



ERF-SDM Simulations of a Convection Cloud Chamber: Model Development, Benchmark Evaluation, and Aerosol-Cloud-Turbulence Interactions

Jungmin Lee¹, Coleman Kendrick¹, and Debojyoti Ghosh¹, Aaron Lattanzi², Inyeob La³, Emily de Jong¹, Hassan Beydoun¹, Seong Soo Yum^{4,5}, Shaocheng Xie¹, Katie Lundquist¹

¹Lawrence Livermore National Laboratory, Livermore, 94550, United States

²Lawrence Berkeley National Laboratory, Berkeley, 94720, United States

³Graduate School of Information Science, University of Hyogo, Kobe, 651-2197, Japan

⁴Korea Institute of Science and Technology, Seoul, 02792, South Korea

⁵Yonsei University, Seoul, 03722, South Korea

Correspondence to: Jungmin Lee (lee1046@llnl.gov)

Abstract. Convection cloud chambers provide a unique platform for investigating aerosol cloud turbulence interactions under well controlled laboratory conditions and for evaluating numerical cloud microphysics models. This study extends the Energy Research and Forecasting model coupled with the Super Droplet Method (ERF-SDM) to simulate statistically stationary cloud chamber experiments through the implementation of Monin Obukhov similarity theory on all chamber walls, continuous aerosol injection, and wall deposition of super droplets. The model is evaluated using the recent Pi Chamber benchmark configuration from the cloud chamber modeling community and laboratory measurements from the Michigan Technological University Pi Chamber. ERF-SDM successfully represents characteristic chamber circulation and qualitative aerosol-dependent microphysical responses under the prescribed boundary conditions. Process-oriented analyses show that increasing aerosol injection strongly reduces mean and root-mean-square supersaturation, with most of the adjustment occurring between injection rates of 1 and 50 cm⁻³ min⁻¹. Higher injection rates also produce smaller cloud droplets and narrower droplet size distributions. However, the spatial standard deviation of supersaturation does not decrease monotonically, indicating that regulation of the mean thermodynamic state is not accompanied by a corresponding reduction in centered spatial variability. The simulations further demonstrate a transition from an aerosol limited regime at low aerosol injection rates to a vapor limited regime at higher aerosol loading, where competition for available water vapor increasingly limits aerosol activation. These results demonstrate that ERF-SDM, with the new cloud chamber capabilities, can effectively simulate laboratory cloud chamber experiments and investigate the coupled interactions among turbulence, supersaturation fluctuations, aerosol activation, and cloud microphysical evolution, providing valuable insights for understanding aerosol and cloud interactions in Earth system models.



1 Introduction

Clouds influence the Earth's energy balance and hydrological cycle through cloud microphysical processes (Pruppacher and Klett, 1997; Grabowski and Wang, 2013). The activation of aerosol particles into cloud droplets, subsequent condensational growth, and the evolution of droplet size distributions occur over spatial scales ranging from micrometers to meters while interacting continuously with turbulent motions spanning the entire cloud. Because these coupled processes span a wide range of spatial and temporal scales, representing aerosol cloud interactions remains one of the largest sources of uncertainty in atmospheric and climate models (Grabowski and Wang, 2013). One of the central challenges is that cloud droplets both respond to and modify the surrounding supersaturation field. Turbulent mixing continuously generates supersaturation fluctuations, while condensational growth damps those fluctuations through vapor depletion. The competition between these processes controls aerosol activation, droplet growth, and the evolution of droplet size distributions, yet remains difficult to represent accurately in numerical models (Grabowski and Wang, 2013; Chandrakar et al., 2016; Anderson et al., 2024; Krueger and Shaw, 2026).

Investigating these coupled processes in natural clouds remains challenging because aerosol loading, turbulence, and thermodynamic forcing vary simultaneously in space and time. Field observations provide realistic cloud environments but are influenced by continuously evolving meteorological conditions that complicate the interpretation of aerosol, turbulence, and thermodynamic effects. Laboratory cloud chambers provide an attractive alternative because they permit cloud formation under carefully controlled and repeatable boundary conditions while allowing aerosol properties, turbulence intensity, and thermodynamic forcing to be varied independently (Shaw et al., 2020; Krueger and Shaw, 2026). Consequently, convection cloud chambers have become valuable facilities for investigating fundamental aerosol cloud turbulence interactions and for evaluating numerical cloud models under well constrained conditions.

Among laboratory cloud facilities, the Pi Chamber at Michigan Technological University has become one of the most extensively studied platforms for investigating warm cloud microphysics under controlled turbulent conditions. Over the past decade, researchers from Michigan Technological University have used the Pi Chamber to examine aerosol activation, condensational growth, supersaturation fluctuations, droplet size distribution evolution, and aerosol cloud turbulence interactions through a series of laboratory experiments (Chang et al., 2016; Chandrakar et al., 2016; Prabhakaran et al., 2020; Anderson et al., 2024). These experimental studies have been complemented by numerical investigations that reproduced the chamber dynamics and cloud evolution using large eddy simulations and Lagrangian particle-based microphysics (Thomas et al., 2019; Grabowski et al., 2024; Chen et al., 2025; La et al., 2026). Together, these efforts have established the Pi Chamber as a widely adopted benchmark for studying cloud microphysical processes and evaluating numerical cloud models.

Experiments performed in the Pi Chamber have substantially advanced the understanding of aerosol cloud interactions. Measurements have shown that decreasing aerosol loading leads to broader droplet size distributions because droplets compete less strongly for available water vapor and therefore experience a wider range of condensational growth histories (Chandrakar et al., 2016; Prabhakaran et al., 2020). Subsequent studies demonstrated that cloud droplets modify the surrounding



65 supersaturation field through condensational growth, with the efficiency of this buffering depending strongly on aerosol concentration and the relative time scales of turbulence and cloud microphysics (Anderson et al., 2024). Recent numerical investigations further showed that the cloud microphysical Damköhler number provides a useful framework for interpreting the transition between slow microphysical adjustment and rapid supersaturation buffering (Grabowski et al., 2024; Krueger and Shaw, 2026; La et al., 2026). Despite these advances, an outstanding question is how increasing aerosol loading shifts the balance between turbulent mixing and condensational adjustment, and how this transition influences supersaturation fluctuations, droplet size distributions, and aerosol activation across different cloud microphysical regimes.

The insights gained from these laboratory experiments have motivated the development of increasingly sophisticated numerical models capable of reproducing the coupled evolution of turbulence, supersaturation, and cloud microphysics. While traditional bulk microphysics schemes remain computationally efficient, both bulk and spectral bin approaches require assumptions regarding droplet populations, such as prescribed shape parameters in bulk or finite mass resolutions in bins. Furthermore, they often cannot fully represent stochastic condensational growth or activation in turbulent environments (Khain et al., 2015). Lagrangian particle-based methods, particularly the Super Droplet Method introduced by Shima et al. (2009), explicitly represent computational particles that evolve independently within the resolved flow. This approach naturally captures aerosol activation, condensational growth, evaporation, sedimentation, and collision processes without prescribing an analytical droplet size distribution. Recent applications of Lagrangian microphysics to the Pi Chamber have successfully reproduced observed cloud evolution and demonstrated that explicit particle methods provide valuable insight into the mechanisms governing condensational growth and droplet size distribution broadening (Grabowski et al., 2019; Grabowski et al., 2024; La et al., 2026).

Building on more than a decade of experimental and numerical studies, Chen et al. (2025) recently organized the first comprehensive intercomparison of cloud microphysics models using a common Pi Chamber benchmark configuration. The benchmark highlighted both the overall consistency among modern cloud microphysics models and remaining differences in simulated supersaturation, droplet number concentration, and droplet size distributions. Such benchmark experiments provide an important foundation for evaluating new numerical frameworks while enabling process-oriented analyses under carefully controlled conditions.

90 In this study, we extend the Energy Research and Forecasting model (ERF; Lattanzi et al., 2025) coupled with the Super Droplet Method (ERF-SDM; Beydoun et al., 2026) to simulate statistically stationary convection cloud chamber experiments. New model capabilities include Monin Obukhov similarity theory applied to all chamber walls, continuous aerosol injection, and wall deposition of super droplets. We evaluate the model using the community Pi Chamber benchmark of Chen et al. (2025) and laboratory measurements. Beyond model evaluation, we investigate how aerosol loading influences mean supersaturation, spatial supersaturation variability, condensational adjustment time scales, aerosol activation, and droplet size distribution evolution.



Section 2 describes the ERF-SDM framework and the newly implemented cloud chamber capabilities. Section 3 presents the benchmark case configuration. Section 4 evaluates the model and examines the physical mechanisms governing aerosol cloud turbulence interactions. Finally, Section 5 summarizes the major findings and implications of this work.

100 2. ERF-SDM for convection type cloud chamber simulations

2.1 ERF-SDM

The simulations presented in this study were performed using the Energy Research and Forecasting model (ERF; Lattanzi et al., 2025) coupled with the Lagrangian Super-Droplet Method (ERF-SDM; Beydoun et al., 2026). ERF is an open-source atmospheric model developed for high-performance computing systems and designed to efficiently exploit both CPU- and GPU-based architectures. The model solves the fully compressible, nonhydrostatic equations governing atmospheric flow on a staggered Arakawa C-grid using a finite-volume formulation. Its modular framework supports a variety of physical parameterizations and numerical methods, making it suitable for applications ranging from microscale turbulence to regional atmospheric simulations. Detailed descriptions of the governing equations, numerical discretization, and model architecture are provided in Lattanzi et al. (2025).

Cloud microphysics are modeled with the Lagrangian Super-Droplet Method (SDM), originally developed by Shima et al. (2009) and recently implemented in ERF (Beydoun et al., 2026). Unlike conventional bulk or spectral-bin microphysics schemes, SDM explicitly tracks computational particles, referred to as super-droplets, each representing a population of identical physical droplets through an associated multiplicity. Every super-droplet carries its own position and microphysical attributes, including droplet size and aerosol masses, and evolves independently in response to the resolved flow field. This particle-based representation naturally resolves the droplet size distribution without assuming a prescribed functional form and allows cloud activation, condensational growth and evaporation, sedimentation, and stochastic collision-coalescence to be simulated explicitly. The collision-coalescence process is treated using the Monte Carlo algorithm proposed by Shima et al. (2009), while condensation and evaporation are calculated by coupling the Lagrangian particles with the Eulerian thermodynamic fields. Droplet activation and diffusional growth follow Köhler theory, in which the equilibrium vapor pressure over each droplet is governed by the competing curvature (Kelvin) and solute (Raoult) effects. The activation of the prescribed aerosol arises directly from the resolved supersaturation rather than from a separate parameterization. Gravitational sedimentation uses the terminal-velocity relations of Beard (1976). The framework additionally supports mixed-phase processes, including droplet freezing, vapor deposition and sublimation, riming, and melting, which are not active in the warm-cloud configuration considered here.

