JAMES | Journal of Advances in Modeling Earth Systems®

Research Article | Open Access

SuperdropNet: A Stable and Accurate Machine Learning Proxy for Droplet-Based Cloud Microphysics

Shivani Sharma, David S. Greenberg

First published: 31 May 2025 | https://doi.org/10.1029/2024MS004279 | VIEW METRICS

Celeste Tong

ML Journal Club 2026.4.30

Autoregressive emulator

forward operator

stochasticity

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$$

Cloud microphysics at t+Δt

Cloud microphysics at t

Autoregressive emulator → forward operator

stochasticity

$$y = Hx + n$$

Cloud microphysics at t+Δt

Cloud microphysics at t

Cloud microphysics:

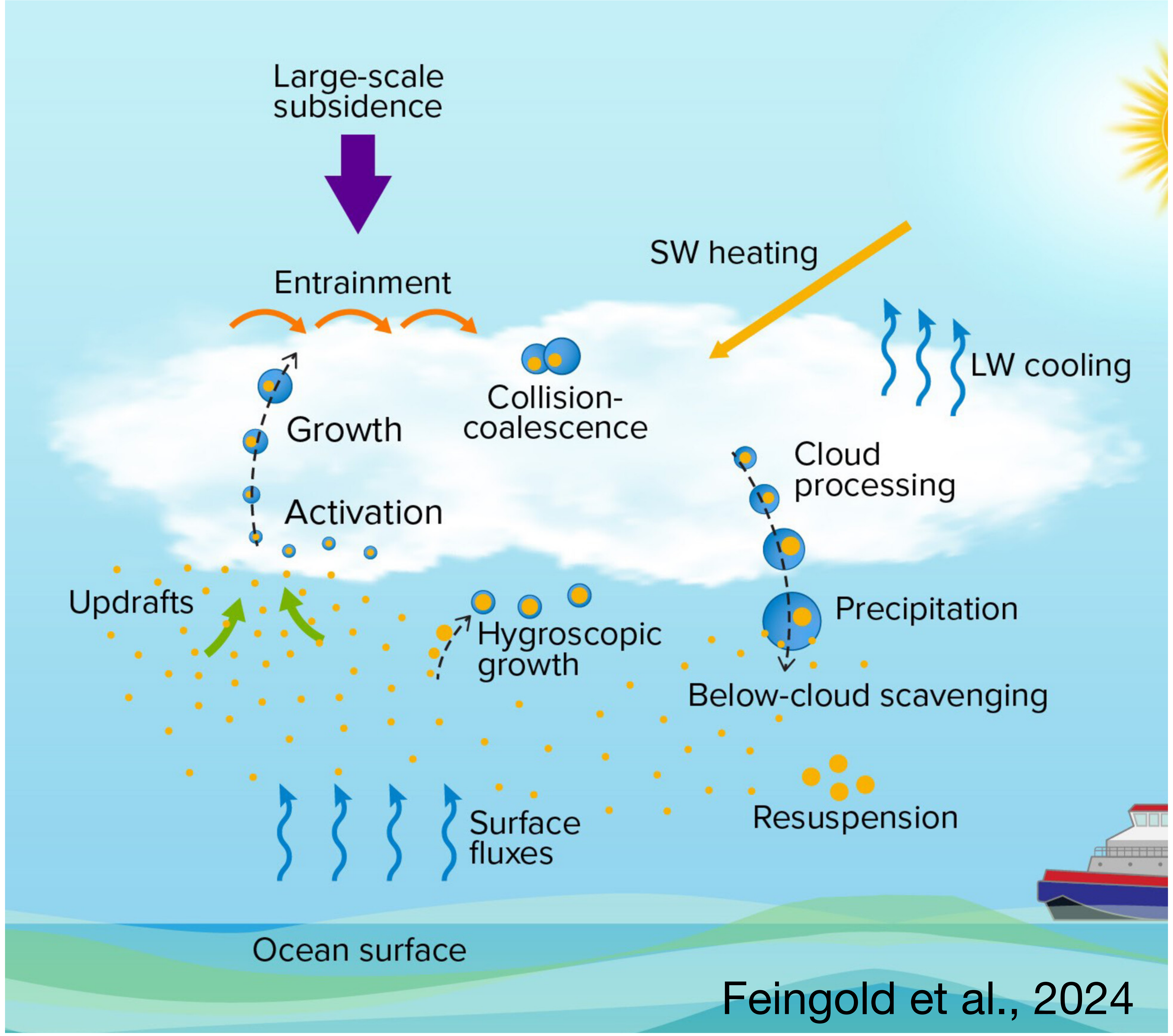
- What and why?
- Current approaches
  - Bulk scheme
  - Super droplet simulations (SDS)

