

# **open-source Python projects for particle-based aerosol/cloud microphysics modelling**

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Jagiellonian University, Kraków, Poland

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DACoPT meeting @ INRIA Sofia Antipolis

## Smoluchowski's coagulation equation (SCE)

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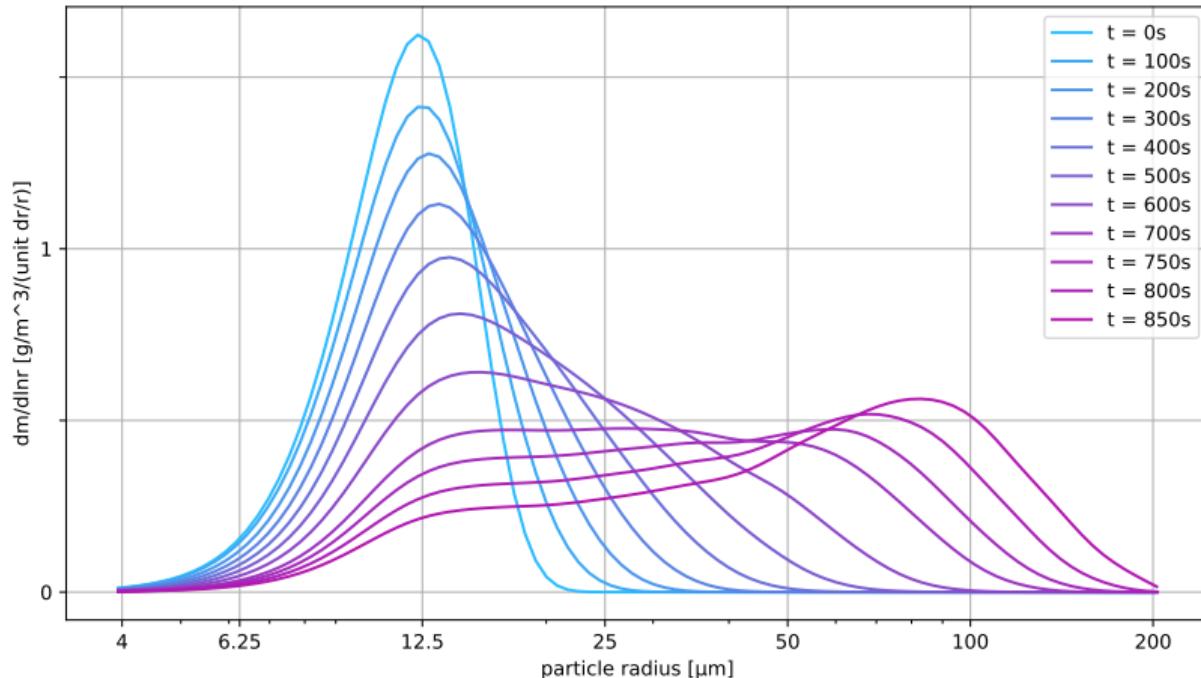
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discretised particle concentration:  $c_i = c(x_i)$  where  $x_i = i \cdot x_0$

$$\dot{c}_i = \frac{1}{2} \sum_{k=1}^{i-1} a(x_k, x_{i-k}) c_k c_{i-k} - \sum_{k=1}^\infty a(x_k, x_i) c_k c_i + \dots \quad (2)$$

# cloud droplet collisional growth



Bartman et al. 2021, LNCS (doi:10.1007/978-3-030-77964-1\_2)

## context: aerosol-cloud-precipitation interactions (scales!)



"Cloud and ship. Ukraine, Crimea, Black sea, view from Ai-Petri mountain"

(photo: Yevgen Timashov / National Geographic)

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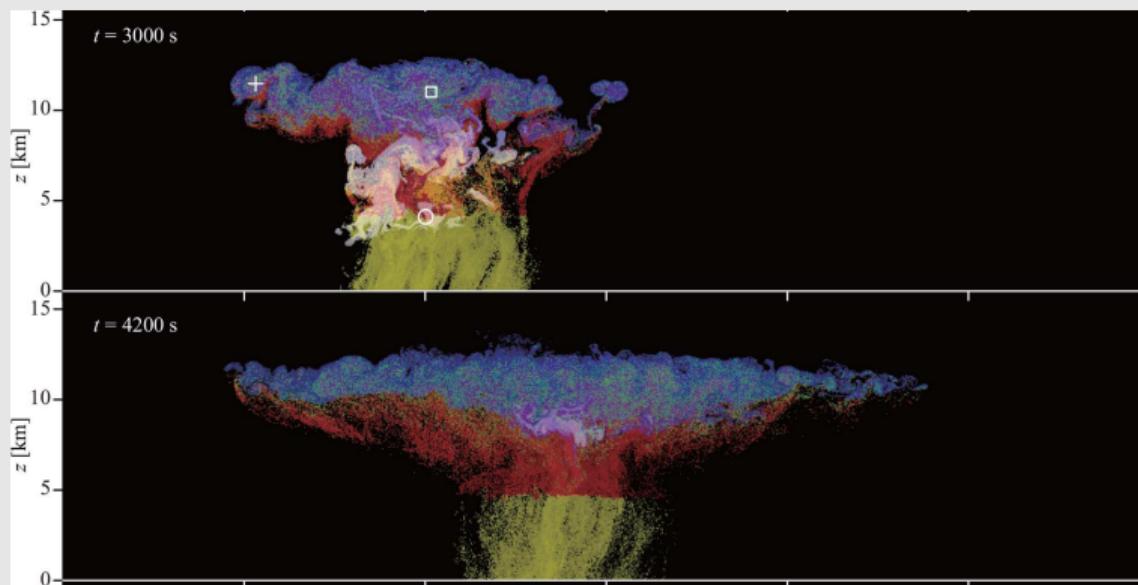
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Shima et al. 2020 (doi:10.5194/gmd-13-4107-2020): mixed-phase



**Figure 1.** Typical realization of CTRL cloud spatial structures at  $t = 2040, 2460, 3000, 4200$ , and  $5400\text{ s}$ . The mixing ratio of cloud water, rainwater, cloud ice, graupel, and snow aggregates are plotted in fading white, yellow, blue, red, and green, respectively. The symbols indicate examples of unrealistic predicted ice particles (Sects. 7.3 and 9.1). See also Movie 1 in the video supplement.

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## SDM

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### interpretation

concentration " $c_i$ " in size bin " $i$ "

besides  $c_i$ , each "particle"  $i$  carries other physicochemical attributes, e.g.  
position  $(x_i, y_i, z_i)$

# super-particles as an alternative to bulk or bin $\mu$ -physics

## Confronting the Challenge of Modeling Cloud and Precipitation Microphysics

Hugh Morrison✉, Marcus van Lier-Walqui, Ann M. Fridlind, Wojciech W. Grabowski, Jerry Y. Harrington,

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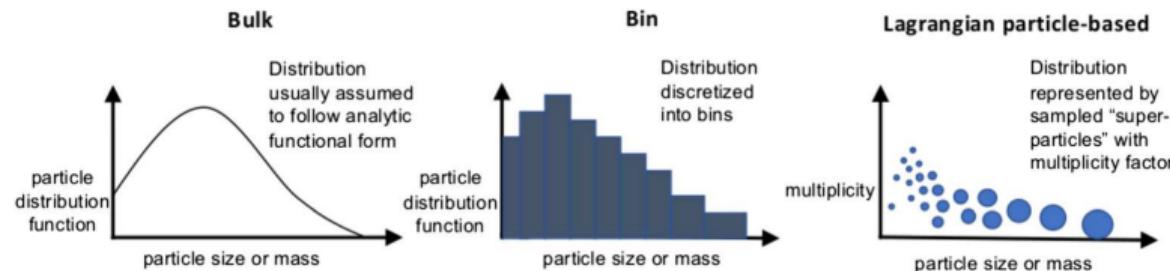
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Journal of Advances in Modeling Earth Systems [10.1029/2019MS001689](https://doi.org/10.1029/2019MS001689)



**Figure 3.** Representation of cloud and precipitation particle distributions in the three main types of microphysics

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KPI: instant and anonymous execution on commodity environment

# PySDM: 2D kinematic Sc test (Morrison & Grabowski '07)

2D flow field

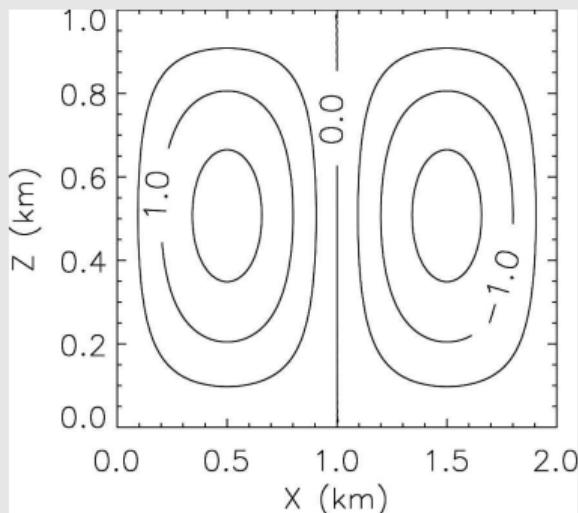
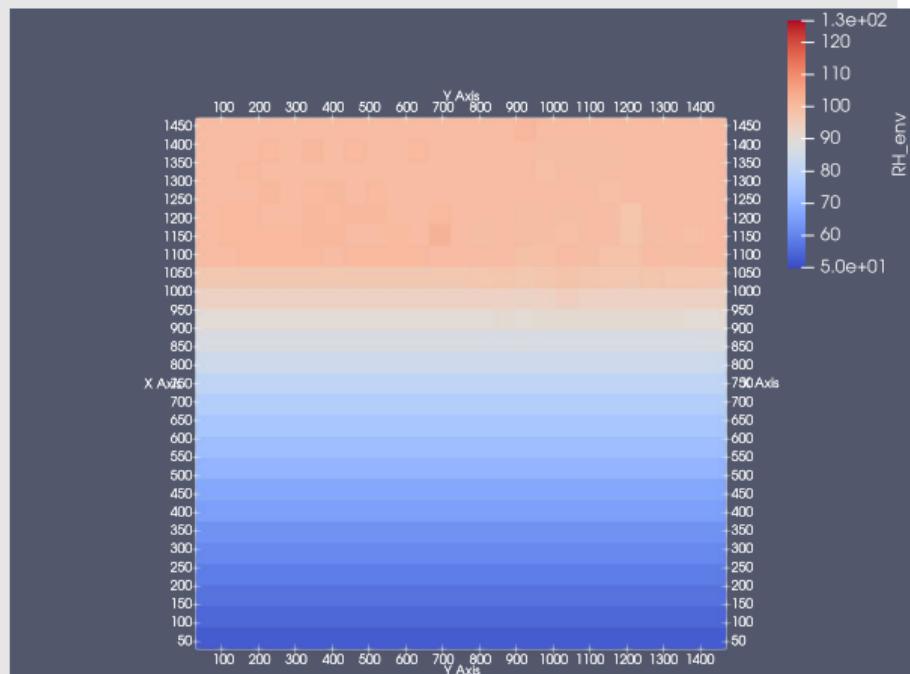
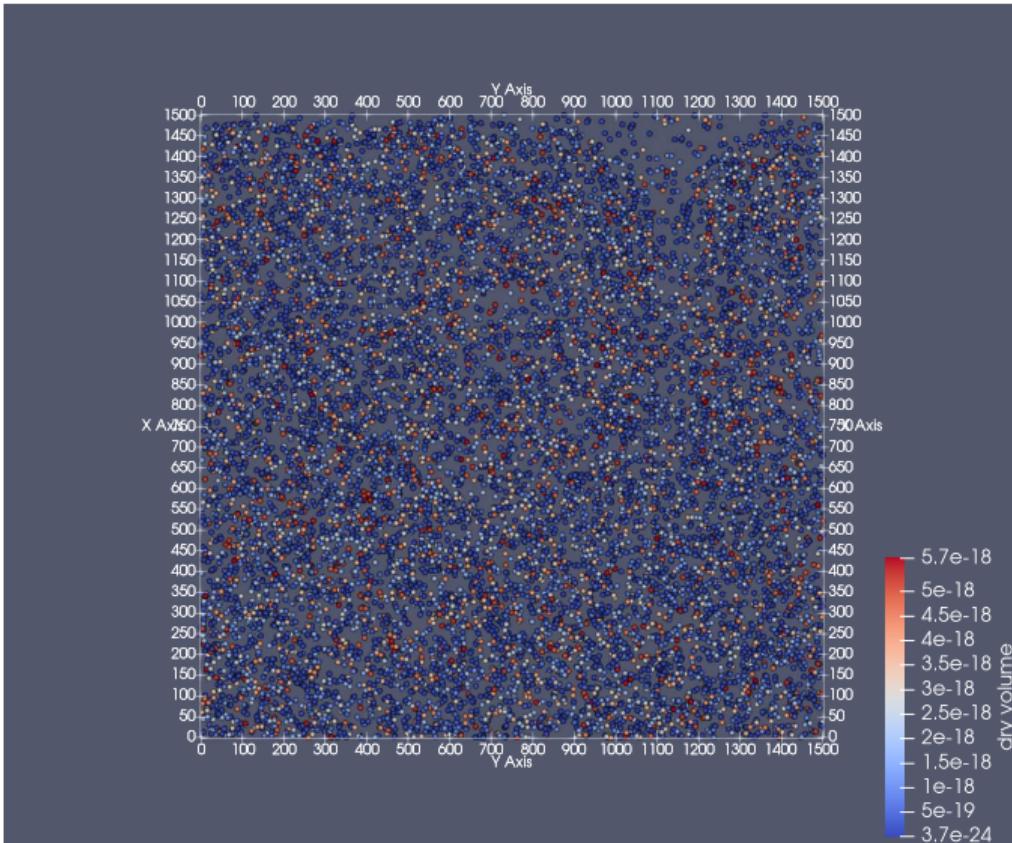


FIG. 1. Time-invariant vertical velocity for the stratocumulus case (contour interval is  $0.5 \text{ m s}^{-1}$ ).

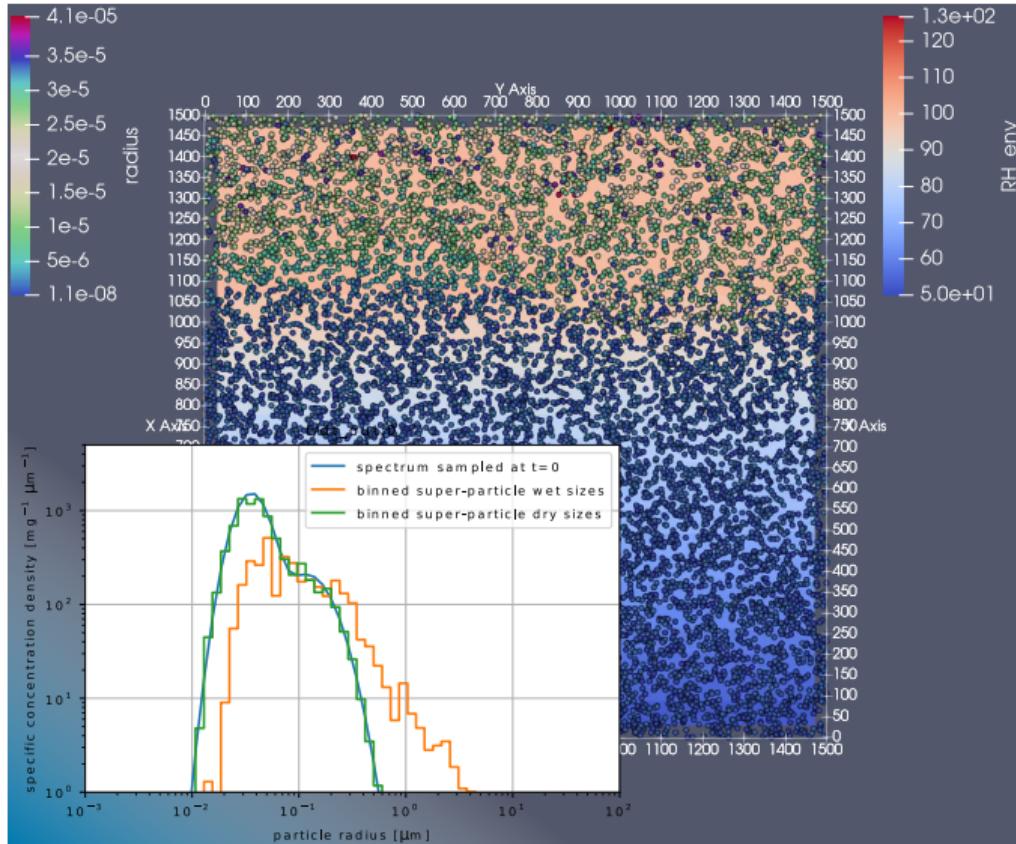
RH profile at t=0



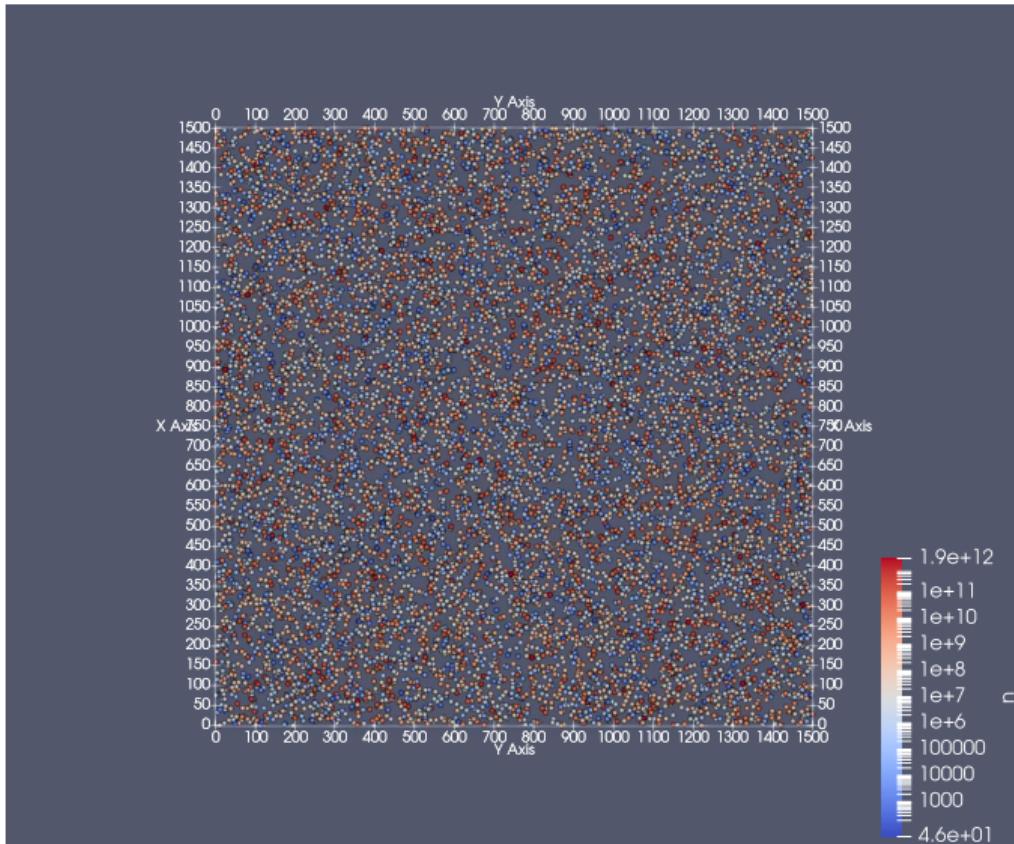
## particle attribute initialisation: dry/wet volume



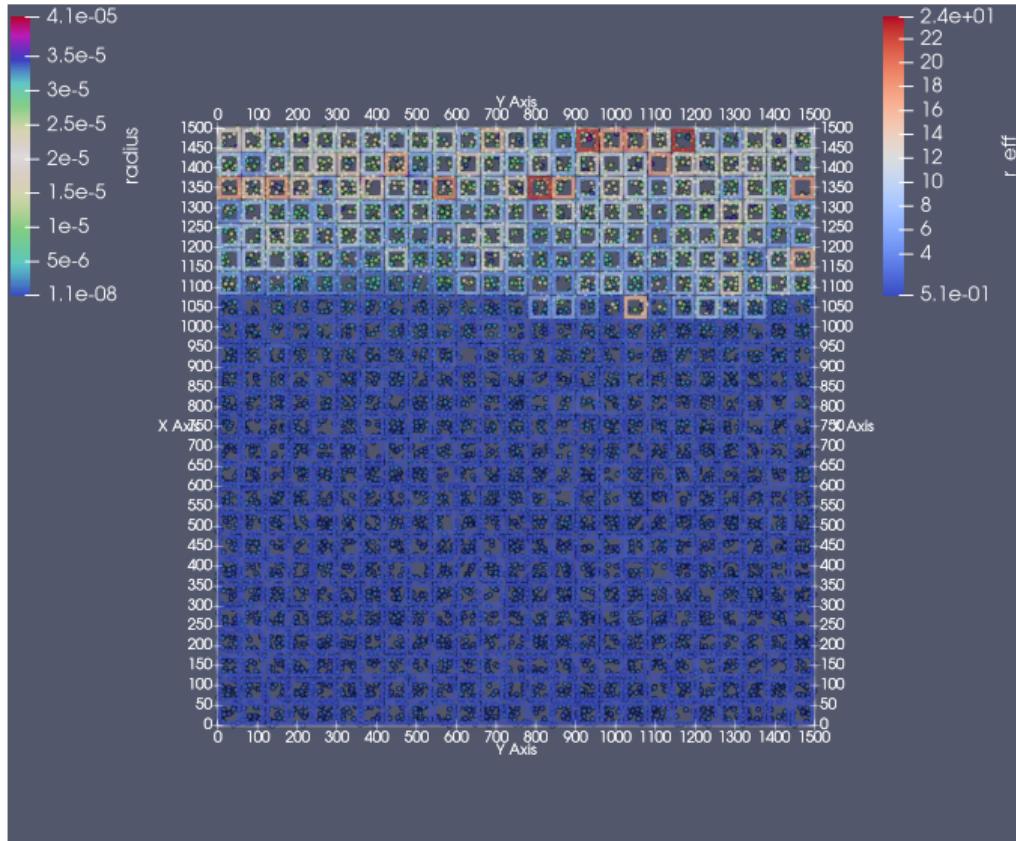
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## particle attribute initialisation: multiplicity