In ERF-SDM, the Eulerian dynamics and Lagrangian microphysics are two-way coupled. The resolved atmospheric flow transports the super-droplets, while latent heating and moisture changes associated with droplet growth or evaporation are mapped back onto the Eulerian grid to update the thermodynamic state. This coupling enables explicit representation of aerosol activation and warm-rain microphysical processes while maintaining consistency with the resolved turbulent flow. Additional



implementation details and verification of the ERF-SDM framework are described by Beydoun et al. (2026). The version of
130 ERF-SDM used to perform the simulations in this study is available on
Zenodo at <https://doi.org/10.5281/zenodo.23018675> (Lee et al., 2026).

2.2 New features to the model for the cloud chamber simulations

2.2.1 Implementing Monin-Obukhov Similarity Theory on all 6 sides of the domain walls

In the ERF-SDM cloud-chamber simulations, turbulent exchange at the solid boundaries is represented with a wall-function
135 formulation based on Monin-Obukhov similarity theory (MOST). The revised implementation applies MOST as a wall
boundary condition on all six faces of the chamber rather than only at the lower z boundary. Thus, the lower, upper, and side
walls are all treated as active turbulent exchange surfaces for momentum, heat, and moisture.

At each wall, the first interior grid cell is sampled to determine the reference state consisting of local tangential wind
speed, potential temperature, and water-vapor mixing ratio. The reference state is then used to diagnose the friction velocity,
140 thermal scale, moisture scale, Obukhov length, turbulent heat flux, moisture heat flux, and tangential shear stresses. The
stability dependence is evaluated iteratively using the same MOST framework on each face, with the local near-wall state and
prescribed wall properties defining the exchange at that boundary.

The computed fluxes and shear stresses at each face are output into the corresponding directional flux or stress array
so that each boundary contributes momentum and scalar exchange in the directional normal to that wall. At each wall,
145 the reference velocity is rotated into the local wall plane to allow the tangential velocity components to be evaluated
correctly at each face. Flux signs are handled with respect to the outward normal of each face so that low and high faces
impose physically consistent wall-normal exchange.

The upper boundary required a special treatment because the physically unstable chamber configuration is imposed from the
top wall downward rather than from a lower surface upward. For the high- z boundary, the local MOST coordinate was
150 redefined so that the top wall is treated as the origin of the wall-normal coordinate. The top boundary is assigned coordinate
level z_0 , and the first grid point inside the domain below the lid is treated as coordinate level z_1 . In practice, this is achieved
by flipping the wall-normal coordinate relative to the global vertical coordinate, so that the local coordinate is zero at the top
wall and increases inward into the chamber. In the code, this is implemented by treating the upper boundary as a high- z face
and swapping the wall and adjacent-cell thermodynamic states in the MOST stability calculation. This makes the top-wall
155 calculation equivalent to a lower-wall unstable surface layer in the local coordinate system, while preserving the physical
location of the flux at the upper boundary. As a result, the MOST stability functions interpret the top boundary as an unstable
driving surface. This treatment is not required on the lateral faces because they do not have a physically unstable condition.

This extension to ERF allows the chamber walls to act as active turbulent exchange surfaces rather than passive lateral or upper
boundaries. Wall effects are therefore represented consistently on the lower, upper, and side boundaries, including the
160 dependence of stress and scalar transfer on local stability and near-wall velocity. This is particularly important for small,



enclosed domains such as a cloud chamber, where all walls can influence the turbulent structure, heat and moisture budgets, and the development of near-wall gradients. The implementation therefore provides a more physically complete representation of wall-driven exchange throughout the computational domain.

2.2.2 Implementation of aerosol injection

165 The aerosol source is implemented within the super droplet framework as a time dependent injection algorithm. Instead of prescribing all aerosol particles only at the initial time, the model introduces new computational particles during the simulation within a user-specified subdomain. Each injection is defined by an input rate, start time, stop time, source volume, and optional source velocity, allowing the aerosol source region to remain fixed or move through the domain. The injected super-droplets carry prescribed aerosol masses and, when needed, water or ice mass. Their aerosol and water/ice masses are assigned from
170 constant, exponential, or lognormal size distributions, so the source can represent either monodisperse particles or a broader aerosol population.

At each step, the algorithm converts the prescribed physical aerosol injection rate into a finite number of super-droplets and assigns each one a multiplicity, which represents the number of physical particles carried by that computational particle. For weak sources, fractional particle counts are accumulated across time steps until enough material has entered the system to
175 create a computationally meaningful injection event. This implementation also includes a per-box high multiplicity option, in which a limited number of super-droplets are randomly scattered throughout the source volume while each particle carries a larger multiplicity. This minimizes the computational cost while preserving the intended aerosol number input. Newly injected particles are placed within the specified source region, assigned unique identifiers, initialized with their aerosol masses, and then evolve with the same transport, collision, and phase change processes as the rest of the super droplet population.

180 2.2.3 Implementation of droplet deposition

Wall deposition of super-droplets is represented by an absorbing boundary treatment. After particle advection, super-droplets that cross the bottom, top, or lateral boundaries specified as solid walls are treated as deposited on that surface. These particles are then deactivated, zeroing their multiplicity, velocity and terminal fall speed, and excluding them from subsequent transport and microphysical evolution. Deactivated particles are deleted from the memory during particle redistribution, so they do not
185 incur storage or computational costs.

This treatment provides a simple representation of irreversible particle loss to chamber surfaces. Deposited particles no longer contribute to airborne number concentration, liquid or ice mass, collision processes, phase change, or aerosol activation within the gas phase. The algorithm therefore captures the depletion of suspended particles by wall contact, which is important in a finite cloud chamber where gravitational settling, turbulent transport, and wall driven circulation can all bring particles to the
190 boundaries. Periodic directions, when used, are not treated as deposition surfaces. A lateral boundary that is neither a solid wall nor periodic instead recycles the particle as fresh aerosol at the opposite face rather than depositing it. Therefore, particles are only removed at boundaries that represent physical chamber walls. However, this treatment is one-way. The



thermodynamic effects of deposited droplets on the chamber walls are not represented. In particular, droplet deposition does not modify the prescribed wall temperature or relative humidity.

195 3 Case Study

3.1 Benchmark study of Chen et al. (2025)

The simulations are based on the large-eddy simulation (LES) benchmark case of Chen et al. (2025), which represents a warm-cloud experiment conducted in the Michigan Technological University Pi Chamber. The benchmark was developed to evaluate cloud microphysics models under controlled laboratory conditions and provides a statistically stationary turbulent cloud driven
200 by prescribed thermal boundary conditions and continuous aerosol injection. Unless otherwise noted, all model parameters are identical to those described by Chen et al. (2025).

The chamber is driven by a fixed temperature difference between the horizontal boundaries. The bottom wall is maintained at 299 K, while the top wall is held at 280 K, producing buoyancy-driven turbulent convection. Both horizontal walls are assumed to be saturated with respect to liquid water. Unlike the benchmark configuration of Chen et al. (2025), which prescribed a
205 constant sidewall temperature of 285 K, the present study sets the sidewall temperature to the arithmetic mean of the top and bottom boundary temperatures (289.5 K). This choice is consistent with the experimental configuration described by Anderson et al. (2024), where the Pi Chamber sidewalls were maintained near the mean temperature of the upper and lower plates rather than at 285 K. Furthermore, the convection-type cloud chamber simulations of La et al. (2026), which adopted an intermediate
sidewall temperature to minimize artificial lateral thermal forcing while preserving the imposed vertical temperature gradient,
210 and a similar treatment has also been used in more general Rayleigh–Bénard convection studies (Stevens et al., 2014).

The sidewall relative humidity is prescribed at 100%, following La et al. (2026) and representing the wetted wall conditions used in laboratory chamber experiments. Thus, all six walls are maintained at saturation with respect to liquid water in the primary simulations. We also performed additional simulations with reduced sidewall relative humidity to obtain a mean chamber supersaturation of approximately 3% before aerosol injection, following the benchmark setup of Chen et al. (2025).
215 This adjustment did not alter the overall qualitative response of droplet microphysical properties to changes in aerosol injection rate (not shown). However, the response of the spatial supersaturation standard deviation differed between the reduced-RH and saturated-wall configurations, as discussed in Section 4.3. Section 4.6 further examines the sensitivity of equilibrium cloud microphysical properties to variations in sidewall relative humidity and the resulting changes in pre-cloud chamber supersaturation.

220 Monodispersed dry NaCl, with a diameter of 125 nm, continuously injected into each cell of the chamber domain throughout the simulation after 30 minutes of spin up. Aerosol particles are represented explicitly by super-droplets, allowing activation and subsequent cloud droplet growth to be simulated without assuming a prescribed droplet size distribution. The aerosol injection rates we tested are 1, 10, 50, 100, 500, 1000 cm³min⁻¹.



The computational domain measures $2\text{ m} \times 2\text{ m} \times 1\text{ m}$ and is discretized using a uniform grid spacing of 3.125 cm in all three directions, yielding $64 \times 64 \times 32$ grid cells. The simulations use a time step of 0.025 s. The simulations are initialized with quiescent flow with no aerosols and integrated until the chamber reaches a statistically stationary state (about 30 minutes) and then the aerosol injection starts and continues for 1 hour. The simulations were run on the Livermore Computing (LC) HPC Tuolumne system using 8 AMD MI300A GPUs (2 nodes) and took about 6 - 12 hours to complete depending on the number of super droplets.

4 Results

4.1 Mean Thermodynamic Properties

Figure 1 shows the evolution of the chamber-mean thermodynamic and turbulence properties for the different aerosol injection rates. Following the analysis of Grabowski et al. (2024), the averages were calculated over the inner chamber volume, excluding grid cells adjacent to the solid boundaries, where strong wall gradients may not be representative of the well-mixed chamber interior. Grabowski et al. (2024) similarly calculated turbulent kinetic energy and other bulk properties over the chamber volume away from the walls and horizontal boundaries. Before aerosol injection begins at 30 min, the simulations converge toward similar turbulent conditions, with a mean TKE of approximately $4 \times 10^{-3}\text{ m}^2\text{ s}^{-2}$. This value is similar to the Pi Chamber measurements reported by Thomas et al. (2019) for comparable forcing. Their measured two-dimensional TKE was approximately $4\text{--}5 \times 10^{-3}\text{ m}^2\text{ s}^{-2}$ for imposed temperature differences of 18-20 K.