Cloud microphysics: small-scale interactions between water vapor, aerosols, liquid droplets, ice crystals, and precipitation particles

- Sub-micron to cm scale
- Evolution of the particle size distribution
  - Mass(t)
  - Concentration(t)
  - Hydrometeor state (t)
- Importance
  - Radiation: albedo and lifetime
  - Weather: amount, timing, type of precipitation

Lamb et al., 2025

Cloud microphysics: small-scale interactions between water vapor, aerosols, liquid droplets, ice crystals, and precipitation particles



Processes:

- Nucleation/activation: aerosols
- Condensation/evaporation: droplet growth/shrinkage by vapor diffusion
- Autoconversion: small cloud droplets colliding to form raindrops
- Accretion: rain collecting cloud droplets
- Self-collection: droplets/drops colliding with same-category particles
- Sedimentation: gravitational settling

and MANY more if there is ice!

Lamb et al., 2025

Challenges of Cloud Microphysics Scheme Development

Uncertainty in cloud microphysics schemes

Physical Processes

Aleatoric

- Homogenous & heterogenous nucleation
- Collision-coalescence-breakup
- Depositional ice growth
- Aggregation
- Secondary Ice Production
- Microphysics-turbulence interactions

Epistemic

- Hydrometeor Representation (Categories, Moments)
- Uncertain physical processes
- Scale-dependence, unresolved processes and heterogeneity

Parameterization Development

Data

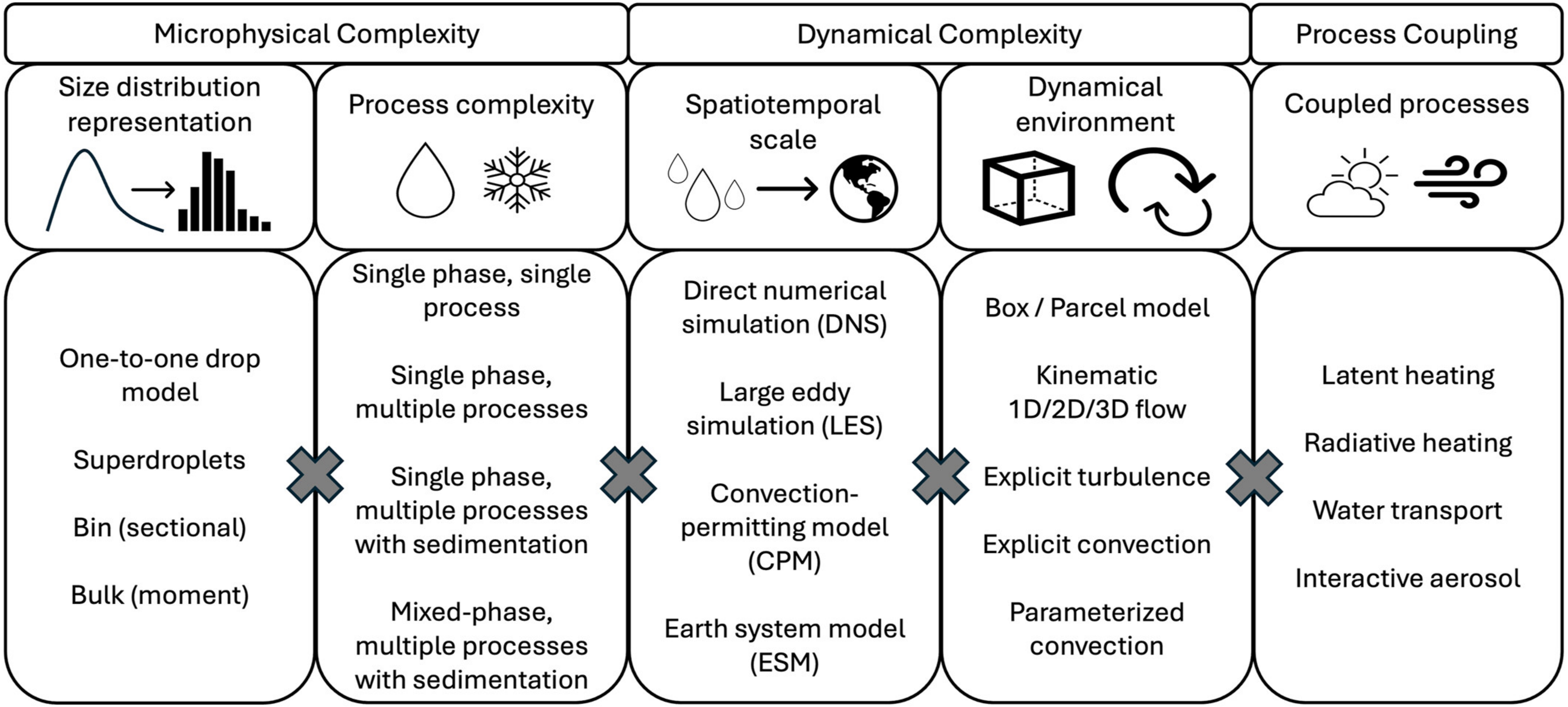
- Measurement uncertainty and bias
- Sparse or regime dependent observations
- Lack of sufficient spatial or temporal resolution
- Microphysical assumptions in retrievals

