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A Model Intercomparison Study of Mixed-Phase Clouds in a Laboratory Chamber

Key Points:

- Liquid microphysics is the main source of inter-model variability with spherical ice crystals assumed and no ice-nucleating particle processes included
- Most models do not reach full glaciation except for those assuming a well-mixed domain or simulating only the core region
- Compared to bin microphysics, Lagrangian microphysics results in greater exposure of particles to supersaturation variability

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Abstract Supercooled liquid water often persists in mixed-phase clouds for hours to days, even though a simple, well-mixed Wegener-Bergeron-Findeisen model predicts rapid depletion of liquid water in the presence of ice. The persistence is well documented, but the relative importance of the maintaining mechanisms remains uncertain. This model intercomparison study addresses this issue by comparing results from 10 model configurations against observations from the Pi Cloud Chamber at Michigan Technological University, which produces cloudy Rayleigh-Bénard convection. To simplify the problem, we exclude ice-nucleating particle processes and assume that the ice crystals are spherical. Each model was first tuned to reproduce the observed steady liquid-cloud state and then run with ice injected at a range of rates. The evolution of spherical ice crystals is consistent across models, but differences emerge in the liquid phase. Most models that simulate the full chamber tend to retain liquid droplets for the entire simulation, because persistent supersaturation near the bottom activates new droplets that replace those that mix into the core and evaporate. In contrast, models that assume a well-mixed domain, exclude the near-wall region, or use coarse resolution do not sustain droplets and undergo complete glaciation. Models that use Lagrangian microphysics expose particles to greater supersaturation variability than bin schemes. Overall, these results demonstrate that liquid persistence in mixed-phase clouds is highly sensitive to the representation of spatial heterogeneity and mixing, and provide guidance for improving microphysical parameterizations in atmospheric models.

Plain Language Summary Mixed-phase clouds contain both liquid droplets and ice crystals.

Accurately representing these clouds in numerical models is important for weather and climate prediction. Mixed-phase clouds can glaciate, becoming entirely composed of ice crystals. The glaciation rate depends on interactions among droplets, ice crystals, and water vapor in turbulent flow. To better understand this process, we used 10 computer models to simulate mixed-phase cloud formation and glaciation in the Pi Cloud Chamber, a controlled laboratory environment. First, we adjusted each model to reproduce the observed liquid-only cloud. We then simplified the process by excluding ice-nucleating-particle processes and assuming spherical ice crystals, then injected ice crystals at different rates to examine glaciation at each rate. All models showed similar evolution in overall liquid and ice properties but differed in their representations of turbulence, chamber-wall properties, and particle removal. Complete glaciation occurred only in simulations with coarser grid resolution or in those that excluded near-wall regions rich in supercooled liquid. These results indicate that accurately simulating mixed-phase clouds requires capturing small-scale processes. Laboratory experiments such as those conducted in the Pi Cloud Chamber can help scientists test and improve cloud models.

1. Introduction

Mixed-phase clouds, characterized by the coexistence of supercooled liquid and ice, play a crucial role in Earth's weather and climate systems (Korolev et al., 2017; Morrison et al., 2011; Mülmenstädt et al., 2021; Tan & Storelvmo, 2019; Tan et al., 2025; Villanueva et al., 2022). Their microphysical processes control phase transitions, precipitation efficiency, radiative properties, and cloud lifetimes, but modeling these processes remains challenging due to uncertainties in parameterizations used in coarse-resolution models (Fan et al., 2011; Klein

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et al., 2009; Korolev & Milbrandt, 2022; Korolev et al., 2017; Tan & Storelvmo, 2016). For example, an intercomparison of observations, single-column models, and cloud-resolving models conducted by Klein et al. (2009) found that the underestimated modeled liquid water path results from overly active interactions between liquid and ice microphysics. Tan and Storelvmo (2016) further showed that global climate models assume an overly rapid glaciation process because they do not account for subgrid-scale (SGS) variability. Atmospheric measurements, on the other hand, are limited by transient cloud behavior and uncertain boundary conditions, which hinder direct validation of model physics.

Controlled cloud chamber experiments, such as those conducted at Michigan Technological University's Pi Convection Cloud Chamber (Chang et al., 2016; Desai et al., 2019), provide robust environments to study mixed-phase clouds under reproducible conditions. Such laboratory facilities are important because they provide controlled boundary conditions and repeatable detailed measurements of aerosol, thermodynamic, and microphysical properties in statistically steady states that can serve as benchmarks for evaluating and improving cloud microphysics parameterizations (Morrison et al., 2020). Combined with high-resolution numerical models like direct numerical simulation (DNS) and large-eddy simulation (LES), which can resolve fine-scale cloud processes such as supersaturation fluctuations and phase transitions, these tools offer valuable insights for model development and validation (S. Krueger & Shaw, 2026). Recognizing the need for such validation, a pioneering model intercomparison study using warm-phase cloud chamber experiments at the Pi Chamber was conducted by S. Chen et al. (2025) at the 10th International Cloud Modeling Workshop (Xue et al., 2022). This study evaluated a range of models, from DNS to LES and 1D turbulence models, to test their ability to simulate steady-state warm clouds under varying aerosol injection rates. While all models captured qualitative microphysical responses, significant quantitative discrepancies were found, such as differences in particle number concentrations due to variations in aerosol activation, supersaturation fluctuations, and particle removal mechanisms like sedimentation and diffusion. These findings underscored the importance of laboratory experiments in constraining models and highlighted the need for targeted studies to address specific physical processes.

Building on previous warm-phase research by S. Chen et al. (2025), this study shifts focus to the complex dynamics of mixed-phase clouds in the Pi Chamber, exploring their transition from supercooled liquid to mixed-phase or fully glaciated states. Mixed-phase processes like ice nucleation, depositional growth, and the Wegener-Bergeron-Findeisen (WBF) process involve significant uncertainties, even in advanced atmospheric models. Experiments by Desai et al. (2019) demonstrated that steady-state mixed-phase clouds can be simulated in controlled environments, showing that the ice fraction is governed by injected ice-nucleating particle (INP) concentrations. Increased INP injection rates caused particle size distributions (PSDs) to evolve from single-mode liquid droplets to bimodal distributions, with decreasing mean droplet sizes and increasing ice fractions due to active WBF processes. Even at high INP rates, supercooled liquid persisted, with maximum ice mass fractions reaching 82%.

Numerical studies have further demonstrated that spatial heterogeneity and turbulent fluctuations significantly impact glaciation processes (Wang, Krueger, et al., 2024). For example, under identical ice injection rates, a bulk model reached full glaciation, while LES retained supercooled liquid, highlighting the importance of resolving turbulence-induced variability. Spatial heterogeneity in cloud phase and turbulence-induced variability have also been shown to influence mixed-phase cloud evolution. Numerical studies using the Pi Chamber setup demonstrated that these processes can affect glaciation: under identical ice injection rates, a bulk model (with no variability) reached full glaciation, while LES (with inherent variability) retained supercooled liquid, highlighting the importance of resolving turbulence-induced variability (Wang, Krueger, et al., 2024). This finding is consistent with evidence from observations and larger-scale modeling studies. Satellite observations reveal substantial spatial heterogeneity in thermodynamic phase within mixed-phase clouds (Coopman & Tan, 2023), while large-scale modeling studies show that representing such subgrid heterogeneity affects WBF processes and mixed-phase cloud persistence (Furtado et al., 2016; Tan, 2025).

Based on the experiment in the Pi Chamber, this study aims to evaluate how models represent mixed-phase cloud microphysics in controlled environments, with the goal of improving their accuracy in simulating turbulent mixed-phase clouds. Section 2 introduces the case setup and models, Section 3 presents the intercomparison results, and Section 4 discusses conclusions and implications for atmospheric modeling.

2. Methods

2.1. Case Overview and Difference From the Pi Chamber Experiment

This model intercomparison case is based on mixed-phase cloud experiments conducted in the Pi Chamber, following the setups described by Desai et al. (2019) and Wang, Krueger, et al. (2024). The wall temperature was adjusted to optimize the liquid water content of the super-cooled cloud in the Pi Chamber. Specifically, the wall temperatures are 4°C, −12°C, and −16°C for the bottom, side, and top walls, respectively, resulting in a mean temperature below the freezing point. The Pi chamber can be configured as in either cylinder or rectangular geometries and is capable of generating and sustaining cloud formation under controlled conditions.

The measurements were conducted in the chamber's cylindrical configuration (2 m diameter, 1 m height; Chang et al., 2016; Desai et al., 2019). To accommodate the structured Cartesian grids used in most atmospheric models, all LES simulations in this intercomparison adopt a rectangular geometry (2 m × 2 m horizontal, 1 m height), following the standard convention for Pi Chamber modeling (e.g., S. Chen et al., 2025; Grabowski, 2020; Mac-Millan et al., 2022; S. Thomas et al., 2019; Wang, Ovchinnikov, Yang, Cantrell, et al., 2024; Yang et al., 2025). The prior rectangular-chamber LES reproduce observed bulk microphysics within reasonable bounds. However, a numerical study by Kia et al. (2025) comparing the two geometries reports that the large-scale circulation drifts freely in the cylindrical chamber but adopts a preferred diagonal orientation in the rectangular box. The geometric effects are most likely to influence the processes in the near-side-wall and corner regions.