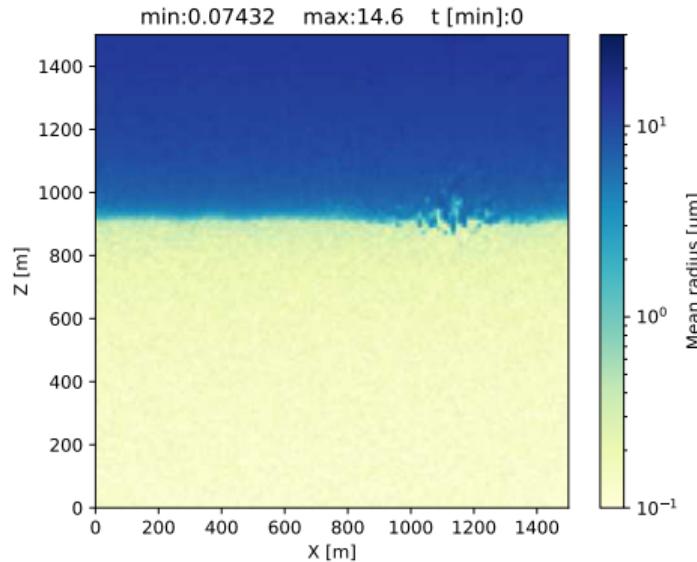
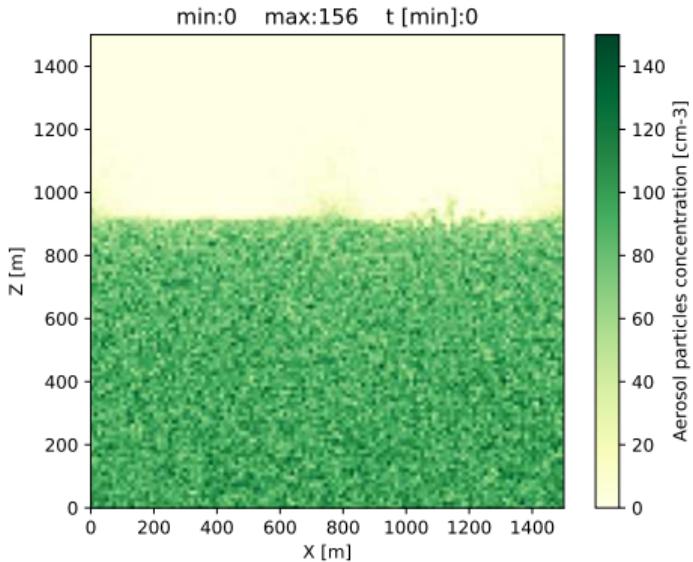
## particle attribute evolution: droplet radius