Algorithmic

- Optimization method
- Posterior inference method
- Parameter tuning method
- Neural network hyperparameter choices, architecture, overfitting
- Metrics/Loss function

Lamb et al., 2025

Modeling Complexity



Lamb et al., 2025

Bulk Moment Schemes (warm rain)

- Tracking the 0th and 1st moments of droplet distribution

L: total mass (1st moment) N: # concentration (0th moment)

$$
\begin{aligned}
L_c &= \int_0^{x^*} x f(x) dx \qquad N_c = \int_0^{x^*} f(x) dx \\
L_r &= \int_{x^*}^{\infty} x f(x) dx \qquad N_r = \int_{x^*}^{\infty} f(x) dx
\end{aligned} \tag{1}
$$

c: cloud; r: rain

f(x): density function of droplets with mass x

Two Moment Bulk Scheme (warm rain)

$$\frac{dL_c}{dt} = -AU - AC \qquad (2)$$

$$\frac{dL_r}{dt} = +AU + AC \qquad (3)$$

$$\frac{dN_c}{dt} = -2AU_n - AC_n - SC_c = \frac{-2}{x^*}AU - \frac{1}{\overline{x_c}}AC - SC_c \qquad (4)$$

$$\frac{dN_r}{dt} = +AU_n + AC_n - SC_r = \frac{1}{x^*}AU - SC_r \qquad (5)$$

c: cloud; r: rain

L: total mass; N: # concentration

AU: auto-conversion (c -> rain rate by converting)