Setups and measurements from the Pi Chamber experiments, including the top, bottom, and side wall temperature, as well as droplet mean radius and concentration at steady-state, were used to constrain the models' initial and boundary conditions. Note that steady-state experiments are highly advantageous for model intercomparison studies such as this work, as they eliminate the need to account for initial conditions and transient responses. Model performance was evaluated using PSDs and domain-mean cloud properties, such as total water content and mean particle radius. Further details of the case description are provided in S. Chen et al. (2024).

In addition to the domain geometry, several other limitations and differences between the Pi Chamber experiment of Desai et al. (2019) and the models used in this work are described below. Desai et al. (2019) injected Snomax as INPs to produce ice crystals, whereas the models in this work directly injected ice crystals with an initial radius of 2 μm to avoid the complexity of the ice nucleation process.

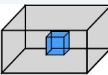
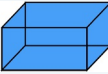
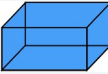
Regarding the PSDs, measurements in the Pi Chamber were obtained using a digital holographic instrument (Holo-Pi, Desai et al., 2018). Holo-Pi is capable of determining both particle size and shape, the latter of which is useful for distinguishing liquid droplets from ice. Because its pixel resolution is 3.5 μm, the theoretical resolution limit is 7 μm (corresponding to two pixels). Therefore, even though all models resolve much smaller particles, a cutoff radius of 3.5 μm was applied to the model output PSDs when calculating the mean radii, number concentrations, and water contents of droplets and ice. In practice, however, noise rejection and particle identification become more robust with increasing particle size up to approximately 6 μm, so the analysis in Section 3.1 used a higher cutoff radius. Wang, Krueger, et al. (2024) showed that applying a cutoff radius affects the calculated mean droplet number concentration and radius, but the contribution of droplets below the cutoff to the total liquid water content is small. Ice properties are barely affected because ice crystals generally exceed the cutoff radius owing to their efficient growth.

Regarding ice behavior, observational measurements in the Pi Chamber experiment have limitations in distinguishing ice from liquid, whereas the models can separate ice and liquid in their output. Nevertheless, the ice crystals in the Pi Chamber are small enough that they can reasonably be assumed to be spherical (Desai et al., 2019), and we therefore use the same assumption in the models. Also, because of the short particle lifetime in the Pi Chamber, collisions (e.g., droplet-droplet collision, ice aggregation, and riming) and ice habit evolution are not considered in any of the models in this study. In other words, the WBF process in the models is represented solely by depositional growth of ice crystals and evaporation of liquid droplets.

2.2. Procedures

The numerical experiments follow three stages: a dry dynamic spin-up stage, a liquid-phase stage, and a mixed-phase stage. The spin-up stage aims to establish steady-state turbulence and thermodynamic conditions before aerosol injection.

Table 1
Names and Configurations of the Model Members

Member name	Type	Microphysics scheme	Grid spacing	Side wetness	CCN inj. rate	Simulated domain
Bulk Model		Bulk Scalar - Flux Model		30%	—	
Statistical Model		Statistical Model		—	$10.0 \text{ cm}^{-3} \text{ min}^{-1}$	
DNS Lag	DNS	Lagrangian	0.78125 mm	—	$10.0 \text{ cm}^{-3} \text{ min}^{-1}$	
SAM-HUJbin	LES	HUJ bin	3.125 cm	30%	$10.0 \text{ cm}^{-3} \text{ min}^{-1}$	
SAM-CLbin		Chen-and-Lamb bin		30%	$10.0 \text{ cm}^{-3} \text{ min}^{-1}$	
SAM-Lag		Lagrangian		30%	$10.8 \text{ cm}^{-3} \text{ min}^{-1}$	
UWLCM-Lag				52%	$11 \text{ cm}^{-3} \text{ min}^{-1}$	
OpenFOAM-Lag				80%	$14.4 \text{ cm}^{-3} \text{ min}^{-1}$	
SCALE-SDM-Lag-F				66%	$10 \text{ cm}^{-3} \text{ min}^{-1}$	
SCALE-SDM-Lag-C			6.25 cm	66%	$8 \text{ cm}^{-3} \text{ min}^{-1}$	

In the liquid-phase stage, sea salt aerosols with a diameter of 125 nm are used as cloud condensation nuclei (CCN) and are injected to form supercooled liquid droplets at sub-freezing temperatures. Although this is different from the polydisperse aerosols used in Desai et al. (2019), several recent works showed that in most cases, the cloud properties are not sensitive to the aerosol size (Fahandezh Sadi et al., 2026; Gali et al., 2025). A steady state in liquid-phase microphysics, characterized by a mean droplet radius of $7.75 \mu\text{m}$ and a number concentration of 25 cm^{-3} (following Desai et al., 2019), is achieved by tuning the model parameter: For models simulating the full chamber domain, both side-wall wetness and CCN injection rates are adjusted to match the observed droplet properties. For models simulating only the core region, a forcing on mean supersaturation is prescribed to represent the water vapor and heat exchange between the core and the surrounding area. In these core-only models particle sedimentation is implemented as a probabilistic removal due to the absence of chamber walls. Both the mean supersaturation forcing and particle sedimentation are tuned to obtain the observed droplet radius and number concentration. The CCN injection rate will remain constant throughout the entire simulation. This stage is used for constraining and calibrating the liquid-phase condition before ice injection in mixed-phase stage. However, because of the challenge in matching both droplet properties (S. Chen et al., 2025), we prioritize droplet size over number concentration.

After the liquid-phase steady state is established, ice crystals with an initial radius of $2 \mu\text{m}$ are uniformly injected into the domain (Wang, Krueger, et al., 2024). Ice-particle injection rates range from 0.5 to $15 \text{ cm}^{-3} \text{ min}^{-1}$. In each simulation, ice is injected with a fixed rate until a new steady state is reached.

2.3. Models

Seven models were used in the intercomparison, including four LES models, one DNS model, one statistical model, and one bulk scalar mixing model (hereafter referred to as the “bulk model”). The SAM-LES model was run with three different microphysics schemes, and the SCALE-SDM LES model was run with two different grid spacings, resulting in a total of 10 sets of simulations. All LES models simulate the entire chamber with a rectangular geometry of $2 \text{ m} \times 2 \text{ m}$ in the horizontal and 1 m in the vertical direction. The DNS and statistical models focus on the central, well-mixed region of the chamber, employing a cubic domain of $20 \times 20 \times 20 \text{ cm}$. The model configurations are summarized in Table 1.

Across the model configurations, the WBF process is represented through ice deposition and cloud-droplet evaporation, calculated based on the supersaturation with respect to spherical ice and liquid droplet,

Table 2

The Modeling Approach for Diffusional Growth of Liquid and Ice in Each Model

Member name	Diffusional growth (liquid/ice)
Bulk Model	Diffusional growth on domain mean $\bar{s}_p$, $\bar{N}_p$, $\bar{r}_p$ (Wang, Krueger, et al., 2024)/same form with $\bar{s}_{ice}$
Statistical Model	Diffusional growth driven by stochastic s_{liquid} from stochastic differential equation (Sarnitsky et al., 2025)/same with s_{ice}
DNS-Lag	Lagrangian diffusional growth on linearized single- s_{liquid} field (Sardina et al., 2015)/same with s_{ice}
SAM-HUbin	Diffusional growth across 33 mass-doubling liquid bins (Khain et al., 2004)/33 mass-doubling ice bins
SAM-CLbin	Twomey-activation + diffusional growth on 33 mass-doubling bins, prognostic N and mass (J.-P. Chen & Lamb, 1994; Yang et al., 2023)/33 mass-doubling ice bins
SAM-Lag	Köhler curvature + solute diffusional growth, Lagrangian (Hoffmann et al., 2015)/diffusional growth with S_i
UWLCM-Lag	Köhler-based SDM condensation with solute and curvature effects (Arabas et al., 2015); aerosols treated identically to droplets without activation parameterization/spherical ice super-particle deposition
OpenFOAM-Lag	Köhler theory with deliquescence and efflorescence (Niedermeier et al., 2020)/depositional growth following S. Chen et al. (2023)
SCALE-SDM-Lag-F	SDM solving Köhler-based condensation and evaporation using the implicit Euler scheme (S.-i. Shima et al., 2009)/ice deposition and sublimation without the curvature and solute effects using the explicit Euler scheme (S. Shima et al., 2020)
SCALE-SDM-Lag-C	

respectively. The model-specific treatments are summarized in Table 2. The 10 model configurations differ along two aspects. First, in their treatment of the diffusional kernel: the supersaturation field driving the growth (domain-mean, stochastic, or fully resolved), the discretization of the particle population (bins, prognostic moments, or Lagrangian super-particles), and the treatment of the haze and small-radius regime (Köhler theory or threshold/bin truncation). Second, in the simulated domain: entire-chamber models (the bulk model and all LES) include the walls and tune physical boundary parameters (side-wall wetness, CCN injection rate), whereas core-only models (the statistical model and DNS-Lag) only simulate the central region far from the walls with a prescribed supersaturation forcing scheme and a probabilistic sedimentation parameterization, both of which are tuned to match the observed liquid-phase steady state. More detailed information for each model is provided below.