# sample aerosol-cloud-precipitation interactions simulation

Computational grid: 128x128

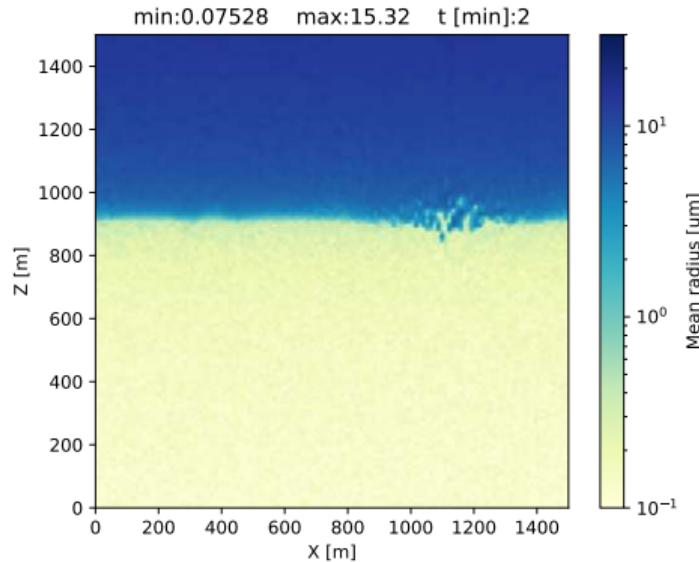
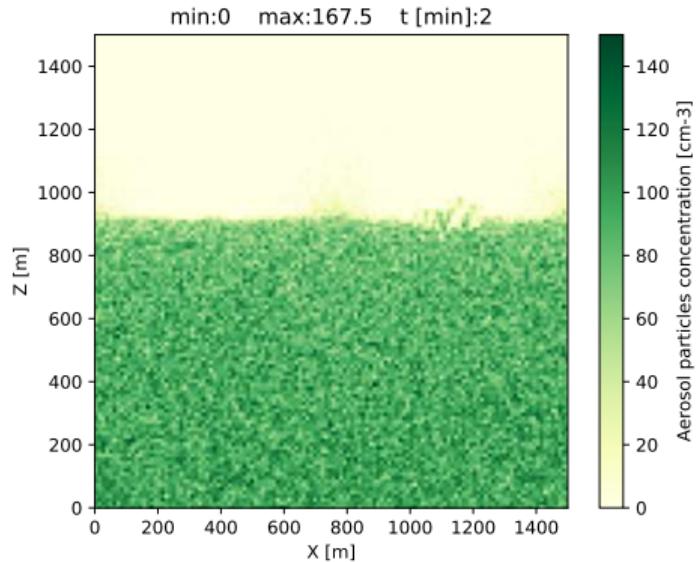
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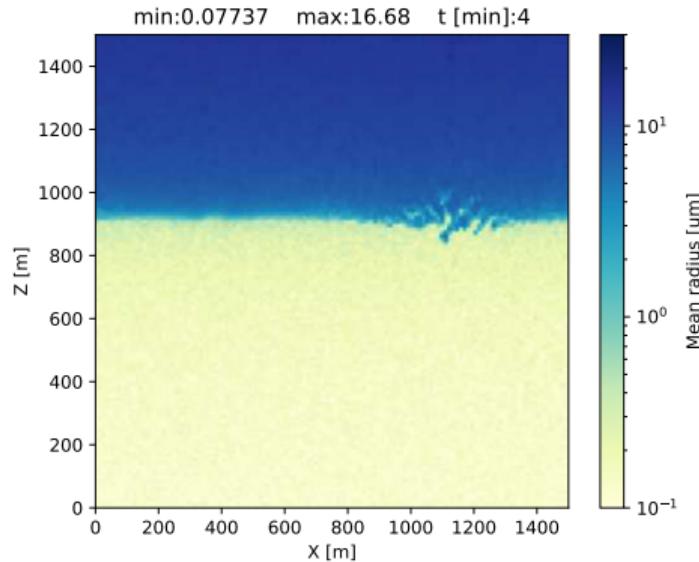
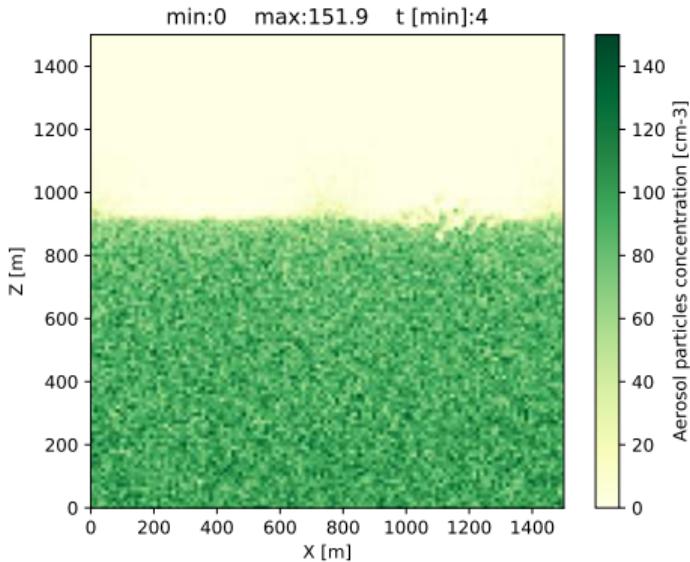
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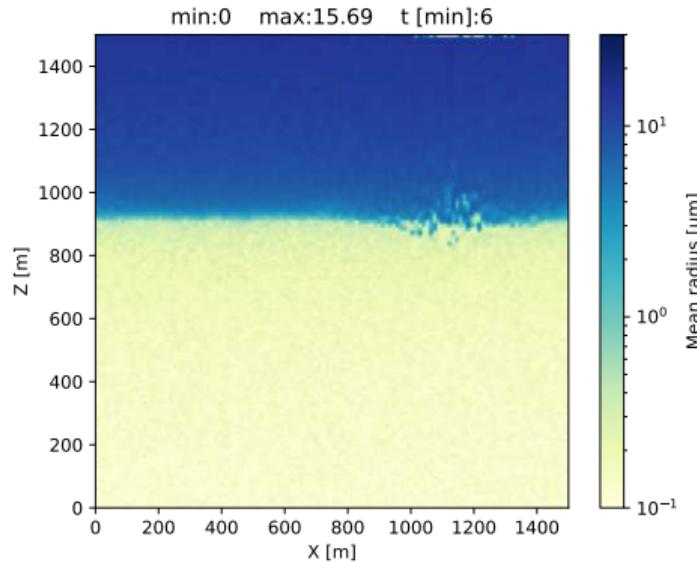
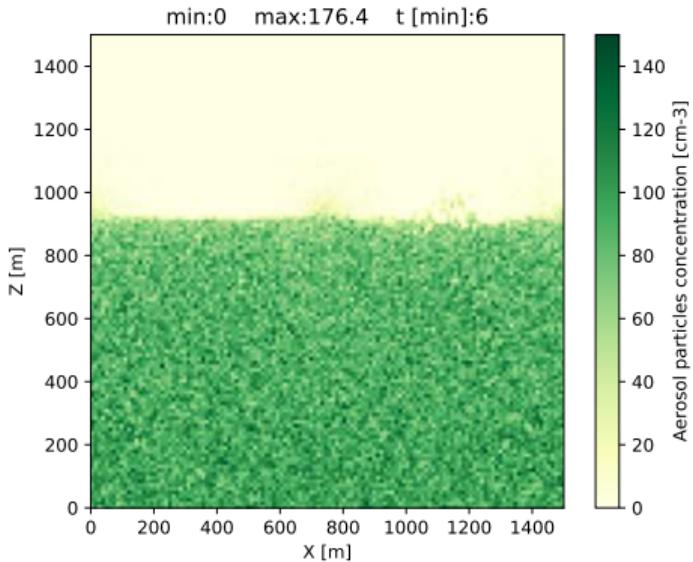
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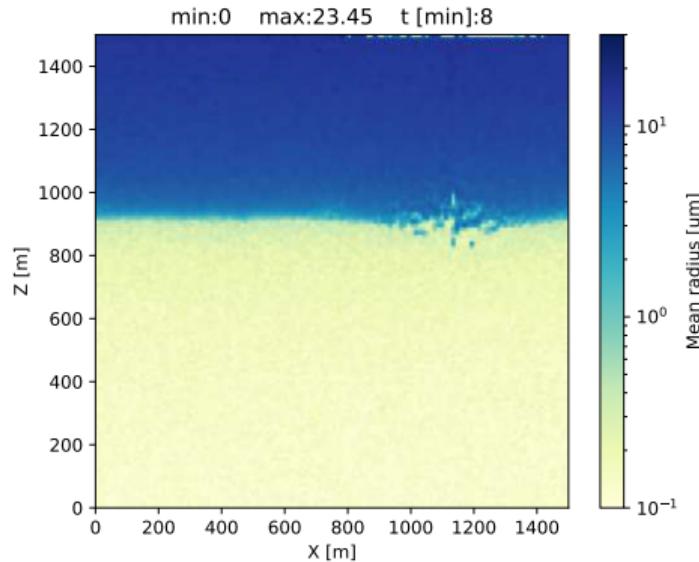
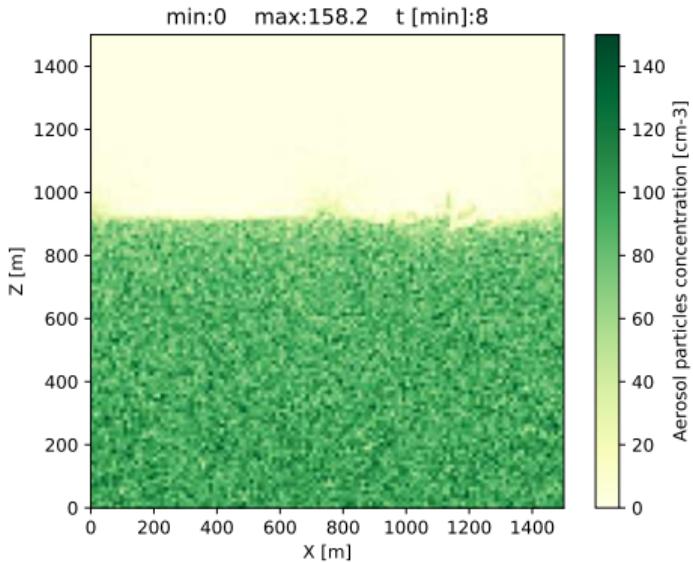
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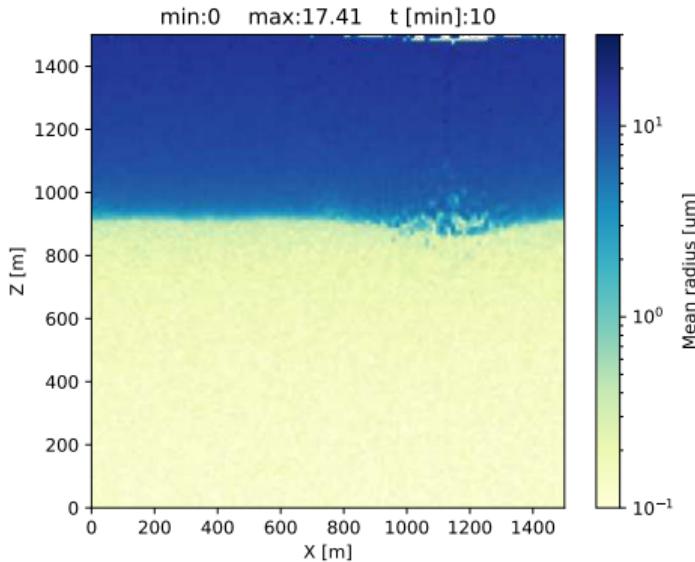
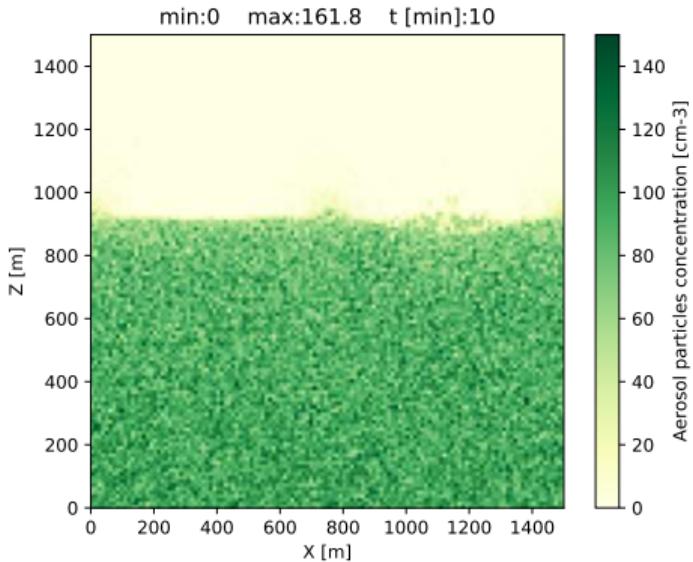
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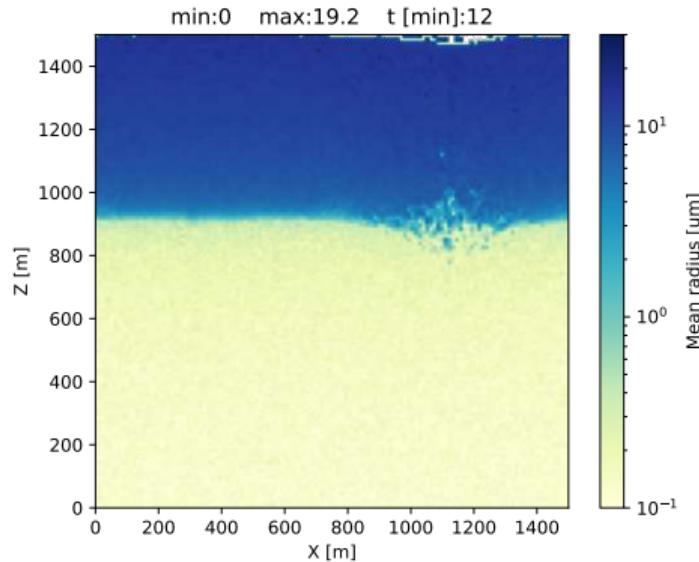
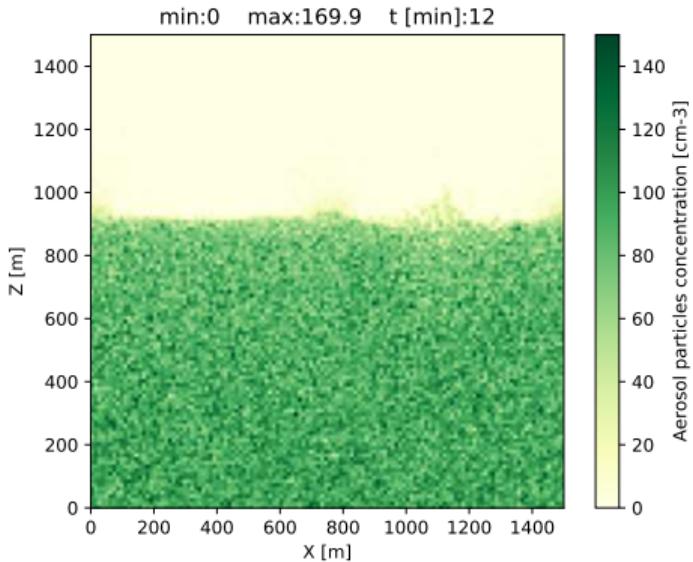
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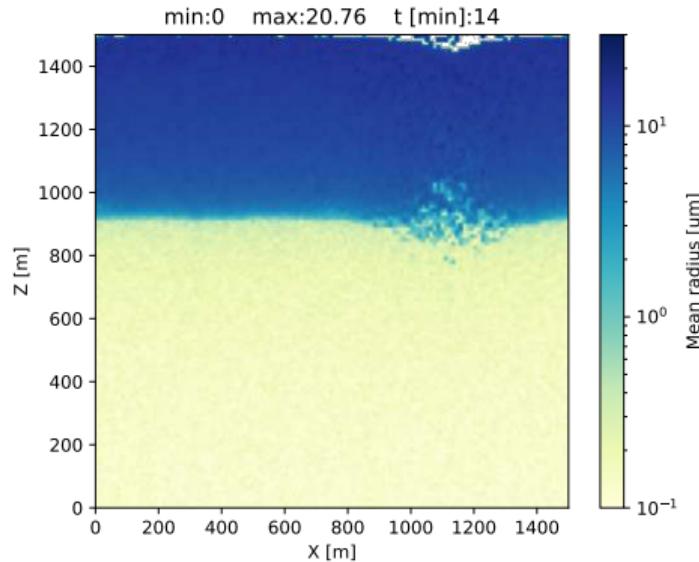
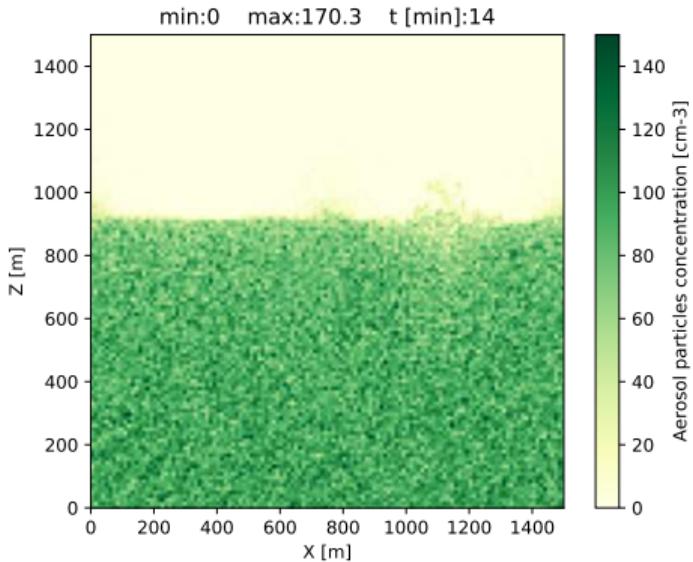
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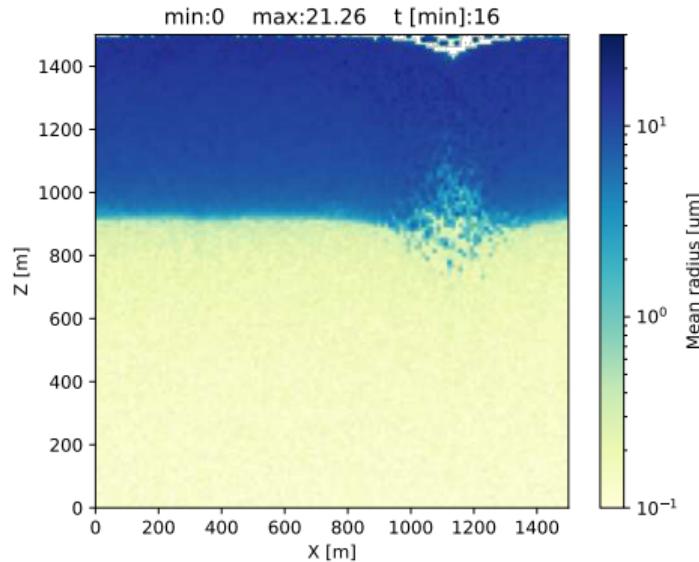
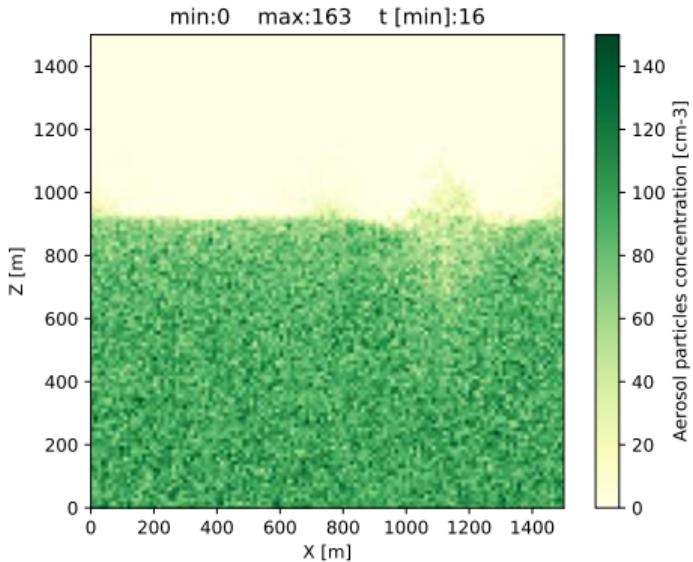
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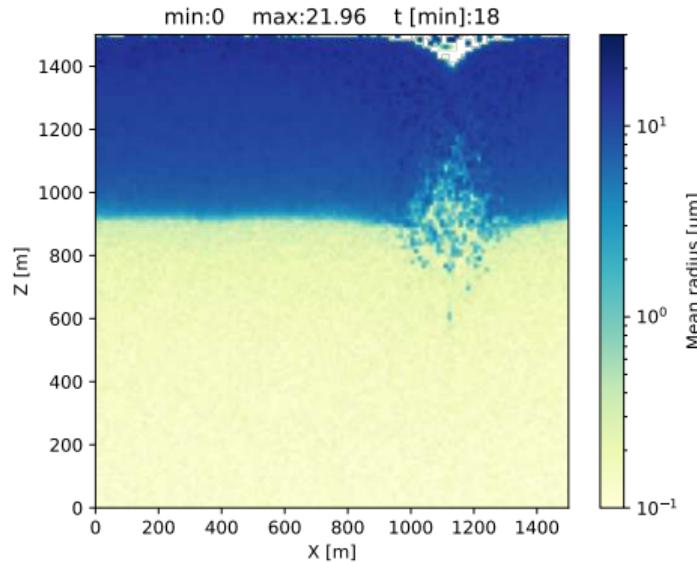
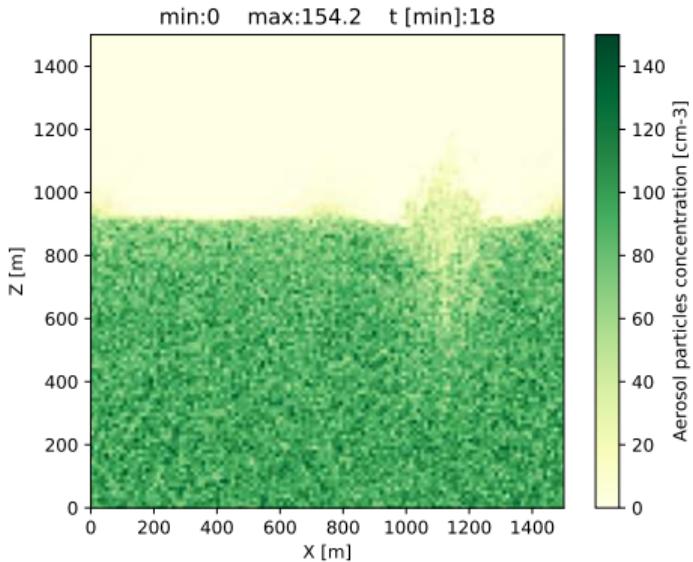
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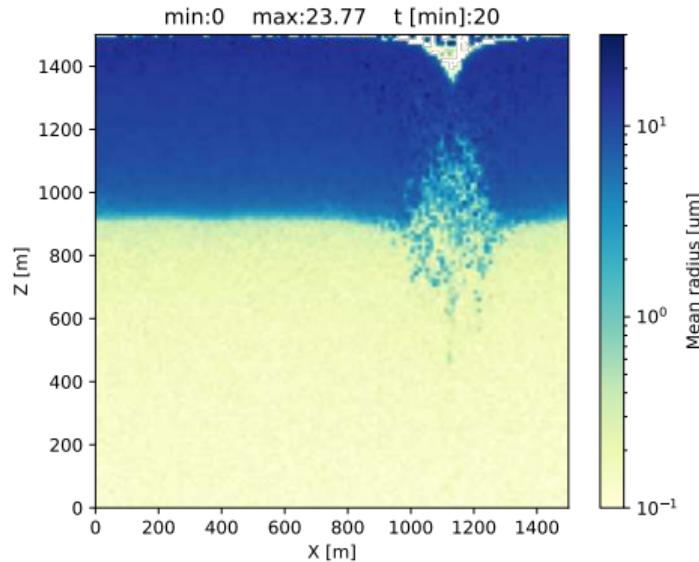
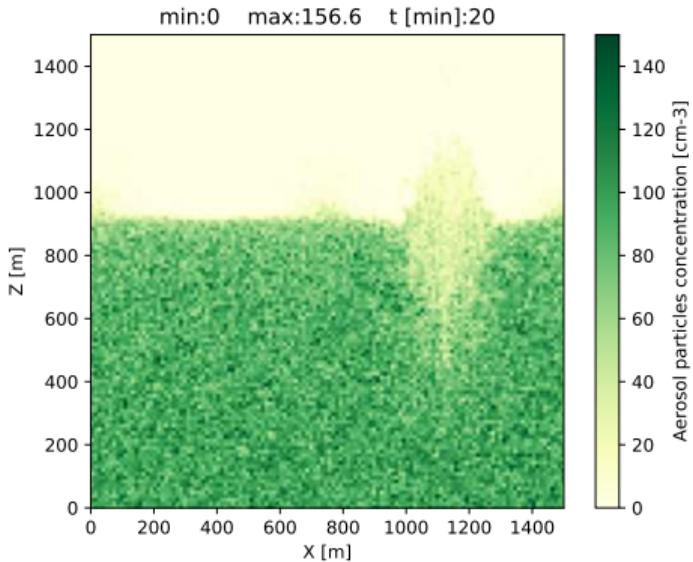
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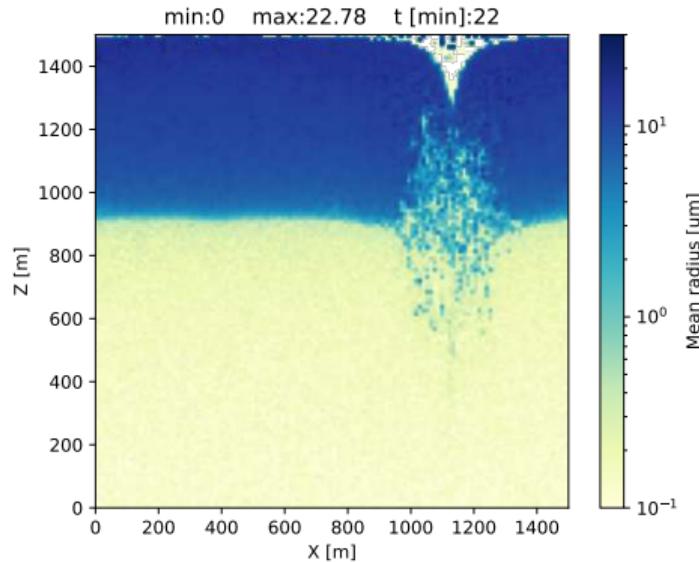
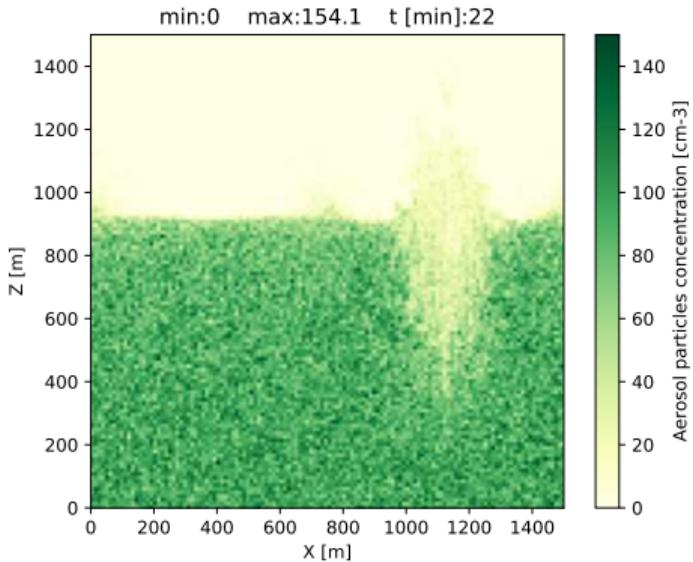
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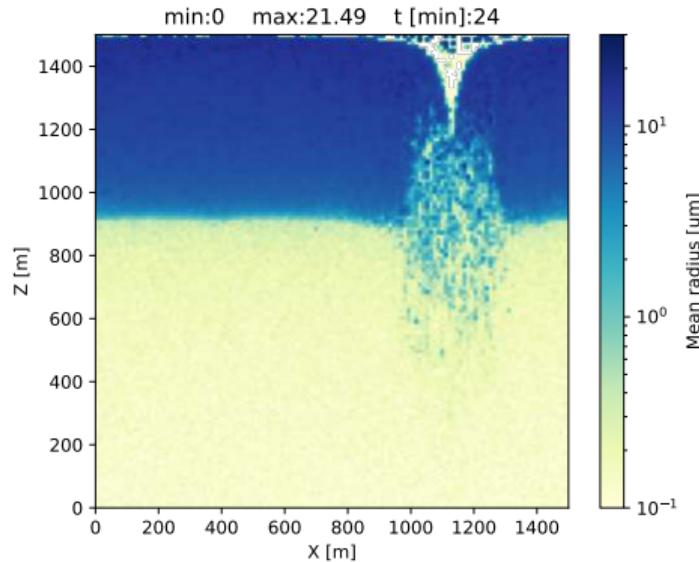
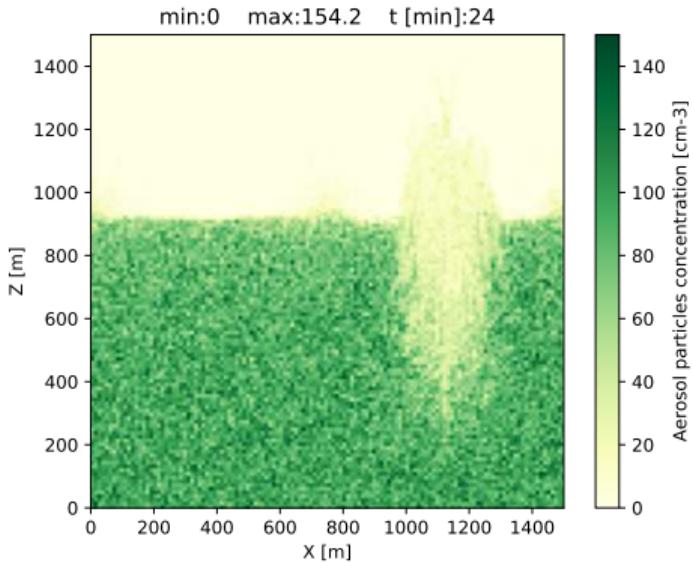
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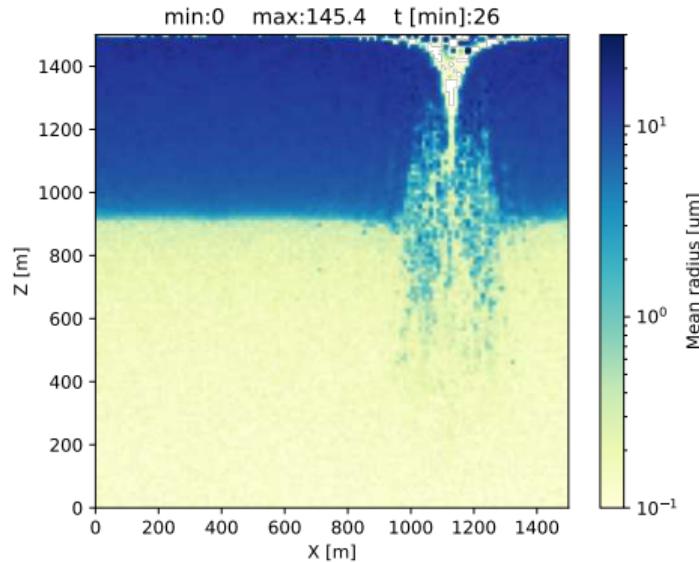
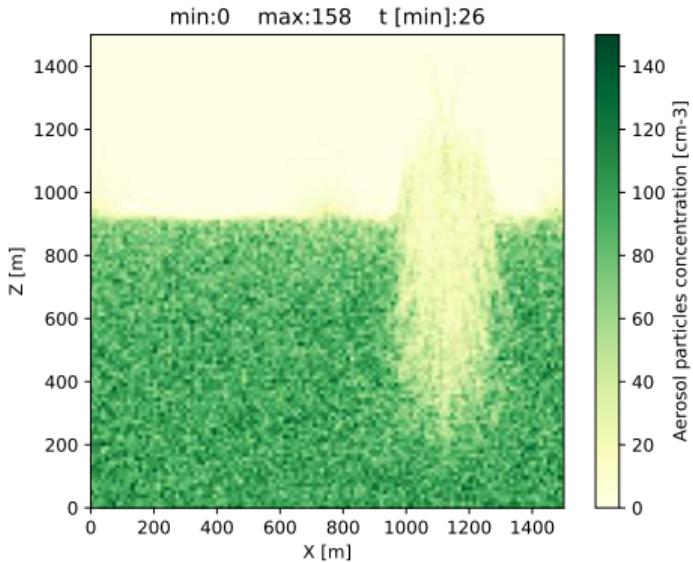
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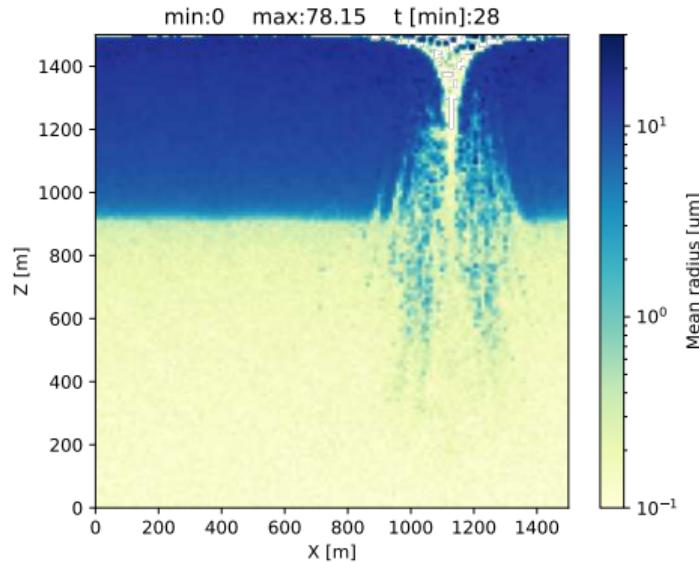
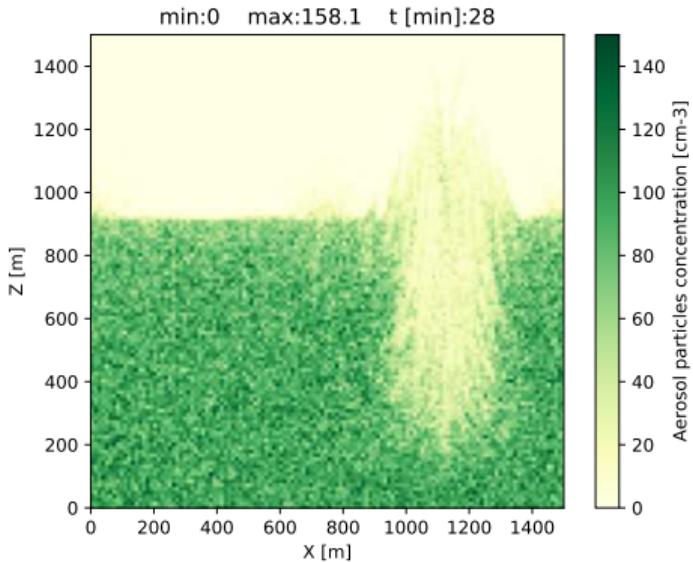
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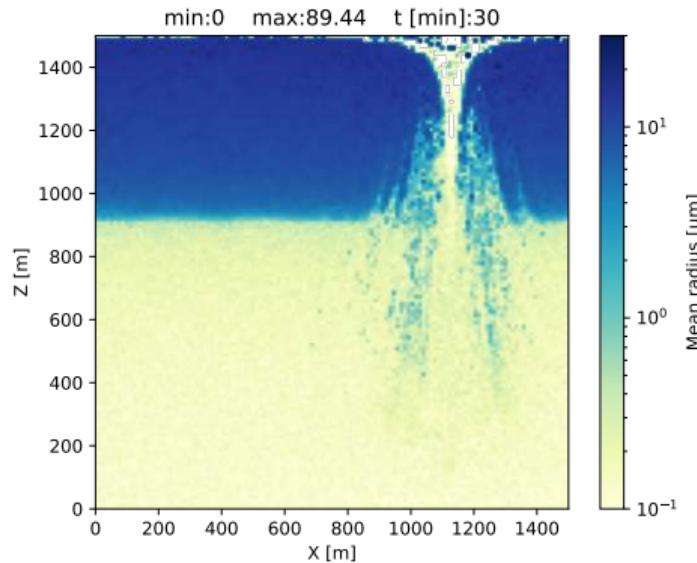
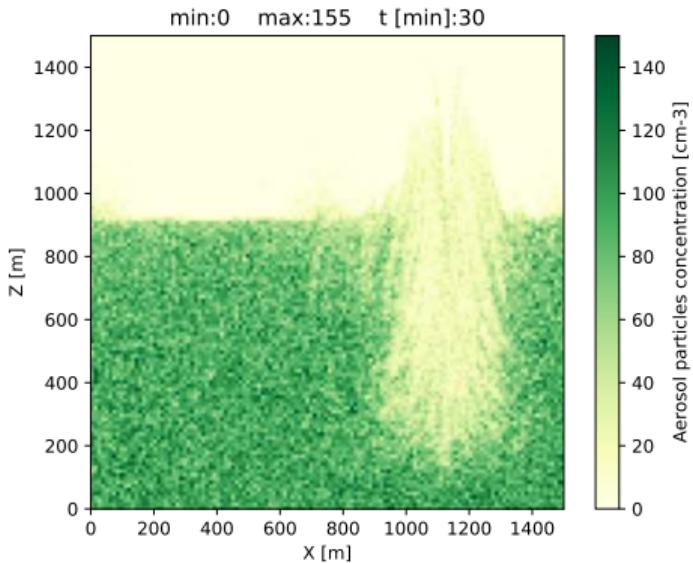
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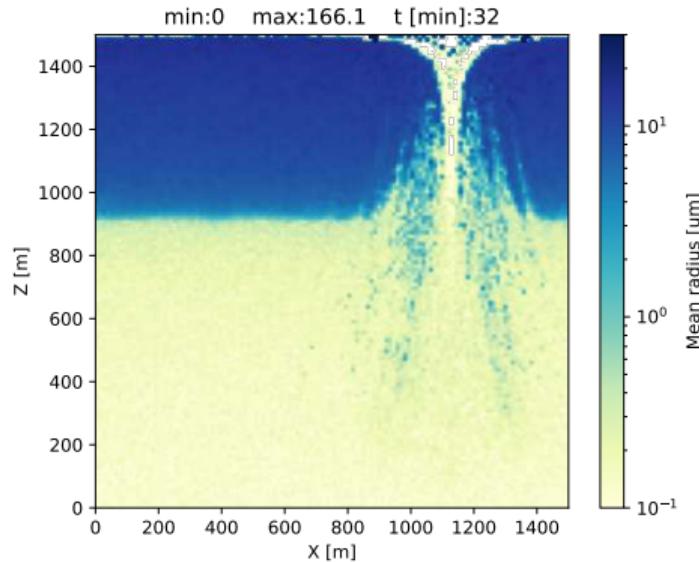
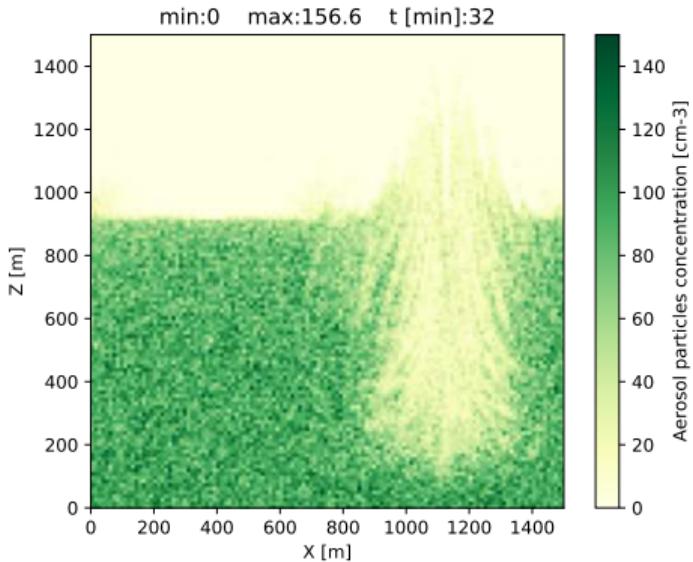
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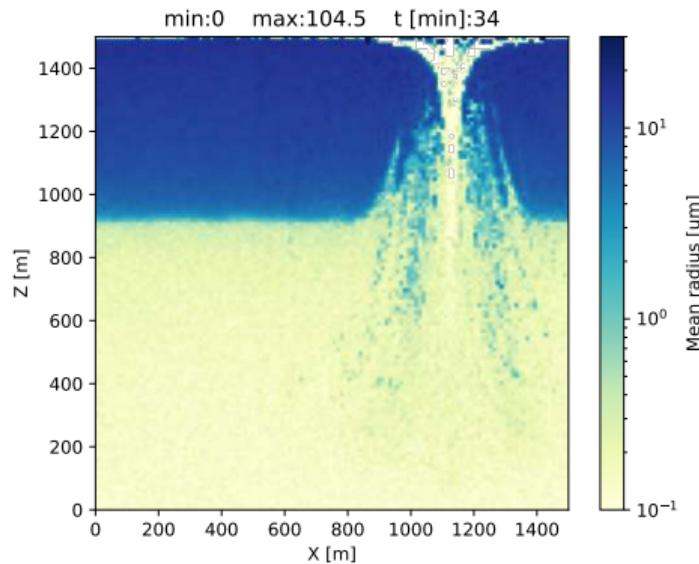
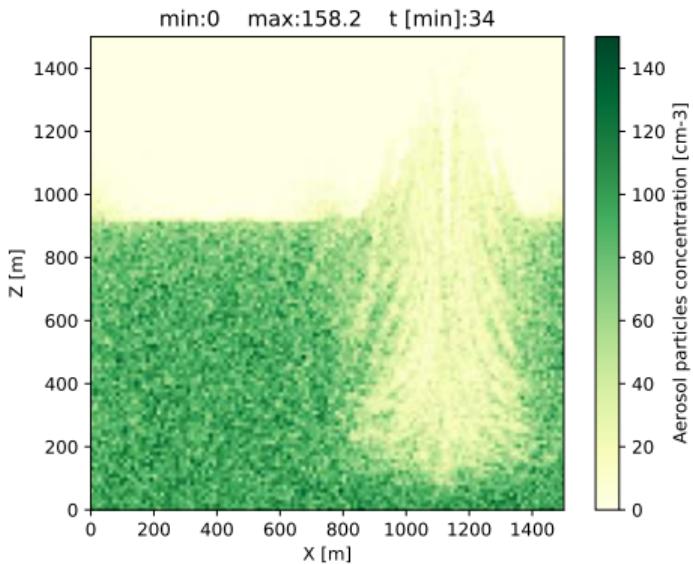
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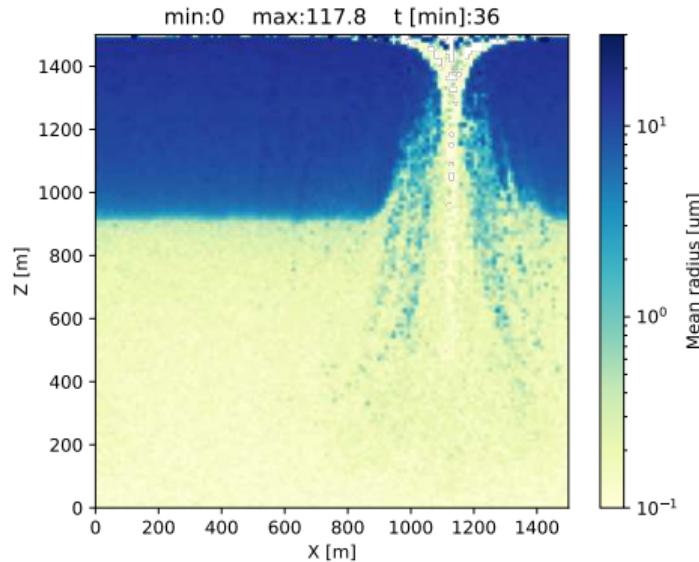
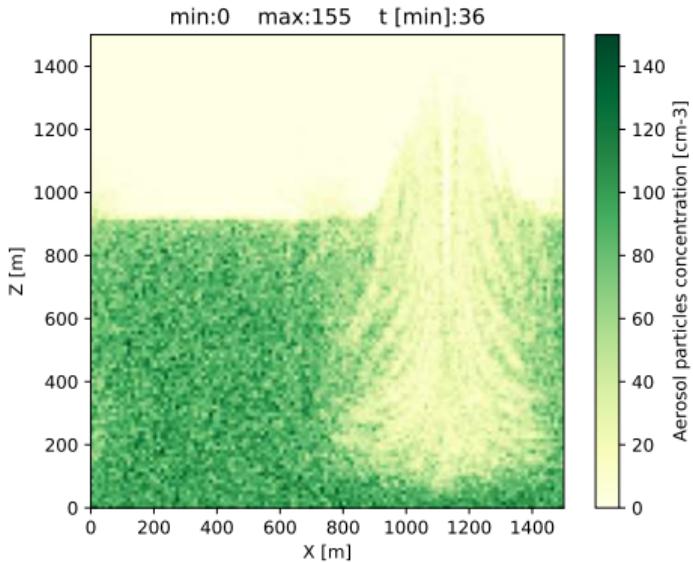
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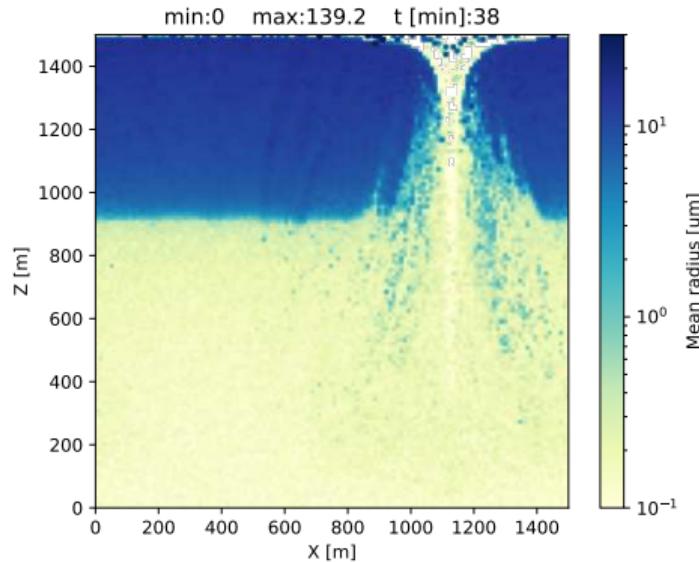
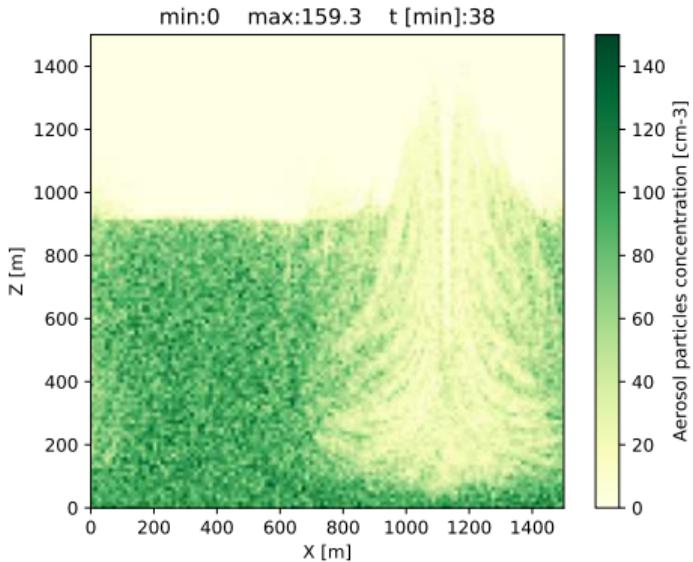
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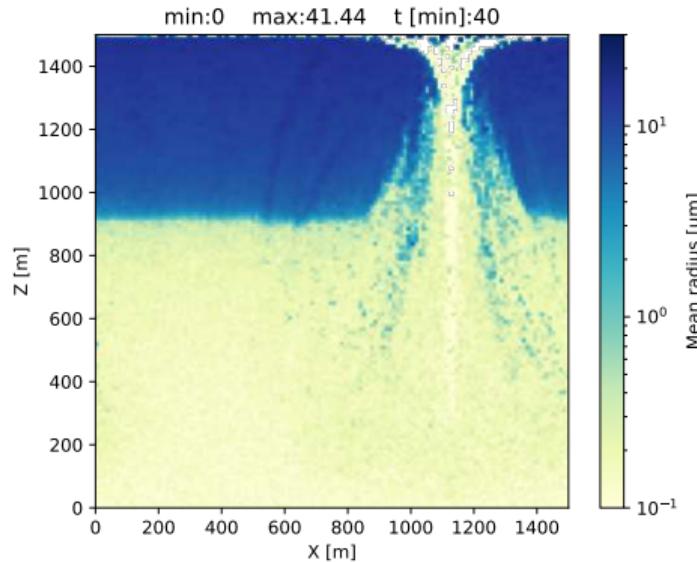
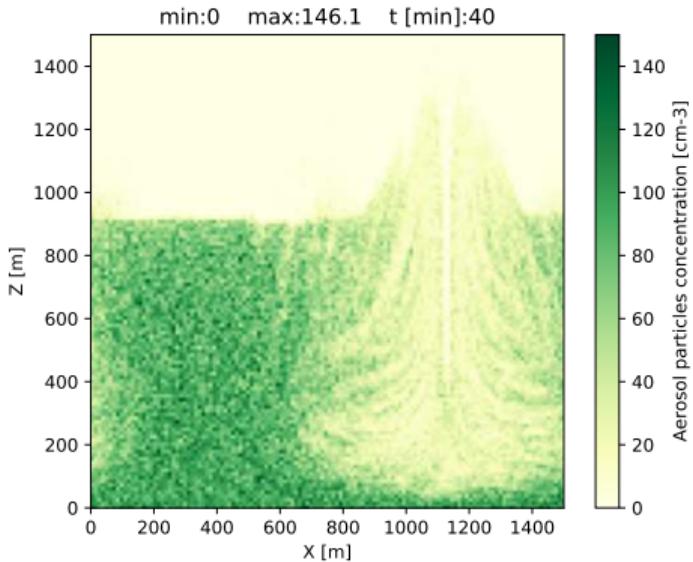
Computational particles:  $2^{21}$