Aerosol injection and the subsequent activation and condensational growth of droplets produced a rapid thermodynamic adjustment. Condensation removed water vapor from the gas phase and released latent heat, resulting in an increase in the chamber-mean temperature and a decrease in specific humidity. Together, these changes reduced the relative humidity and supersaturation of the chamber interior. This response was consistent with the Pi Chamber observations of Anderson et al. (2024), who reported a decrease in water vapor mixing ratio, a corresponding increase in temperature from latent heating, and a reduction in saturation ratio following cloud formation. In the ERF-SDM simulations, higher aerosol injection rates generally produced greater temperature increases and a decrease in chamber-mean specific humidity, consistent with enhanced condensational heating and water vapor depletion associated with the activation and growth of more droplets.

Figure 2 illustrates the flow and thermodynamic structures of the simulated cloud chamber before aerosol injection. The chamber developed a large-scale moist Rayleigh–Bénard circulation driven by buoyancy generated from the imposed temperature difference between the warm lower boundary and the cold upper boundary. Figure 2a shows the mean velocity field averaged over the y direction and over the final 5 min of the spin-up period. The flow organized into a single anti-clockwise circulation cell, with warm air rising along the right side of the chamber, horizontal transport beneath the upper boundary, descending motion along the left side, and return flow near the bottom boundary. Although the chamber was maintained by a 19 K temperature difference between the top and bottom boundaries, Figure 2b shows that the chamber interior was nearly isothermal. Away from the boundary layers, the horizontal temperature difference remained below approximately



0.14 K, indicating efficient turbulent mixing within the core of the chamber. The weak horizontal temperature gradient reflects the large-scale circulation, with slightly warmer air occupying the ascending branch on the right side of the chamber and slightly cooler air associated with the descending branch on the left side. Figure 2c shows the relative humidity field inside the chamber. The chamber interior was nearly homogeneous, consistent with vigorous turbulent mixing. Small humidity differences were confined primarily near the side walls, where the humidity is lower than the rest of the chamber.

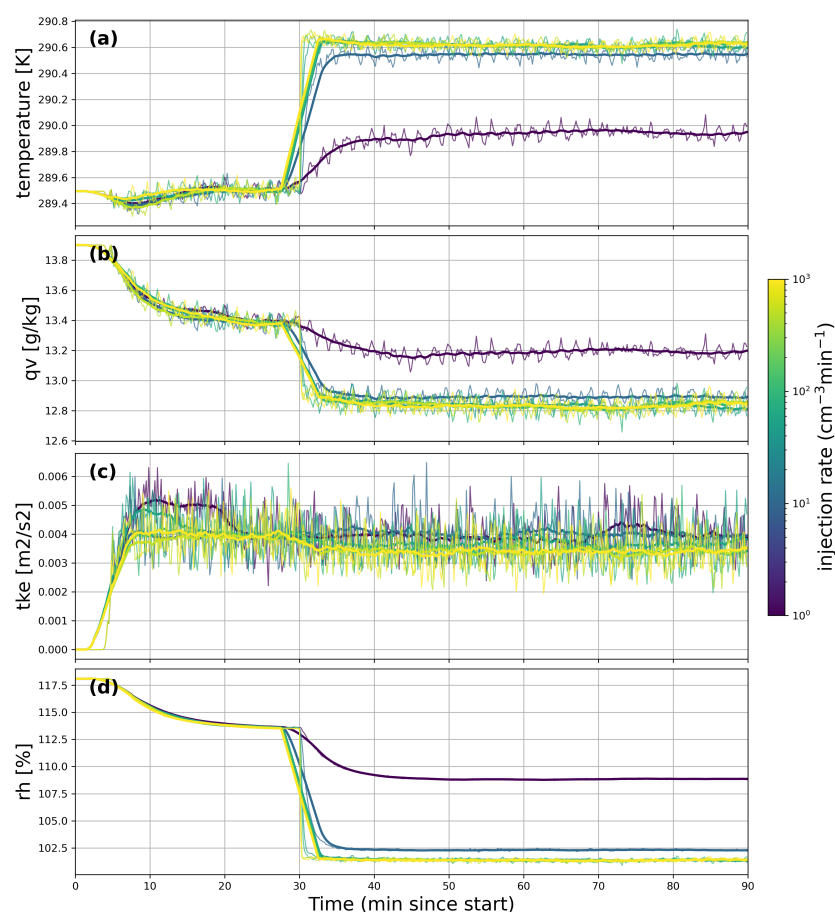


Figure 1. Time series of inner-volume-averaged chamber properties: (a) temperature, (b) specific humidity, (c) turbulent kinetic energy, and (d) relative humidity. The inner-volume average excludes grid cells adjacent to the chamber boundaries. Colors denote aerosol injection rates, and aerosol injection begins at 30 min. Thin lines show model output at 10-s intervals, while thick lines show the smoothed time series. Injection rates are 1, 10, 50, 100, 500, 1000 $\text{cm}^{-3}\text{min}^{-1}$.

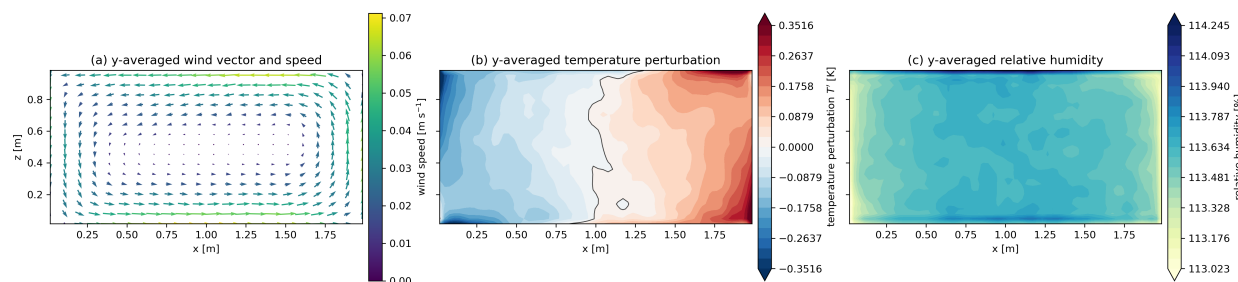


Figure 2. (a) x-z wind vector where color represents the speed, (b) temperature perturbation, and (c) relative humidity. All fields are averaged across y axis and time averaged from 25 to 30 min into the simulation.

4.2 Mean Microphysical Properties

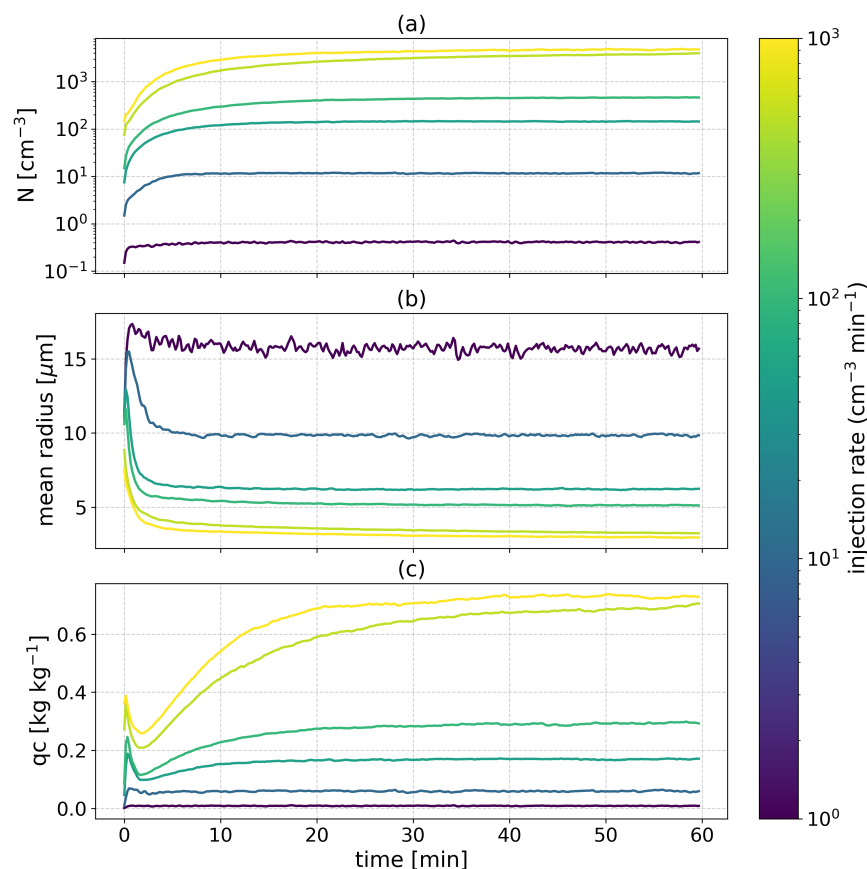


Figure 3. Time series of domain-averaged microphysical quantities as shown in (a) droplet number concentration, (b) mean radius, (c) specific humidity for liquid water. Different colors represent different aerosol injection rates. Time series starts from the beginning of the aerosol injection. Injection rates are 1, 10, 50, 100, 500, 1000 $\text{cm}^{-3}\text{min}^{-1}$.



Following the onset of aerosol injection (after 30-min of spin-up), all simulated microphysical quantities evolved rapidly before approaching statistically stationary values, indicating that the chamber reached a quasi-equilibrium microphysical state. This steady state resulted from the balance among continuous aerosol injection, condensational growth, turbulent transport, and droplet deposition at the chamber walls (Figure 3). To note is that here cloud droplets are defined as particles with radii greater than or equal to 1.5 μm , following the definition adopted in the Pi Chamber benchmark study of Chen et al. (2025).

The equilibrium microphysical properties exhibited a strong dependence on aerosol injection rate. Increasing the aerosol injection rate produced progressively larger droplet number concentrations (Figure 3a), while the mean droplet radius decreased (Figure 3b). At the same time, the domain-averaged cloud water mixing ratio increased (Figure 3c). These trends are consistent with the activation of a larger number of cloud droplets under higher aerosol loading, resulting in increased droplet concentrations, smaller characteristic droplet sizes, and greater liquid water contents. The simulated equilibrium values of droplet number concentration, mean droplet radius, and cloud water mixing ratio fall within the range reported by the participating models in the Pi Chamber model intercomparison study of Chen et al. (2025), demonstrating that ERF-SDM reproduces the characteristic microphysical behavior of the benchmark case. Similar relationships between aerosol loading, droplet number concentration, mean droplet size, and liquid water content have also been reported in laboratory measurements and numerical simulations of the Pi Chamber (e.g., Anderson et al., 2024; Grabowski et al., 2024).