The bulk model, described in Wang, Krueger, et al. (2024), solves budget equations for two scalars, temperature and water vapor mixing ratio, with an assumption of well-mixed (uniform) domain. This assumption is generally valid for Rayleigh-Bénard convection, except near the chamber walls. The mean supersaturation is computed as a function of the domain-average temperature, $\bar{T}$, and water vapor mixing ratio, $\bar{q}$. The equilibrium values of $\bar{T}$ and $\bar{q}$ are determined by the net fluxes of sensible and latent heat from the chamber walls and droplets. A bulk aerodynamic formulation is used to model the area-integrated fluxes of temperature and water vapor from the walls. The flux velocity scale for the bottom and top walls, V_0 , is derived from the vertical flux of sensible and latent heat implied by the Nusselt number. For the side walls, the flux velocity scale is assumed to be $0.42 V_0$ and the side-wall wetness is 0.30 (Wang, Krueger, et al., 2024). The net vapor flux to each type of particle (i.e., the net condensation or deposition rate) is proportional to the mean supersaturation with respect to the phase of the particle, $\bar{s}_p$, the particle number concentration, N_p , and the mean radius, $\bar{r}_p$, which itself depends on $\bar{s}_p$ only (S. K. Krueger, 2020). The subscript p indicates the phase of the particle (liquid or ice). Given number concentrations and densities of droplets and ice, and the area and temperature of each wall, the bulk model predicts equilibrium values of $\bar{T}$ and $\bar{q}$, and therefore, of $\bar{s}_{ice}$, $\bar{s}_{liquid}$, $\bar{r}_{ice}$, and $\bar{r}_{liquid}$. Instead of injecting ice particles, we keep $\bar{N}_{liquid}$ as 25 cm^{-3} and vary $\bar{N}_{ice}$, as conducted by Wang, Krueger, et al. (2024).

The statistical model, described in detail by Sarnitsky et al. (2025), was developed for homogeneous isotropic turbulence and is therefore applied to the chamber's well-mixed core region. It uses a stochastic differential equation to simulate supersaturation fluctuations experienced by droplets and ice particles. This equation is

derived from the mapping-closure mixing model (Pope, 1991), assuming Gaussian supersaturation fluctuations in a well-mixed condition, where droplets and ice particles experience supersaturation fluctuations with identical statistics. DNS simulations of the same core region confirms both Gaussianity and the well-mixed assumption. A great challenge in formulating the model is to correctly represent the mixing between the core region and the rest of the chamber. To simulate this, both mean and variance of supersaturation are forced. The mean supersaturation for liquid, $\bar{s}_{\text{liquid}}$, is forced by adding a term $-(\bar{s}_{\text{liquid}} - \bar{s}_0)/\tau$ to the evolution equation for $\bar{s}$ (Desai et al., 2019; Saito et al., 2019). Here $\tau = 60$ s is a relaxation time consistent with the time it takes for the chamber to relax to equilibrium (S. Chen et al., 2024; Desai et al., 2019). The parameter $\bar{s}_0$ controls the target mean supersaturation, which is also affected by phase changes. In this study, $\bar{s}_0$ is set to 3% to yield the prescribed steady-state droplet radii and number concentration in the liquid-phase stage, which is similar to the value (3.1%) used by Desai et al. (2019), and lower than the 5.97% found by SAM LES (Wang, Krueger, et al., 2024) and suggested by the case description (S. Chen et al., 2024). However, 5.97% is the prescribed steady-state value of the chamber's core region in the spin-up stage (before injecting CCN). During the liquid-phase stage, the mean supersaturation over the entire chamber decreases. Although $\bar{s}_0$ is time-dependent in reality, a constant value is used here for simplicity. The supersaturation variance is held constant at 2%, as prescribed in the case description (S. Chen et al., 2024). To represent particle sedimentation from the core region to the rest of the chamber, particles are removed probabilistically based on their Stokes settling speeds (S. Chen et al., 2024). It is found that reducing the settling speed by a factor of $\alpha = 0.8$ compared with the case description improves agreement on target droplet radii and numbers in the liquid-phase stage. The CCN injection rate is taken to be $10 \text{ cm}^{-3} \text{ min}^{-1}$, as specified in the case description. Note that the previously published statistical model simulation of the Pi chamber by Sarnitsky et al. (2025) used $\bar{s}_0 = 5.97\%$ and $\alpha = 1.0$, and the linearization of the supersaturation function was done near $\bar{s}_0 = 5.97\%$, whereas the current study uses 0%.

The DNS with Lagrangian droplet and ice particles (hereafter referred to as DNS-Lag) is also designed to model homogeneous isotropic turbulence, thus is applied to simulate the chamber's core region. A detailed description of the model is provided by Sarnitsky et al. (2025). DNS-Lag resolves a single supersaturation field governed by a convection-diffusion-reaction equation, rather than two separate fields for water mixing ratio and temperature. This simplification requires supersaturation fluctuations to be small, allowing linearization of the supersaturation function with respect to water vapor mixing ratio. This assumption holds in the well-mixed core region. Additionally, the single supersaturation approach assumes equal diffusivities for temperature and water vapor, which is not an accurate approximation near the walls of the chamber or for the study of the inhomogeneous flow on the scale of the whole chamber (Chandrakar et al., 2020). However, in the core region away from the strong near-wall gradients, this assumption is justified (e.g., Fig. 8 in Chandrakar et al. [2020]), provided the correct supersaturation variance is supplied, as prescribed in the case description (S. Chen et al., 2024). And the accuracy of the single-supersaturation approach has been validated through comparison with the two-equation approach in previous DNS studies (Lanotte et al., 2009; Sardina et al., 2015; Sarnitsky et al., 2025). DNS-Lag uses a standard pseudospectral solver (Fries et al., 2021; Sardina et al., 2015) with triply periodic boundary conditions. To represent mixing between the core region and the rest of the chamber, supersaturation forcing is applied similar to the statistical model. Droplets and ice particles are advected as tracers by the velocity field. Particle removal due to sedimentation is modeled probabilistically using the same approach and parameters as in the statistical model.

All simulations from the statistical model and DNS-lag, including the one to establish the liquid-phase steady state, were conducted for 10 min. A 30-s spinup period was used to establish the fully developed turbulence in DNS-Lag prior to the CCN injection in liquid-phase stage.

The SAM model (System for Atmospheric Modeling, M. F. Khairoutdinov & Randall, 2003), coupled with the single-moment bin microphysics scheme developed by the Hebrew University of Jerusalem group (Khain et al., 2004), is used in both Wang, Krueger, et al. (2024) and this work. This model is referred to as SAM-HUbin hereafter. SAM has been widely used to simulate cloud chambers and their wall fluxes (L. Thomas et al., 2025; S. Thomas et al., 2019; Wang, Jiang, et al., 2026; Wang, Krueger, et al., 2024; Wang, Ovchinnikov, Yang, Cantrell, et al., 2024; Wang, Ovchinnikov, Yang, Schmalfuss, & Shaw, 2024; Wang, Schmalfuß, et al., 2025; Wang, Yang, & Ovchinnikov, 2024; Wang, Yang, et al., 2026; Yang et al., 2022, 2023, 2025). The velocities are solved on an Arakawa staggered C-grid (Arakawa & Lamb, 1977), advected with a second-order central scheme, and dissipated with a turbulent kinetic energy SGS model (Deardorff, 1980). The scalars are advected by a

multidimensional positive definite advection transport algorithm (Smolarkiewicz & Grabowski, 1990) and diffused with a turbulent Prandtl number of 1, following the Reynolds analogy (Kays et al., 1980). The bin microphysics includes 33 mass-doubling bins for CCN, another 33 for liquid, and another 33 for ice. The only difference between the current study and the SAM-HUBin simulations in Wang, Krueger, et al. (2024) is the simulation procedure: Wang, Krueger, et al. (2024) performs a single long simulation with varying ice injection rates, whereas this study performs seven independent simulations, each with a different ice injection rate. Each simulation consists of three 20-min stages: (a) spin up of moist turbulence, (b) liquid-phase stage with CCN injection, and (c) mixed-phase stage with injection of ice. To match the observed droplet radius and number concentration, the side-wall wetness with respect to ice is set to 0.30, and the CCN injection rate is $10 \text{ cm}^{-3} \text{ min}^{-1}$.

The second set of SAM LES was conducted with a different bin microphysics scheme by J.-P. Chen and Lamb (1994). This scheme has been implemented in SAM for Pi chamber simulations by Yang et al. (2022, 2023, 2025). This model is referred to as SAM-CLbin. To maintain consistency with SAM-Hubin, SAM-CLbin also uses 33 mass-doubling bins of dry CCN, droplets, and ice. Unlike SAM-Hubin, which used a single moment scheme (tracking only mass), SAM-CLbin treats both number and mass concentrations as prognostic variables in each bin. CCN activation follows a Twomey-type parameterization, in which CCN become droplets when the environment supersaturation exceeds their critical supersaturation (Yang et al., 2023). The rest of the model setups, including CCN injection rates and side-wall wetness, are identical to those of the SAM-HUBin.