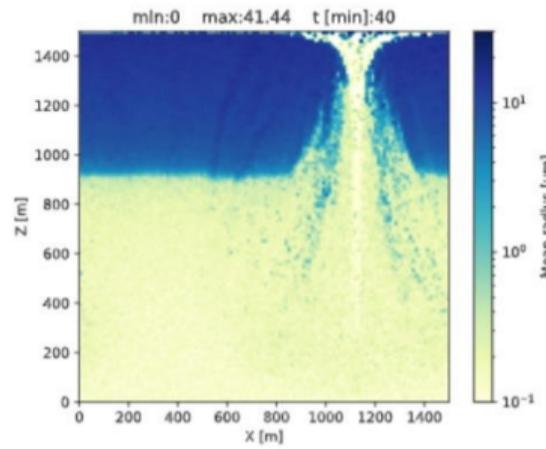
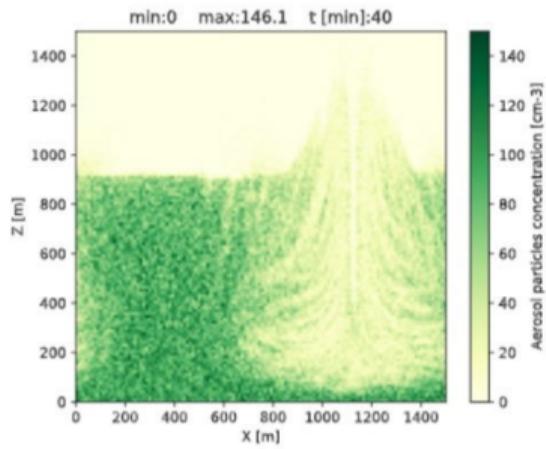


# sample aerosol-cloud-precipitation interactions simulation

Computational grid: 128x128

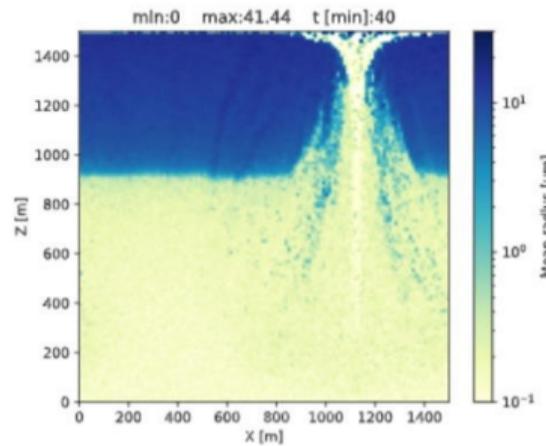
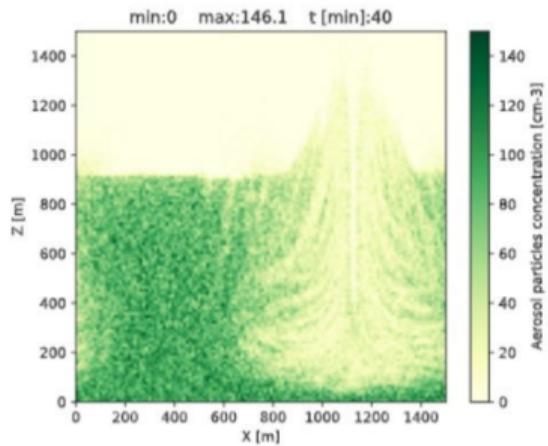
Computational particles:  $2^{21}$



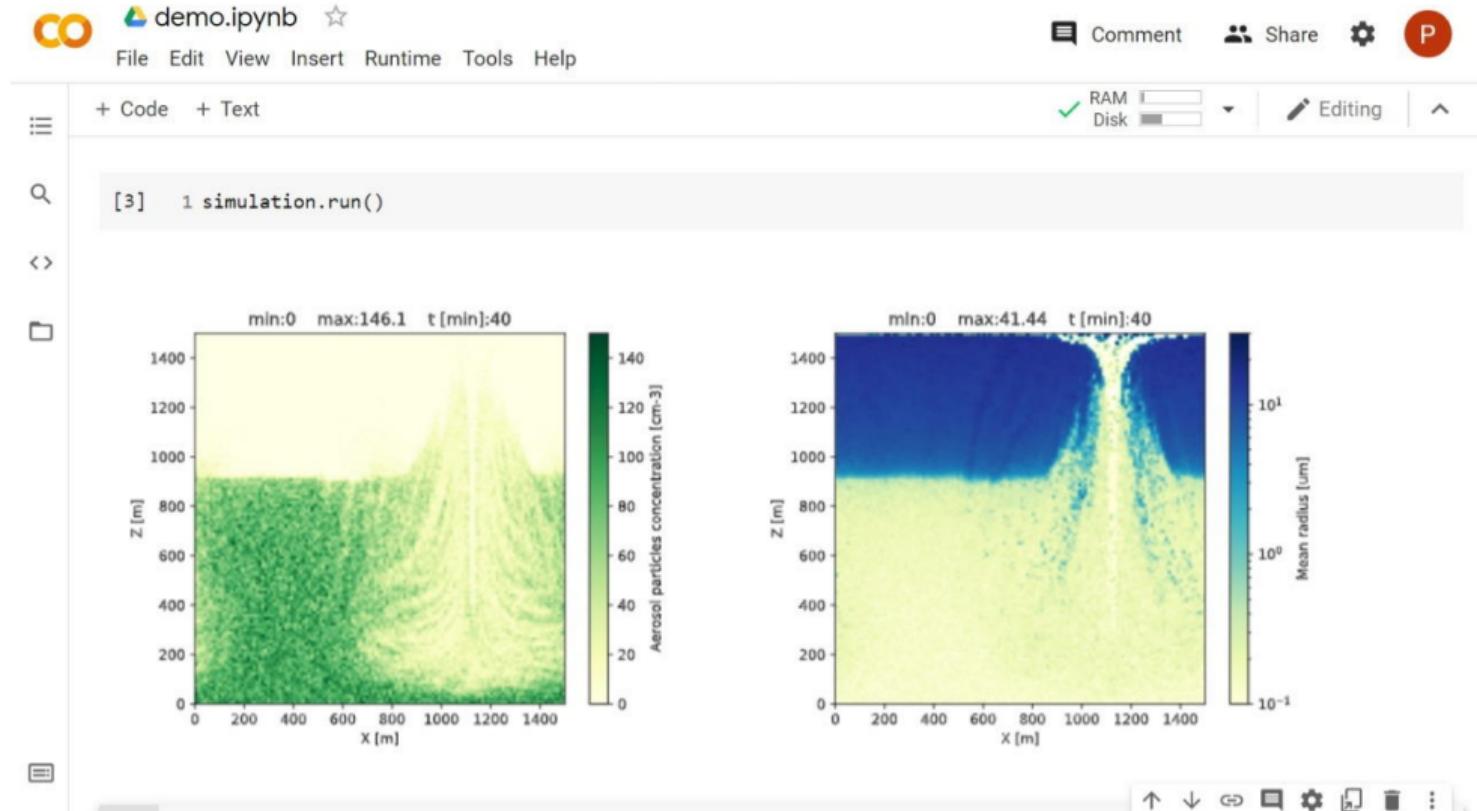


# PySDM: Pythonic

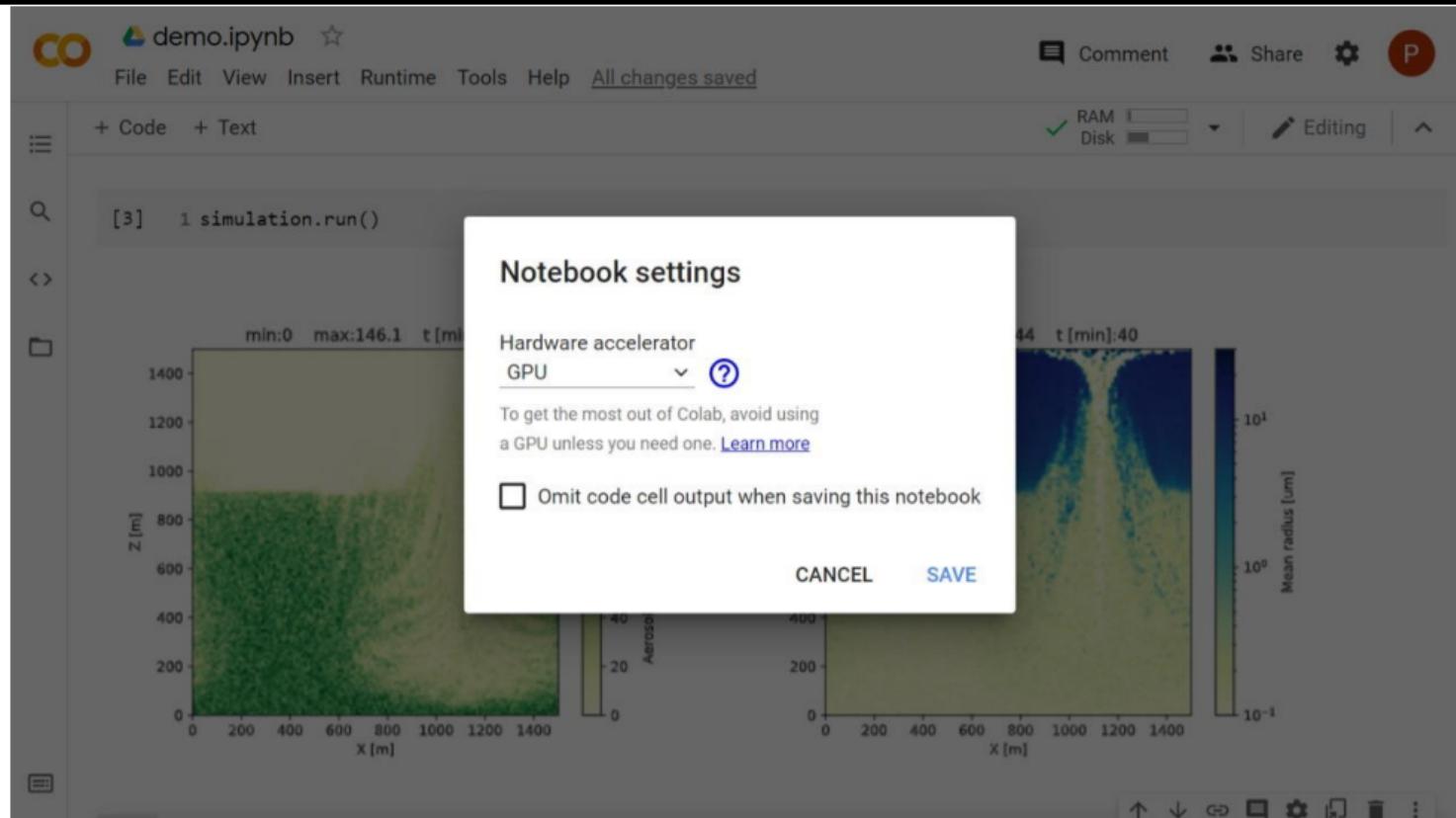
```
[3] 1 simulation.run()
```



# PySDM: Pythonic, Jupyter-friendly



# PySDM: Pythonic, Jupyter-friendly, GPU-enabled



# PySDM: packages



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## PySDM 2.15

[pip install PySDM](#) ⬇️

✓ [Latest version](#)

Released: Dec 30, 2022

Pythonic particle-based (super-droplet) warm-rain/aqueous-chemistry cloud microphysics package with box, parcel & 1D/2D prescribed-flow examples in Python, Julia and Matlab

### Navigation

- [Project description](#)
- [Release history](#)
- [Download files](#)

### Project description

## PySDM

Python 3 · LLVM Numba · CUDA ThrustRTC · Linux · macOS · Windows · Jupyter · Maintained? yes · OpenHub · JOSS · DOI · EU Funding by · PL Funding by · US DOE Funding by

10.21105/joss.03219 · 10.5281/zenodo.7640495 · FNP · NCN · ASR

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# PySDM: users

PySDM v1: particle-based cloud modelling package for warm-rain microphysics and aqueous chemistry

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A key constraint of particle-based methods for modeling cloud microphysics is the conservation of total particle number, which is required for computational tractability. The ...

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# first coupling with an external CFD code (Oleksii Bulenok)

(<https://github.com/CliMA/ClimateMachine.jl/pull/2244>)

## PySDM and ClimateMachine coupling examples in Kinematic setup #2244

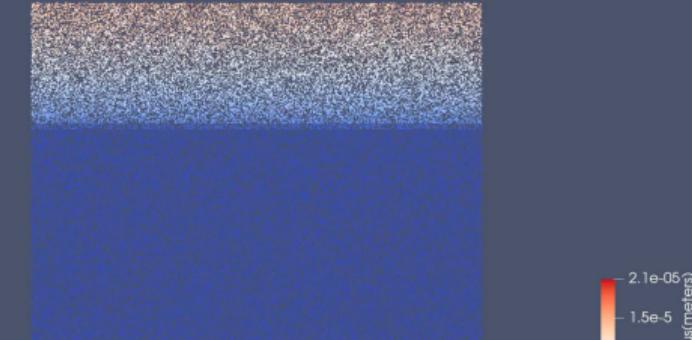
[Open](#) abulenok wants to merge 16 commits into [CliMA:master](#) from [abulenok:ob-pysdmachine](#)

Conversation 32    Commit 16    Checks 10    Files changed 17    +2,528 -1

abulenok commented on 27 Oct 2021

This PR includes a coupling logic for ClimateMachine.jl and [PySDM](#). PySDM is a particle-based aerosol/cloud microphysics package written entirely in Python. This PR depicts how Python modules can be leveraged within ClimateMachine.jl including the continuous integration setup. The initial set of tests included here is based on the kinematic 2D example previously used as a test case in both PySDM and ClimateMachine.jl. In the tests added in this PR, ClimateMachine.jl handles air motion and total water transport, while PySDM handles representation of aerosol and liquid water transport as well as phase changes leading to formation of cloud water. Output from PySDM is handled using VTK files. Example animation with an evolution of radius computed from particle properties is shown below:

[output.mp4](#)



Reviewers

- slayoo
- charleskawczynski
- daresinger
- jakebolewski
- edejong-calltech
- tapios

Assignees

- trontrytel

Labels

- Microphysics

Projects

- None yet

Milestone

- No milestone

Development

Successfully merging this pull request may close these issues.

