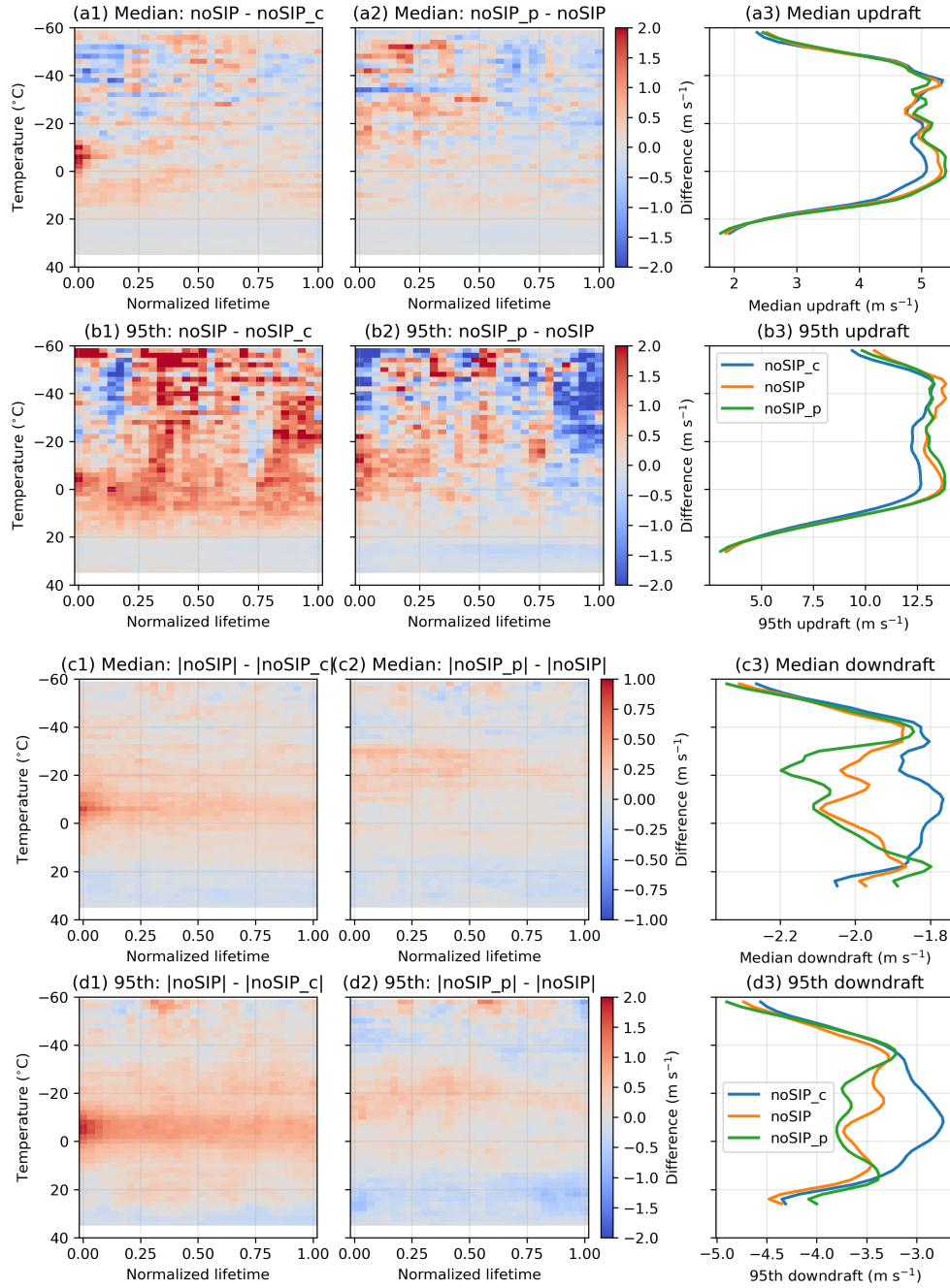


Figure 4.11: Differences in (a1,a2) median updrafts, (b1,b2) 95th updrafts, (c1,c2) median downdrafts, and (d1,d2) 95th downdrafts of noSIP_c and noSIP_p relative to noSIP. Red (blue) colors indicate stronger (weaker) warming and cooling. (a3,b3,c3,d3) show lifetime-averaged vertical profiles of median updrafts, 95th updrafts, median downdrafts, and 95th downdrafts from noSIP_c, noSIP, and noSIP_p, respectively.

that could melt into smaller rain drops in noSIP_{-p}, also enhancing latent cooling. These microphysical signatures contradict the reduced cooling diagnosed in Fig. 4.10 (b2,b3). This discrepancy highlights the need for further investigation into why cleaner aerosol conditions appear to enhancing latent cooling more effectively than polluted conditions. Nevertheless, the stronger cooling in cleaner aerosol conditions near surface implies more intense cold pools, which can trigger secondary convection initiation (e.g., Torri et al. 2015). Consistently, our cloud tracking shows more cloud cells in cleaner than in polluted simulations (Fig. 4.3 (g)).

From clean (noSIP_{-c}) to semi-polluted (noSIP), LWC (20 to -10 °C) and IWC increase, latent heating strengthens throughout the column, updrafts are stronger (20 to ~ -30 °C), and latent cooling/downdrafts intensify at temperatures < 15 °C but weaken at lower levels. From semi-polluted (noSIP) to polluted (noSIP_{-p}), LWC generally decreases (driven by rainwater loss), IWC responses are mixed, enhancements in latent heating/updrafts occur in early lifetime, and cooling/downdrafts are stronger in higher levels but weaker at lower levels. In summary, aerosols invigorate both updrafts and downdrafts in clouds most strongly when increasing from clean to semi-polluted conditions, while further pollution can weaken heating/cooling and limit updrafts/downdrafts.

4.3.4 Dual effects of SIP and aerosols

With three SIP mechanisms active, increasing aerosol loading from clean (3SIP_{-c}) to semi-polluted (3SIP), and further to polluted (3SIP_{-p}), persistently enhances cloud water and reduces rainwater (Fig. 4.13 (b1-b4)), leading to reduced LWC in the low level and enhanced LWC aloft (Fig. 4.12 (a2,a3,b1)). Increased CCN loading (3SIP_{-pw}) is the main driver to the LWC changes from 3SIP to 3IP_{-p}, while increased IN loading (3SIP_{-pi}) show mixed responses (Fig. 4.12 (b2,b3)). IWC also increases with enhanced

aerosol loadings across lifetime, but the enhancement is stronger from 3SIP_c to 3SIP than 3SIP to 3SIP_p, which even shows IWC reductions during late lifetime at temperatures < -40 °C (Fig. 4.12 (c2,c3)). These IWC changes are primarily governed by snow mass increases, while graupel and cloud ice decrease in more polluted environments on a lifetime average basis (Fig. 4.13 (a1-a4)). Both enhanced CCN and IN loadings increase IWC (Fig. 4.12 (d2,d3)), but through different pathways. Greater CCN loading favors snow growth and reduce graupel mass, while greater IN loading enhances both snow and graupel masses (Fig. 4.13 (a3,a4)).