The third set of SAM LES uses a Lagrangian particle method, referred to as SAM-Lag. It shares the same dynamical core as the other two SAM LES models described above. The Lagrangian cloud microphysical scheme originates from Hoffmann et al. (2015) and has been progressively refined and applied in subsequent studies (e.g., Hoffmann, 2020; Hoffmann et al., 2019). SAM-Lag was recently compared to SAM-CLbin in a warm-phase cloud chamber setup (Yang et al., 2023). Similar to other Lagrangian cloud microphysical schemes, this scheme uses individually simulated computational particles, each representing a multitude of identical hydrometeors. Cloud microphysical process rates (condensation/evaporation, deposition/sublimation) are scaled accordingly to represent the corresponding effect on the thermodynamic fields of SAM, with which the cloud microphysics are two-way coupled to the SAM dynamical core. For the transport of the computational particles, velocity fields are interpolated to particle positions using a scheme that maintains the incompressibility of the flow (cf. Grabowski et al., 2018). The particle growth equation for haze and droplets considers both curvature and solute effects (Hoffmann et al., 2015). For this intercomparison several adaptations were made in the cloud microphysical scheme: ice crystals are assumed to be spherical for calculating deposition and sublimation; nucleation processes are excluded, with ice crystals injected with a prescribed radius of $2 \mu\text{m}$; and particle sedimentation is modeled using a simple velocity parameterization proportional to the square of particle radius for all hydrometeors. The number of computational particles is not fixed, but a balance of particle injections and sedimentation. During liquid-phase stage (CCN injection), about 25 computational particles per grid box represent hydrometeors. In mixed-phase stage (with ice injection), the number of computational particles per grid box increases to about 30, 38, 51, 75, 110, and 120 for ice injection rates of 0.5, 1.5, 3.0, 5.0, 10.0, and $15 \text{ cm}^{-3} \text{ min}^{-1}$, respectively. Note that the concentration of computational particles did not converge for injection rates $\geq 5.0 \text{ cm}^{-3} \text{ min}^{-1}$. To match the prescribed droplet size and concentration, SAM-Lag uses a side-wall wetness of 0.3 and a CCN injection rate of $10.8 \text{ cm}^{-3} \text{ min}^{-1}$. To gain reliable statistics, each simulation includes a 5 min spin-up period without hydrometeor, followed by 40 min of liquid-phase stage (CCN injection), followed by 20 min of mixed-phase stage (CCN and ice injection).

The UWLCM model (University of Warsaw Lagrangian Cloud Model, Dziekan et al., 2019) is an LES model with an Eulerian dynamical core and Lagrangian particle microphysics, similar to SAM. This LES model is referred to as UWLCM-Lag. Advection is solved with the multidimensional positive-definite advection transport algorithm (Smolarkiewicz & Grabowski, 1990) on a dual, Arakawa C-grid. Smagorinsky model is used for SGS turbulence (Smagorinsky, 1963). Droplets, ice crystals and CCN are modeled using the particle-based scheme by Arabas et al. (2015), which implements the Super-Droplet Method (SDM) (S.-i. Shima et al., 2009). Each simulation begins with a 5-min spin-up period, followed by a 12-min of liquid-phase period to reach steady-state droplet statistics, and a 10-min mixed-phase period. To match the observed droplet radius and number concentration, sidewall wetness is set to 0.52, and the CCN injection rate is $11 \text{ cm}^{-3} \text{ min}^{-1}$. Particles are injected uniformly in each grid cell. Each super-droplet represents two real liquid droplets or CCN, which results in approximately 450 super-droplets per grid cell in liquid-phase stage. In the mixed-phase stage, spherical ice

super-particle representing 1 or 2 real ice crystals are injected. The total number of computational particles per grid cell during the mixed-phase stage ranges between 500 and 1,600 depending on the ice injection rates. Rigid boundary conditions are applied, and particles are removed upon contact with the walls. In this version, the latent heat of sublimation is set equal to that of condensation, but estimates using the bulk model show that the resulting particle size, water content, and supersaturation exhibit negligible differences, with the temperature difference being less than 0.05 K within the tested range.

The OpenFOAM (Open Field Operation And Manipulation) with Lagrangian microphysics, referred to as OpenFOAM-Lag, is another LES model. A finite volume method solver named buoyantPimpleFoam from OpenFOAM's development branch (version 20200614) served as base for the simulation of the continuous phase, and was extended to include a transport equation for water vapor. The governing equations are solved with second order accurate schemes, and the Smagorinsky model was used for SGS turbulence (Smagorinsky, 1963). For particle tracking, OpenFOAM's built-in Lagrangian library, the kinematicCloud, was used and extended to include cloud microphysics and heat and mass transfer with the continuous phase, following the approach of Niedermeier et al. (2020). Heat transfer is calculated using the correlation from Ranz and Marshall (1952). The model includes deliquescence/efflorescence effects, and droplet growth follows Köhler theory. Ice particle growth follows the equation in S. Chen et al. (2023). Droplets and ice particles are injected randomly throughout the domain at every time step. OpenFOAM uses a parcel approach (e.g., Gosman & Loannides, 1983), similar to the SDM. Each parcel represents a multitude of real particles with identical properties: five for CCN and liquid droplets; and one to nine for ice crystals depending on the injection rates (1, 1, 2, 3, 6, 9 for injection rates of 0.5, 1.5, 3.0, 5.0, 10.0, and $15 \text{ cm}^{-3} \text{ min}^{-1}$, respectively). Particle motion is computed by integrating Newton's second law to obtain their velocity and from that their displacement per time step. Forces acting on the particles include the sphere drag force with an empiric drag coefficient correlation from Schiller and Naumann (1933) and a correction for small particles according to Cunningham (1910), the gravitational force, and a force representing Brownian motion. Both the spin-up stage and liquid-phase stage are 20 min each, the mixed-phase stage is run for 10 min. As in UWLCM, particles are removed upon contact with walls.

The SCALE-SDM, referred to as SCALE-SDM-Lag, is an LES with Lagrangian microphysics. It consists of two components: SCALE (Scalable Computing for Advanced Library and Environment) and SDM. SCALE is a versatile numerical model designed for weather and climate simulations on Earth and other planets (Nishizawa et al., 2015; Sato et al., 2015). SCALE solves the compressible Navier–Stokes equations for moist air using a finite volume method on an Arakawa-C staggered grid (Arakawa & Lamb, 1977). In the current setup, advection of dynamical variables is calculated with a fourth-order central difference scheme, while tracers are advected using the third-order upwind scheme with Koren's filter (1993). A second-order central difference scheme is employed for other spatial derivatives. Time integration is performed using the fourth order Runge–Kutta scheme for dynamical variables and the three-step Runge–Kutta scheme by Wicker and Skamarock (2002) for tracers. The SGS turbulence parameterization employs the Smagorinsky scheme (Smagorinsky, 1963) with the corrections of Brown et al. (1994) and Scotti et al. (1993). To ensure numerical stability, a fourth-order hyper-diffusion term is applied, with a nondimensional coefficient set to 10^{-4} (Nishizawa et al., 2015). SCALE incorporates SDM for resolving CCN, cloud, and precipitation particle microphysics (S. Shima et al., 2020; S.-i. Shima et al., 2009). Condensation and evaporation are solved using an implicit Euler scheme to handle stiffness. SCALE-SDM-Lag is tested with two grid spacings: 3.125 cm (fine resolution, referred to as SCALE-SDM-Lag-F) and 6.25 cm (coarse resolution, referred to as SCALE-SDM-Lag-C). Each simulation consists of three 30-min stages: a dynamical spin-up period, a liquid-phase stage, and a mixed-phase stage. For SCALE-SDM-Lag-F, the sidewall wetness with respect to ice is set as 0.66, and the CCN injection rate is $10 \text{ cm}^{-3} \text{ min}^{-1}$ to match the observed droplet radius and number concentration. The time steps for dynamics, tracer advection, and microphysics are $0.5 \times 10^{-4} \text{ s}$, 0.02 s, and 0.02 s, respectively. Both sea salt and ice super-droplets are injected every 0.02 s with a rate of 10 super-droplets per grid box per min. For SCALE-SDM-Lag-C, to match the observed droplet radius and number concentration, the sidewall wetness is set the same as in SCALE-SDM-Lag-F, with a slightly lower CCN injection rate ($8 \text{ cm}^{-3} \text{ min}^{-1}$). The time steps for dynamics, tracer advection, and microphysics are $1.0 \times 10^{-4} \text{ s}$, 0.04 s, and 0.04 s, respectively. Both CCN and ice super-droplets are injected every 0.04 s with the rate of 10 super-droplets per grid box per min.

3. Results

Section 3.1 presents a comparison between observations from Desai et al. (2019) and the models performed in this work. All observational data are taken from Desai et al. (2019). Because observational measurements have limitations in distinguishing between ice and liquid, the comparison is based on the statistics of the total PSD (including both liquid and ice) above a cutoff radius limited by the instrumentation's resolution (see Section 2.2). Section 3.2 analyzes modeled liquid and ice properties separately across the models to assess the glaciation behavior.