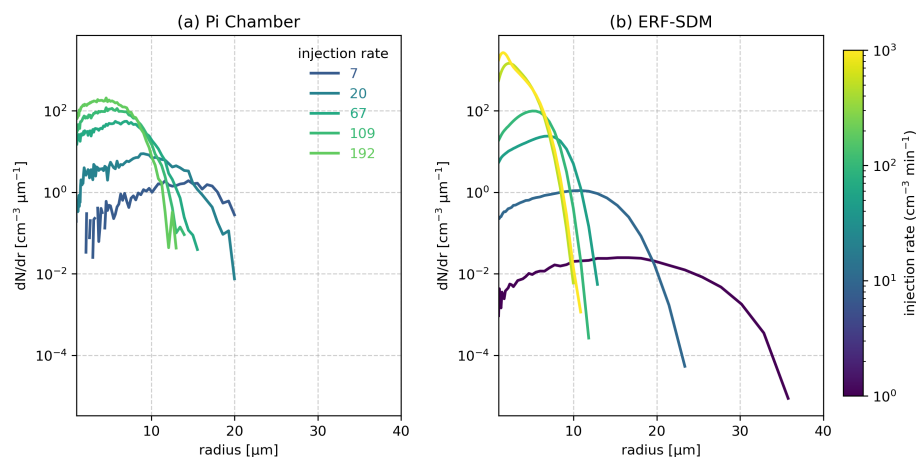


Figure 4. Droplet size distributions (DSDs) at steady-state from (a) Pi Chamber experiments and (b) ERF-SDM simulations. Different colors indicate different injection rates.

Figure 4 compares the steady-state droplet size distributions (DSDs) measured in the Pi Chamber with those simulated by ERF-SDM for different aerosol injection rates. Only cloud droplets with radii greater than or equal to 1.5 μm are included in this analysis, consistent with the definition adopted throughout this study and in the benchmark simulations of Chen et al. (2025).

The Pi Chamber measurements (Figure 4a), adapted from Prabhakaran et al. (2020) for the 18 K temperature difference case, exhibit a clear dependence of the DSD on aerosol injection rate. As the injection rate decreases, the droplet size distribution



becomes progressively broader while shifting toward larger droplet radii. Previous studies have attributed this broadening primarily to condensational growth in a turbulent supersaturated environment. Under lower aerosol loading, droplets experience weaker competition for available water vapor, allowing supersaturation fluctuations generated by turbulent mixing to produce a wider range of droplet growth histories and, consequently, a broader size distribution (Chandrakar et al., 2016; Prabhakaran et al., 2020; Grabowski et al., 2024).

The ERF-SDM simulations reproduce the same qualitative behavior (Figure 4b). The simulated DSD broadened as the aerosol injection rate decreased, while the distributions became progressively narrower with increasing injection rate. For injection rates of approximately $100 \text{ cm}^{-3} \text{ min}^{-1}$ and above, however, the DSD exhibited relatively little sensitivity to further increases in aerosol injection rate. This weak sensitivity may partly reflect the absence of an explicit treatment of subgrid-scale turbulent supersaturation fluctuations, which could contribute to variability in droplet activation and condensational growth. In addition, the prescribed dry aerosols were perfectly monodisperse, whereas small variations in dry aerosol diameter in laboratory experiments could introduce additional variability in activation and subsequent droplet growth. These potential contributions require further investigation. The simulated DSDs and their dependence on aerosol injection rate were also comparable to those reported by the participating models in the Pi Chamber model intercomparison of Chen et al. (2025), providing additional confidence that ERF-SDM captured the dominant microphysical processes governing droplet growth in the chamber.

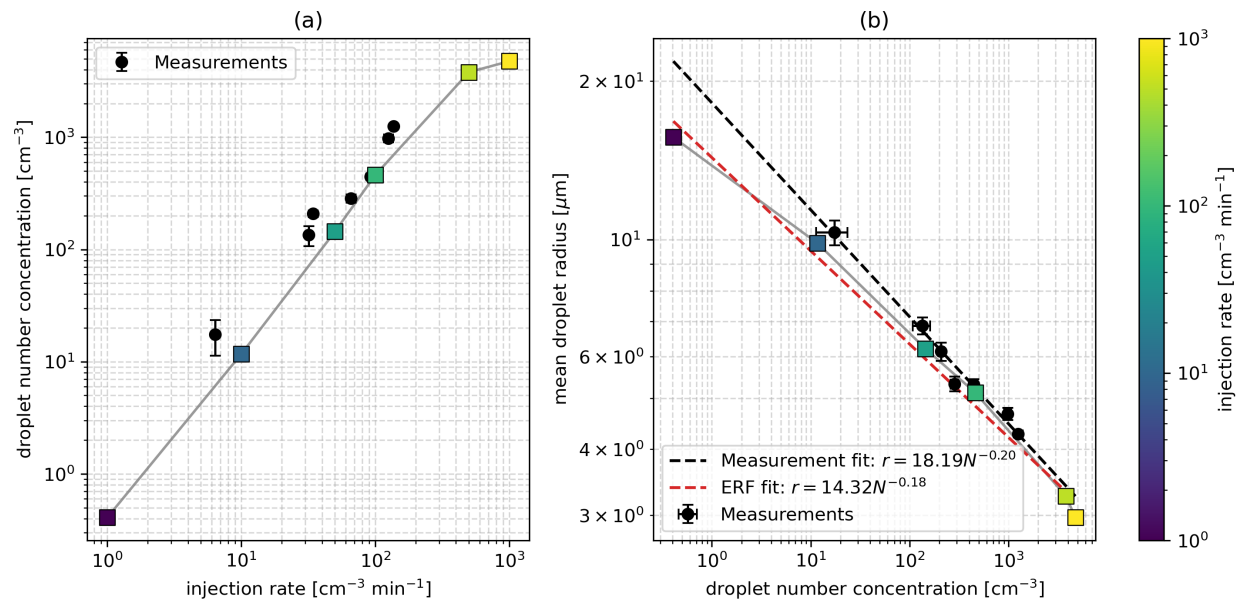


Figure 5. Scatter plot between (a) injection rate and droplet number concentrations and (b) droplet number concentration and mean droplet radius. Pi-Chamber measurements are given in black line.

Figure 5 compares the simulated equilibrium droplet number concentration and mean droplet radius with the Pi Chamber measurements reported by Anderson et al. (2024). The measurements were obtained with a top-to-bottom wall temperature difference of 16 K. Anderson et al. (2024) reported the aerosol concentration in the airstream injected into the chamber in units



of kpcc, where 1 kpcc corresponds to 10^3 particles cm^{-3} . These values were converted to chamber-equivalent aerosol
320 injection rates according to

$$J_{aer} = \frac{C_{inj} Q_{inj}}{V_{ch}},$$

where C_{inj} is the aerosol concentration in the injected airstream, $Q_{inj} = 2 L min^{-1}$ is the volumetric flow rate, and V_{ch} is the
chamber volume. For C_{inj} in kpcc, Q_{inj} in $L min^{-1}$, and the Pi Chamber volume of $3.14 \times 10^6 cm^3$, with J_{aer} expressed in
325 $cm^{-3} min^{-1}$. Consequently, the aerosol concentrations of 10, 50, 54, 103, 146, 196, and 214 kpcc reported by Anderson et al.
(2024) correspond to chamber-equivalent aerosol injection rates of 6.4, 31.8, 34.4, 65.6, 93.0, 124.9, and $136.3 cm^{-3} min^{-1}$,
respectively.

Figure 5a compares aerosol injection rate with the equilibrium droplet number concentration. Both the measurements and the
simulations exhibit a monotonic increase in droplet number concentration with increasing aerosol injection rate. ERF-SDM
330 reproduced the observed dependence over nearly two orders of magnitude in injection rate, demonstrating that the model
realistically captured aerosol activation and the establishment of equilibrium droplet populations within the chamber.

Figure 5b compares the relationship between droplet number concentration and mean droplet radius. Both the measurements
and the simulations exhibited an inverse power-law relationship, whereby larger droplet concentrations corresponded to
smaller mean droplet radii. Fitting the relationship in the form $r_{mean} = aN^b$ yielded $r_{mean} = 18.19N^{-0.20}$ for the Pi Chamber
335 measurements and $r_{mean} = 14.32N^{-0.18}$ for ERF-SDM. The similar exponents indicate that ERF-SDM reproduced the
observed sensitivity of droplet size to droplet number concentration. However, the smaller fitted prefactor for ERF-SDM is
consistent with the simulated mean droplet radii being systematically lower than the measurements. The inverse relationship
reflects increasing competition for available water vapor as aerosol loading increases, so that the available condensate is
distributed among a larger droplet population. Consequently, droplets remained smaller under high-aerosol conditions.

340 The underestimation of droplet radius may arise from differences between the experimental and simulated conditions,
including uncertainties in the chamber supersaturation or simplifications in the numerical representation of aerosol activation
and condensational growth. Nevertheless, the agreement in the overall scaling behavior indicates that ERF-SDM captures the
dominant physical processes controlling the equilibrium cloud microphysics in the Pi Chamber.