Increasing aerosol loadings from clean (3SIP_c) to semi-polluted (3SIP) enhances latent heating throughout the cloud lifetime, but further pollution (3SIP_p) produces weaker latent heating enhancements during early lifetime and reduced latent heating later (Fig. 4.14 (a2,a3)). Aerosol loading increases also intensify latent cooling at temperatures < 15 °C while reducing cooling at higher temperatures, with the more polluted condition showing a similar pattern but of smaller magnitude (Fig. 4.14 (c2,c3)). These changes in latent heating and cooling largely resemble those without SIP, i.e., from noSIP_c to noSIP and further to noSIP_p (Figs. 4.10). However, with SIP, the heating response is dampened for the clean to semi-polluted transition but amplified for the semi-polluted to polluted transition, and the cooling response is also amplified for the clean to semi-polluted transition. Furthermore, increasing CCN alone (3SIP_pw) leads to increased latent heating near 20 °C, prolongs the period of enhanced heating time (Fig. 4.14 (b3)), and amplifies the same cooling pattern as in 3SIP versus 3SIP_p (Fig. 4.14 (d3)). In contrast, increasing IN alone (3SIP_pi) yields mixed heating responses and reduces cooling on a lifetime-average basis (Fig. 4.14 (b2,d1,d2)).

Vertical velocity responses also mirror those without SIP. Stronger median updrafts are evident from 3SIP_c to 3SIP between 20 and -20 °C and from 3SIP to 3SIP_p between 20 and ~ -15 °C, but with weaker median updrafts aloft in both transitions (Fig. 4.15).

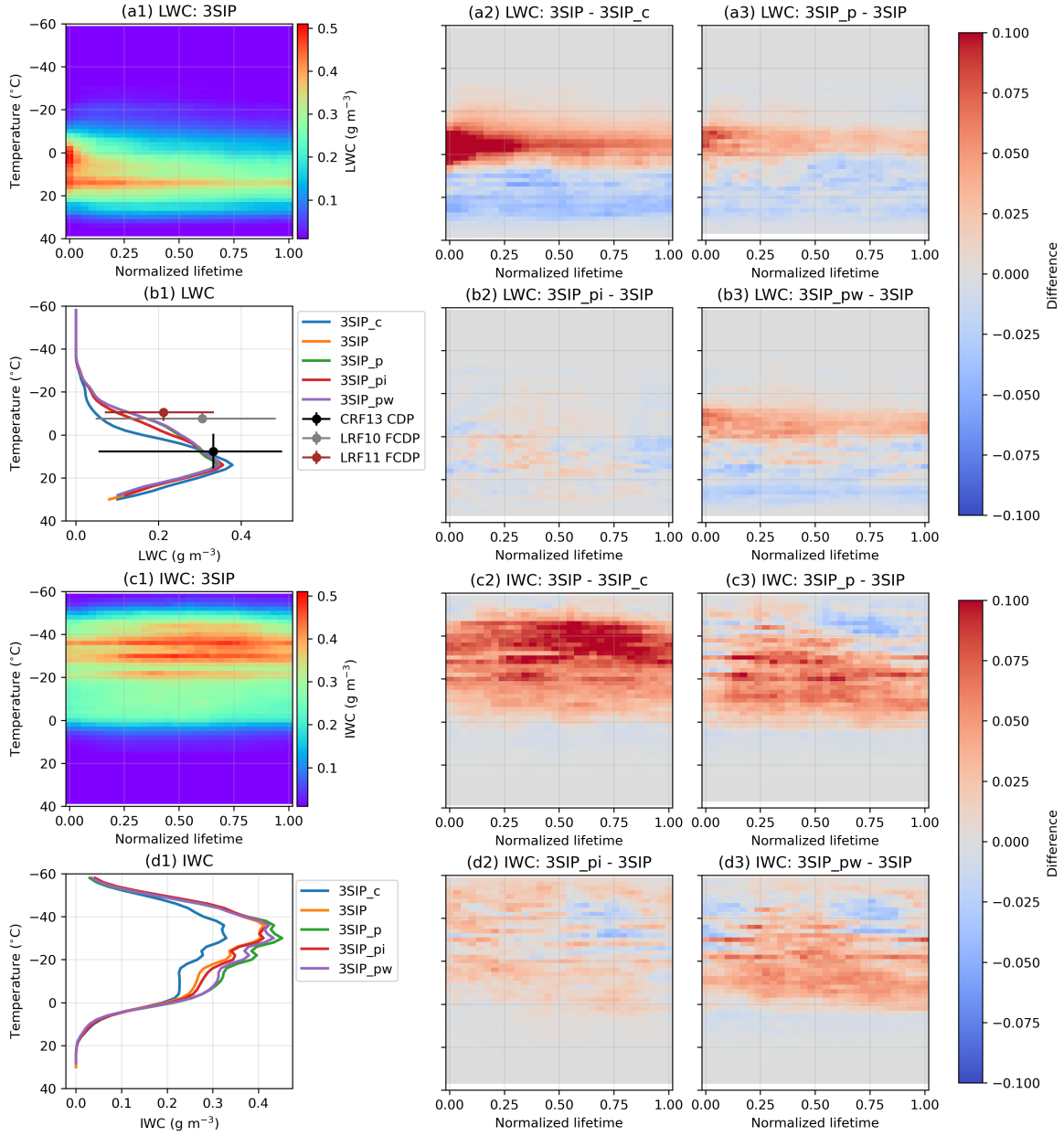


Figure 4.12: Similar to Fig. 4.4 but for 3SIP and differences between (a2,c2) 3SIP_c, (a3,c3) 3SIP_p, (b2,d2) 3SIP_pi, (b3,d3) 3SIP_pw and 3SIP.