3.1. Comparison of Observation and Models

In the liquid-phase steady state (i.e., prior to ice injection), all models showed reasonable agreement with the observed mean droplet radius by tuning the model parameters detailed in Section 2.3 (Figure 1). Specifically, the deviation from the target radius of $7.75\ \mu\text{m}$ is within 3%. As we prioritize matching the radius over the number concentration (as noted in Section 2.2), the largest deviation in droplet number concentration is 20.5% in UWLCM-Lag. That said, the variation in droplet number concentration within the simulated domain can easily exceed $10\ \text{cm}^{-3}$ (see Fig. 4 in Wang, Krueger, et al. [2024]). Additionally, as shown in the later analysis, the statistics from UWLCM-Lag fall within the range of the other LES models, indicating that the tuning has achieved a reasonably consistent liquid-phase starting point.

Figure 2 shows the PSDs under two INP injection rates in the observations and model simulations. For particles with radii larger than $3.5\ \mu\text{m}$, both the observations and simulations suggest two broad size populations, corresponding to smaller-radius droplets and larger-radius ice particles. From Figures 2a and 2b, the increase in the INP (ice) injection rate reduces the radii of both populations, resulting in an increased number concentration of the ice population and a larger number of liquid droplets being deactivated. In models that simulate only the chamber core region (the statistical model and DNS-Lag), the liquid population in Figure 2b is narrow and sharp because glaciation (as shown later in Figure 7a) causes the liquid droplets to deactivate into aerosols. In contrast, all models that simulate the entire chamber, except for SCALESDM-Lag-C, show a broader liquid population, indicating a presence of droplets remaining in the domain. See also the discussion of Figure 7. Because not all INP are nucleated in the Pi Chamber, hereafter we will compare the trend using the particle number concentration instead of the INP injection rate.

Additionally, the observed number concentration in the liquid population is significantly less than those in the models. As mentioned earlier, Holo-Pi has a roll-off in the detection probability for droplet radii below approximately $6\ \mu\text{m}$. To ensure a reliable comparison, this higher cutoff radius should be used. The PSDs in Desai et al. (2019) indicate that all cases exhibit a decreased number concentration when the radius is less than $6\ \mu\text{m}$, consistent with this instrument limitation.

Accordingly, we compare the microphysical statistics from observations and models using only particles with radii greater than $6\ \mu\text{m}$. The results are presented in Figure 3, which reveals similar trends in both the observations and the models. Specifically, taking the observations as an example, Figure 3a shows that as the INP injection rate increases, the evaporation of liquid first causes a reduction in total number concentration, along with an increase in mean radius due to efficient ice growth that shifts the mean radius from smaller liquid droplets toward larger ice particles. At intermediate INP injection rates ($0.5\text{--}3.0\ \text{cm}^{-3}\ \text{min}^{-1}$), the decrease in droplet number is roughly balanced by the increase in ice number, leading to a nearly constant total number concentration and an increase in mean radius. When the INP injection rate increases from 3.0 to $5.0\ \text{cm}^{-3}\ \text{min}^{-1}$, the increase in crystal number exceeds the droplet loss, causing the total number concentration to increase. Meanwhile, the mean radius changes from increasing to decreasing: it initially increases because the weighting shifts from liquid droplets to ice particles, but then decreases because the ice-particle radius continues to decrease owing to increasingly strong competition among ice particles, and because ice particles now dominate the mean radius. Figure 3b confirms that the ice radius decreases with increasing ice number concentration. Although the shapes of the curves vary among models, similar turning points are observed in both the mean radius and total water content, consistent with the observed trends.

3.2. Analysis of Liquid and Ice in the Models

As the same ice injection rate can produce different ice number concentrations across models, we use N_{ice} as a more reliable metric to verify inter-model differences. Figure 4 shows the resulting N_{ice} from all models except for

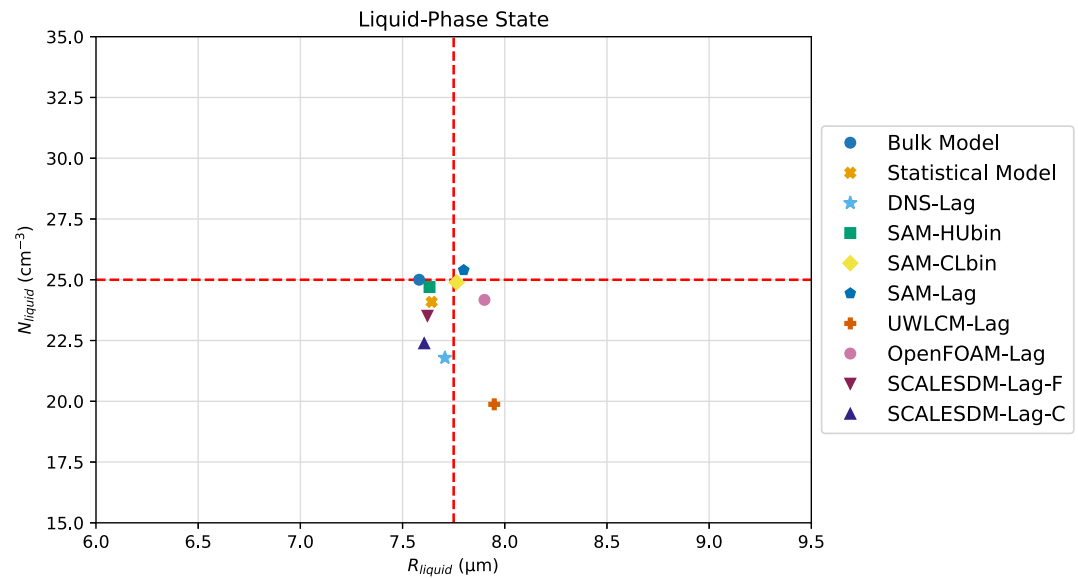


Figure 1. The mean droplet radius and number concentration at steady-state during the liquid-phase stage by each model compared to the Pi Chamber observation. The observational constraints on droplet radius (7.75 μm) and number concentration (25 cm^{-3}) are indicated by red dashed lines.

the bulk model, which specifies the resulting N_{ice} directly instead of injecting ice. All models agree on the trend of increasing N_{ice} with the ice injection rate. SCALE-SDM-Lag-C with a coarser grid spacing apparently produces the highest N_{ice} . One possible explanation is that within each grid cell, particles experience a single supersaturation value representing the cell mean, that is, the sub-grid scale is treated as instantaneously well-mixed. A coarser grid therefore enlarges this implicit homogenization volume, which reduces the supersaturation fluctuations that particles experience (as shown later in Figure 6) and prevents resolution of the localized near-bottom supersaturated layer that sustains liquid droplets in finer-grid simulations (as shown later in Figure 8b). Both effects favor faster glaciation.

Changes in ice and liquid mass fractions as functions of N_{ice} are shown in Figures 5a and 5b. Here, an ice mass fraction of 1 or a liquid mass fraction of 0 indicates full glaciation. Although all models follow similar trends, the bulk model reaches full glaciation at a distinct threshold, whereas the other models approach full glaciation more gradually as N_{ice} increases. All models agree well on the ice water content (Figure 5c), indicating that differences in ice mass fraction among models are primarily due to variations in liquid-phase processes (Figure 5d). In other words, although all models use the same diffusional growth equation for both liquid and ice phases (Table 2), liquid

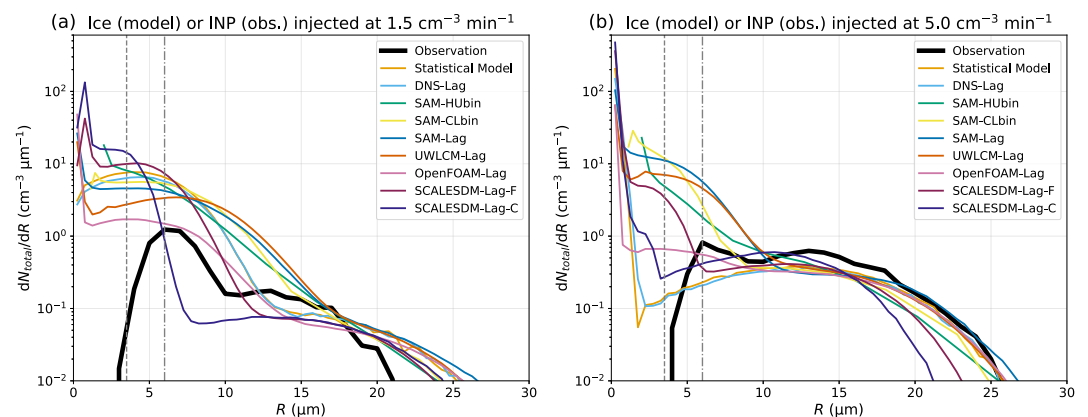


Figure 2. The total particle size distribution (including liquid and ice) at two injection rates of ice (for models) or ice-nucleating particle (for observation). Vertical lines indicate the thresholds used in this work: the dashed lines show a radius of 3.5 μm , and the dotted-dashed lines show a radius of 6 μm .