4.3 Aerosol-Cloud-Turbulence Interaction

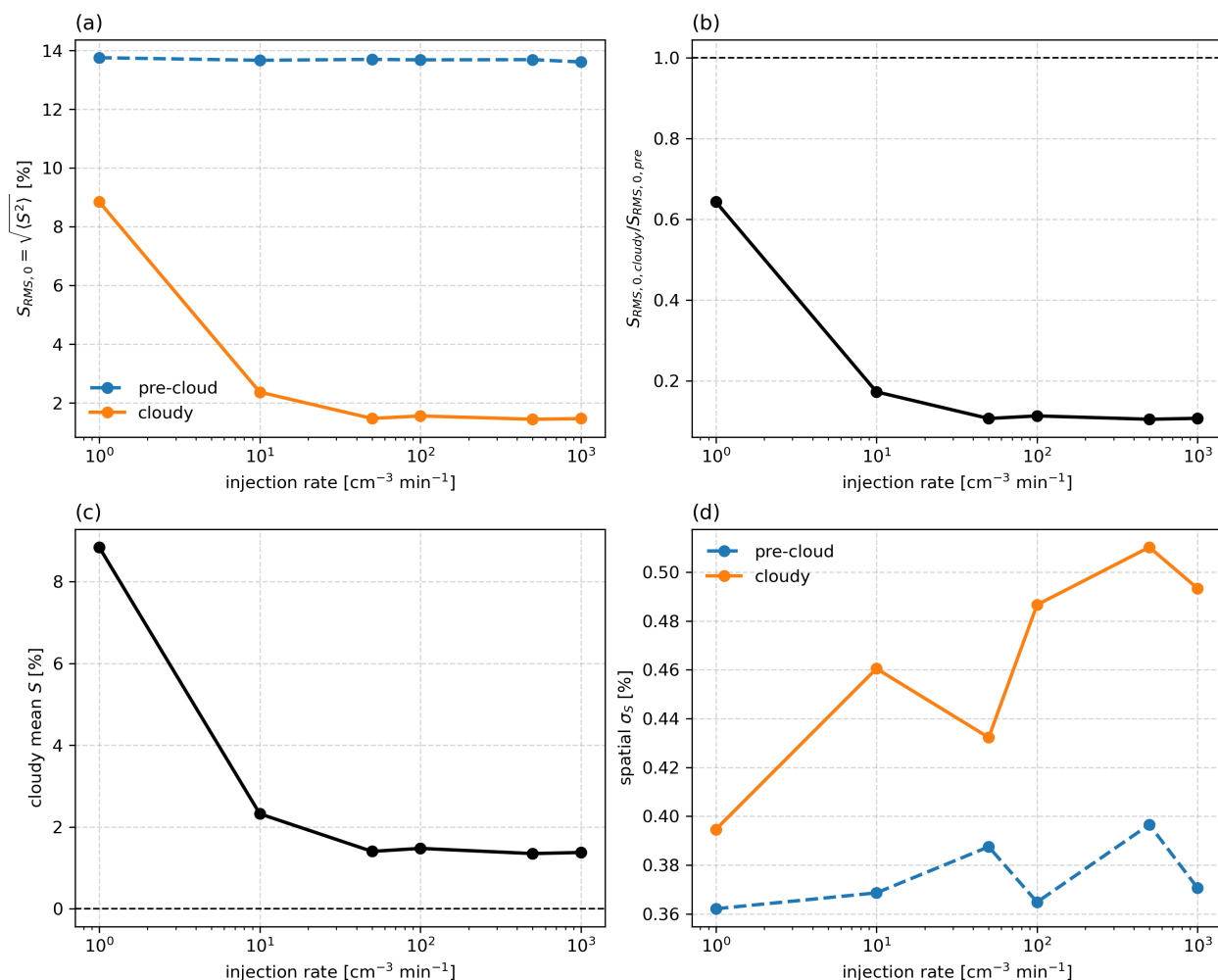


Figure 6. Influence of aerosol injection rate on supersaturation regulation. (a) Root-mean-square supersaturation relative to saturation during the pre-cloud and cloudy periods. (b) Ratio of time-averaged cloudy to pre-cloud, $S_{RMS,0}$, with values below unity indicating a reduced total departure from saturation. (c) Mean cloudy-period supersaturation. (d) Spatial standard deviation of supersaturation during the pre-cloud and cloudy periods.

Figure 6 examines how aerosol injection modifies the chamber's mean supersaturation and its spatial variability under saturated-wall conditions. Statistics were calculated over the inner chamber volume, defined by ($x=0.3\text{--}1.7$) m, ($y=0.3\text{--}1.7$) m, and ($z=0.2\text{--}0.8$) m. Spatial statistics were evaluated independently at each output time and then averaged over the pre-cloud period of 20–30 min and the cloudy period of 80–90 min. To quantify the total departure from saturation, we use the root-mean-square supersaturation relative to saturation,

$$S_{RMS,0} = \sqrt{\langle S^2 \rangle} = \sqrt{\bar{S}^2 + \sigma_S^2}$$



where ($S=0$) denotes saturation, angle brackets denote a spatial average over the inner chamber volume, and $\bar{S}$ and σ_S are the spatial mean and standard deviation at each output time. This metric includes both the mean supersaturation and fluctuations about that mean. Consequently, it distinguishes a chamber state close to saturation from one that is spatially uniform but strongly supersaturated.

360 Before aerosol injection, the simulations exhibited similar thermodynamic conditions, with $S_{RMS,0}$ ranging from 13.61% to 13.76% (Figure 6a), consistent with their common boundary forcing. Following aerosol injection and cloud formation, cloudy-period RMS supersaturation decreased sharply across the three lowest injection rates, from 8.85% at $1 \text{ cm}^{-3} \text{ min}^{-1}$ to 2.37% at $10 \text{ cm}^{-3} \text{ min}^{-1}$ and 1.47% at $50 \text{ cm}^{-3} \text{ min}^{-1}$. At injection rates of $50\text{--}1000 \text{ cm}^{-3} \text{ min}^{-1}$, the values remained within approximately 1.44–1.56%, indicating diminishing sensitivity to further increases in aerosol injection.

365 Figure 6b expresses this adjustment as the ratio of the time-averaged cloudy RMS supersaturation to its corresponding pre-cloud value. The ratio decreased from 0.643 at $1 \text{ cm}^{-3} \text{ min}^{-1}$ to 0.173 at $10 \text{ cm}^{-3} \text{ min}^{-1}$ and 0.107 at $50 \text{ cm}^{-3} \text{ min}^{-1}$, corresponding to reductions of approximately 36%, 83%, and 89%, respectively. At injection rates of $50\text{--}1000 \text{ cm}^{-3} \text{ min}^{-1}$, the ratio remained between 0.105 and 0.114. Thus, most of the aerosol-dependent regulation occurred between 1 and $50 \text{ cm}^{-3} \text{ min}^{-1}$, followed by a plateau at higher injection rates.

370 The reduction in RMS supersaturation primarily reflected a decrease in the mean supersaturation (Figure 6c). The cloudy-period mean decreased from 8.84% at $1 \text{ cm}^{-3} \text{ min}^{-1}$ to 2.32% at $10 \text{ cm}^{-3} \text{ min}^{-1}$ and remained within approximately 1.35–1.48% at injection rates of $50\text{--}1000 \text{ cm}^{-3} \text{ min}^{-1}$. These results are consistent with enhanced condensational consumption of water vapor as aerosol injection increased, shifting the chamber toward saturation while retaining a positive mean supersaturation. The centered spatial variability exhibited a different response (Figure 6d). The time-averaged spatial standard deviation ranged

375 from approximately 0.36–0.40% during the pre-cloud period and 0.40–0.51% during the cloudy period. Cloudy-period values exceeded their corresponding pre-cloud values in all cases and showed no monotonic decrease with increasing injection rate. For example, the lowest-injection case had a relatively small cloudy-period standard deviation of approximately 0.40%, despite maintaining a mean supersaturation of 8.84%. Its narrow supersaturation distribution therefore reflected a relatively uniform, strongly supersaturated chamber interior rather than effective regulation toward saturation.

380 Additional sensitivity simulations with sidewall relative humidity reduced to 50% exhibited a different response of supersaturation variability to aerosol injection (not shown). In those simulations, the spatial standard deviation of supersaturation decreased with increasing aerosol injection rate, whereas no corresponding monotonic reduction occurred under saturated-sidewall conditions. Nevertheless, the overall qualitative response of droplet microphysical properties to aerosol injection remained similar between the two configurations. This contrast suggests that the response of centered

385 supersaturation variability is sensitive to the chamber's moisture boundary conditions. One possible explanation is that changing sidewall humidity modifies the balance between the generation and removal of supersaturation variability through wall exchange, turbulent transport, and microphysical adjustment. The absence of a decrease in spatial standard deviation under saturated-wall conditions therefore does not, by itself, imply an absence of condensational damping. Identifying the



processes responsible for the contrasting responses would require a supersaturation variance budget or an analysis of
390 supersaturation-anomaly decay.

Figure 6 consequently demonstrates strong aerosol-dependent regulation of the mean and RMS supersaturation, with the largest
adjustment occurring between injection rates of 1 and 50 $\text{cm}^{-3} \text{min}^{-1}$. The reduced RMS ratio primarily reflects removal of the
large positive mean supersaturation, rather than a narrowing of the spatial supersaturation distribution. These diagnostics
therefore support condensational regulation of the bulk thermodynamic state but do not establish suppression of turbulent
395 supersaturation fluctuations or faster decay of supersaturation anomalies

4.4 Damköhler Number Analysis

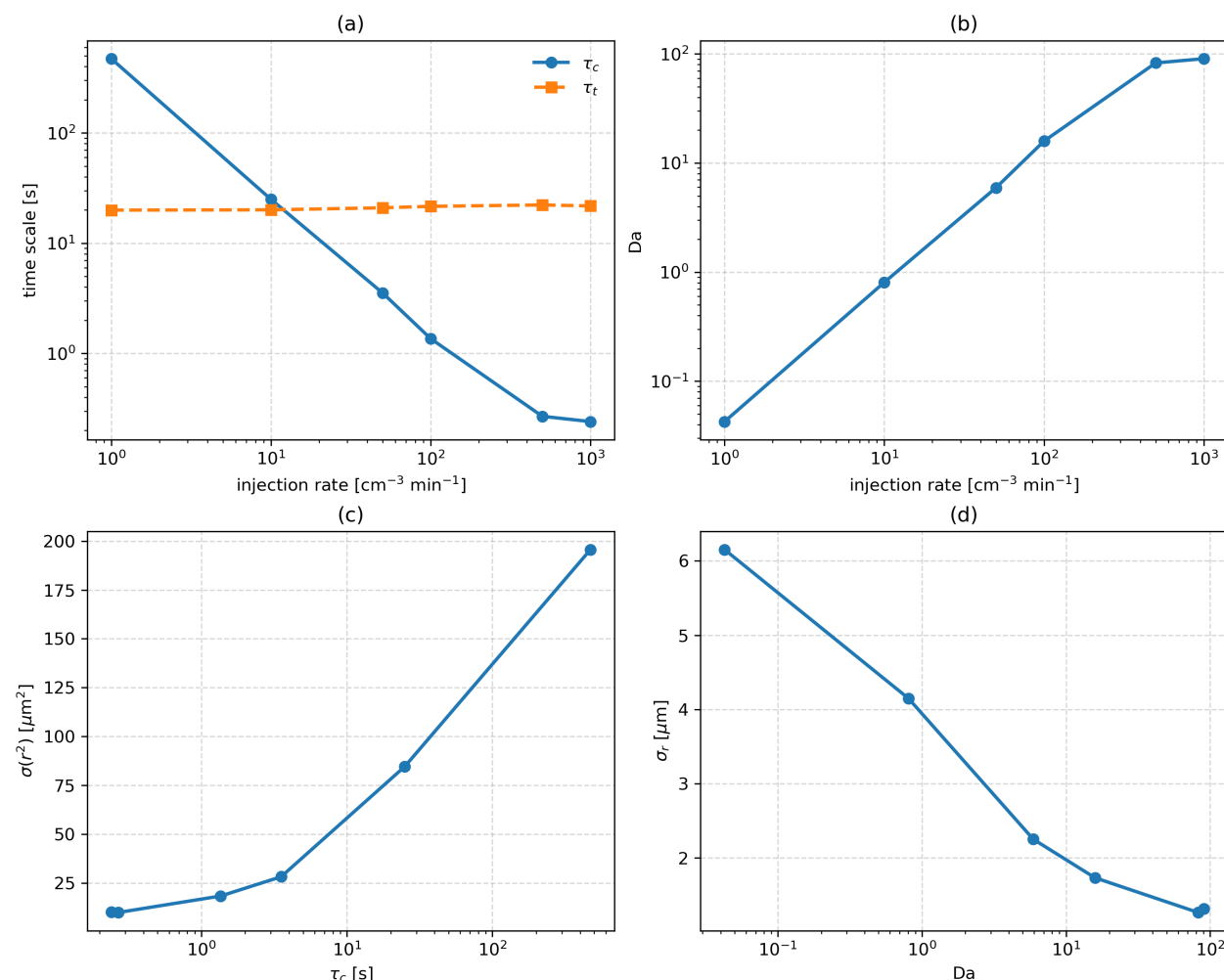


Figure 7. Dependence of characteristic time scales and droplet spectral widths on aerosol injection. (a) Phase-relaxation time
400 (τ_c) and the large-eddy turnover-time proxy (τ_t) as functions of aerosol injection rate. (b) Cloud microphysical Damköhler



number (Da). (c) Spectral width of the squared-radius distribution, $\sigma(r^2)$, as a function of phase-relaxation time. (d) Radius spectral width, σ_r , as a function of the Damköhler number.