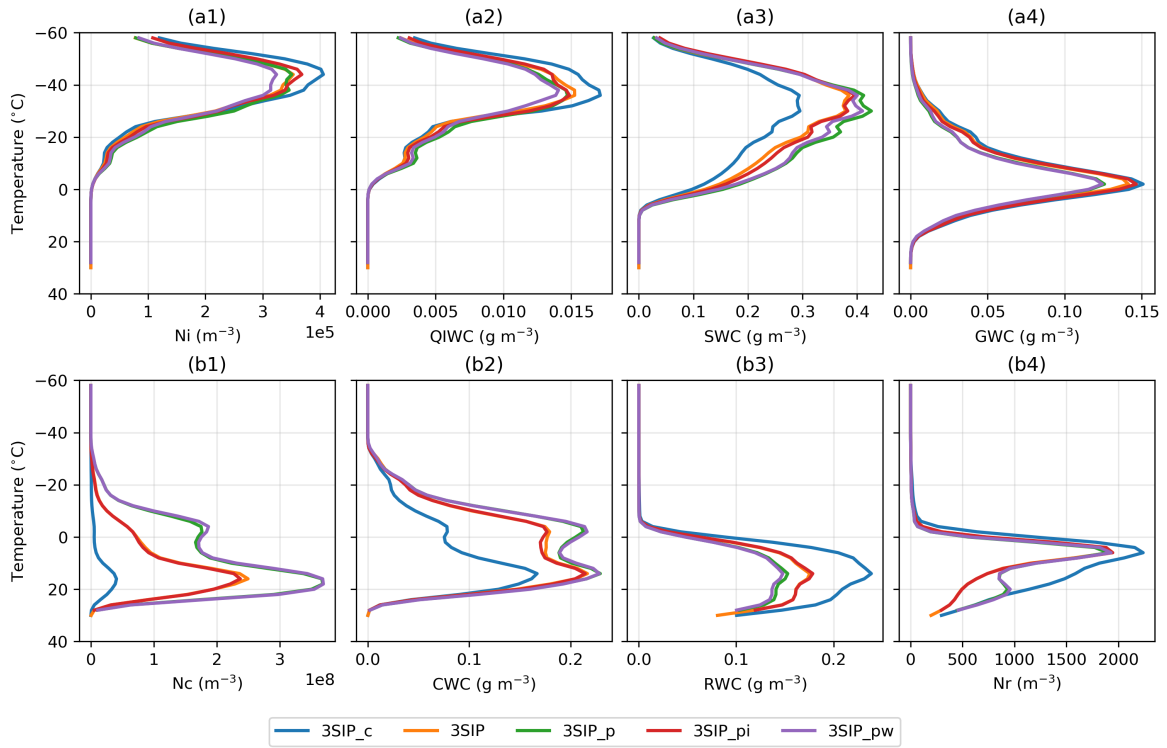


Figure 4.13: Similar to Fig. 4.5 but for 3SIP runs under different aerosol conditions.

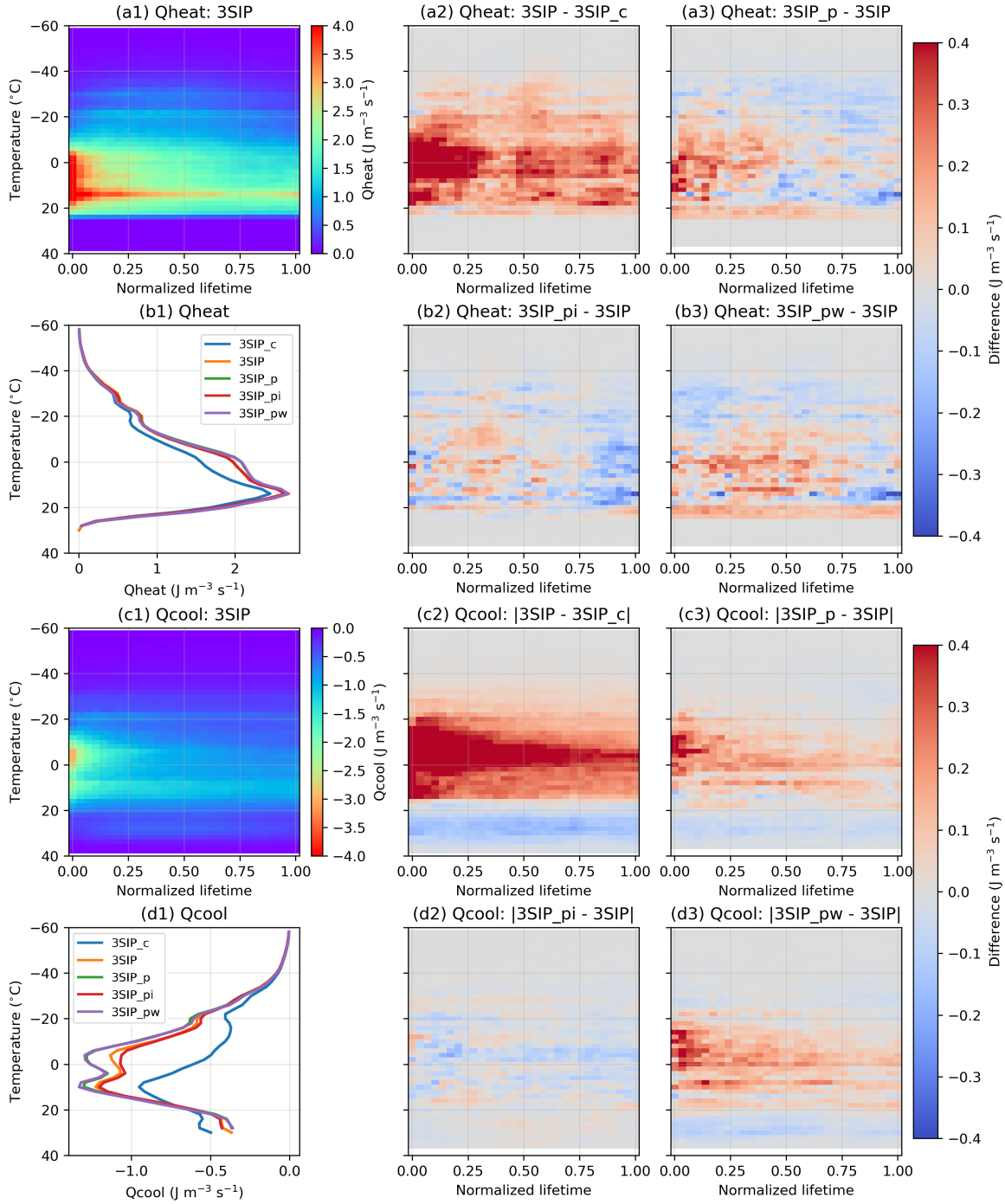


Figure 4.14: Similar to Fig. 4.6 but for 3SIP runs under different aerosol conditions.