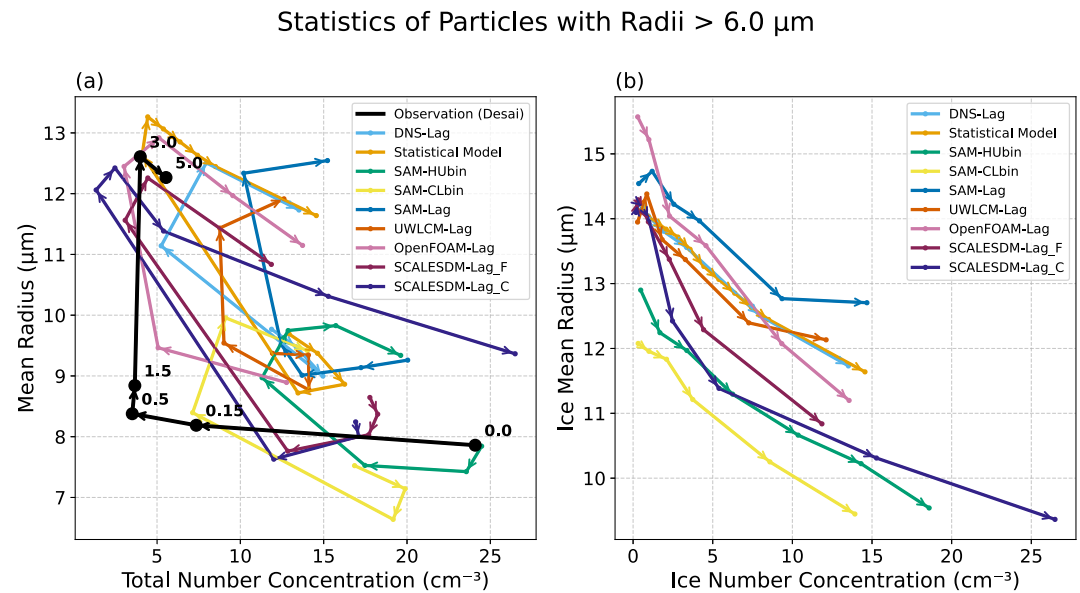


Figure 3. The relationships between (a) mean particle radius and number concentration and (b) ice radius and ice number concentration (simulated results only). Black curves with labeled values indicate observed ice-nucleating particle (INP) injection rates (unit: cm⁻³ min⁻¹), and arrows along each curve indicate the direction of increasing ice (model) or INP (observation) injection rate.

trends diverge while ice trends converge. This occurs because, under the same thermodynamic environment, supersaturation with respect to ice is much larger than that with respect to liquid. When the environment is slightly supersaturated with respect to liquid, ice grows efficiently because its growth is insensitive to local supersaturation fluctuations. Liquid, by contrast, lies near the transition between the mean-supersaturation-dominant and fluctuation-mediated growth regimes (Prabhakaran et al., 2020), where small inter-model differences in S_l can shift droplets between regimes and modify aerosol activation, thereby amplifying inter-model spread in the liquid phase.

Near the glaciation threshold, Figures 5c and 5d illustrate that changes in slope are more pronounced in the liquid water content than in the ice water content. Among the models, OpenFOAM shows the first significant drop in liquid water content (at $N_{ice} \approx 0.3$ cm⁻³), followed by SCALE-SDM and then the other models. In SCALE-SDM, coarser grid spacing results in more efficient glaciation (i.e., lower liquid water content at the same N_{ice}) because particles in each grid cell experience a single supersaturation value (the cell mean), so a coarser grid implies a larger sub-grid volume over which the simulation assumes instantaneous well-mixing. Before the liquid

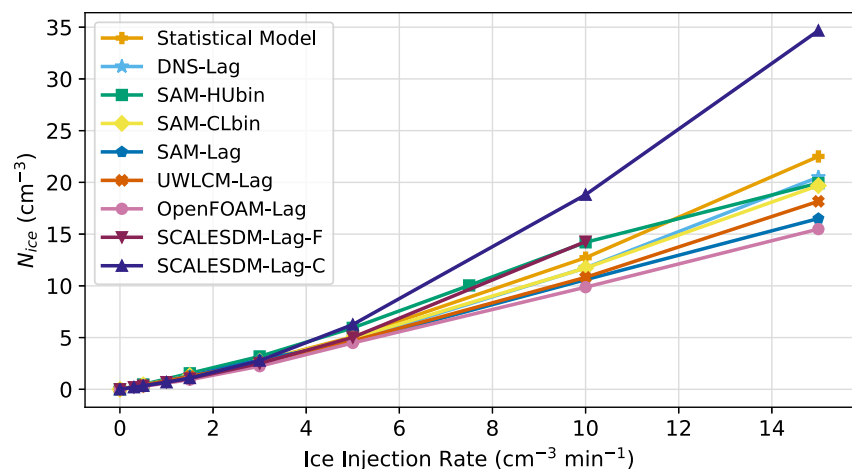


Figure 4. Ice number concentration at steady-state versus the ice injection rate given by each model.

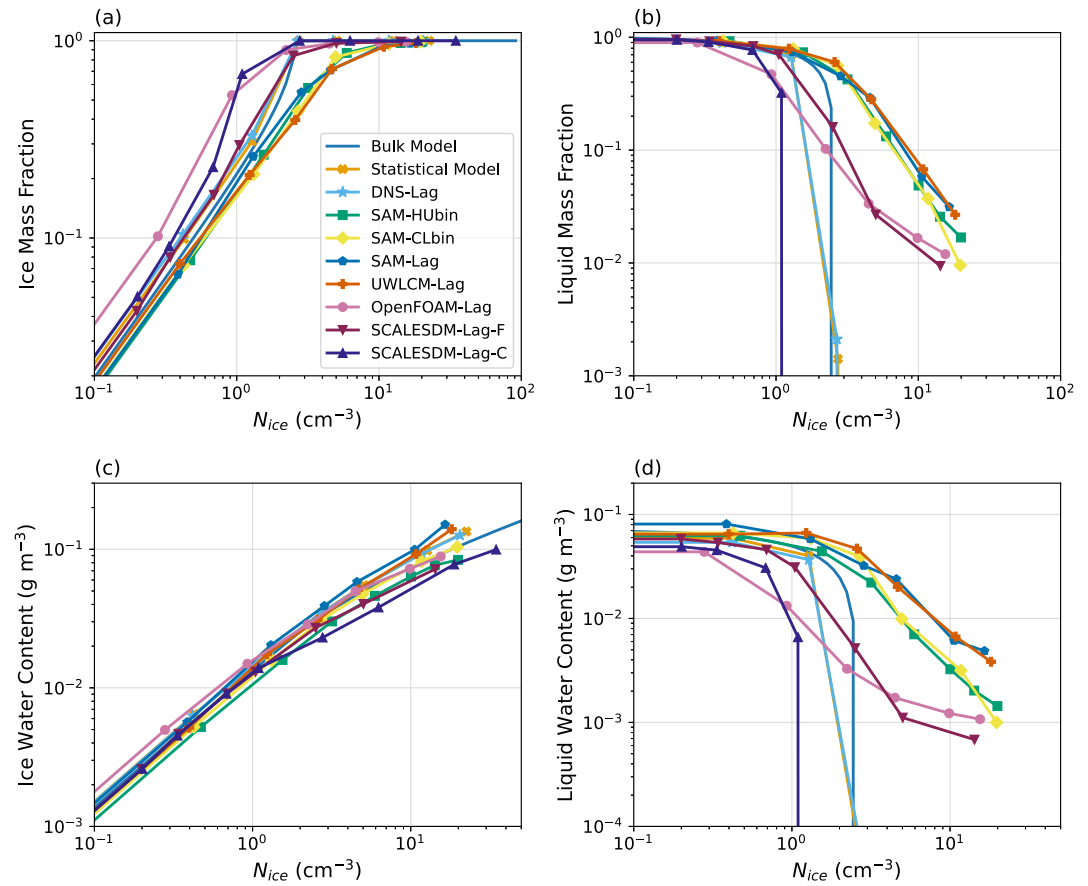


Figure 5. Ice mass fraction (a), liquid mass fraction (b, note that the data extending below the lower bound of the y-axis are zero), ice water content (c), and liquid water content (d) versus ice number concentration.

water content starts to drop (when $N_{ice} < 0.3 \text{ cm}^{-3}$), OpenFOAM shows the lowest liquid water content (Figure 5d), which may be related to the supersaturation: the mean supersaturation in the bulk area in OpenFOAM is negative for all ice injections, whereas other models reach negative only when ice number concentrations exceed certain values (Figure 6a). Note that because depositional growth of ice cannot cause the air to become subsaturated with respect to ice, the supersaturation discussed in this work mainly refers to that with respect to liquid.