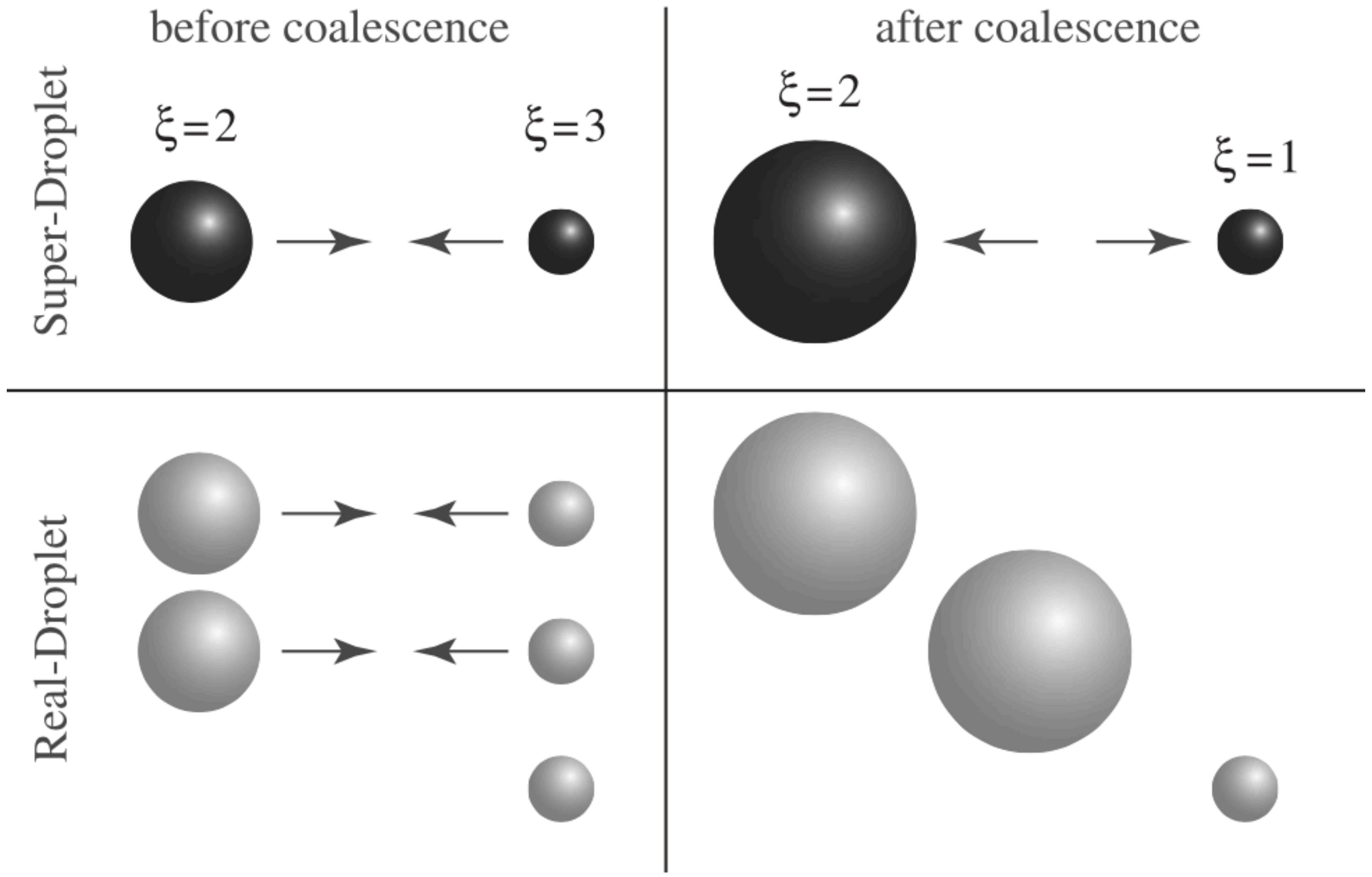
AC: accretion (c -> r rate by collision)

SC: self-collision (no c <-> r)

Seifert & Beheng, 2006

Super Droplet Simulations (SDS)

- Superdroplets:
  - Multiple droplets of the same size in vicinity
  - Attributes: # of real droplets, size, position, etc.
- Setup (Lagrangian):
  - SDs advect as particles through the flow field
  - Condensation/evaporation and sedimentation are computed per-SD using standard equations.
  - Collision (stochastic): Monte Carlo random sampling of pairs of SD



Shima et al., 2009

Bulk vs. SDS

- Prognostic variables
- Assume a gamma distribution
- Computes AU, AC, SC rates from closed-form expressions derived by integrating the collision kernel over the assumed gamma PSD
- Cheap

- Explicit simulation
- No assumptions of PSD
- Computes coalescence stochastically via Monte Carlo
- More realistic and general

SuperdropNet:

- Cheap
- No PSD assumption

surrogate of H based on autoregression

$$\mathbf{y} = \hat{\mathbf{H}}\mathbf{x} + \mathbf{n}$$

stochasticity handled explicitly

Bulk moments and thermodynamics at t

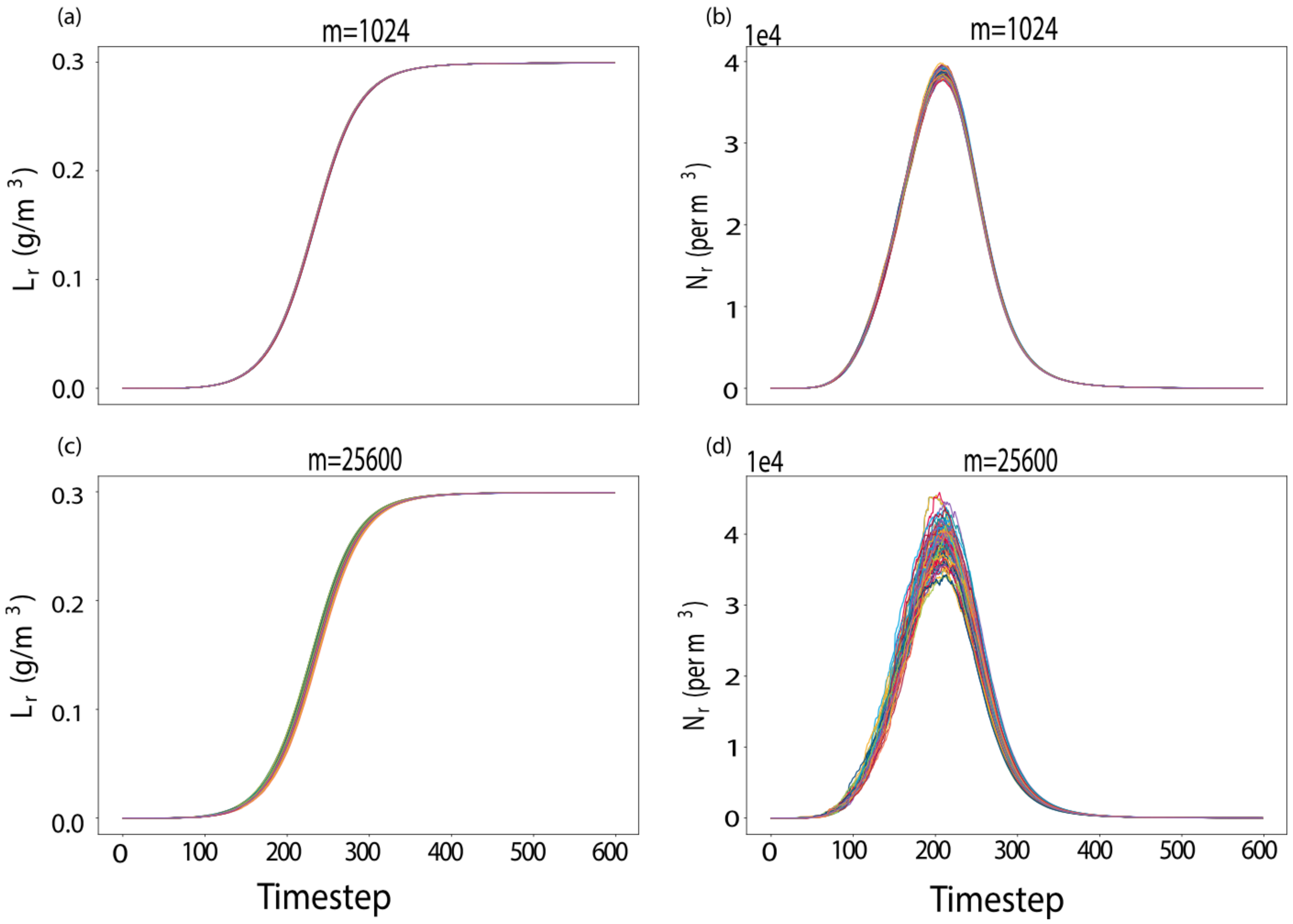
Bulk moments at t+Δt

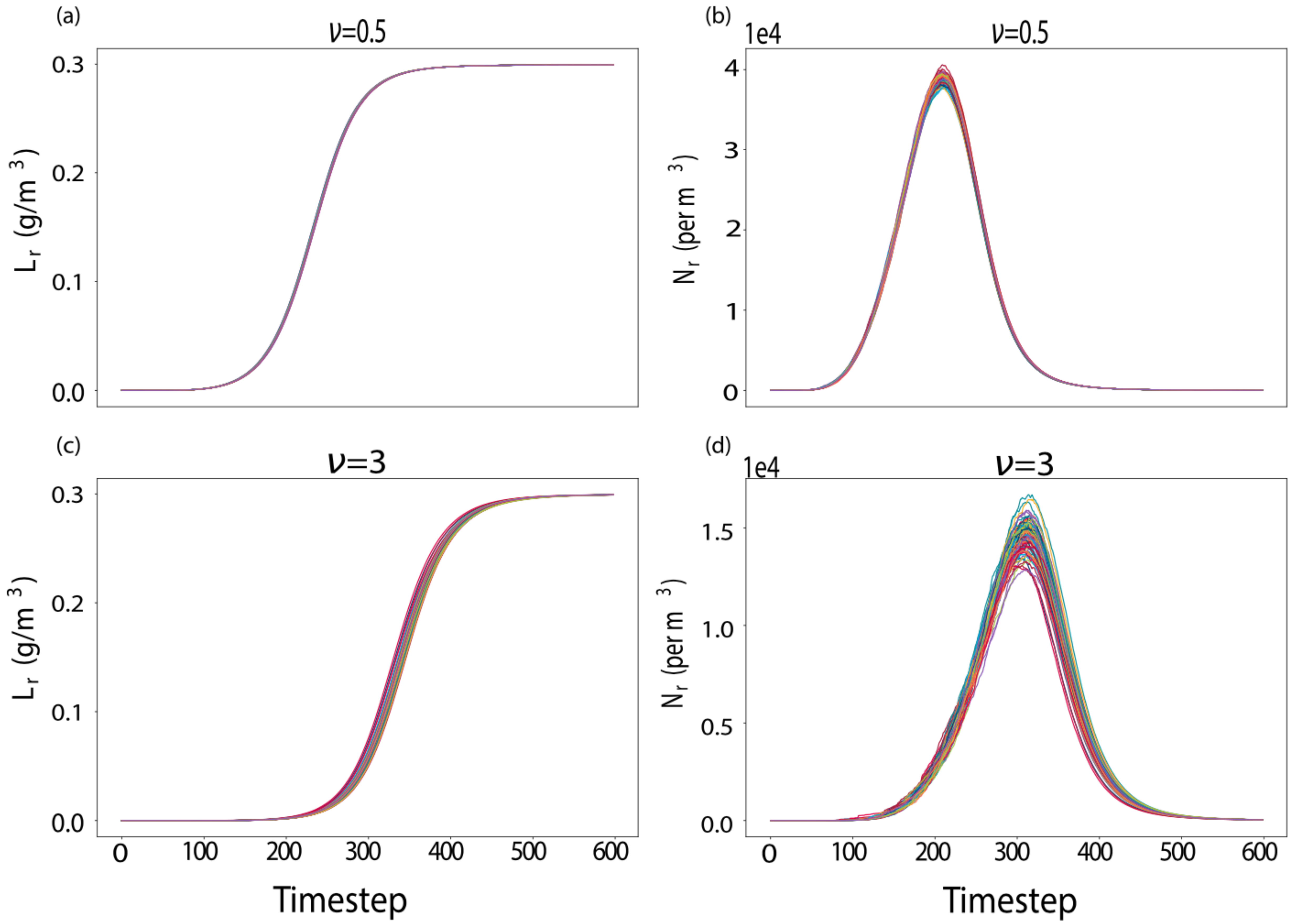
mass & # conc. of cloud and rain particles

from SD simulations

- Stochasticity in collision
  - different results with the same initial condition
  - overfitting and instability

- To limit stochasticity
  - Chose parameters generating lower variability
  - Averaged over 100 simulations





Setup

- Constraints:
  - Mass conservation: $\hat{L}_r$ as residuals
  - Irreversibility: $\hat{\Delta} L_c \leq 0$ (only in training)
  - L, N ≥ 0 (not in training)
- Architecture:
  - Fully connected
  - 3 layers x 200 neurons
  - ReLU

rollout length

$$\mathcal{M}^{(k)}(y_t) = \overbrace{\mathcal{M} \circ \mathcal{M} \circ \cdots \circ \mathcal{M}}^{k \text{ times}}(y_t) \approx y_{t+k} \tag{7}$$

$$\mathcal{M}^{(t)}(y_0) \approx y_t, \quad \forall t \tag{8}$$

$$\mathcal{M}(y_t) = y_t + h_\theta(y_t, \phi)\Delta t \approx y_{t+1} \tag{10}$$

- k=1: only knows 1 step ahead
  - compounding errors
- large k: loss computed at every intermediate step t+Δt, t+2Δt, ..., t+kΔt
  - self-correction
  - but can diverge if initial condition is out-of-distribution
- Solution: “the learning curriculum” / warm start
  - Start with k=1, train until convergence
  - Use weights of k=1 to initiate training of k=2, repeat for k ≤ 25