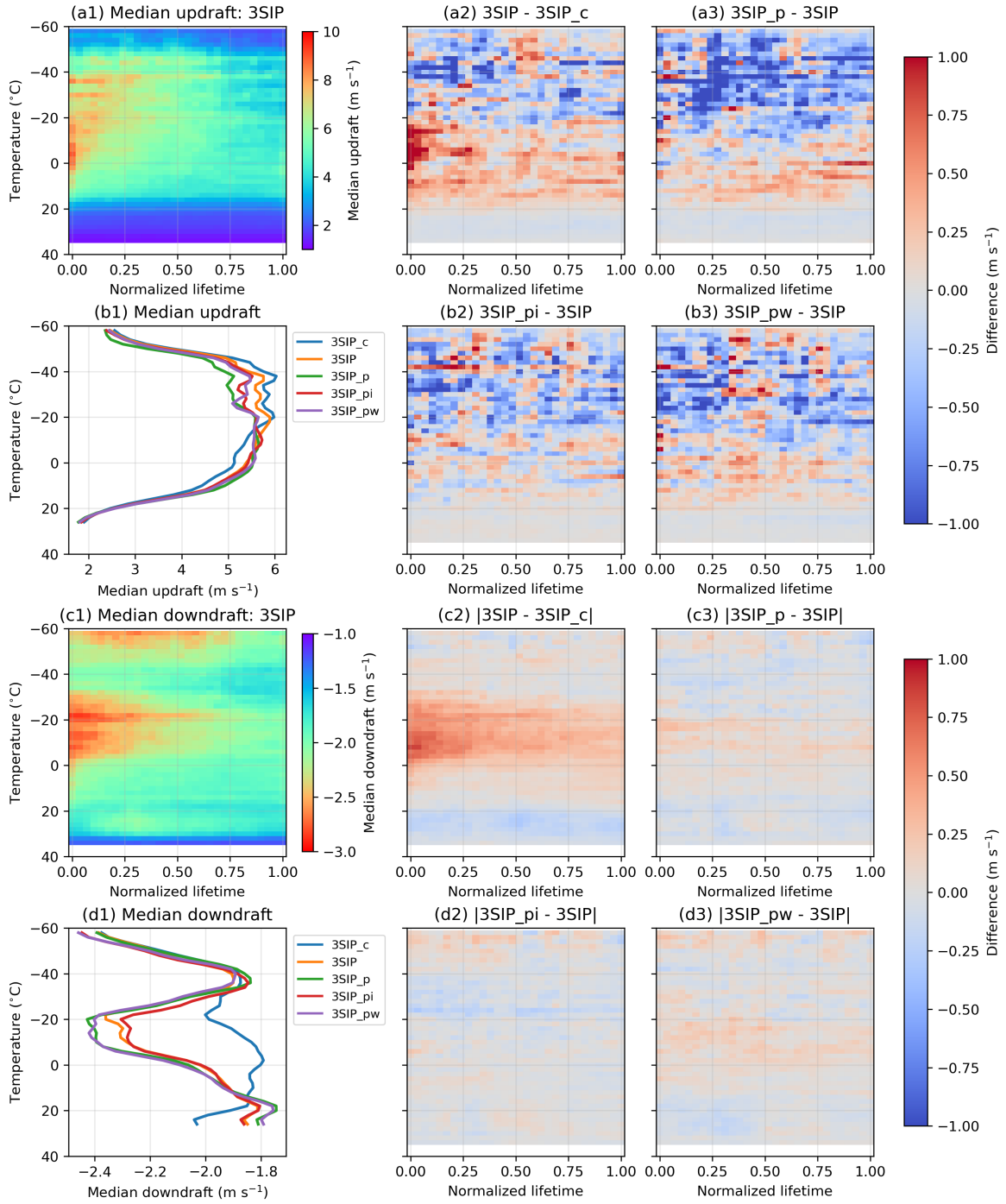


Figure 4.15: Similar to Fig. 4.7 but for 3SIP runs under different aerosol conditions.

Lifetime-averaged profiles show that clean-to-semi-polluted aerosols enhance median updrafts at temperatures < -15 °C, while further pollution adds no substantial updraft increase. Aloft, updrafts weakening with increasing aerosols is more pronounced (Fig. 4.15). The same holds true for the 95th-percentile and maximum updrafts (not shown). Downdrafts intensify (weaken) at temperatures lower (higher) than 20 °C in polluted conditions, with stronger magnitude in the clean-to-semi-polluted transition (Fig. 4.15 (c2,c3)). 3SIP_{pw} shows a similar effect to 3SIP_p in downdrafts, whereas 3SIP_{pi} slightly decreases lifetime-averaged downdrafts relative to 3SIP (Fig. 4.15 (d1-d3)).

Overall, under clean-to-semi-polluted conditions, SIP dampens aerosol-induced latent heating and confines updraft invigoration to lower, narrower layers, while amplifying aerosol-driven cooling and downdrafts. In contrast, under semi-polluted-to-polluted conditions, SIP enhances latent heating (particularly during the early lifetime) but further restricts updraft invigoration to shallow layers, while slightly reducing aerosol-induced cooling and downdraft effects.

4.3.5 Aerosol impacts on cloud ice crystal production

To address the research question (2), we examine the cloud ice crystal production rates by primary and secondary mechanisms under varying aerosol conditions (Figs. 4.16 and 4.17). Primary ice production (PIP) via heterogeneous freezing is far more efficient than any SIP pathway, with more than two orders of magnitude higher process rates (Fig. 4.16 (d)). However, its activity is largely confined to -25 and -45 °C, with nearly no contributions at higher temperatures (Fig. 4.17). Increasing aerosol loadings, especially CCN loadings (3SIP_{pw}), substantially enhances heterogeneous freezing rates, but increased IN alone (3SIP_{pi}) shows only small enhancements and is shifted down to lower levels relative to 3SIP (Figs. 4.16(d) and 4.17 (d)).

HM is insensitive to polluted IN (3SIP_{pi}) and reduced aerosols (3SIP_c), but is

suppressed by $\sim 20\%$ under polluted aerosols and polluted CCN (3SIP_p and 3SIP_pw) relative to 3SIP (Fig. 4.16 (c)), due to reduced graupel mass (Fig. 4.13 (a4)). Consistent with its dependence on rainwater availability (Hu et al. 2025), FFD is substantially enhanced in clean aerosols (3SIP_c) and reduced in polluted aerosols and polluted CCN cases (3SIP_p and 3SIP_pw) (Fig. 4.16 (a)), with the clearest differences between -10 and -15 °C (Fig. 4.17). Meanwhile, polluted IN (3SIP_pi) has little influences on FFD. IICOL rates increase from clean to polluted aerosol conditions (Fig. 4.16 (b)), as there are more snow particles with increasing aerosols that provide colliding opportunities (Fig. 4.13 (a3)). Polluted IN also increases IICOL's fractional contributions to total ice production at homogeneous freezing temperatures (Fig. 4.17 (d)).