None yet

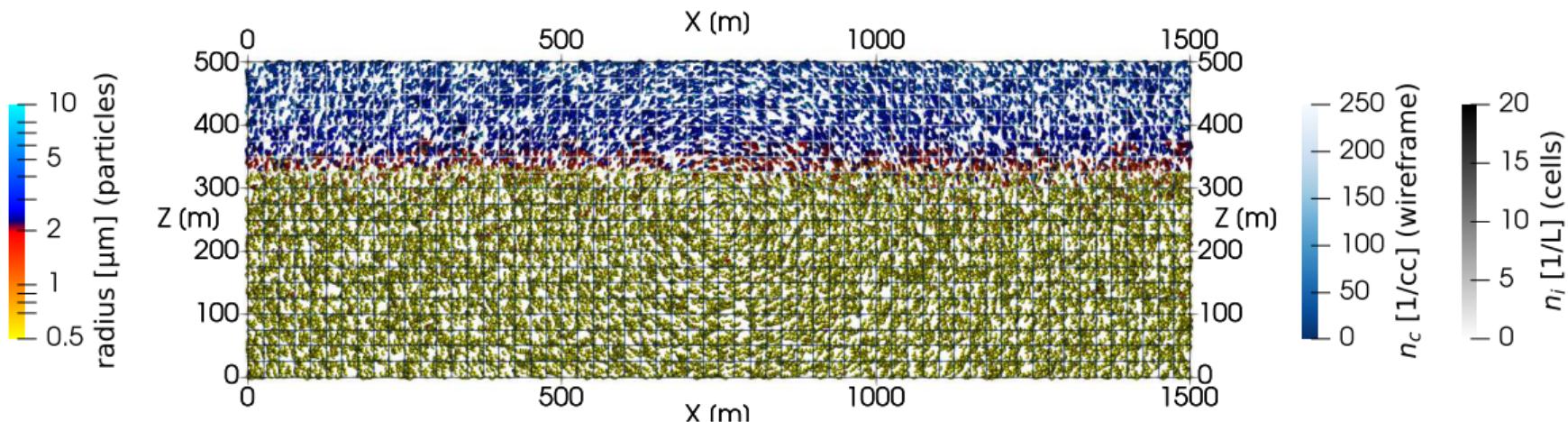
## teaser: Monte-Carlo immersion freezing in PySDM (singular or time-dependent)



[https://www.reuters.com/markets/commodities/  
making-snow-stick-wind-challenges-winter-games-slope-makers-2021-11-29/](https://www.reuters.com/markets/commodities/making-snow-stick-wind-challenges-winter-games-slope-makers-2021-11-29/)

# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

Time: 30 s (spin-up till 600.0 s)

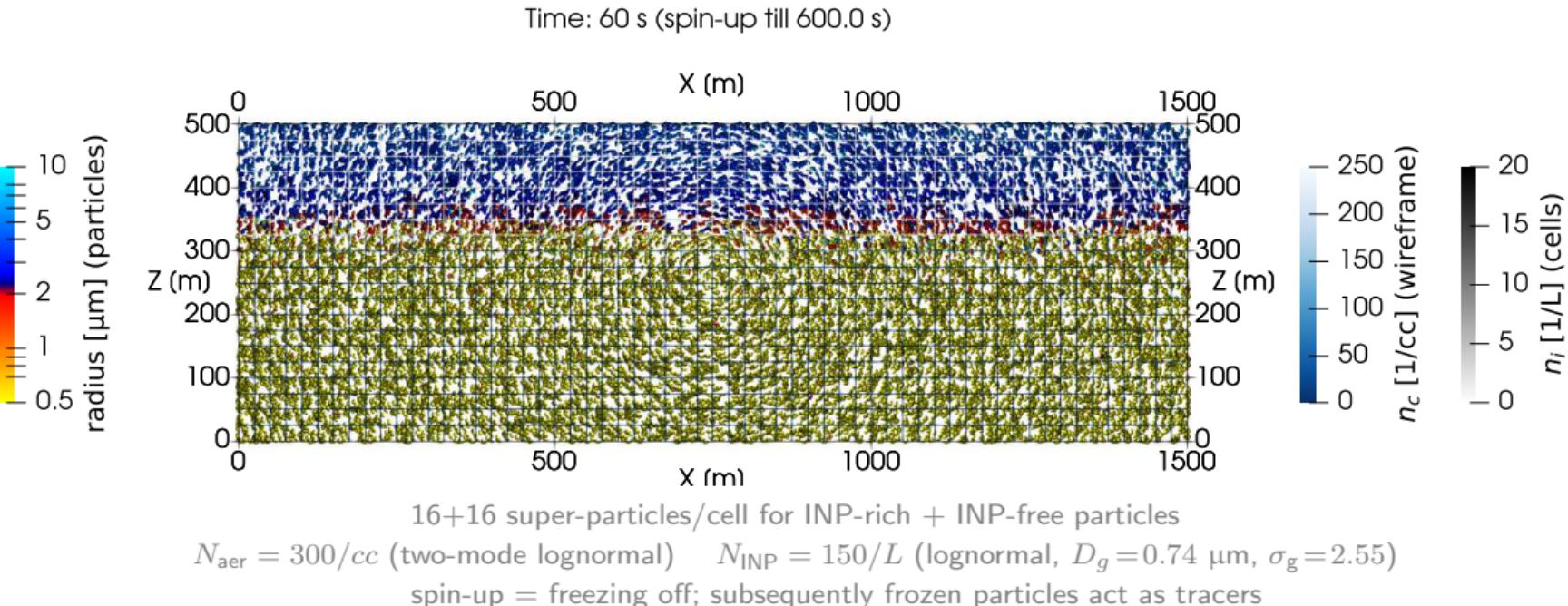


16+16 super-particles/cell for INP-rich + INP-free particles

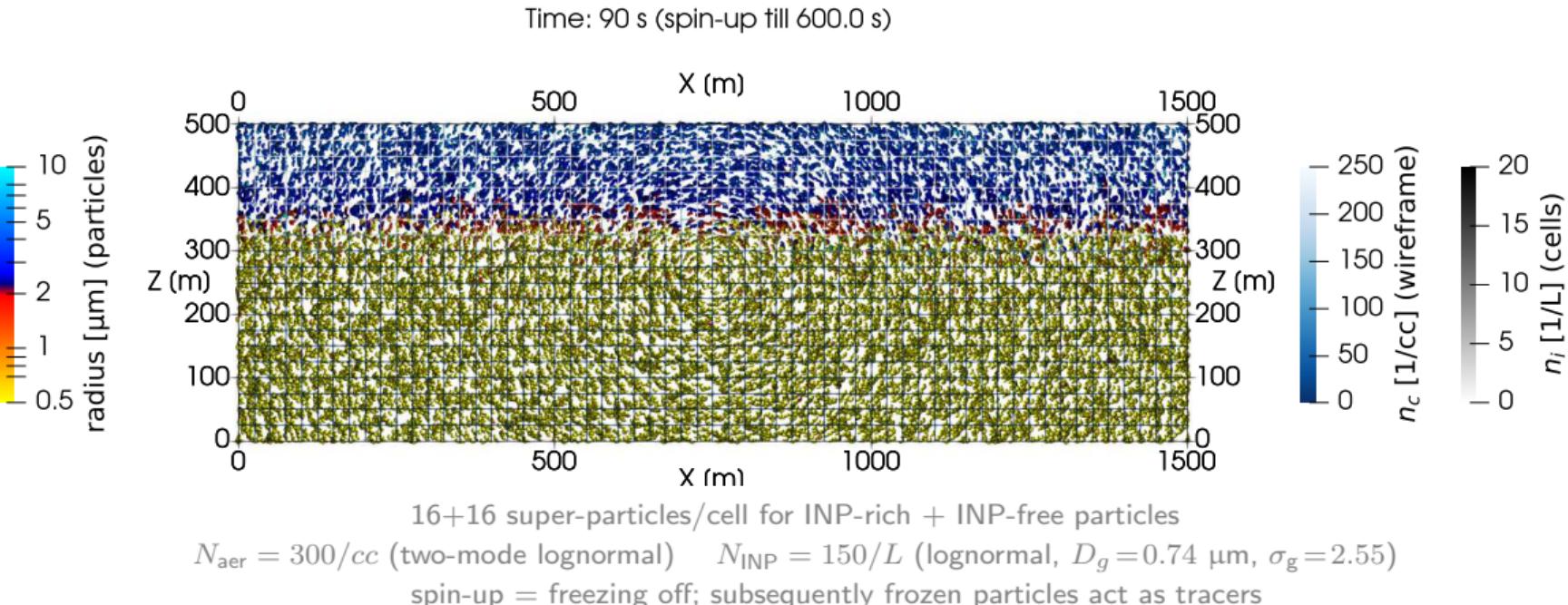
$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \text{ } \mu\text{m}$ ,  $\sigma_g = 2.55$ )

spin-up = freezing off; subsequently frozen particles act as tracers

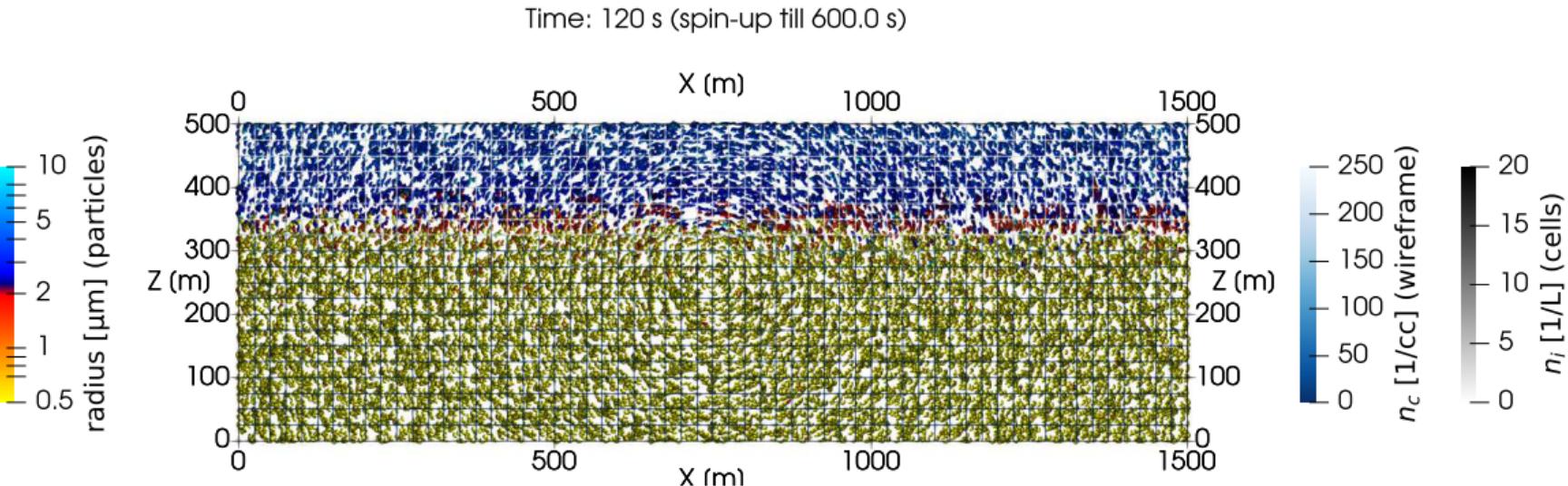
# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

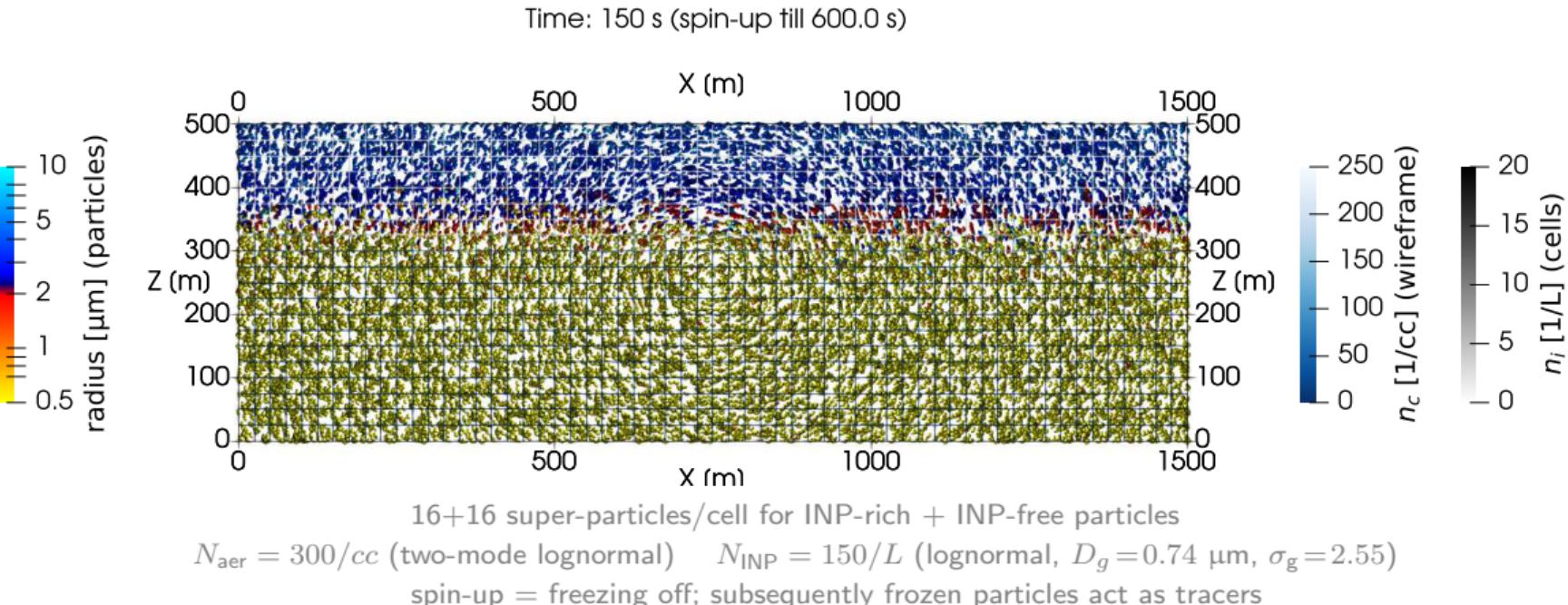


16+16 super-particles/cell for INP-rich + INP-free particles

$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \mu\text{m}$ ,  $\sigma_g = 2.55$ )

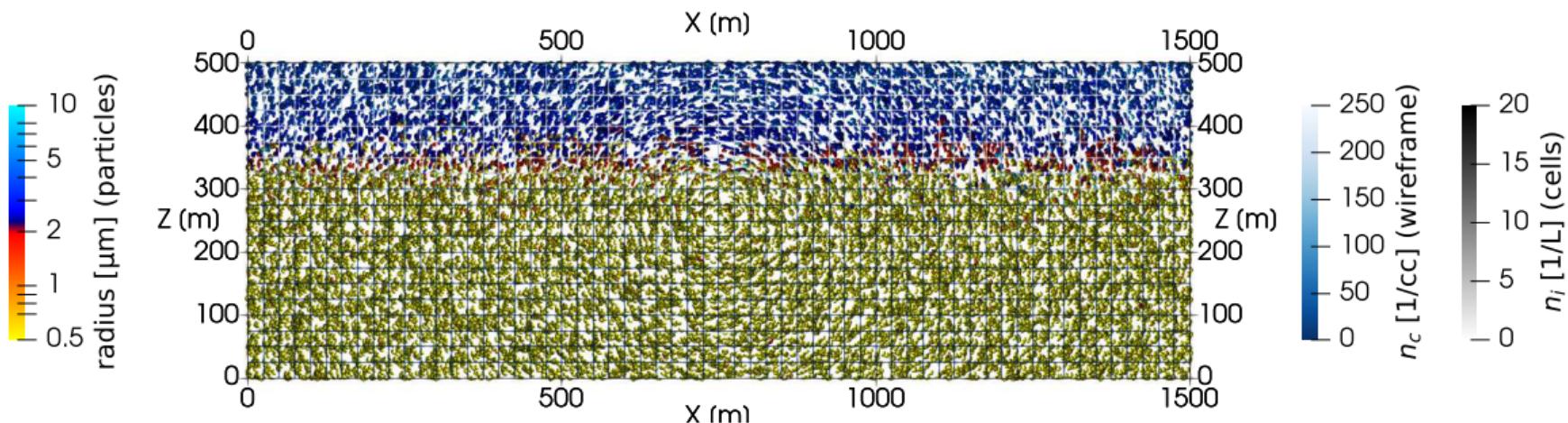
spin-up = freezing off; subsequently frozen particles act as tracers

# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

Time: 180 s (spin-up till 600.0 s)



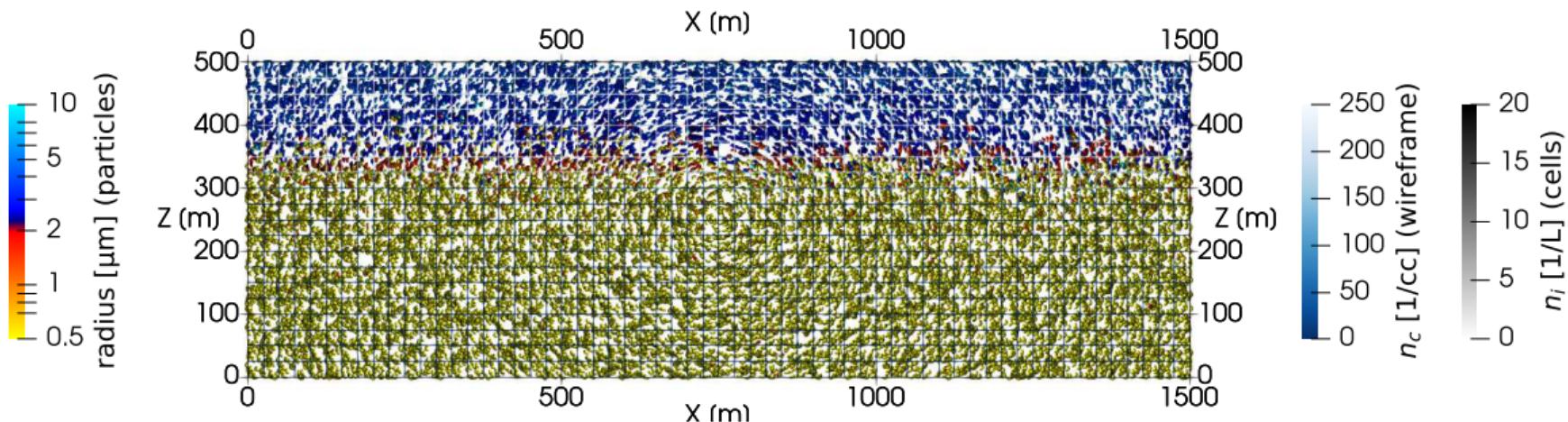
16+16 super-particles/cell for INP-rich + INP-free particles

$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \mu\text{m}$ ,  $\sigma_g = 2.55$ )

spin-up = freezing off; subsequently frozen particles act as tracers

# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

Time: 210 s (spin-up till 600.0 s)



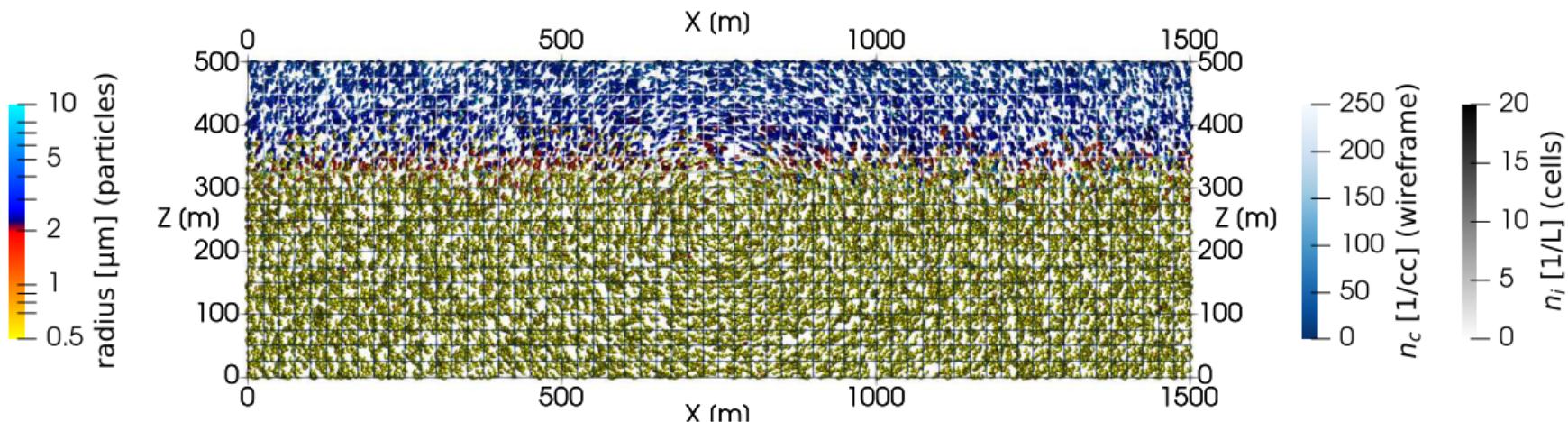
16+16 super-particles/cell for INP-rich + INP-free particles

$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \text{ } \mu\text{m}$ ,  $\sigma_g = 2.55$ )

spin-up = freezing off; subsequently frozen particles act as tracers

# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

Time: 240 s (spin-up till 600.0 s)