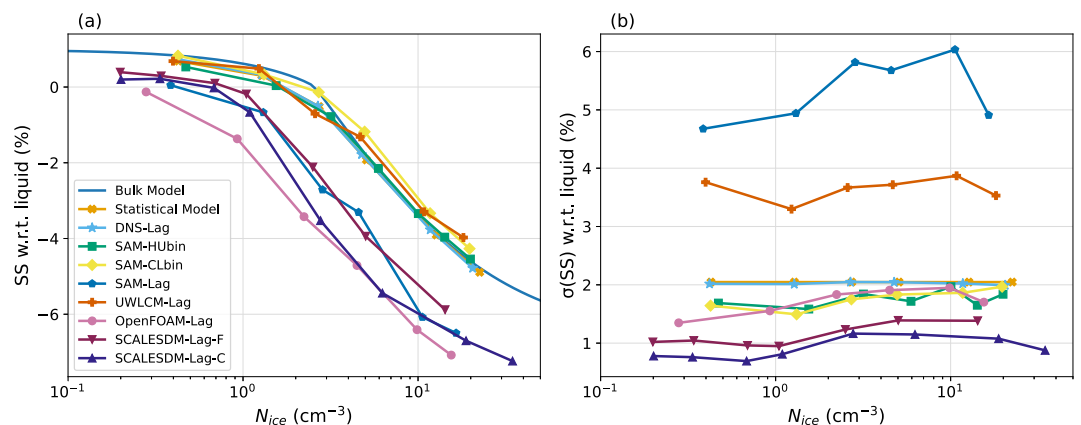


Figure 6. The (a) mean supersaturation and (b) standard deviation of supersaturation with respect to liquid versus ice number concentration in the bulk area excluding 12.5 cm near the walls.

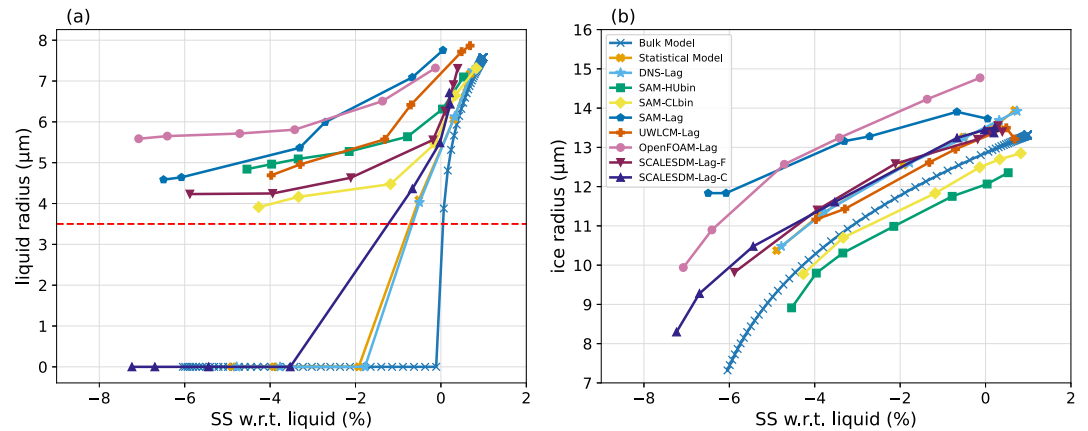


Figure 7. The mean (a) liquid and (b) ice radii versus supersaturation with respect to liquid. The red dashed line indicates the cut-off radius.

Cloud glaciation is strongly affected by reduced supersaturation which leads to the evaporation of liquid. Because supersaturation has strong variations near the walls, for LES models that include the walls, the region within a distance of 12.5 cm from the walls is excluded from the calculation of mean and standard deviation of supersaturation. Figure 6a shows that mean supersaturation generally decreases with increasing N_{ice} , eventually falling below zero at certain points. To accurately represent mean supersaturation for models that simulate only core regions, it is crucial to account for the exchange of water vapor and temperature between the core region and the rest of the chamber. For the statistical model and DNS-Lag, accurate representation of the mean supersaturation requires careful tuning of the forcing scheme, which represents the wall-to-core thermodynamic exchange that entire-chamber models resolve explicitly.

In contrast to the mean supersaturation, supersaturation fluctuations show no clear trend with ice number concentration (Figure 6b). The bulk model assumes a well-mixed domain and does not consider supersaturation fluctuations. The statistical model and DNS-Lag use a prescribed constant supersaturation fluctuation. Among the LES models, SCALE-SDM exhibits the lowest supersaturation fluctuation, which reduces further with coarser grid spacing due to resolving less turbulence. SAM-Lag exhibits the highest supersaturation fluctuation, followed by UWLCM-Lag. SAM-HUBin, SAM-CLbin, and OpenFOAM-Lag show a similar intermediate level.

The relationship between mean particle size and supersaturation is examined in Figure 7. Both liquid and ice particles decrease in size as supersaturation reduces. When the mean liquid radius falls to 0 μm , it indicates that no droplets above the detection threshold remain, signifying full glaciation. Figure 7a shows that, in addition to the bulk model, which has previously shown full glaciation (Wang, Krueger, et al., 2024), DNS-Lag, the statistical

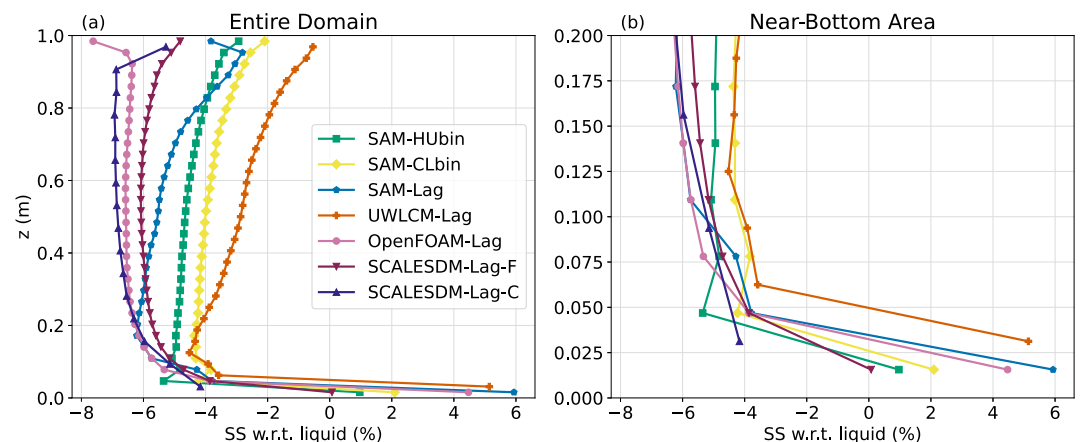


Figure 8. The vertical profile of supersaturation with respect to liquid as ice injection rate is $10 \text{ cm}^{-3} \text{ min}^{-1}$.

model, and SCALE-SDM-Lag-C also predict full glaciated clouds. The reasons are as follows: As discussed in Section 2.2, DNS-Lag and the statistical model describe only the core region of the chamber. While the models account for particle sedimentation, they do not account for particle entrainment from regions outside the core. This is often acceptable, since the chamber is approximately well-mixed and particle properties in the core resemble those in the broader chamber domain, excluding near-wall regions. However, for the current case, the bottom of the chamber remains persistently supersaturated with respect to liquid (see Figure 8), except in SCALE-SDM-Lag-C, where the lowest resolved point is farther from the bottom. This allows continuous CCN activation. Droplets produced in this region can be advected to the core, sustaining liquid phase there. This is a mechanism not captured by core-only models. SCALE-SDM-Lag-C by contrast likely predicts early full glaciation due to an enhanced mixing within its coarser grid spacing, which homogenizes the domain. A comparison with SCALE-SDM-Lag-F reveals that refining the grid spacing increases both supersaturation and its fluctuations (Figure 6), as well as the liquid droplet size in most cases (Figure 7, except for one case in which the mean supersaturation is positive), thereby preventing full glaciation. Figure 7b demonstrate that among the LES models, those using Lagrangian microphysics generally produce larger ice particles compared to bin microphysics. This may be due to a weaker correlation between Lagrangian particles and the supersaturation field compared to bin microphysics (as further illustrated in Figure 9), allowing particles to experience greater supersaturation variations and grow larger (Chandrakar et al., 2016; MacMillan et al., 2022). For core-only models, the statistical model and DNS-Lag include a simplified particle removal scheme to represent sedimentation. A reduction in particle sedimentation rate compared to the Stokes removal specified in S. Chen et al. (2024) is made to match the target liquid-phase steady state (Section 2.3). This adjustment allows larger particles to remain longer in the simulation domain, increasing the mean ice radius. However, it does not affect the mean liquid radius, as liquid are smaller and less influenced by sedimentation.

Previous work by Wang, Krueger, et al. (2024) shows that liquid droplets tend to survive near the bottom region, where moisture and heat fluxes are strongest, creating a supersaturated area. Figure 8 confirms that all LES models agree on this vertical structure, with supersaturation peaking near the bottom. However, SCALE-SDM-Lag-C, due to a coarser grid spacing, failed to resolve this localized supersaturation, resulting in complete glaciation.