Overall, increased aerosol loadings (especially CCN) suppresses HM and FFD in relatively warm mixed-phase layers but favors IICOL and heterogeneous freezing aloft. In other words, increased CCN loadings shift SIP from rain and graupel dominated mixed-phase processes to snow dominated cold processes higher up in the atmosphere. This redistribution is more pronounced when transitioning from clean to semi-polluted than from semi-polluted to polluted conditions.

4.3.6 Precipitation

Figure 4.18 shows precipitation rate as a function of normalized cell lifetime, addressing the final research question of this work. Consistent with findings in Chapter 3, including SIP generally reduces precipitation rates and accelerates ice rainout, but with one exception here: IICOLonly, which produces higher precipitation rates throughout the cloud lifetime (Fig. 4.18 (a)). The precipitation reductions by FFD and HM primarily arise from warm-rain pathway suppression, as FFD directly diverts rainwater to snow and graupel and HM produces small ice splinters that favor cloud ice and snow growth at higher levels and yield more numerous but smaller supercooled rain drops (Fig. 4.5

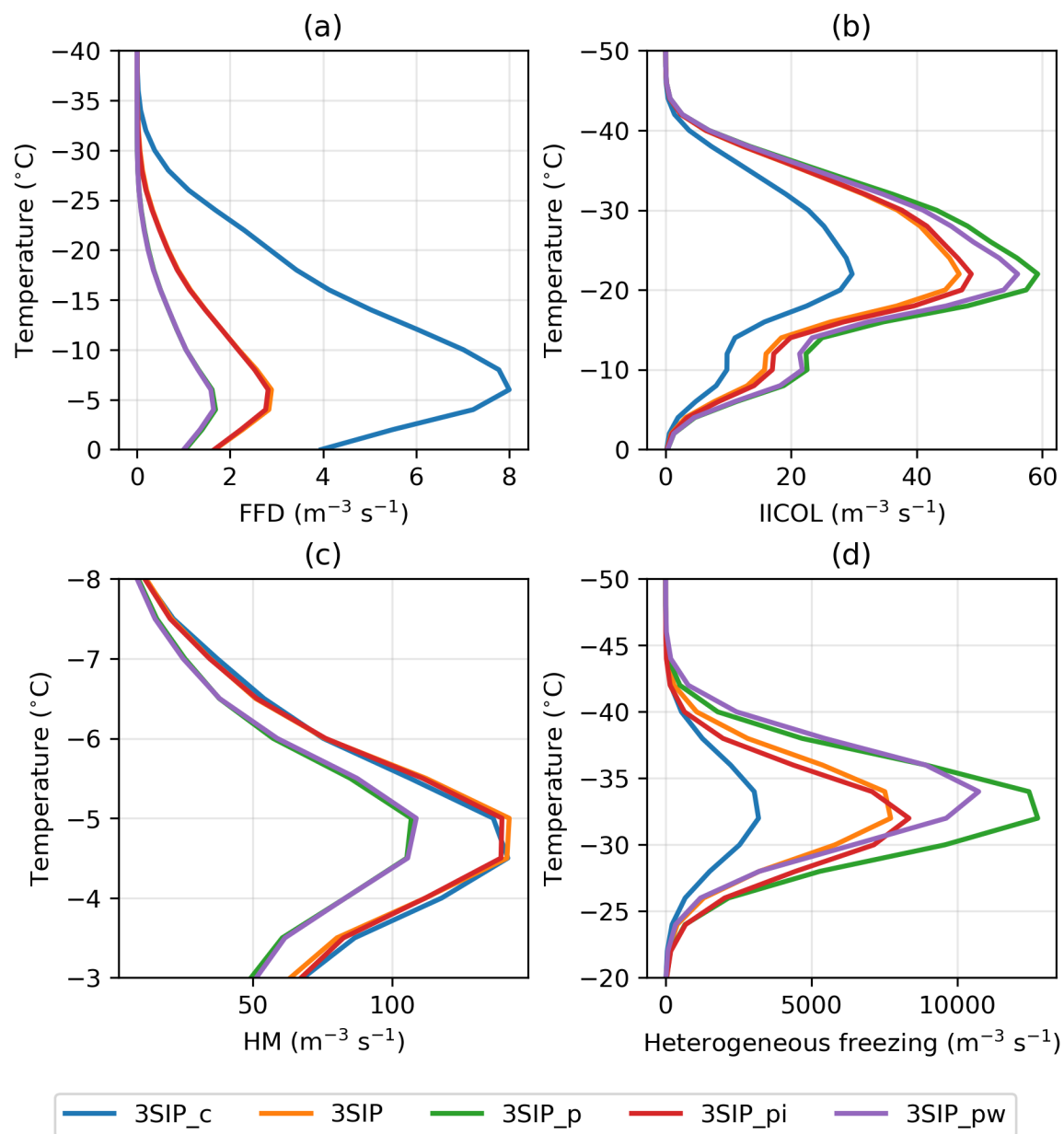


Figure 4.16: Lifetime-averaged vertical profiles of cloud ice crystal number production rates ($\text{m}^{-3} \text{s}^{-1}$) by (a) FFD, (b) IICOL, (c) HM, and (d) heterogeneous freezing from 3SIP simulations under different aerosol conditions.