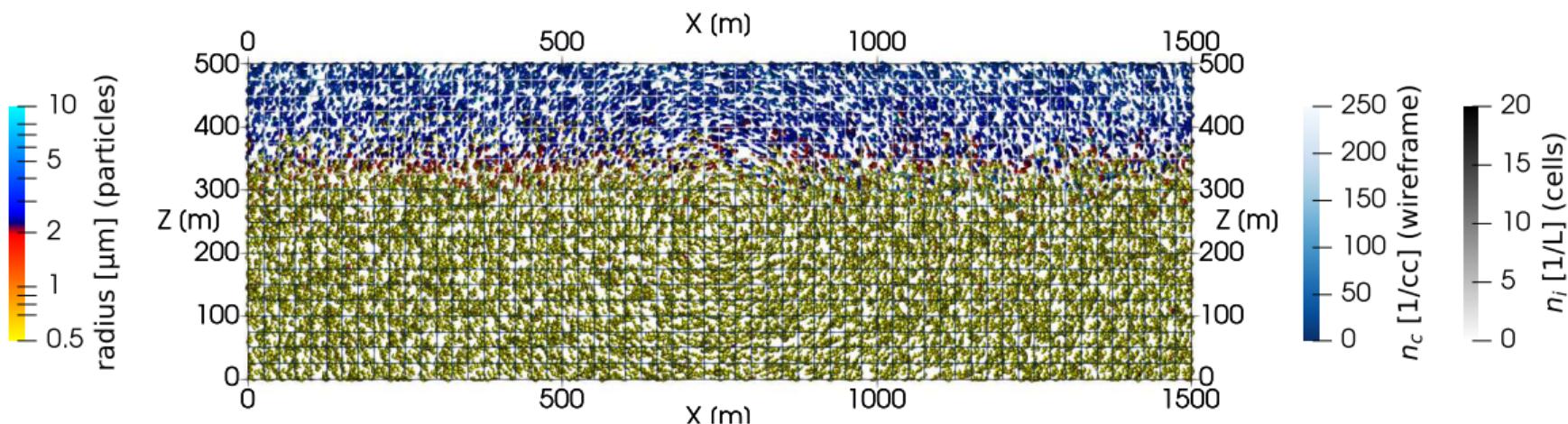
16+16 super-particles/cell for INP-rich + INP-free particles

$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \text{ } \mu\text{m}$ ,  $\sigma_g = 2.55$ )

spin-up = freezing off; subsequently frozen particles act as tracers

# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

Time: 270 s (spin-up till 600.0 s)

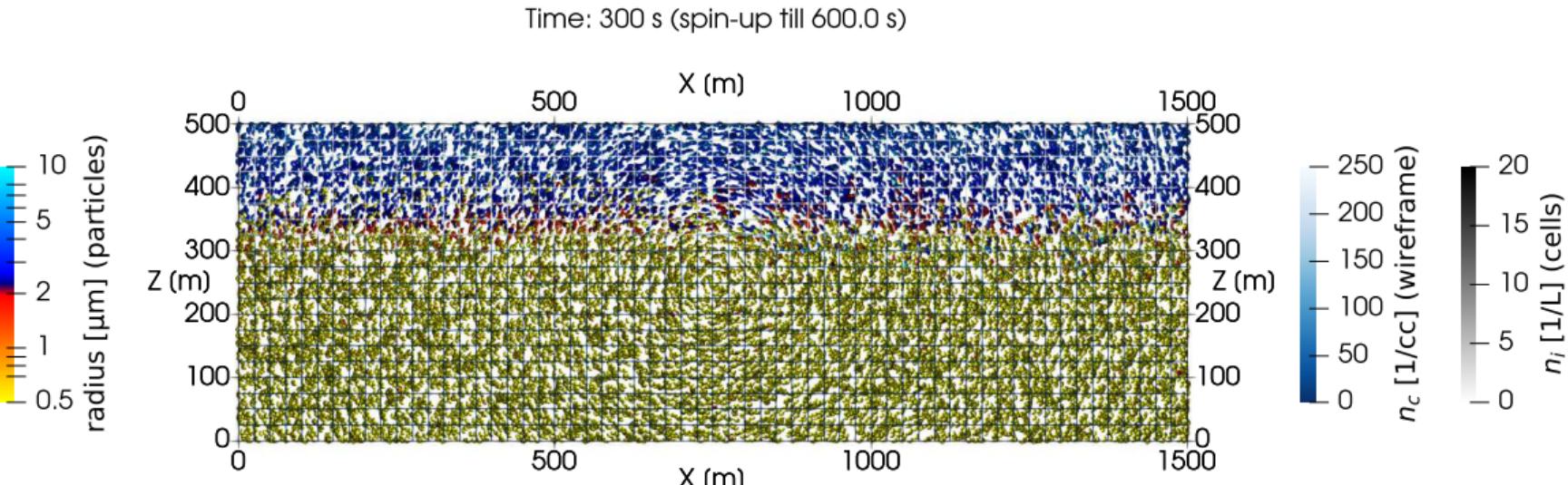


16+16 super-particles/cell for INP-rich + INP-free particles

$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \text{ } \mu\text{m}$ ,  $\sigma_g = 2.55$ )

spin-up = freezing off; subsequently frozen particles act as tracers

# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

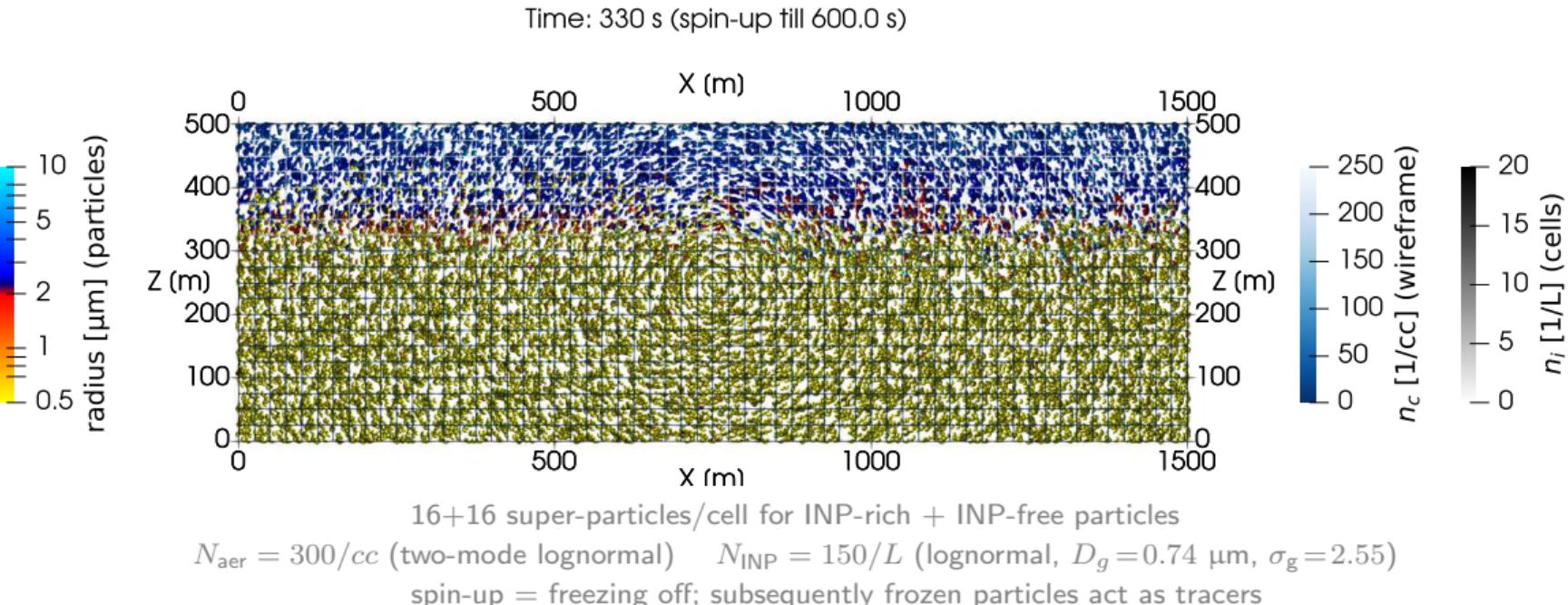


16+16 super-particles/cell for INP-rich + INP-free particles

$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \mu\text{m}$ ,  $\sigma_g = 2.55$ )

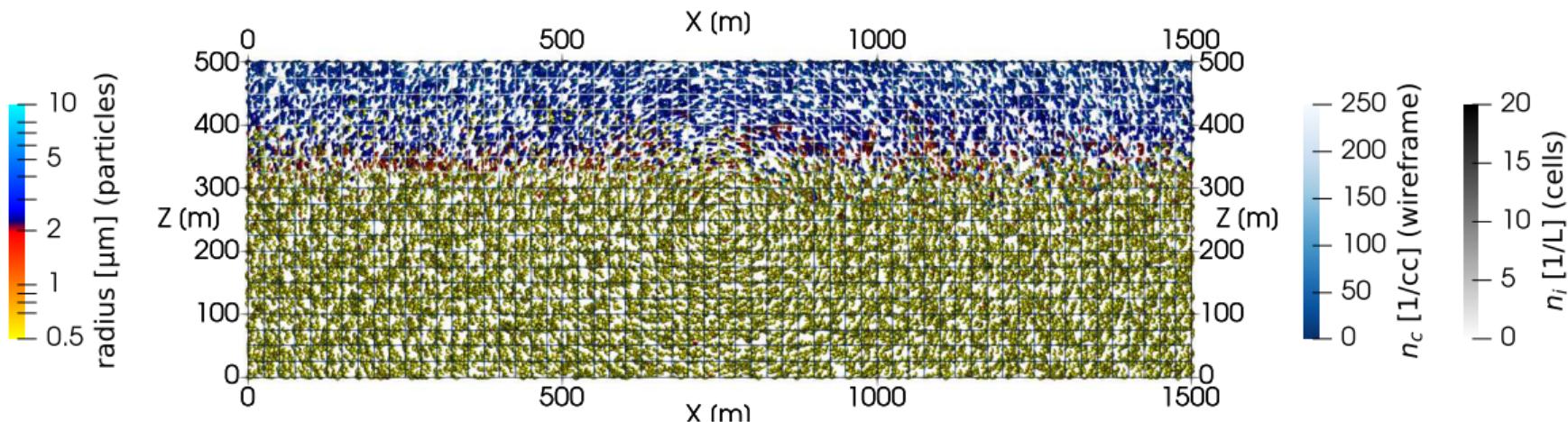
spin-up = freezing off; subsequently frozen particles act as tracers

# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

Time: 360 s (spin-up till 600.0 s)

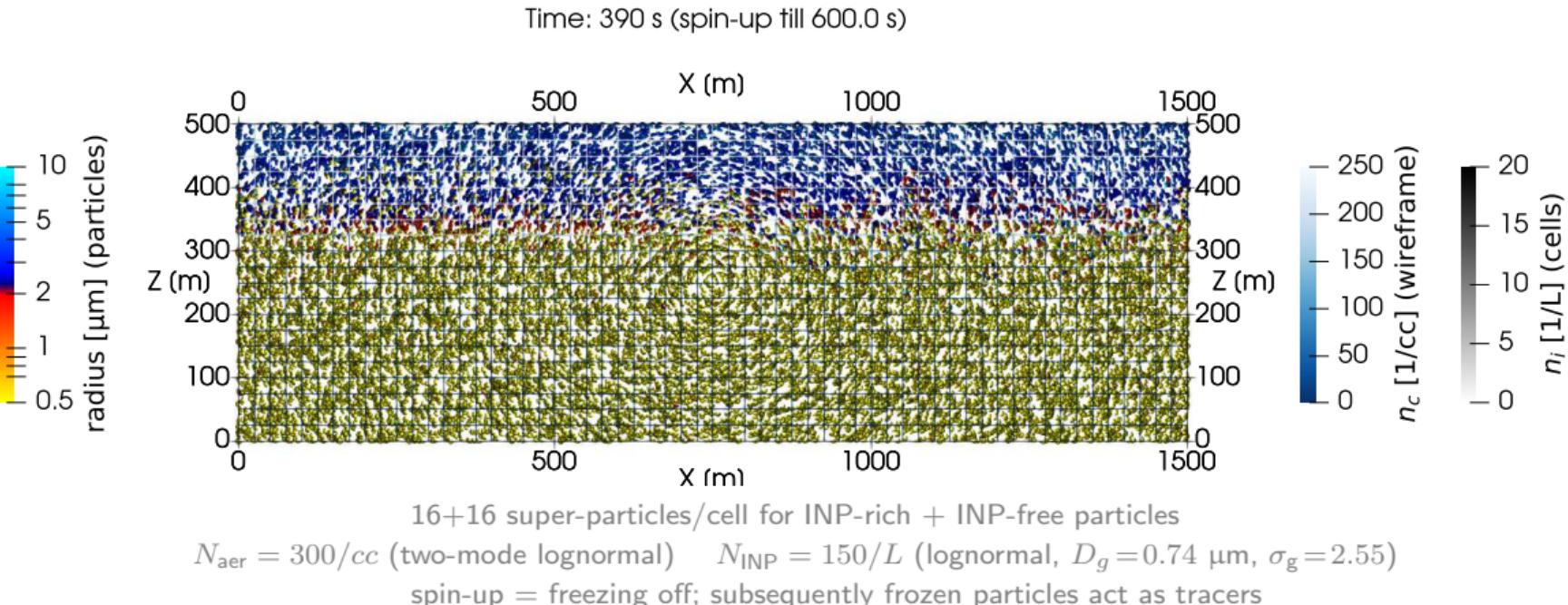


16+16 super-particles/cell for INP-rich + INP-free particles

$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \text{ } \mu\text{m}$ ,  $\sigma_g = 2.55$ )

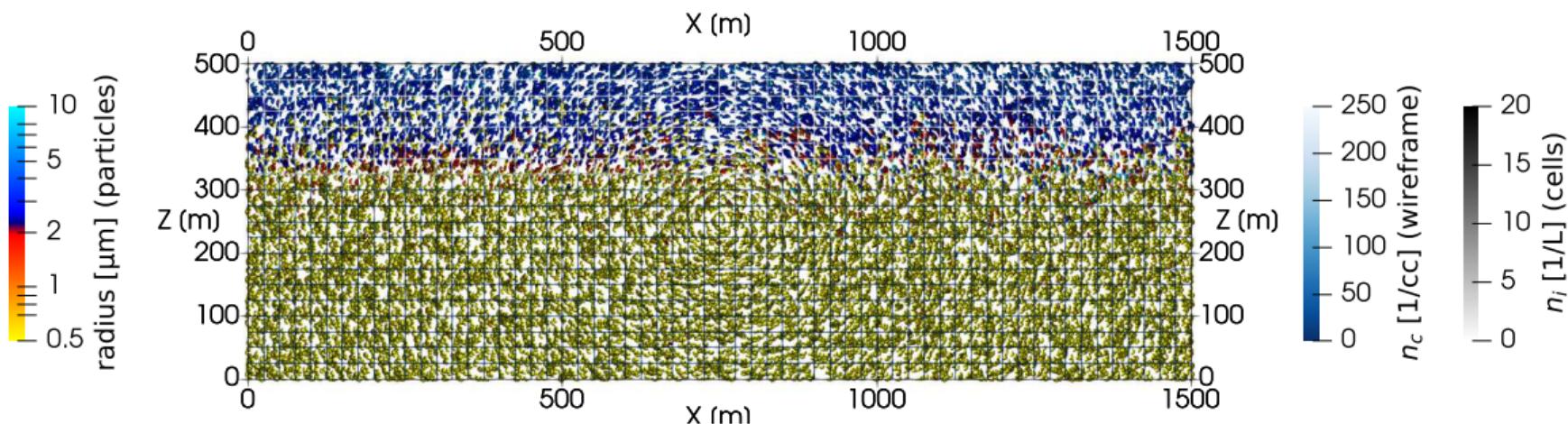
spin-up = freezing off; subsequently frozen particles act as tracers

# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

Time: 420 s (spin-up till 600.0 s)

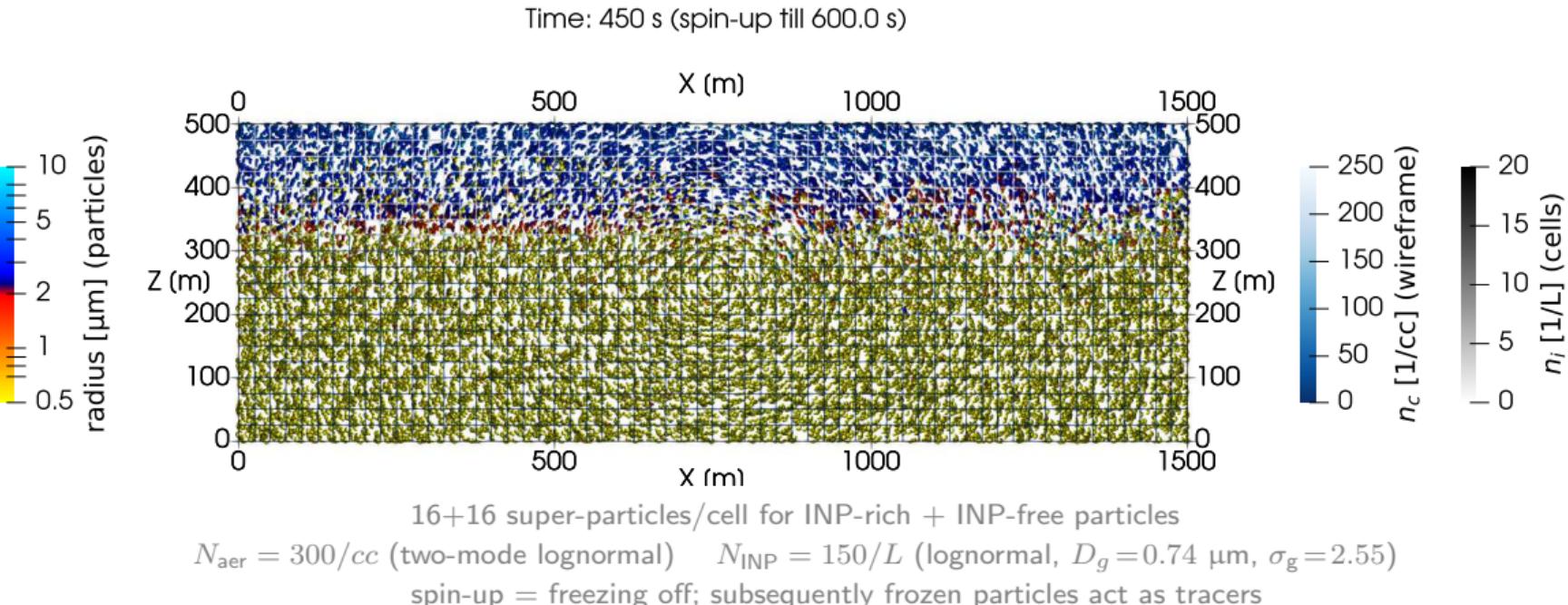


16+16 super-particles/cell for INP-rich + INP-free particles

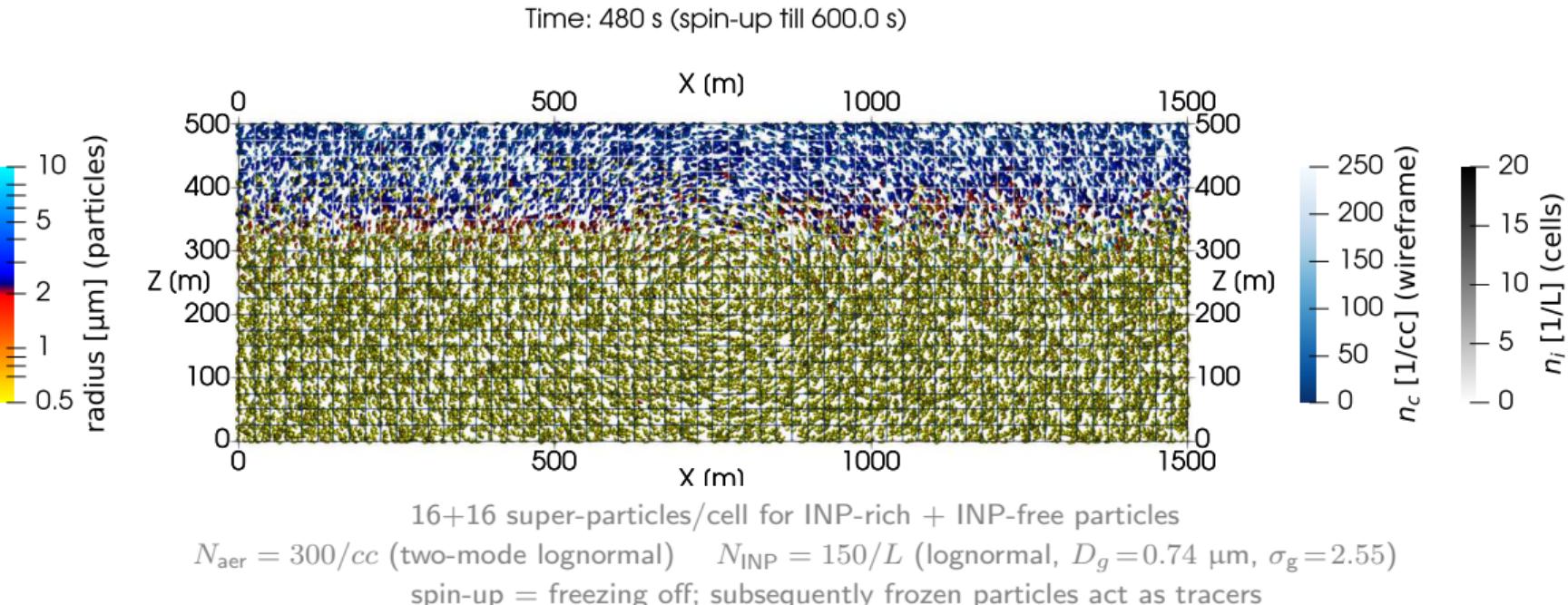
$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \text{ } \mu\text{m}$ ,  $\sigma_g = 2.55$ )

spin-up = freezing off; subsequently frozen particles act as tracers

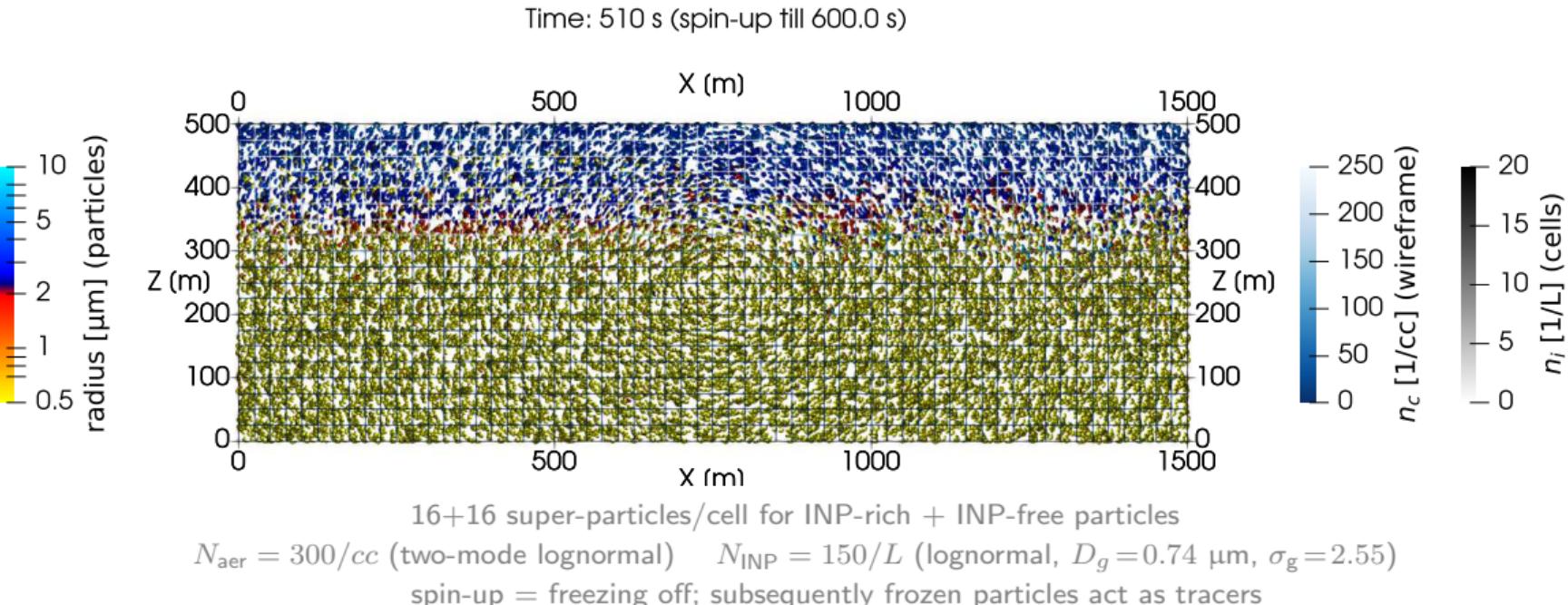
# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