Figure 9 illustrates y - z cross sections through the x coordinate of the maximum supersaturation from the LES models. The top and bottom boundaries are saturated with respect to their temperatures, and supersaturation is highest in the region near the bottom (due to the larger temperature difference there) and is gradually mixed upward into the bulk region by turbulence. Although SCALE-SDM-Lag-C is able to produce a localized supersaturation region near the center of the bottom, the area is very small and insufficient to maintain the droplets. Additionally, the correlation coefficients between supersaturation and liquid water content in the models employing bin microphysics are all higher than those using the Lagrangian approach, implying that Lagrangian particles are less coupled with the supersaturation fields. Although neither the Pi Chamber nor the real atmosphere provides three-dimensional observations of supersaturation and liquid water content for verification, the coupling between them depends on the microphysical relaxation time (which helps coupling) and the turbulent mixing time (which leads to decoupling). We expect that as more turbulence is resolved, the two fields become increasingly decoupled; therefore, a reduction in their correlation coefficient is a good indicator.

4. Conclusions

This study presents a comprehensive intercomparison of ten mixed-phase cloud simulations of the Pi Cloud Chamber. The primary objectives are to evaluate each model's ability to reproduce the observed quasi-steady mixed-phase cloud state, understand the convergence or discrepancy among models, and identify the factors influencing cloud glaciation mechanisms under controlled laboratory conditions. Key findings from the intercomparison include:

- All models reasonably reproduce the observed mean droplet radius in the liquid-phase stage (i.e., before ice injection) by tuning model parameters, such as (for simulating the entire domain) side-wall wetness and CCN injection rates, or (for simulating only the core region without the walls) supersaturation forcing and particle settling rates.
- The DNS and statistical models, which simulate only the core region of the chamber, require external forcing to account for wall effects. Despite simplified assumptions, such as homogeneous isotropic turbulence in the

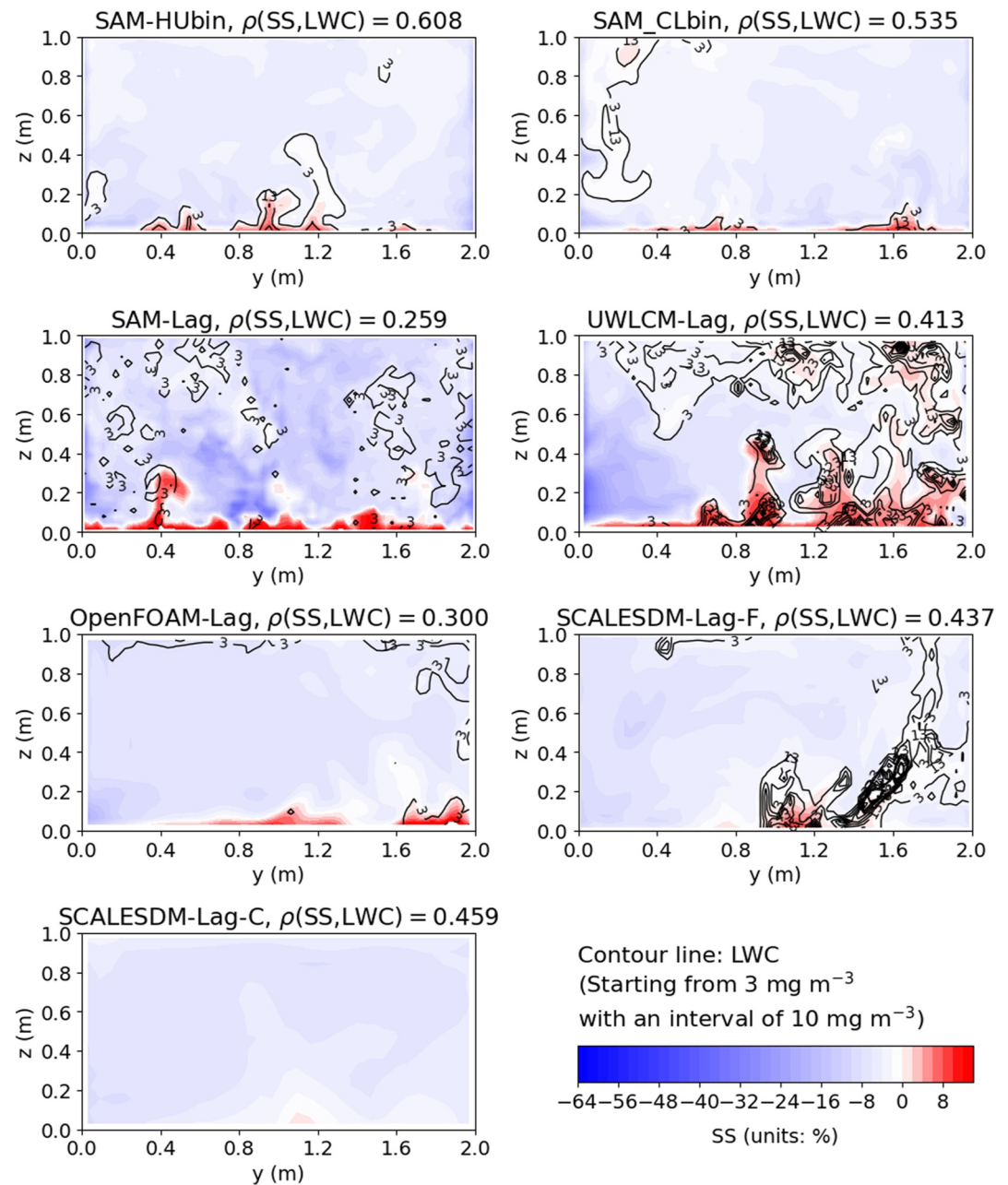


Figure 9. The y - z cross sections of supersaturation with respect to liquid (shading) and liquid water content (contour lines) as the ice injection rate is $10 \text{ cm}^{-3} \text{ min}^{-1}$. The locations of the cross sections are chosen to include the maximum supersaturation. The correlation coefficient (ρ) between supersaturation and liquid water content in the entire domain is shown in the title of each subpanel.

core region and directly solving for the supersaturation equation instead of both temperature and water vapor, both models effectively captured the key glaciation trends when appropriately forced, demonstrating the utility of reduced-complexity approaches.

- Greater inter-model variability is observed in predicting liquid-phase processes than in ice microphysics, which leads to model divergence in the glaciation process.
- Supersaturation plays a central role in cloud evolution. In most cases, even under negative mean supersaturation with respect to liquid, droplets persist due to strong supersaturation fluctuations, especially near the bottom of the chamber where the mean supersaturation is largest.

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- Most LES models do not achieve full glaciation within the tested ice injection rate range. The bulk model and coarse-resolution LES fully glaciate due to enhanced mixing and reduced spatial heterogeneity. The statistical and DNS models reach full glaciation because they exclude the near-wall region.
- Bin microphysics exhibits stronger coupling between supersaturation and liquid water content, while Lagrangian schemes produce larger ice particles and lower number concentrations, likely due to weaker coupling and greater exposure to supersaturation variability.

These findings highlight the importance of resolving fine-scale turbulence and supersaturation variability for accurately simulating mixed-phase cloud processes. They also demonstrate that, even when some bulk statistics (such as ice water content) show little variability, the processes underlying these bulk statistics can differ dramatically because of differences in model configurations, such as grid resolution, domain extent, and microphysical schemes. Furthermore, this cloud chamber-based modeling study underscores the value of laboratory facilities in providing reproducible, well-constrained environments for model evaluation. Additionally, the model simulations not only help to interpret laboratory results (e.g., Lagrangian tracking particles of different phases, explaining why achieving full glaciation is so challenging) but also assist in identifying key locations for sensor placement to enhance laboratory experiments. Lastly, this intercomparison study lays the groundwork for future efforts to improve the representation of mixed-phase clouds in atmospheric models, ultimately contributing to more accurate weather and climate predictions.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The post-processed data are available on Zenodo from Wang, Chen, et al. (2025). The models used for this work are available as follows:

1. The bulk model used in this study is openly available on Zenodo from S. Krueger (2025). The Zenodo record includes the full source code, documentation, and an example simulation.
2. The code for the DNS model is available on Zenodo from Sardina (2025).
3. The code for the Statistical model is available on Zenodo from Sarnitsky (2025).
4. The SAM model was developed by Dr. Marat Khairoutdinov (M. F. Khairoutdinov & Randall, 2003) and is publicly available from M. Khairoutdinov (2022).
5. OpenFOAM is an open source available from OpenCFD Ltd (2020). The version of OpenFOAM used for this work is OpenFOAM-dev 20200614.
6. The UWLCM model and its dependencies, libcloudph++ and libmpdata++, are open-source available to download at Zenodo. The versions used in this studies are: (a) UWLCM 1.1p (Dziekan, Singer, et al., 2025), (b) libcloudph++ 2.1.1p: (Dziekan, Arabas, et al., 2025), (c) libmpdata++ 1.2.1p: (Arabas et al., 2025).
7. SCALE-SDM: Version SCALE 5.2.6-SDM 2.2.2 (Nishizawa et al., 2018; S.-i. Shima, 2020) with modifications for sidewalls and particle injection is available on Zenodo from S.-i. Shima and Enokido (2025).

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