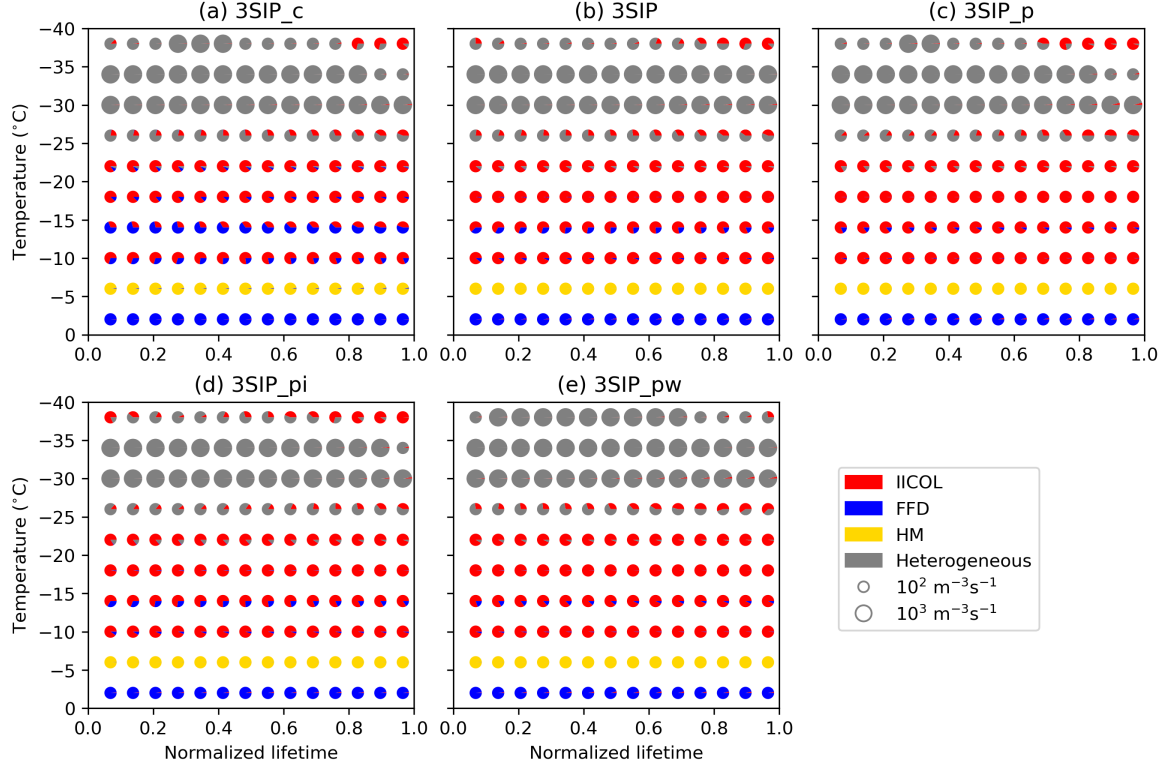


Figure 4.17: Relative contributions of different ice production mechanisms to the total cloud ice crystal number concentrations as a function of temperatures and normalized cloud lifetime. Results are from (a) 3SIP, (b) 3SIP_c, (c) 3SIP_p, (d) 3SIP_pi, and (e) 3SIP_pw simulations. Pie charts demonstrate the relative contributions of each ice production mechanism. The sizes of pies are scaled to the ice production rates, and different colors represent different ice production mechanisms, as shown in the legend.

(a3,a4,b3,b4)). IICOL influences precipitation mainly through the cold-rain pathway. In Chapter 3, IICOLonly reduced precipitation because snow-to-graupel conversion was limited. Under the semi-polluted aerosol condition here, however, graupel mass is increased (Fig. 4.5 (a4)) and the cold-rain pathway is enhanced, leading to stronger precipitation in IICOLonly. Nevertheless, this cold-rain enhancement remains much weaker than the warm-rain suppression by FFD and HM, leading to a net effect of reduced precipitation rates in 3SIP.

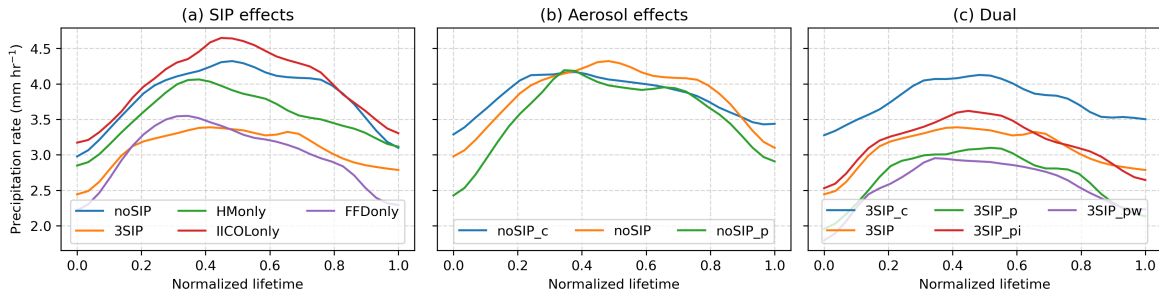


Figure 4.18: Precipitation rate (mm hr⁻¹) of selected cells as a function of normalized cell lifetime.

Without SIP, increasing aerosol loadings from clean (noSIP_c) to semi-polluted (noSIP) suppresses and delays precipitation in early lifetime (Fig. 4.18 (b)), as the more numerous but smaller cloud droplets in the semi-polluted environment need longer time to grow to precipitation-size rain drops. The subsequent rainout of the enhanced ice particles in noSIP (Fig. 4.8 (b1,b3)) then produces higher precipitation rates during the mid-to-late lifetime. Further increasing aerosol loadings from semi-polluted (noSIP) to polluted (noSIP_p) results in even stronger warm-rain suppression early on, but unlike the clean-to-semi-polluted transition, precipitation remains suppressed throughout the entire cloud lifetime in noSIP_p.

With SIP, the precipitation-suppressing effect of aerosols is amplified (Fig. 4.18 (c)). Enhancing aerosol loadings from clean (3SIP_c) to semi-polluted (3SIP) and further to polluted (3SIP_p) leads to persistent precipitation suppression. CCN-driven pollution

(3SIP_pw) suppresses precipitation most strongly, while IN-driven pollution (3SIP_pi) partly offsets the suppression through enhanced IICOL.

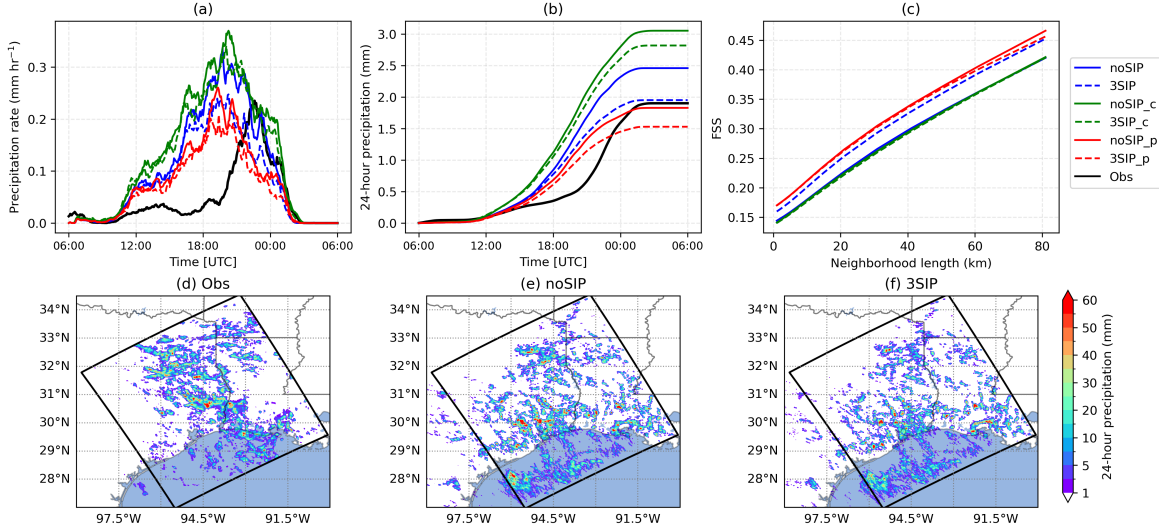


Figure 4.19: Time series of (a) precipitation rate (mm hr^{-1}) and (b) 24-hour cumulative precipitation (mm) from observations (Obs) and WRF simulations averaged over the analysis region. (c) Fractions skill score (FSS) as a function of neighborhood length (km) calculated from 4-minute precipitation aggregated between 09Z-03Z at the 95th precipitation percentile. Spatial distribution of 24-hour total precipitation (mm) from (d) Obs, (e) noSIP, and (f) 3SIP simulations, respectively. Black boxes in (d-f) indicate the analysis region.