Rollout length k

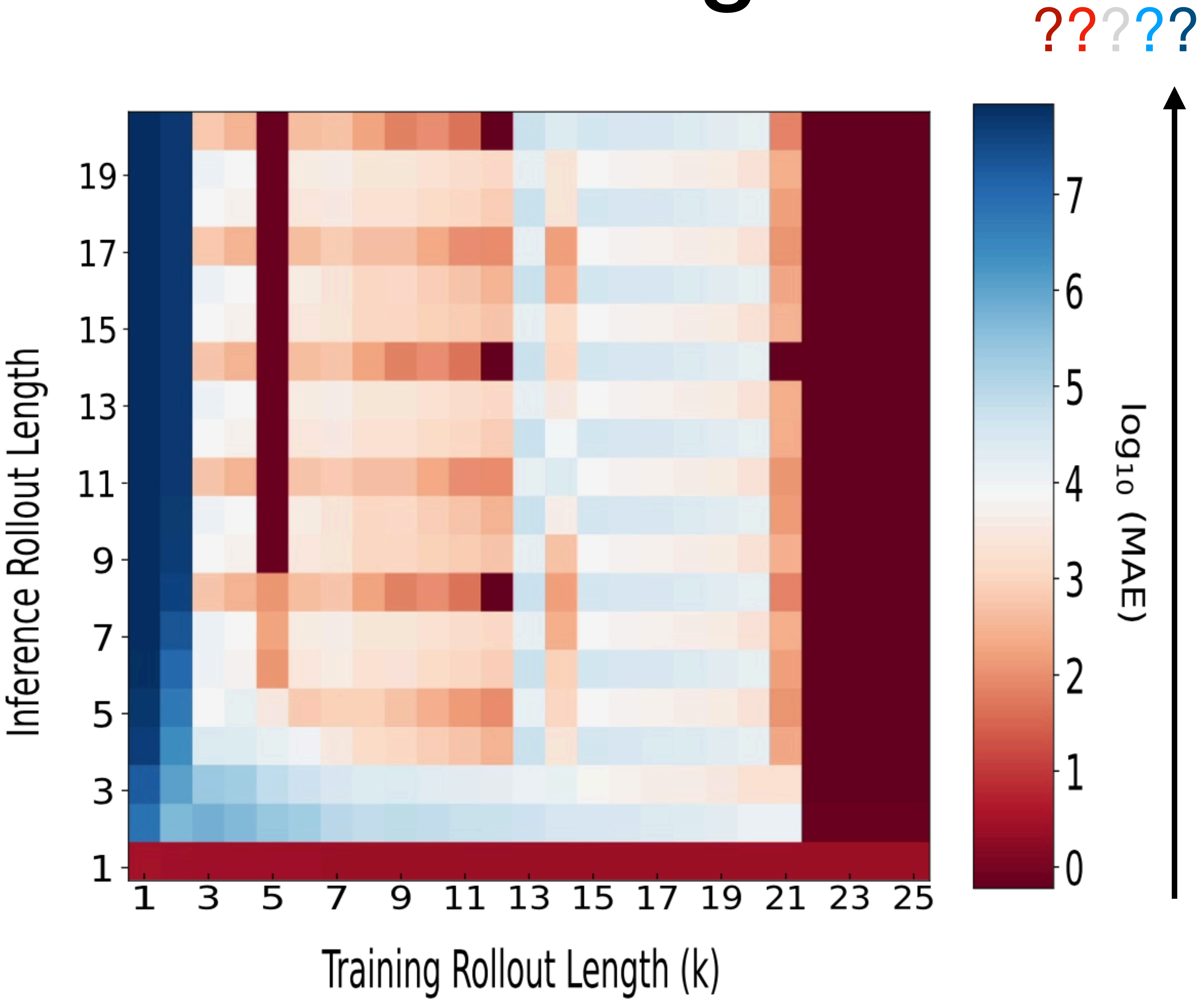


Fig. 8b

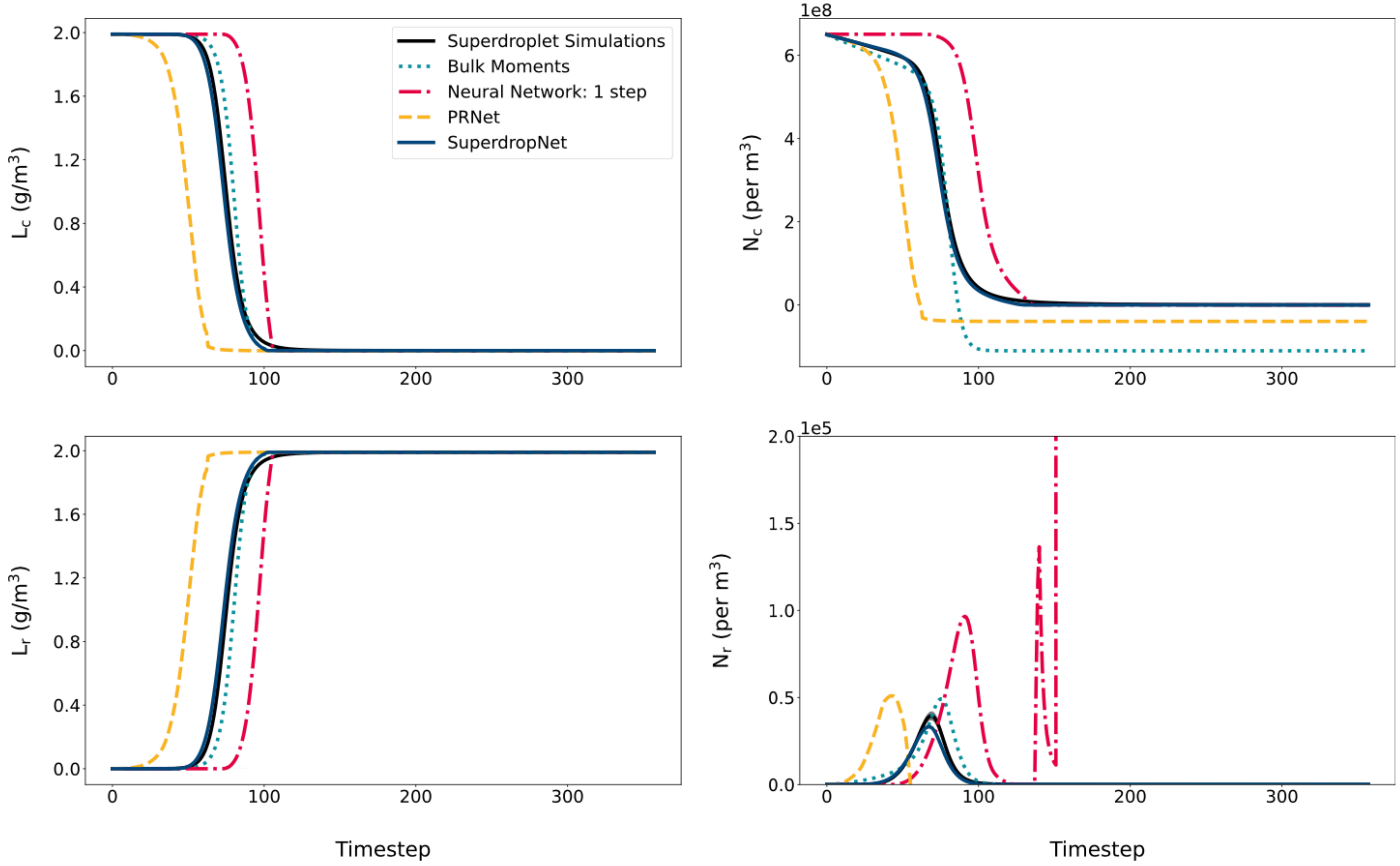


Figure 4. Superdroplet-derived bulk moments (black lines) compared to rollouts from a neural network trained to predict 1 step into the future (red-dashed lines), SuperdropNet (blue solid line), PRNet (yellow-dashed lines) and from a classical bulk moment scheme (blue-dotted lines). Results are shown for a simulation with $L_0 = 2$ g/m^3, $r_0 = 9\mu$m, $\nu = 0$. Shaded region indicates ± 1 standard deviation over 100 superdroplet simulations. A single time step corresponds to 20 s of simulation time.