Previous Pi Chamber studies established the conceptual framework linking aerosol loading, condensational phase-relaxation time, supersaturation fluctuations, and droplet size distribution broadening. Chandrakar et al. (2016) demonstrated that low aerosol loading produces a longer phase-relaxation time relative to the turbulent time scale, allowing supersaturation fluctuations to persist and generate broader droplet size distributions. Chandrakar et al. (2018) further developed this framework by relating droplet size dispersion to the competing time scales of turbulent supersaturation forcing and condensational adjustment. Thus, the underlying relationship among aerosol loading, microphysical time scales, supersaturation variability, and droplet spectral width is well established from previous Pi Chamber experiments. Here, we examine how the estimated microphysical and turbulent time scales vary with aerosol injection and how their relative magnitudes relate to the regulation of mean and RMS supersaturation identified in Figure 6. Figure 7 also examines the association between these time scales and droplet size distribution width.

The cloud microphysical phase-relaxation time, τ_c , was estimated as

$$\tau_c = \frac{1}{4\pi D_v N r_{\text{mean}}},$$

where $D_v = 2.5 \times 10^{-5} \text{ m}^2 \text{ s}^{-1}$ is the water vapor diffusivity, N is the cloud droplet number concentration, and r_{mean} is the multiplicity-weighted mean cloud droplet radius. The turbulent time-scale was approximated using the large-eddy turnover-time proxy

$$\tau_t = \frac{L}{w_{\text{rms}}},$$

where $L = 1.0 \text{ m}$ is the chamber height and w_{rms} is the root-mean-square vertical velocity fluctuation across each cells within the chamber core. This quantity serves as a proxy for the turbulence time scale used in previous Pi Chamber studies (e.g., Chandrakar et al., 2016, 2018; Anderson et al., 2024). The cloud microphysical Damköhler number was then defined as

$$Da = \frac{\tau_t}{\tau_c},$$

which measures the relative importance of condensational adjustment and turbulent mixing. Values of $Da < 1$ indicate that the estimated condensational adjustment time exceeds the turbulent time-scale proxy, whereas $Da > 1$ indicates faster condensational adjustment relative to that proxy. These relative time scales characterize the potential microphysical response but do not, by themselves, determine the magnitude of the equilibrium supersaturation variance.

Figure 7a shows that the turbulent time-scale proxy varied relatively little across aerosol injection rates, whereas the phase-relaxation time shortened substantially as injection increased. According to the expression for τ_c , this decrease reflects an increase in the product of droplet number concentration and mean radius, with the increase in droplet concentration



outweighing the accompanying decrease in mean droplet size. The aerosol dependence of the estimated adjustment time therefore arises from changes in the droplet population.

Consequently, Da increased with aerosol injection rate (Figure 7b), indicating progressively faster condensational adjustment relative to the turbulent time-scale proxy. The association between shorter phase-relaxation times and lower mean and RMS supersaturation in Figure 6 is consistent with more effective regulation of the bulk thermodynamic state. However, this correspondence should be distinguished from a demonstrated reduction in centered supersaturation variability, which did not decrease monotonically under saturated-wall conditions.

Figure 7c relates the width of the squared-radius distribution, $\sigma(r^2)$, to the phase-relaxation time. The squared-radius spectral width increased systematically with increasing τ_c , indicating that broader droplet size distributions were associated with slower condensational adjustment. Within the theoretical framework of Chandrakar et al. (2018), slower microphysical adjustment can permit supersaturation anomalies to influence droplet growth over longer periods. However, the persistence of those anomalies was not directly diagnosed here. The observed relationship between spectral width and phase-relaxation time is therefore consistent with that framework but does not independently establish the temporal behavior of supersaturation fluctuations in these simulations.

Figure 7d similarly shows that smaller Da values were associated with broader droplet size distributions, whereas larger Da values were associated with narrower distributions. Together, these relationships connect aerosol-dependent changes in the droplet population to the estimated condensational adjustment time and droplet spectral width. Nevertheless, the narrower DSDs at higher injection rates cannot be attributed solely to a reduction in supersaturation fluctuation amplitude, because Figure 6d shows no corresponding monotonic decrease in the spatial standard deviation. Differences in the temporal correlations of supersaturation experienced by droplets, activation histories, and particle removal may also contribute to the spectral response. Distinguishing these mechanisms would require additional diagnostics, such as Lagrangian supersaturation histories, supersaturation-anomaly decay, or a supersaturation variance budget.



4.5 Aerosol Activation and Haze-Cloud Partitioning

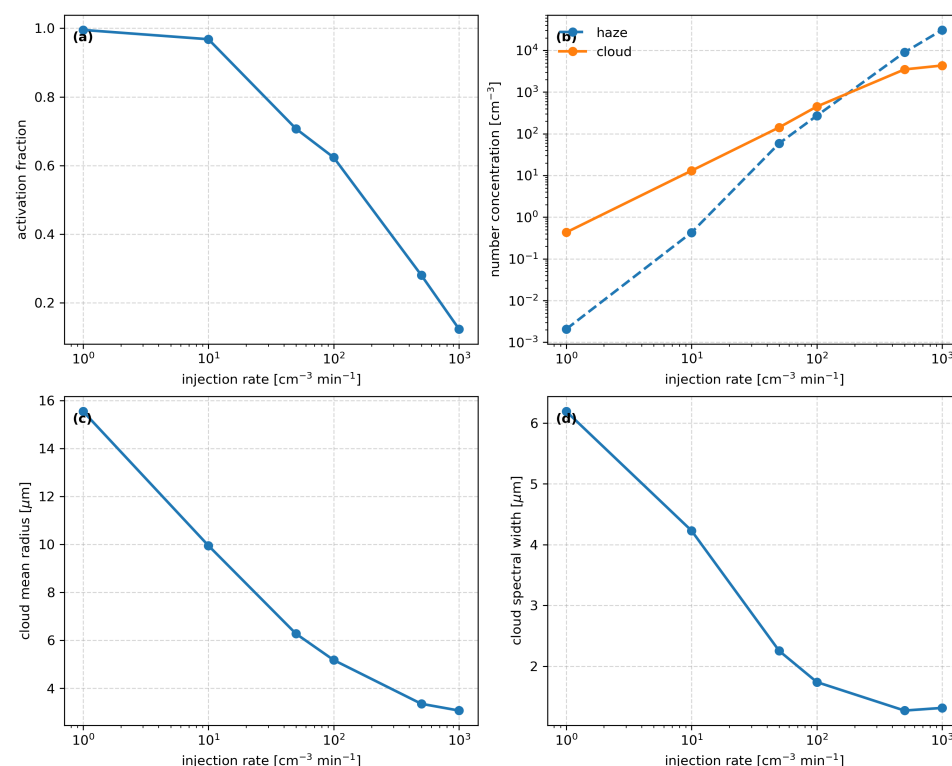


Figure 8. Aerosol activation and cloud microphysical response to increasing aerosol injection rate. (a) Activation fraction. (b) Haze and cloud droplet number concentrations. (c) Cloud-droplet mean radius. (d) Cloud-droplet radius spectral width. Haze and cloud droplets are separated using a wet-radius threshold of $1.5 \mu\text{m}$.

To further investigate how aerosol loading modifies cloud development, Figure 8 separates the particle population into activated cloud droplets and haze particles using a wet-radius threshold of $1.5 \mu\text{m}$. Particles with radii greater than or equal to $1.5 \mu\text{m}$ were classified as cloud droplets, while smaller particles were classified as haze droplets. The activation fraction was defined as the ratio of activated cloud droplets to the total particle number concentration.

Figure 8a shows that the activation fraction decreases systematically with increasing aerosol injection rate. At the lowest injection rate ($1 \text{ cm}^{-3} \text{min}^{-1}$), nearly all particles activated into cloud droplets, yielding an activation fraction of 0.99. The activation fraction then decreased to 0.97 at $10 \text{ cm}^{-3} \text{min}^{-1}$, 0.71 at $50 \text{ cm}^{-3} \text{min}^{-1}$, 0.62 at $100 \text{ cm}^{-3} \text{min}^{-1}$, and only 0.28 and 0.12 at injection rates of 500 and $1000 \text{ cm}^{-3} \text{min}^{-1}$, respectively. This trend demonstrated that increasing aerosol loading did not proportionally increase the activated cloud droplet population because progressively stronger competition for available water vapor limited activation.

The evolution of haze and cloud droplet number concentrations is shown in Figure 8b. Both populations increased with aerosol injection rate. However, their responses differed substantially. Cloud droplet number concentration increased rapidly at low



470 and moderate injection rates before beginning to level off above approximately $500 \text{ cm}^{-3} \text{ min}^{-1}$. In contrast, haze particle concentration continued to increase by several orders of magnitude, eventually exceeding the cloud droplet concentration. At the highest injection rates, most additional aerosol therefore remained as haze rather than growing into cloud droplets. These results indicate that the chamber transitions from an aerosol-limited regime at low injection rates to a vapor-limited regime at high aerosol loading.

475 The effects of increasing vapor competition are also reflected in the cloud droplet (radius $\geq 1.5 \mu\text{m}$) size statistics. As shown in Figure 8c, the cloud droplet mean radius decreased monotonically from approximately $15.5 \mu\text{m}$ at the lowest injection rate to about $3.1 \mu\text{m}$ at $1000 \text{ cm}^{-3} \text{ min}^{-1}$. Likewise, the cloud droplet radius spectral width decreased from approximately $6.2 \mu\text{m}$ to about $1.3 \mu\text{m}$ (Figure 8d). Thus, increasing aerosol loading produced progressively smaller and more narrowly distributed cloud droplets, consistent with the trends previously identified in the droplet size distributions (Figure 4) and the Damköhler analysis (Figure 7).