Finally, Figure 4.19 compares MRMS precipitation with WRF simulations in time and space. Observed precipitation begins around 09Z on 17 June 2022, remains light until 20Z, intensifies to a peak near 23Z, then weakens and ends by 03Z on 18 June (Fig. 4.19 (a,b)). The 24-hour accumulated precipitation is scattered along the Louisiana coast and west of the TX/LA border (Fig. 4.19 (d)). The WRF runs capture the onset and cessation times but overestimate precipitation rates and amounts (Fig. 4.19 (a,b)), suggesting wet biases in the WRF model. No WRF run reaches the useful FSS (> 0.5) at neighborhood length ≤ 80 km (Fig. 4.19 (c)), indicating notable displacement errors.

The WRF simulations produce excessive precipitation over the Gulf of Mexico and a westward displacement inland (Fig. 4.19 (e,f)). The overprediction and displacement

of precipitation in simulations arise from excessive moisture transport from the Gulf to inland through 1000-700 hPa, especially on 850 hPa (not shown). Therefore, the wet bias and location errors are driven primarily by mesoscale forcings rather than microphysics. Nevertheless, SIP and aerosol conditions strongly modulate precipitation and mitigate the wet bias (Fig. 4.19 (a,b)). Among all runs, 3SIP provides the most skillful precipitation forecasts in terms of amounts, rates, and spatial distribution (Fig. 4.19(a-c)), underscoring the importance of including additional SIP and realistic aerosol treatments in NWP models.

4.4 Summary

The WRF Model with the aerosol-aware, SIP-included Thompson microphysics scheme was used to simulate a sea breeze convection case during the ESCAPE/TRACER field campaigns. Cloud tracking with Tobac was applied to both simulated and observed clouds to examine the impacts of SIP and aerosols on DCCs throughout their lifetime. Comparisons with airborne in situ measurements show that all WRF simulations reproduced LWC within the observed temperature ranges. The main findings of the effects of SIP and aerosols on DCCs and precipitation are summarized below.

- **SIP effects** SIP tends to produce more cloud cells, shorten cell lifetime, and enlarge cloud area. SIP effectively diverts condensate from liquid in low levels to ice in high levels, leading to both enhanced latent heating and cooling, and stronger updrafts and downdrafts in high levels. This condensate redistribution generally reduces and accelerates precipitation as it suppresses the warm-rain processes (FFD and HM activities). However, under the semi-polluted aerosol conditions, when graupel mass is increased, IICOL can enhance the cold-rain pathway and increase precipitation. Nevertheless, the net effect of three SIP

mechanisms is precipitation suppression.

- **Aerosol effects without SIP** From clean to semi-polluted increases LWC (due to cloud water enhancements) and IWC, enhances latent heating and updrafts, strengthens in-cloud latent cooling and downdrafts, suppresses precipitation during early lifetime but increases it during mid-to-late lifetime. Further pollution leads to decreased LWC (due to rain water loss), mixed ice-phase responses, enhanced latent heating and updrafts in early lifetime or near 20°C but reduced otherwise, stronger latent cooling and downdrafts in higher levels but weaker at lower levels, and suppressed precipitation throughout cloud lifetime.
- **Dual effects of SIP and aerosols** Increasing aerosol loadings tend to produce less cloud cells, lengthen cell lifetime, decelerate cloud propagation speed, and enlarge cloud area. Meanwhile, enhanced aerosol loadings suppresses HM and FFD processes but enhances IICOL and heterogeneous freezing processes aloft. From clean to semi-polluted, SIP dampens aerosol-induced latent heating and updrafts invigoration, while amplifying latent cooling and downdrafts. From semi-polluted to polluted conditions, SIP enhances latent heating during the early lifetime but further restricts updraft invigoration to shallow and low levels, while slightly reducing latent cooling and downdrafts. Furthermore, with SIP, precipitation is persistently suppressed with increasing aerosol loadings throughout cloud lifetime. Among polluted cases, CCN-driven pollution suppresses precipitation the most, while IN-driven pollution increases precipitation via enhanced IICOL.

In this study, we also found enhanced cooling under cleaner aerosol conditions. It is likely that under cleaner aerosol conditions, the more precipitation leads to enhanced evaporative cooling and stronger cold pools, which also trigger secondary convection initiation, as supported by the larger number of tracked cells in cleaner than in more

polluted conditions. This effect is more pronounced when SIP is included, likely due to more ice melting thus stronger cooling effect. However, these interpretations require further confirmation. For example, future work could examine the rain drop size distribution below cloud base and evaporative cooling rates to better quantify this effect. Furthermore, previous researches reported that heterogeneous freezing in polluted clouds is less efficient due to the smaller sized cloud droplets, i.e., smaller cloud droplets freeze at lower temperatures (e.g., Altaratz et al. 2014; Coopman et al. 2020). However, our results show that with SIP, heterogeneous freezing is more efficient in polluted clouds, and IN-pollution shifts heterogeneous freezing to slightly higher temperatures. These results suggest potential feedback between SIP mechanisms and heterogeneous freezing under varying aerosol conditions, which warrants further investigation.

Chapter 5

Summary and Future Work

5.1 Summary

A 24-hour and 1-km convection-allowing ensemble (CAE) is executed using the Weather Research and Forecasting (WRF) model during the ESCAPE (Experiment of Sea Breeze Convection, Aerosols, Precipitation and Environment) field campaign in June 2022. This CAE consists of 48 members, encompassing three initial/boundary conditions (ICs/BCs), four microphysics schemes each with two different aerosol loadings, and two planetary boundary layer (PBL) schemes.

In Chapter 2, we present a comprehensive evaluation of the 1-km CAE precipitation forecasts against observations on eight SBC cases observed during ESCAPE. Our results show that (1) the multi-ICs/BCs design improves light-to-moderate precipitation forecasts but not necessarily for the rarest (> 99 th percentile) precipitation events, (2) increasing horizontal grid spacing from 3-km to 1-km reduces precipitation biases and displacement errors, and (3) the Thompson microphysics (Thompson et al. 2008) and the Mellor-Yamada-Nakanishi-Niino (MYNN) eddy-diffusivity mass-flux (EDMF) PBL (Olson et al. 2019) schemes produce the least-biased SBC precipitation forecasts. Additionally, results in Chapter 2 underscore the importance of cloud microphysics in precipitation forecasts in deep convection and advocate for continued microphysics parameterization development, such as secondary ice production (SIP) processes, which have long been underrepresented in NWP models.