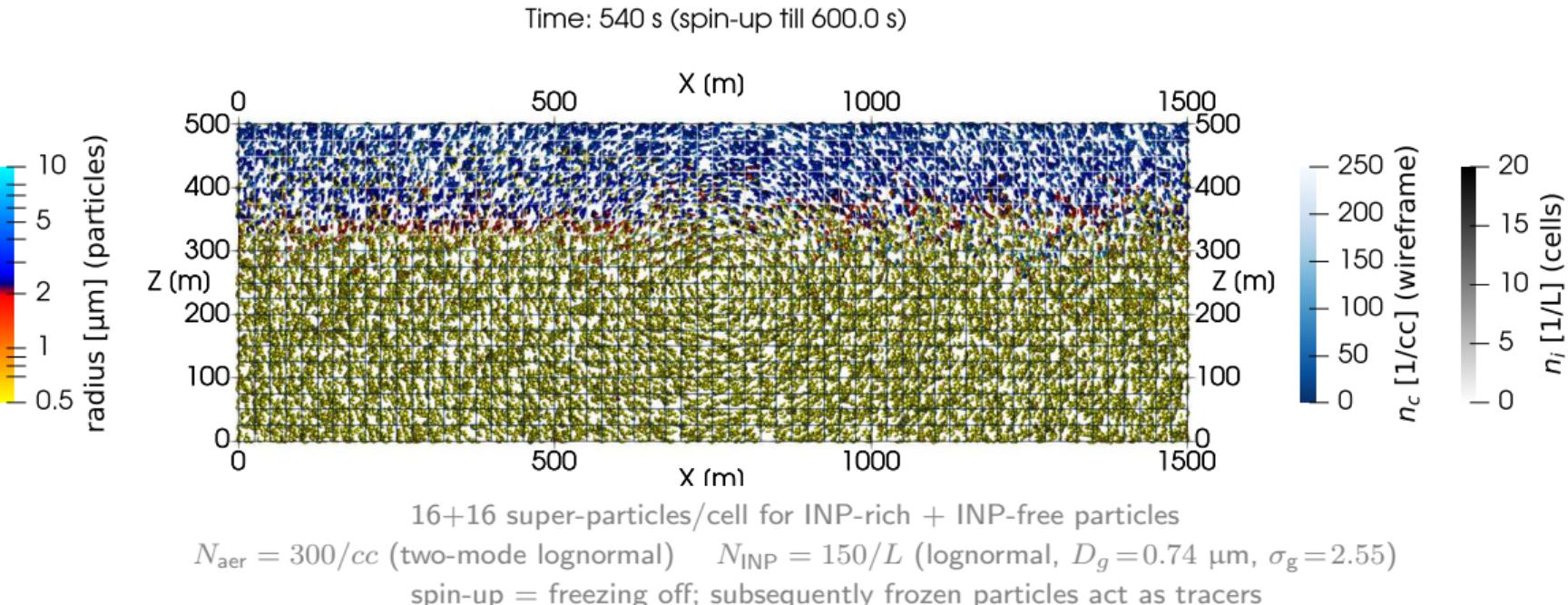
# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



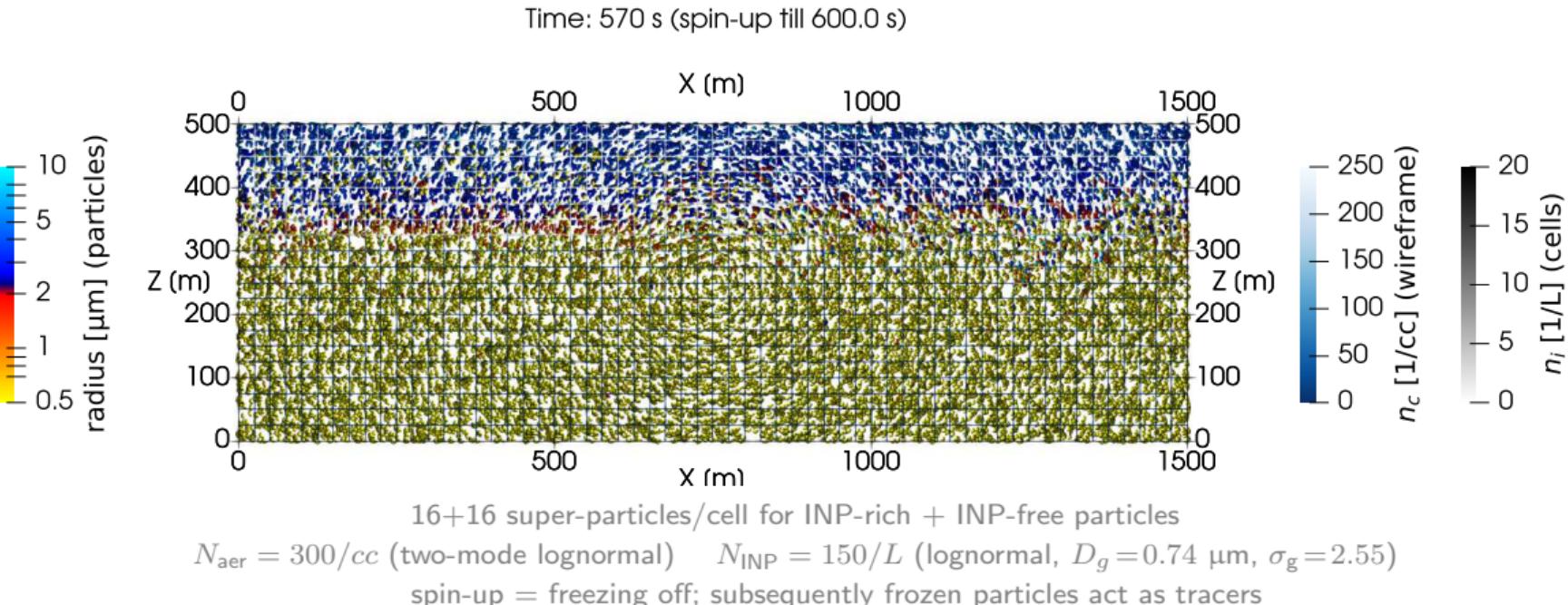
# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



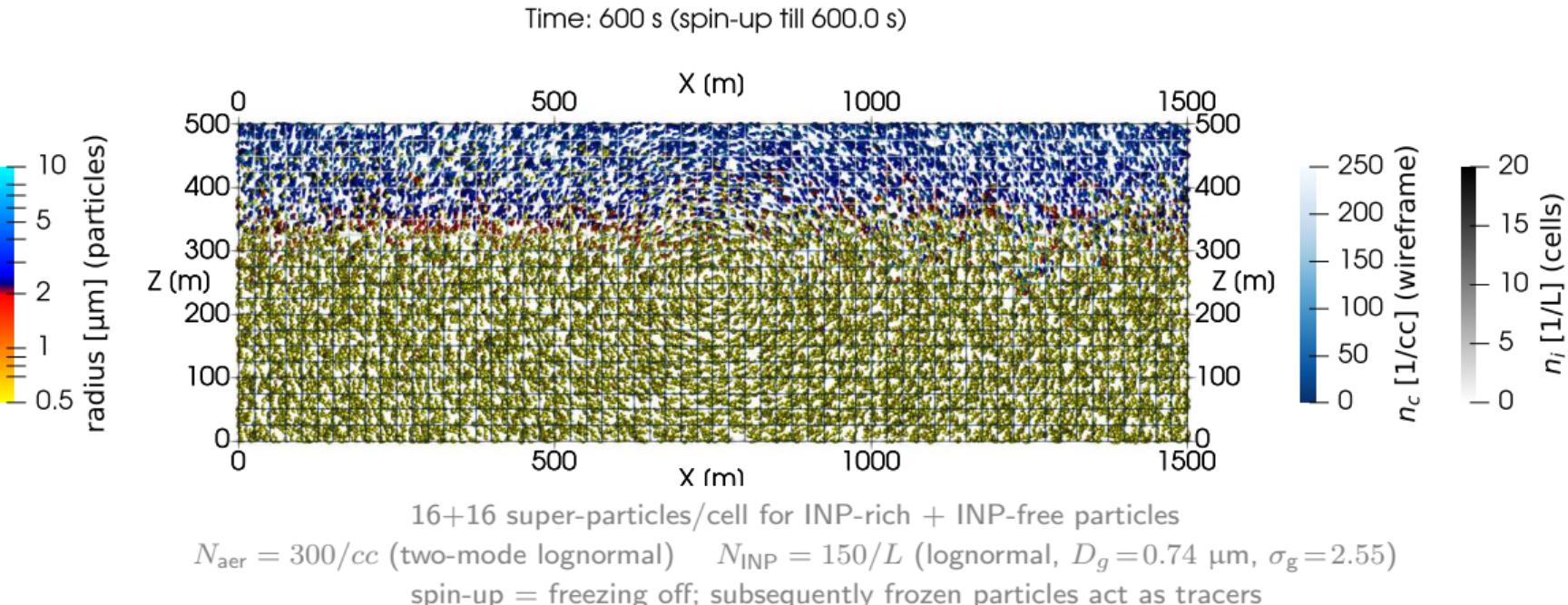
# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

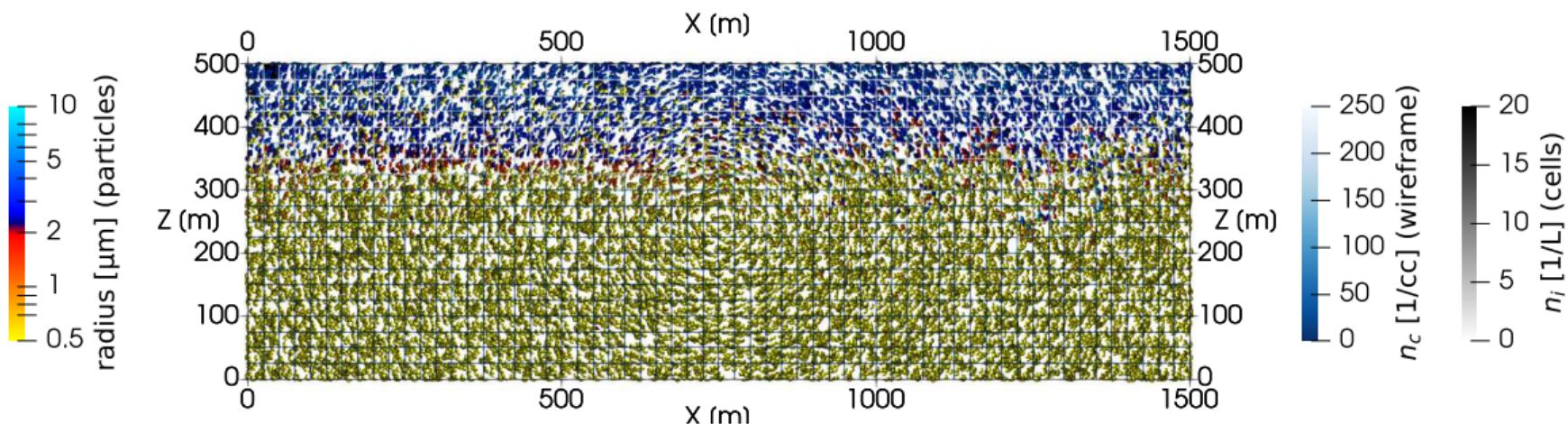


# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

Time: 630 s (spin-up till 600.0 s)

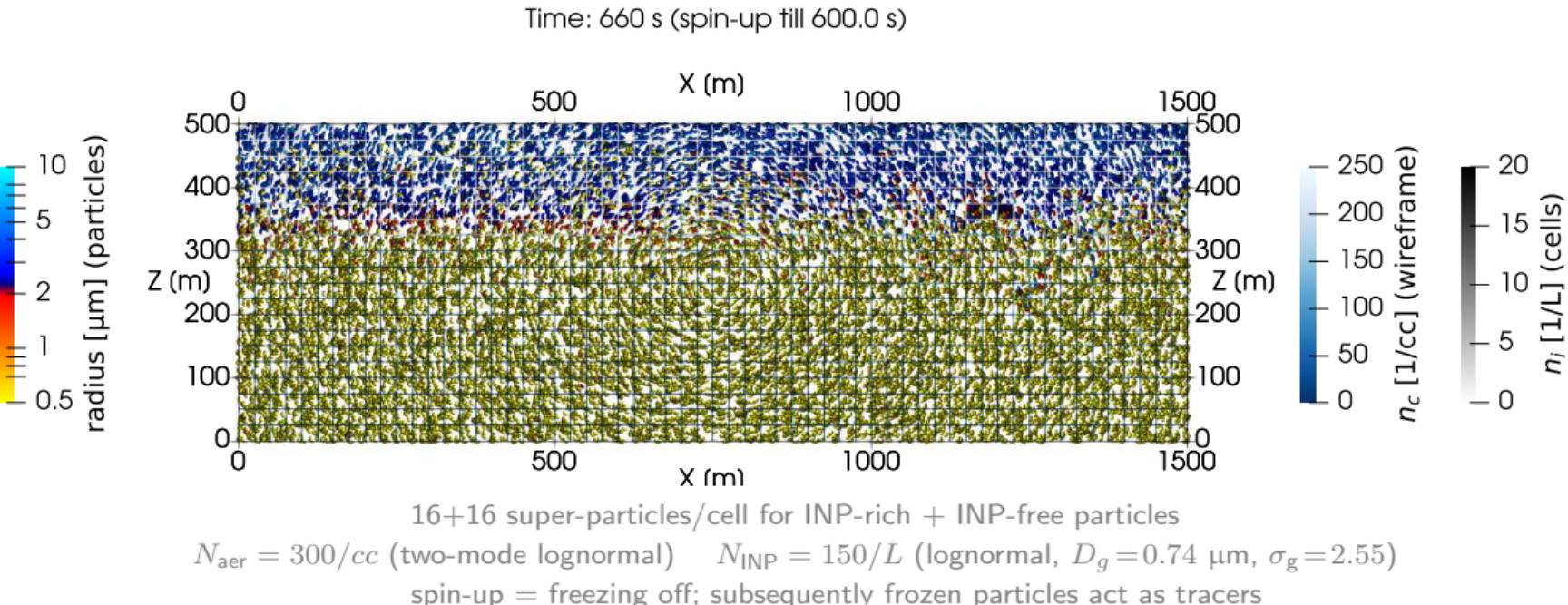


16+16 super-particles/cell for INP-rich + INP-free particles

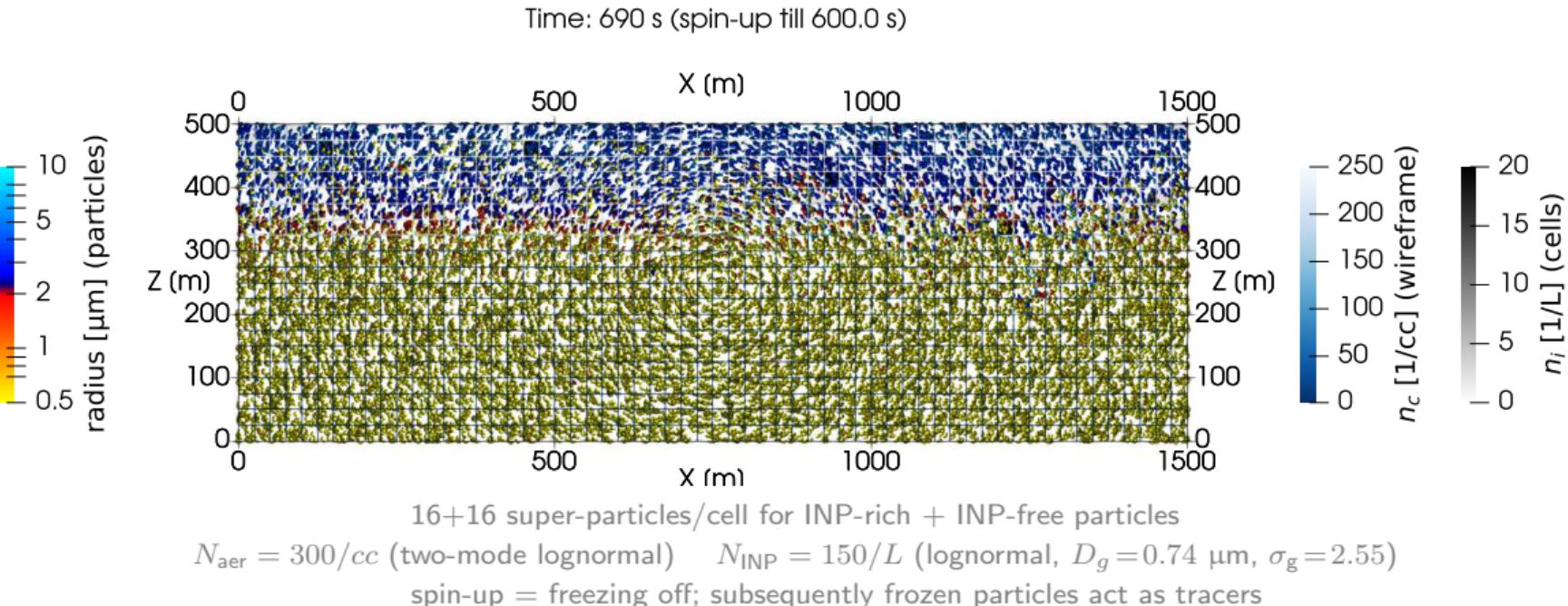
$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \text{ } \mu\text{m}$ ,  $\sigma_g = 2.55$ )

spin-up = freezing off; subsequently frozen particles act as tracers

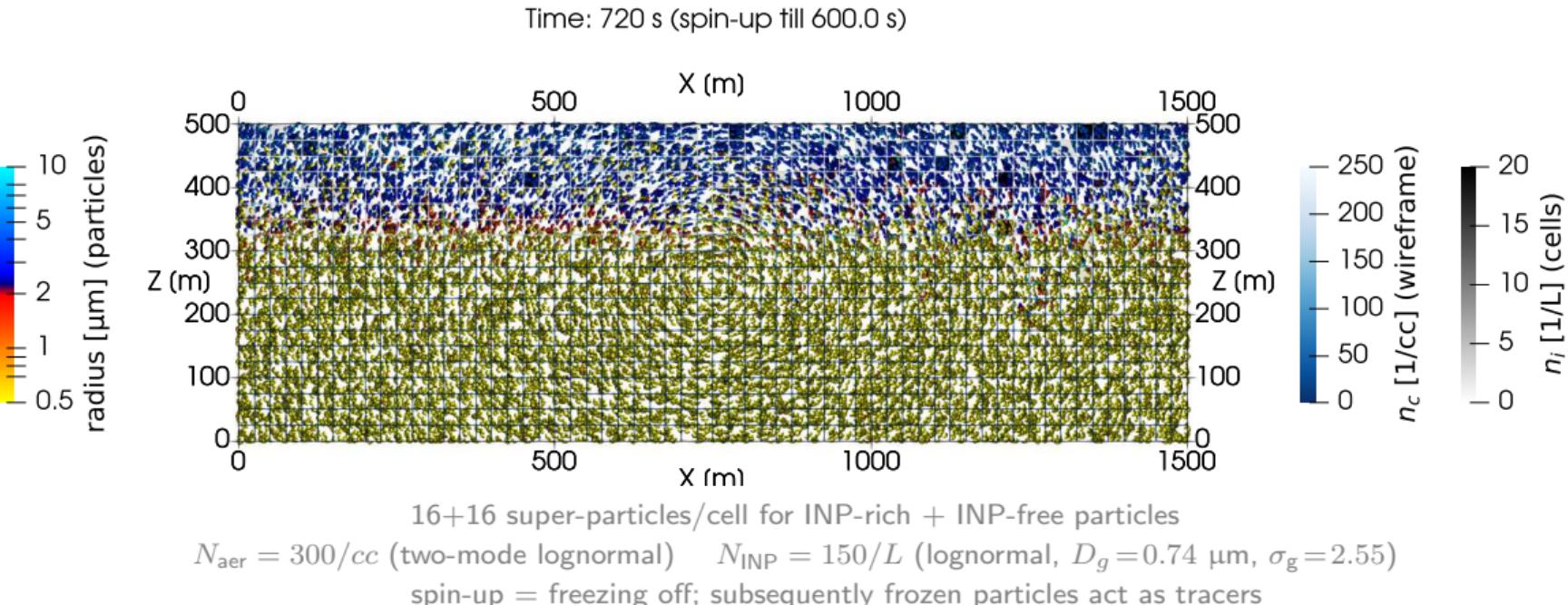
# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