480 Figure 8 demonstrated that increasing aerosol injection changed how available water vapor was partitioned among aerosol particles. Under clean conditions, nearly all particles activated and grew into relatively large cloud droplets because water vapor was abundant relative to aerosol number. As aerosol loading increased, water vapor became the limiting resource, causing an increasing fraction of particles to remain as haze while the activated cloud droplets became smaller and more uniform in size. This behavior is consistent with previous Pi Chamber studies showing that aerosol activation depends not only on the mean supersaturation but also on turbulent supersaturation fluctuations and vapor competition (Prabhakaran et al., 2020; Grabowski et al., 2024).



4.6 Sensitivity of Equilibrium Cloud Properties to Chamber Supersaturation

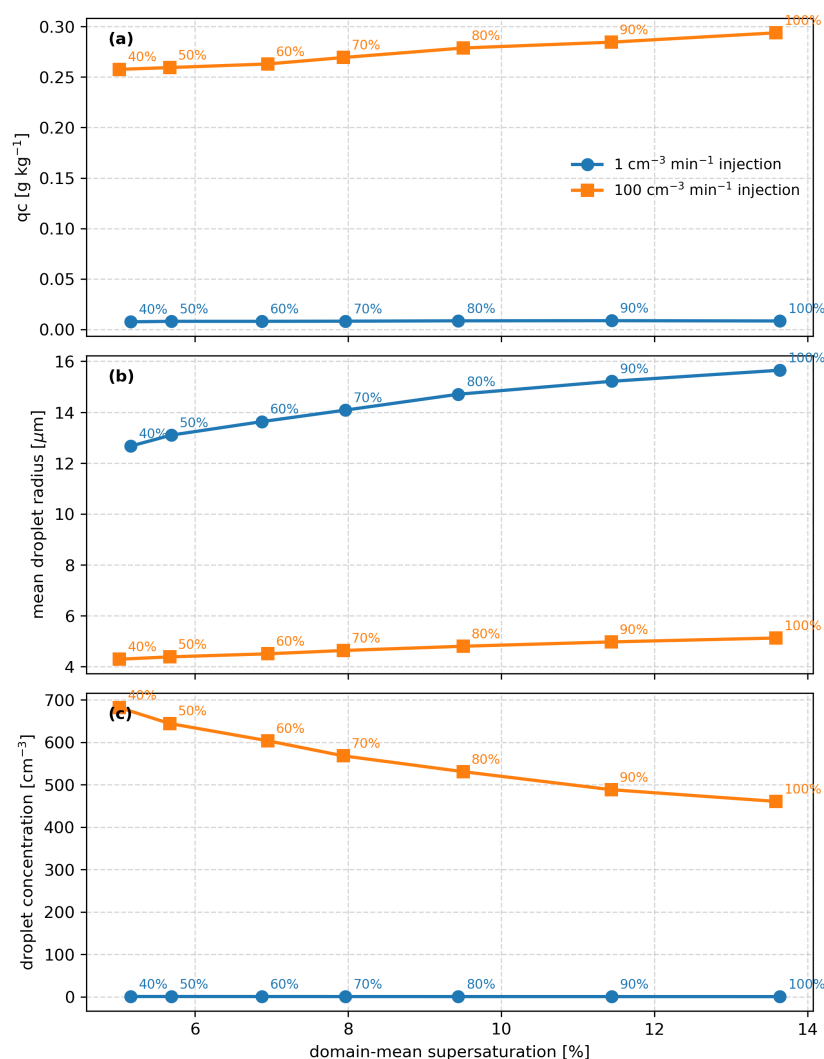


Figure 9. Sensitivity of equilibrium cloud microphysical properties to the pre-cloud chamber supersaturation for aerosol injection rates of 1 and 100 $\text{cm}^3 \text{min}^{-1}$. The horizontal axis shows the domain-mean supersaturation averaged during the 20–30 min pre-cloud period. Annotated % number represents the prescribed sidewall relative humidity. Panels show (a) domain-volume-averaged cloud water mixing ratio, (b) cloud-droplet mean radius, and (c) cloud droplet number concentration averaged over the final 10 min of each simulation.

To investigate the sensitivity of the equilibrium cloud state to the chamber thermodynamic environment, a series of simulations was performed in which the sidewall relative humidity was varied while maintaining fixed aerosol injection rates of 1 and 100 $\text{cm}^3 \text{min}^{-1}$. The resulting domain-mean supersaturation, averaged during the 20–30 min pre-cloud period, ranged from approximately 5.0% to 13.6% for both injection-rate series. Figure 9 compares the final 10-min domain-volume-averaged



cloud water mixing ratio, mean droplet radius, and droplet number concentration as functions of the pre-cloud chamber supersaturation.

Figure 9a shows that the cloud water mixing ratio increased with increasing chamber supersaturation for both injection-rate series, reflecting the greater condensational growth supported by a more supersaturated environment. However, the two curves were clearly separated. At comparable supersaturation, the $100 \text{ cm}^{-3} \text{ min}^{-1}$ simulations maintained approximately 32-36 times more cloud water than the $1 \text{ cm}^{-3} \text{ min}^{-1}$ simulations. Thus, although supersaturation controlled the amount of condensate formed within each series, aerosol injection rate remained the dominant control on the equilibrium liquid water content.

A similar behavior is evident for the mean droplet radius (Figure 9b). Increasing chamber supersaturation produced larger cloud droplets for both aerosol injection rates, consistent with enhanced condensational growth. Nevertheless, the high-injection simulations consistently produced much smaller droplets, with mean radii ranging from approximately 4.3 to 5.1 μm compared with 12.7 to 15.7 μm in the low-injection simulations. At comparable supersaturation, the mean droplet radius in the high-injection cases was only about one-third of that in the low-injection cases, reflecting the stronger competition for available water vapor among the much larger droplet population.

Figure 9c compares the equilibrium droplet number concentration. In contrast to cloud water and droplet radius, droplet number concentration decreased with increasing pre-cloud supersaturation within each injection-rate series. The high-injection simulations maintained approximately 461–682 cm^{-3} , whereas the low-injection simulations remained below 0.7 cm^{-3} . At comparable supersaturation, the droplet number concentration differed by roughly three orders of magnitude between the two series. These results indicate that the equilibrium droplet population is governed primarily by aerosol availability rather than by the initial chamber supersaturation.

In Figure 9c, at high injection rate, droplet concentration decreased with increasing supersaturation. The decrease suggests that stronger condensational growth indirectly enhances a process that removes droplets from the chamber. To investigate this behavior, boundary-deactivation records were analyzed for the $100 \text{ cm}^{-3} \text{ min}^{-1}$ injection cases. Along this fixed-injection sequence, increasing the pre-cloud mean supersaturation from 5.0% to 13.6% increased the final mean droplet radius from 4.3 to 5.1 μm and the cloud water mixing ratio from 0.26 to 0.3 g kg^{-1} , while decreasing the retained droplet concentration from 682 to 461 cm^{-3} . During the post-injection interval, the boundary-deactivation rate increased monotonically from 3.01 to 3.37 million computational superdroplets per minute, an increase of approximately 11.8%. The active-particle population also exhibited a 1.6-fold increase in mean terminal velocity, from 1.6 to 2.6 mm s^{-1} . Together, these results support the following mechanism. Higher supersaturation strengthens condensational growth, producing larger droplets with greater terminal velocities. These droplets are then removed more rapidly at the chamber boundaries, leaving fewer droplets in the domain despite the greater cloud water content. The direct number concentration sink is therefore boundary deactivation, whereas enhanced condensation contributes indirectly by producing larger, faster-settling droplets. The available boundary diagnostic combines removal through the bottom, top, and lateral boundaries and therefore does not isolate gravitational sedimentation from removal through the other boundary faces. The terminal-velocity trend supports sedimentation as an important removal



mechanism but does not establish it as the sole pathway. Consequently, the analysis demonstrates that increasing supersaturation is associated with enhanced total boundary removal, while definitive attribution would require face-resolved deactivation diagnostics.

Figure 9 demonstrates that chamber supersaturation primarily organizes the microphysical response within a given aerosol-loading regime, whereas aerosol injection rate determines the dominant equilibrium cloud state. Increasing supersaturation promotes greater condensational growth, leading to larger droplets and higher cloud water contents. Within the $100 \text{ cm}^{-3} \text{ min}^{-1}$ series, the resulting increase in droplet size and terminal velocity is accompanied by enhanced boundary removal, explaining how a more strongly supersaturated chamber can retain fewer droplets while containing more condensed water. However, the large separation between the low- and high-injection simulations indicates that aerosol loading remains the stronger control on the overall equilibrium cloud properties.

5 Conclusions

This study introduced new cloud chamber capabilities within the Energy Research and Forecasting model coupled with the Super-Droplet Method (ERF-SDM) and evaluated the framework using the warm-cloud Pi Chamber benchmark of Chen et al. (2025). The new developments include Monin-Obukhov similarity theory applied consistently to all six chamber walls, continuous aerosol injection, and wall deposition of super-droplets, enabling statistically stationary simulations of turbulent cloud evolution under laboratory conditions. The primary simulations prescribed saturation at all six chamber walls, with the sidewall temperature set to the arithmetic mean of the top and bottom boundary temperatures. Additional sensitivity simulations examined how changes in sidewall relative humidity and the resulting chamber supersaturation influenced the equilibrium cloud state under clean and polluted aerosol conditions.

The ERF-SDM simulations reproduced the characteristic chamber circulation and qualitative aerosol-dependent microphysical responses. Prior to aerosol injection, the simulations developed a statistically stationary moist Rayleigh–Bénard circulation with turbulent kinetic energy comparable to laboratory measurements. Following aerosol injection, the model reproduced the expected thermodynamic adjustment associated with latent heating and vapor depletion, while the equilibrium droplet number concentration, mean droplet radius, cloud water mixing ratio, and droplet size distributions showed realistic dependence on aerosol injection rate. Comparisons with laboratory measurements and the multi-model benchmark of Chen et al. (2025) showed similar qualitative relationships between aerosol injection and cloud microphysical properties, although the simulated cloud droplets were systematically somewhat smaller than those observed experimentally.

The supersaturation diagnostics demonstrated strong regulation of the chamber's mean thermodynamic state as aerosol injection increased. Mean and RMS supersaturation decreased sharply between injection rates of 1 and $50 \text{ cm}^{-3} \text{ min}^{-1}$ and exhibited comparatively little sensitivity to further increases. However, the centered spatial standard deviation did not decrease monotonically under saturated-wall conditions, and cloudy-period values exceeded their corresponding pre-cloud values. The reduction in RMS supersaturation therefore primarily reflected a decrease in the mean supersaturation. Increasing aerosol



565 injection also produced smaller droplets and narrower droplet size distributions, but these changes cannot be attributed solely to suppression of the diagnosed supersaturation variability. The Damköhler-number analysis provides a complementary framework for interpreting the relative time scales of condensational adjustment and turbulent mixing, while direct assessment of supersaturation-anomaly damping requires additional diagnostics.