In Chapter 3, we implement two additional SIP mechanisms: fragmentation of freezing rain drop (FFD) and ice-ice collisional breakup (IICOL), into the Thompson microphysics scheme. Idealized simulations are performed for two cases to investigate the influences of SIP mechanisms on precipitation formation in deep convection using the WRF Model.

Results in Chapter 3 show that SIP systematically reduces surface precipitation by redistributing condensate from liquid at low levels to ice at high levels, without drastically removing condensate from the cloud system. This water repartitioning suppresses mainly the warm-rain pathway, but can also suppress the cold-rain pathway depending on graupel availability. Furthermore, SIP shifts latent heating to lower and shallower levels and in early cloud lifetime. While the median updraft responses are different in the two cases, SIP shows the potential to invigorate the 95th and maximum updrafts and elevate cloud tops in active updraft regions. FFD substantially enhances IICOL and HM (Hallett-Mossop process, the default SIP mechanism in the Thompson scheme), but IICOL and HM have only limited impacts on FFD. Interactions between IICOL and HM can be competitive or synergistic, depending on graupel availability. Comparisons to airborne in situ observations confirm the necessity of including additional SIP in NWP models to better simulate ice particles in deep convection. However, other options of SIP parameterizations should also be explored as the current ones are still largely uncertain.

Aerosol-cloud interactions are one of the largest sources of uncertainty in precipitation forecasts, yet their impacts on deep convection remain an open topic. Cold-phase invigoration is one of the most debated hypotheses on how aerosol loadings can impact updrafts and precipitation in deep convection. This hypothesis has fueled many observational, modeling, and theoretical studies, but few of them have considered the potential influences of SIP.

In Chapter 4, we use the SIP-included, aerosol-aware Thompson microphysics scheme to simulate a SBC case that triggered deep convection and heavy rainfall observed on 17 June 2022 during ESCAPE. A cloud tracking algorithm is applied to investigate the dual effects of SIP and aerosols on deep convection and precipitation throughout cloud lifetime.

Without SIP, increasing aerosol loadings from clean to semi-polluted conditions increases both liquid (large cloud water enhancements) and ice condensates, strengthens latent heating and updrafts, latent cooling and downdrafts, suppresses precipitation in early lifetime but enhances precipitation later on. Further increasing aerosol loadings from semi-polluted to polluted, however, yields decreased liquid (substantial rainwater loss) and mixed ice responses, stronger latent heating and updrafts occur only in early lifetime and are overall weakened, and precipitation is persistently suppressed throughout cell lifetime.

With SIP, increasing aerosol loadings from clean to semi-polluted conditions dampens latent heating and confines updraft invigoration to shallower, lower levels. Further pollution leads to further confinement of updraft invigoration, even though enhances latent heating during the early lifetime. Moreover, with SIP, precipitation is persistently suppressed with increasing aerosol loadings throughout cloud lifetime. Only IN-driven pollution increases precipitation due to enhanced IICOL. We also found that enhanced aerosol loadings suppresses HM and FFD processes but enhances IICOL and heterogeneous freezing processes aloft.

When SIP is not considered, our results corresponding to the first aerosol loading enhancements are generally consistent with the cold-phase invigoration hypothesis, but further enhancements lead to divergent outcomes. When SIP is considered, our results show even opposite outcomes from the cold-phase invigoration, despite that heterogeneous freezing rates are enhanced with increasing aerosol loadings in our re-

sults, which should, in theory, accelerate freezing of lofted cloud droplets and make cold-phase invigoration more likely. Nevertheless, our results demonstrate that SIP should be considered when investigating aerosol-cloud-precipitation interactions.

Finally, WRF Model simulations with three SIP and realistic aerosol loadings produce the most skillful precipitation forecasts compare to observations, highlighting the importance to include additional SIP and proper aerosol treatments in NWP models to improve precipitation forecasts.

5.2 Future work

The 1-km CAE described in Chapter 2 naturally serves as a large database that ensures statistical robustness and allows many future work topics, for example, cold pools, which are generated through evaporation and melting of precipitation particles, and play a fundamental role in convection initiation, propagation, duration, and intensity. Future work can investigate how different microphysics treatments of rain, snow, and graupel impact cold pool formation, as the 1-km CAE already considers four different cloud microphysics schemes. Meanwhile, an ensemble-based database of cold pool characteristics including strength, depth, propagation speed, and longevity, can be constructed, to examine how choices of ICs/BCs and PBL, and varying aerosol loadings modulate cold pool properties and explore the effects of environmental parameters (such as high versus low RH, strong versus weak shear) on cold pools.

Furthermore, results from Chapters 3 and 4 collectively demonstrate the critical role of SIP in shaping cloud microphysics, thermodynamics, dynamics, and even aerosol-cloud-precipitation interactions. Yet, one important component is still missing: the influence of SIP on cloud radiative effects. By redistributing liquid condensate into numerous ice particles, SIP inevitably alters cloud optical and radiative properties,

particularly in deep convective anvils.

Anvil clouds produced by deep convection are prevalent in the tropics (Kiehl 1994) and are a leading source of uncertainty in the recent assessment of climate sensitivity by the World Climate Research Programme (WCRP; Sherwood et al. 2020). These clouds are highly reflective of incoming shortwave (SW) radiation while simultaneously trapping the outgoing longwave (LW) radiation emitted by the Earth’s surface and lower atmosphere (Kiehl 1994). Although the SW and LW effects are individually strong, they nearly cancel each other out on climatological scales, resulting in a near-zero net cloud radiative effect in the tropics (Kiehl 1994; Harrison et al. 1990). Despite longstanding knowledge of this balancing effect, questions remain regarding its underlying mechanisms and susceptibility to climate change (Hartmann 2016). Moreover, global climate models (GCMs) struggle to represent the balanced radiative effect in the tropics well (Hartmann and Berry 2017; Bock and Lauer 2024). Previous estimates of anvil cloud feedback are altogether inconclusive, due to the fact that anvils can exert either a positive or negative cloud radiative effect at different stages of their life cycle (Hartmann et al. 2018) and with different microphysical properties, e.g., ice microphysics (Jensen et al. 2018; Atlas et al. 2024).

Future research can therefore extend the present work by examining how SIP-driven changes in cloud phase partitioning and ice microphysics feed back onto anvil radiative properties, and how these processes influence cloud feedback and climate sensitivity.

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