The activation analysis further demonstrated that increasing aerosol loading fundamentally changes how available water vapor is partitioned among aerosol particles. At low injection rates, nearly all particles activated into cloud droplets, representing an aerosol-limited regime. As aerosol loading increased, however, the activated cloud droplet concentration began to level off while the interstitial haze population continued to increase rapidly, indicating a transition toward a vapor-limited regime in which competition for available water vapor increasingly limits activation. The activation response and reduced mean supersaturation are consistent with stronger competition for available water vapor at higher aerosol injection rates.

575 Sensitivity experiments further showed that increasing chamber supersaturation within a given aerosol-loading regime promoted greater condensational growth, resulting in larger cloud droplets and higher cloud water contents. At the higher aerosol injection rate, increasing supersaturation was also associated with lower equilibrium droplet number concentrations and enhanced removal at the chamber boundaries. This response highlights the combined influence of condensational growth and particle removal on the equilibrium droplet population. However, the large separation between the low- and high-injection simulations demonstrated that aerosol loading remained the dominant control on the equilibrium cloud state, while chamber supersaturation modulated the microphysical response within each aerosol-loading regime.

Overall, the present study demonstrates that ERF-SDM provides a physically consistent framework for simulating convection cloud chamber experiments and reproduces both the equilibrium cloud properties and the underlying aerosol–cloud–turbulence interactions observed in the Pi Chamber. The combination of explicit Lagrangian microphysics with resolved turbulent flow makes ERF-SDM a valuable tool for interpreting laboratory cloud experiments, evaluating cloud microphysics parameterizations, quantifying the coupled influences of aerosol loading and thermodynamic forcing, and investigating the fundamental processes linking aerosol activation, supersaturation fluctuations, and condensational growth under controlled conditions. These capabilities offer process-level insights that can guide the development of more accurate aerosol and cloud representations in Earth system models. Future applications of this framework can extend to additional laboratory configurations, sensitivity studies of aerosol and thermodynamic forcing, and mixed-phase cloud chamber experiments, further strengthening the connection between laboratory observations and atmospheric cloud processes.

Code and data availability

595 The version of ERF-SDM used to generate the data presented in this manuscript is available on Zenodo (DOI: 10.5281/zenodo.23018675).



Author contributions

Jungmin Lee contributed to conceptualization, methodology, validation, formal analysis, investigation, data curation, visualization, and writing the original draft. Cole Kendrick, Debojyoti Ghosh, and Aaron Lattanzi contributed to software development. Inyeob La, Emily de Jong, Hassan Beydoun, Seoung Soo Yum, Shaocheng Xie, and Katie Lundquist contributed to manuscript review and editing. Shaocheng Xie and Katie Lundquist acquired funding.

Competing interests

The authors declare that they have no competing interests.

Disclaimer

Copernicus Publications remains neutral with regard to jurisdictional claims made in the text, published maps, institutional affiliations, or any other geographical representation in this paper. While Copernicus Publications makes every effort to include appropriate place names, the final responsibility lies with the authors. Views expressed in the text are those of the authors and do not necessarily reflect the views of the publisher.

Acknowledgements

This manuscript has been authored by Lawrence Livermore National Security, LLC under Contract No. DE-AC52-07NA27344 with the U.S. Department of Energy. The United States Government retains, and the publisher, by accepting the article for publication, acknowledges that the United States Government retains a non-exclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for United States Government purposes. LLNL-JRNL-. S.S. Yum was supported by KIST Institutional Grant 26E0111. The authors used generative artificial intelligence (AI) tools to assist with language editing and the development of Python scripts for analyzing the simulation results. The authors thank Fan Yang and Wojciech Grabowski for helpful discussions during the development of the model.

Financial support

This work was supported by internal funding from Lawrence Livermore National Laboratory.

Review statement

The review statement will be added by Copernicus Publications listing the handling editor as well as all contributing referees according to their status anonymous or identified.



References

- Anderson, J. C., I. Helman, R. A. Shaw, and W. Cantrell (2024), Droplet growth or evaporation does not buffer the variability in supersaturation in clean clouds, *Journal of the Atmospheric Sciences*, **81**, 225–233, <https://doi.org/10.1175/JAS-D-23-0104.1>
- Beard, K. V. (1976). Terminal Velocity and Shape of Cloud and Precipitation Drops Aloft. *Journal of the Atmospheric Sciences*, 33(5), 851–864. [https://doi.org/10.1175/1520-0469\(1976\)033%253C0851:TVASOC%253E2.0.CO;2](https://doi.org/10.1175/1520-0469(1976)033%253C0851:TVASOC%253E2.0.CO;2)
- Beydoun, H., et al. (2026), *ERF-SDM: A Lagrangian Super-Droplet Method implementation in the Energy Research and Forecasting model. (Use the final published citation when available.)*
- Chandrakar, K. K., W. Cantrell, R. A. Shaw, S. G. Ciochetto, J. M. Raymond, A. K. Knopf, and Coauthors (2016), Aerosol indirect effect from turbulence induced broadening of cloud droplet size distributions, *Proceedings of the National Academy of Sciences*, **113**, 14243–14248, <https://doi.org/10.1073/pnas.1612686113>
- Chandrakar, K. K., W. Cantrell, and R. A. Shaw (2018), Influence of turbulent fluctuations on cloud droplet size dispersion and aerosol indirect effects, *Journal of the Atmospheric Sciences*, **75**, 3191–3209, <https://doi.org/10.1175/JAS-D-18-0006.1>
- Chang, K., L. Bench, M. Brege, W. Cantrell, and R. A. Shaw (2016), A laboratory facility for studying turbulence cloud interactions: The Pi Chamber, *Bulletin of the American Meteorological Society*, **97**, 2343–2358, <https://doi.org/10.1175/BAMS-D-15-00203.1>
- Chen, S., Krueger, S. K., Dziekan, P., Enokido, K., MacMillan, T., Richter, D., et al. (2025). A model intercomparison study of aerosol-cloud-turbulence interactions in a cloud chamber: 1. Model results. *Journal of Advances in Modeling Earth Systems*, 17, e2024MS004562. <https://doi.org/10.1029/2024MS004562>
- Grabowski, W. W., and L. P. Wang (2013), Growth of cloud droplets in a turbulent environment, *Annual Review of Fluid Mechanics*, **45**, 293–324, <https://doi.org/10.1146/annurev-fluid-011212-140750>
- Grabowski, W. W., H. Morrison, S. Shima, G. C. Abade, P. Dziekan, and H. Pawlowska (2019), Modeling of cloud microphysics: Can we do better?, *Bulletin of the American Meteorological Society*, **100**, 655–672, <https://doi.org/10.1175/BAMS-D-18-0005.1>



655

Grabowski, W. W., Y. Kim, and S. S. Yum (2024), CCN activation and droplet growth in Pi Chamber simulations with Lagrangian particle-based microphysics, *Journal of the Atmospheric Sciences*, **81**, 1201–1212, <https://doi.org/10.1175/JAS-D-24-0004.1>

660

Khain, A. P., K. D. Beheng, A. Heymsfield, A. Korolev, S. O. Krichak, Z. Levin, M. Pinsky, V. Phillips, T. Prabhakaran, A. Teller, et al. (2015), Representation of microphysical processes in cloud-resolving models: Spectral (bin) microphysics versus bulk parameterization, *Rev. Geophys.*, **53**, 247–322. doi:[10.1002/2014RG000468](https://doi.org/10.1002/2014RG000468).

665

Krueger, S., & Shaw, R. A. (2026). Colloquium: Convection-cloud chambers: Experiment and theory. *Reviews of Modern Physics*, **98**(1), 011001. <https://doi.org/10.1103/wnnk-qgvj>

670

La, I., W. W. Grabowski, Y. Kim, S. Kim, and S. S. Yum (2026), Lagrangian particle based simulation of aerosol dependent vertical variation of cloud microphysics in a laboratory convection cloud chamber, *Atmospheric Chemistry and Physics*, **26**, 5213–5235, <https://doi.org/10.5194/acp-26-5213-2026>

675

Lee, J., Kendrick, C., & Ghosh, D. (2026). ERF-SDM for convection type cloud chamber [Computer software]. Zenodo. <https://doi.org/10.5281/zenodo.23018675>

680

Lattanzi, A., Almgren, A., Quon, E., Natarajan, M., Kosovic, B., Mirocha, J., et al. (2025). *ERF: Energy research and forecasting model*. *Journal of Advances in Modeling Earth Systems*, **17**, e2024MS004884. <https://doi.org/10.1029/2024MS004884>

685

Prabhakaran, P., Shawon, A. S. M., Kinney, G., Thomas, S., Cantrell, W., & Shaw, R. A. (2020). The role of turbulent fluctuations in aerosol activation and cloud formation. *Proceedings of the National Academy of Sciences*, **117**(29), 16831–16838. doi:[10.1073/pnas.2006426117](https://doi.org/10.1073/pnas.2006426117)

Pruppacher, H. R., and J. D. Klett (1997), *Microphysics of Clouds and Precipitation* (2nd ed.), Kluwer Academic Publishers, Dordrecht, Netherlands.

685

Shaw, R. A., and Coauthors, 2020: Cloud–Aerosol–Turbulence Interactions: Science Priorities and Concepts for a Large-Scale Laboratory Facility. *Bull. Amer. Meteor. Soc.*, **101**, E1026–E1035, <https://doi.org/10.1175/BAMS-D-20-0009.1>.



Shima, S., Kusano, K., Kawano, A., Sugiyama, T. and Kawahara, S. (2009), The super-droplet method for the numerical simulation of clouds and precipitation: a particle-based and probabilistic microphysics model coupled with a non-hydrostatic model. Q.J.R. Meteorol. Soc., 135: 1307-1320. <https://doi.org/10.1002/qj.441>

Stevens RJAM, Lohse D, Verzicco R. Sidewall effects in Rayleigh–Bénard convection. Journal of Fluid Mechanics. 2014;741:1-27. doi:10.1017/jfm.2013.664

695 Thomas, S., M. Ovchinnikov, F. Yang, D. van der Voort, W. Cantrell, S. K. Krueger, and R. A. Shaw (2019), Scaling of an atmospheric model to simulate turbulence and cloud microphysics in the Pi Chamber, *Journal of Advances in Modeling Earth Systems*, **11**, 1981–1994, <https://doi.org/10.1029/2019MS001670>

700