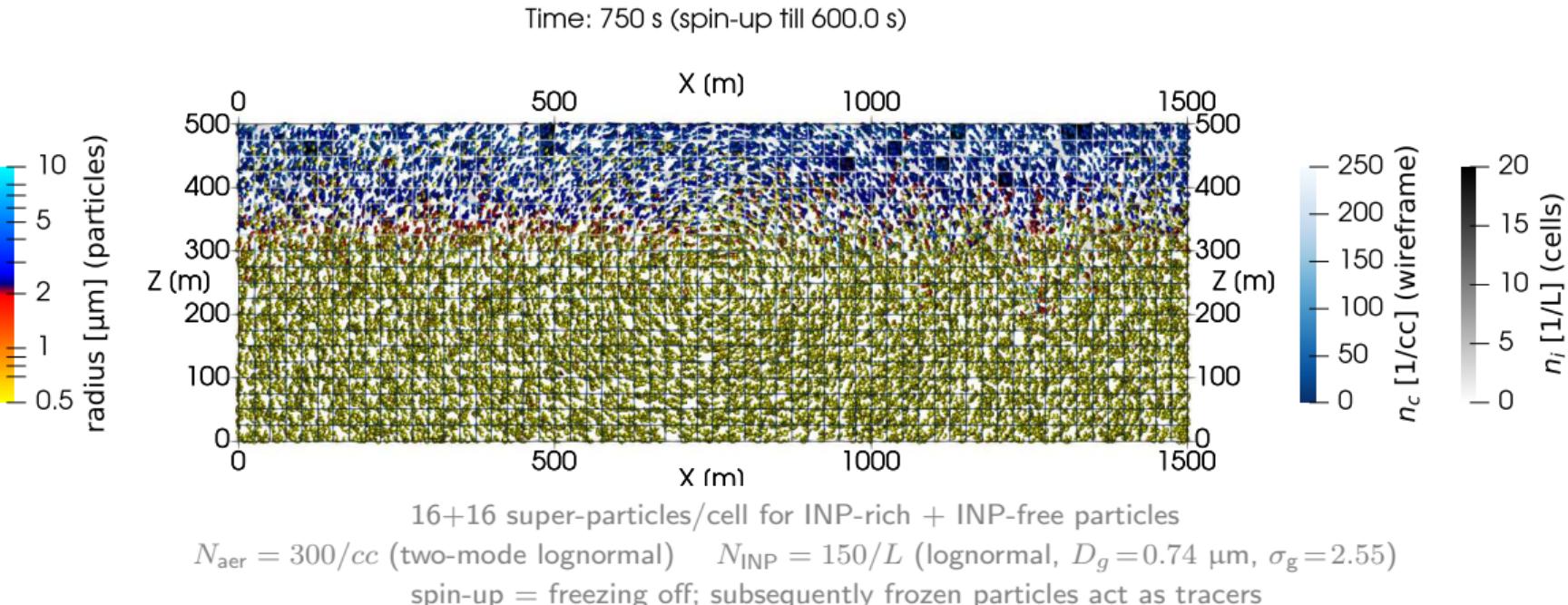
# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

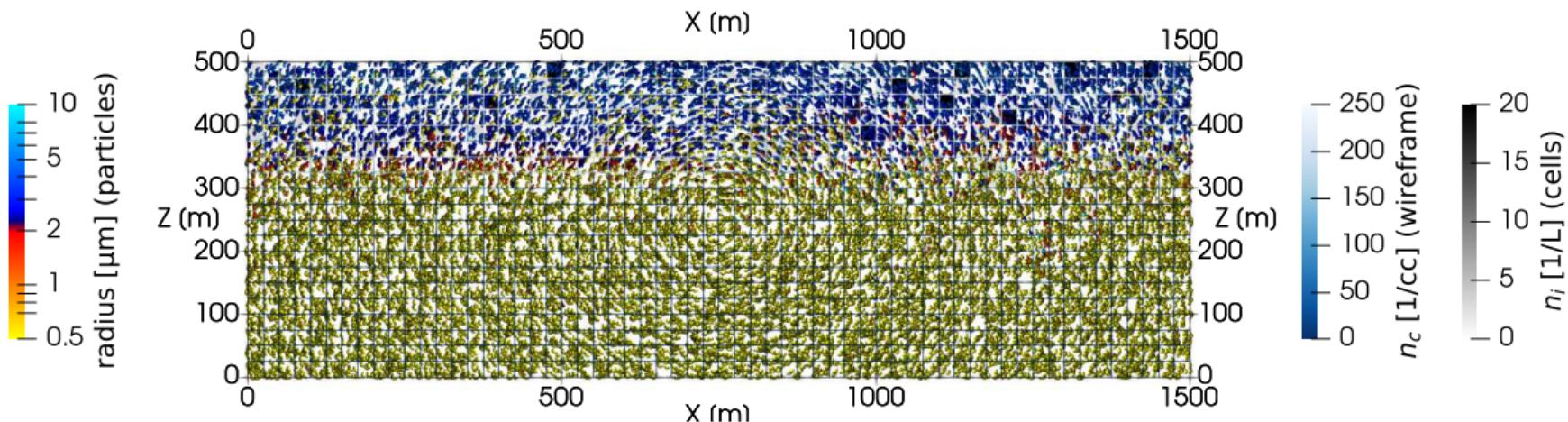


# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

Time: 780 s (spin-up till 600.0 s)



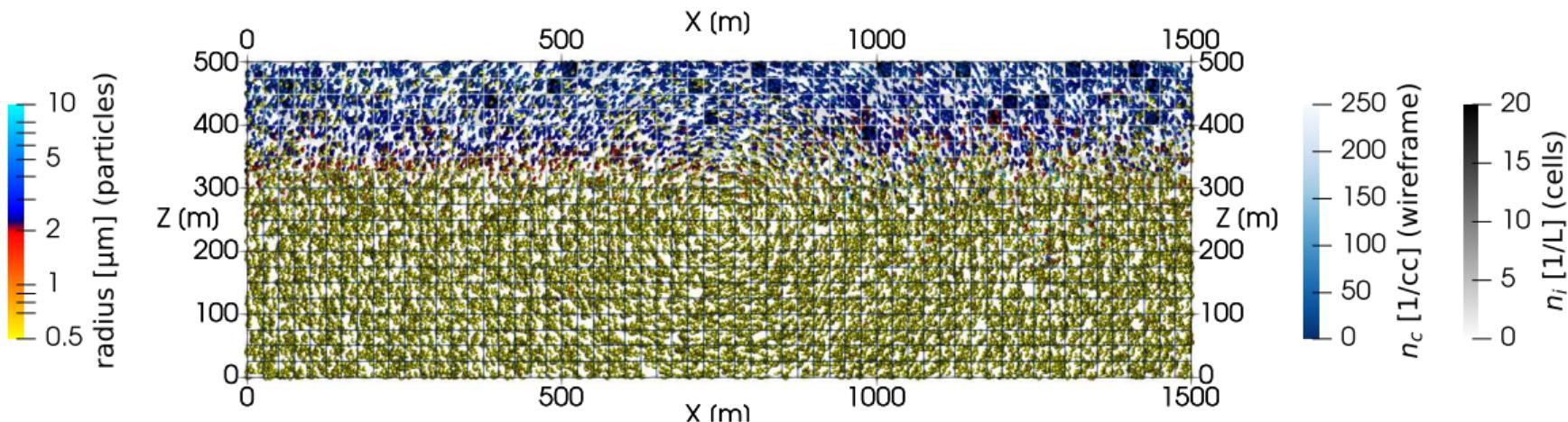
16+16 super-particles/cell for INP-rich + INP-free particles

$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \text{ } \mu\text{m}$ ,  $\sigma_g = 2.55$ )

spin-up = freezing off; subsequently frozen particles act as tracers

# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

Time: 810 s (spin-up till 600.0 s)

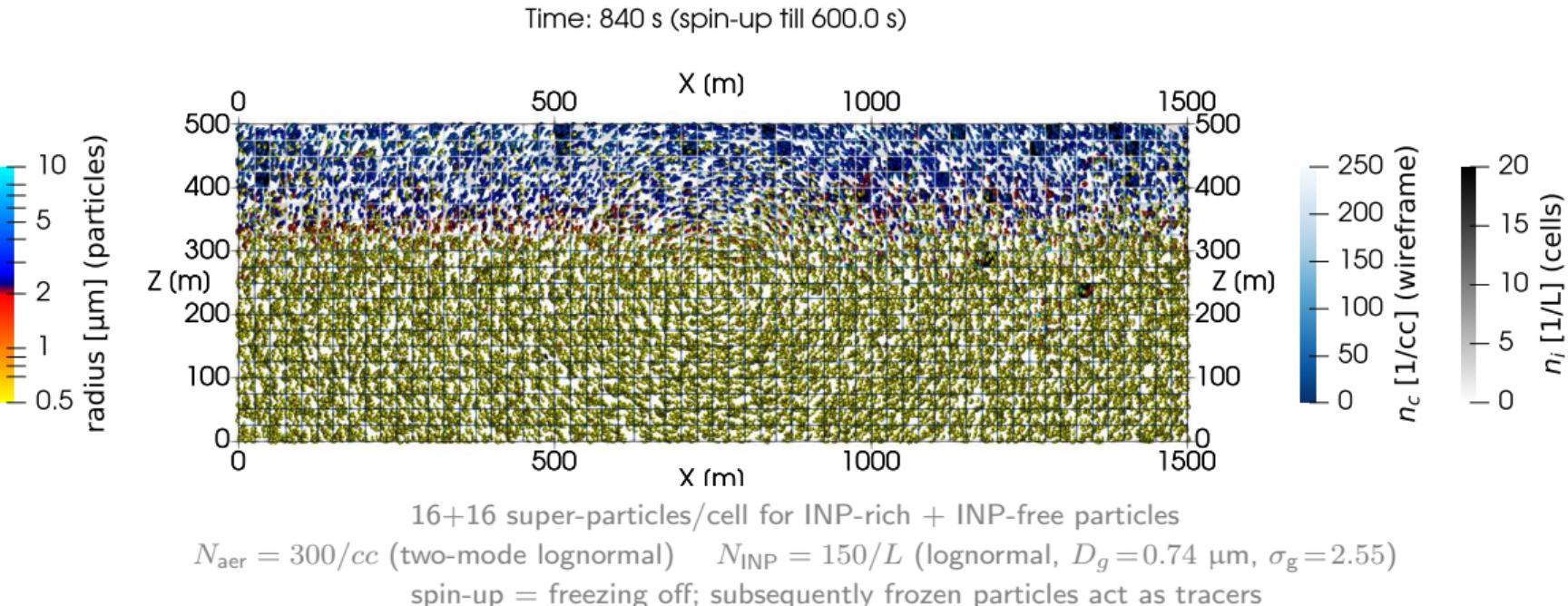


16+16 super-particles/cell for INP-rich + INP-free particles

$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \text{ }\mu\text{m}$ ,  $\sigma_g = 2.55$ )

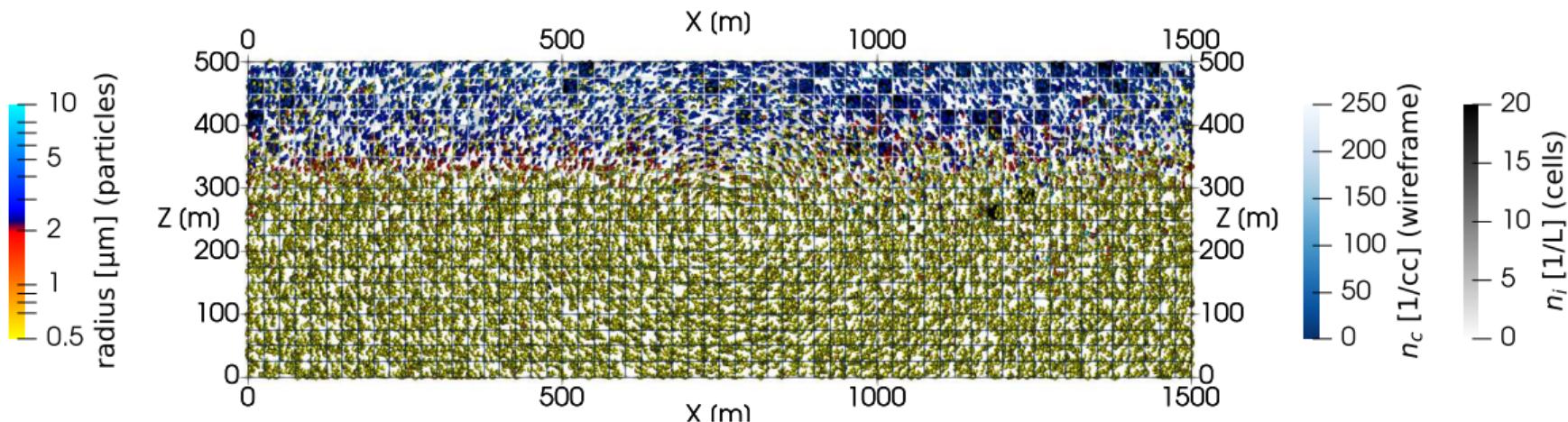
spin-up = freezing off; subsequently frozen particles act as tracers

# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

Time: 870 s (spin-up till 600.0 s)

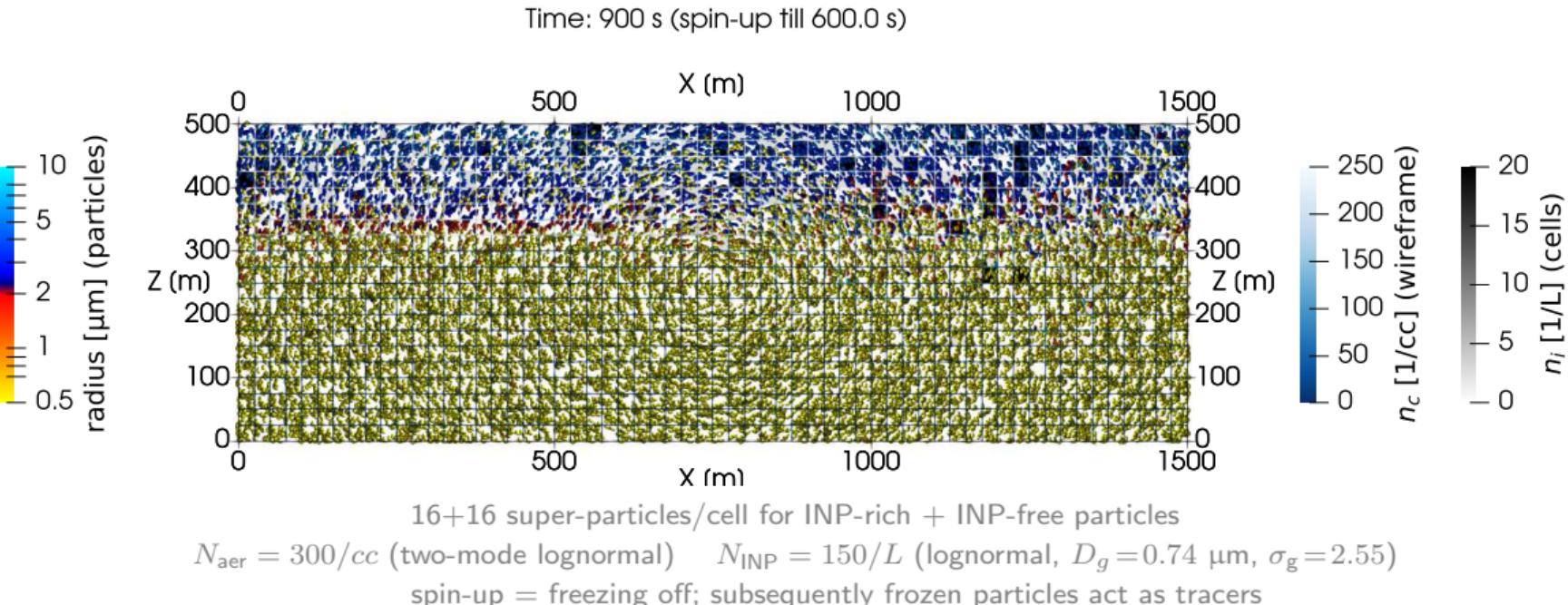


16+16 super-particles/cell for INP-rich + INP-free particles

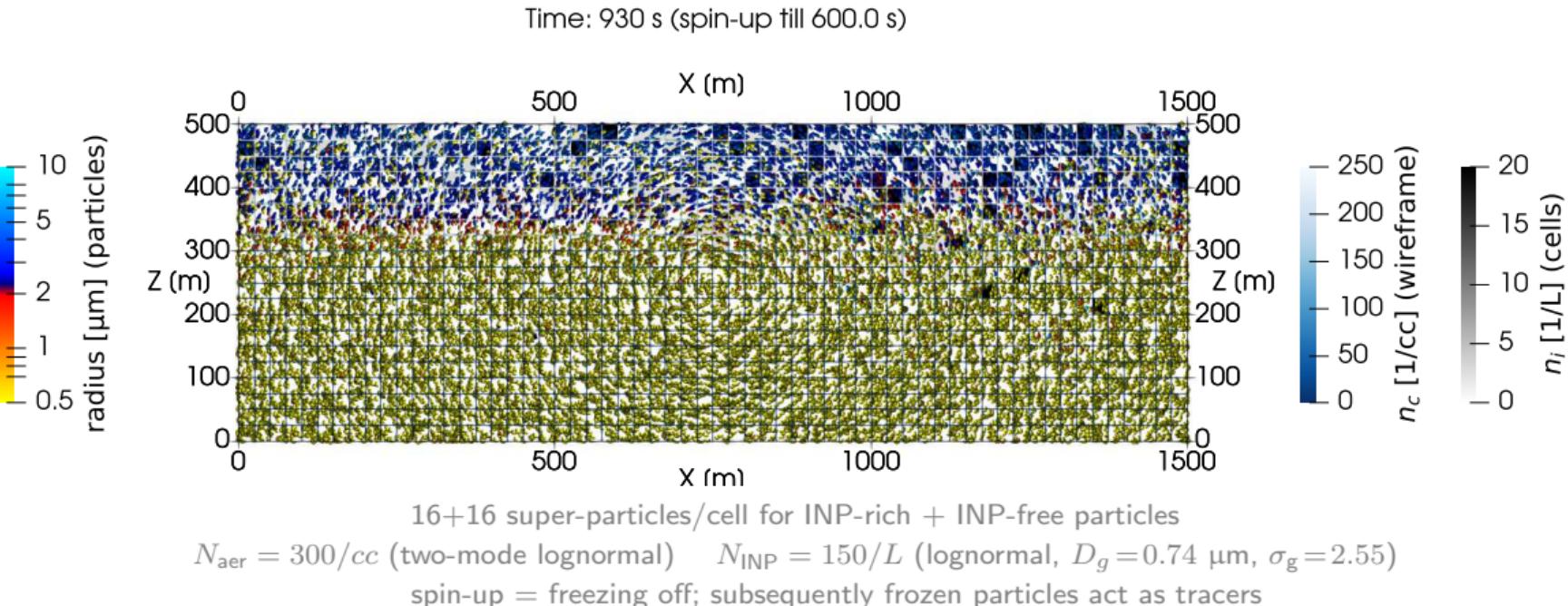
$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \text{ } \mu\text{m}$ ,  $\sigma_g = 2.55$ )

spin-up = freezing off; subsequently frozen particles act as tracers

# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

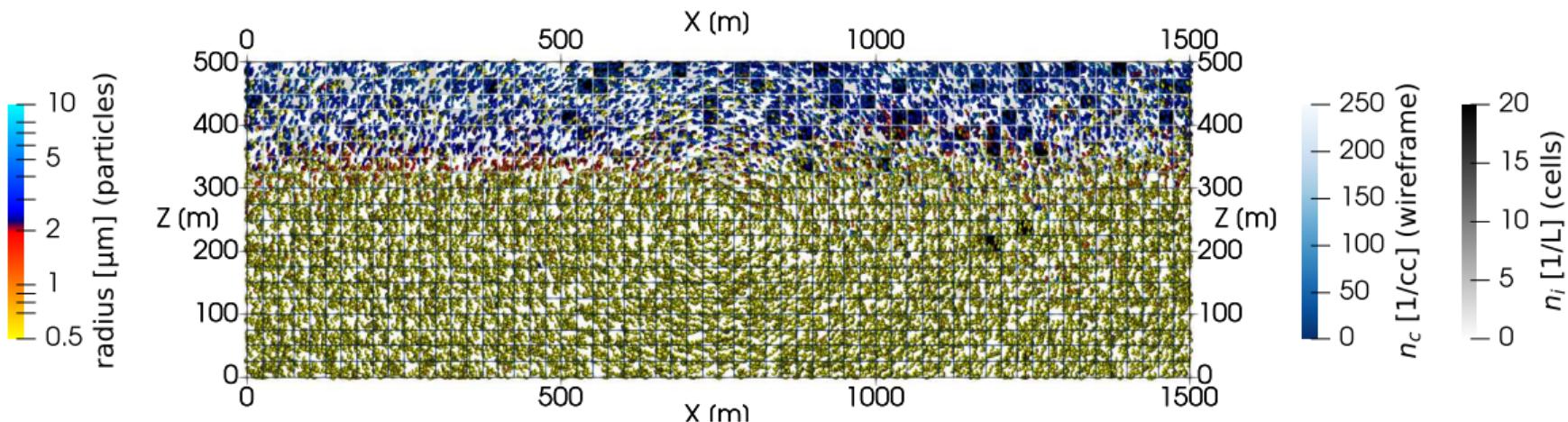


# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

Time: 960 s (spin-up till 600.0 s)

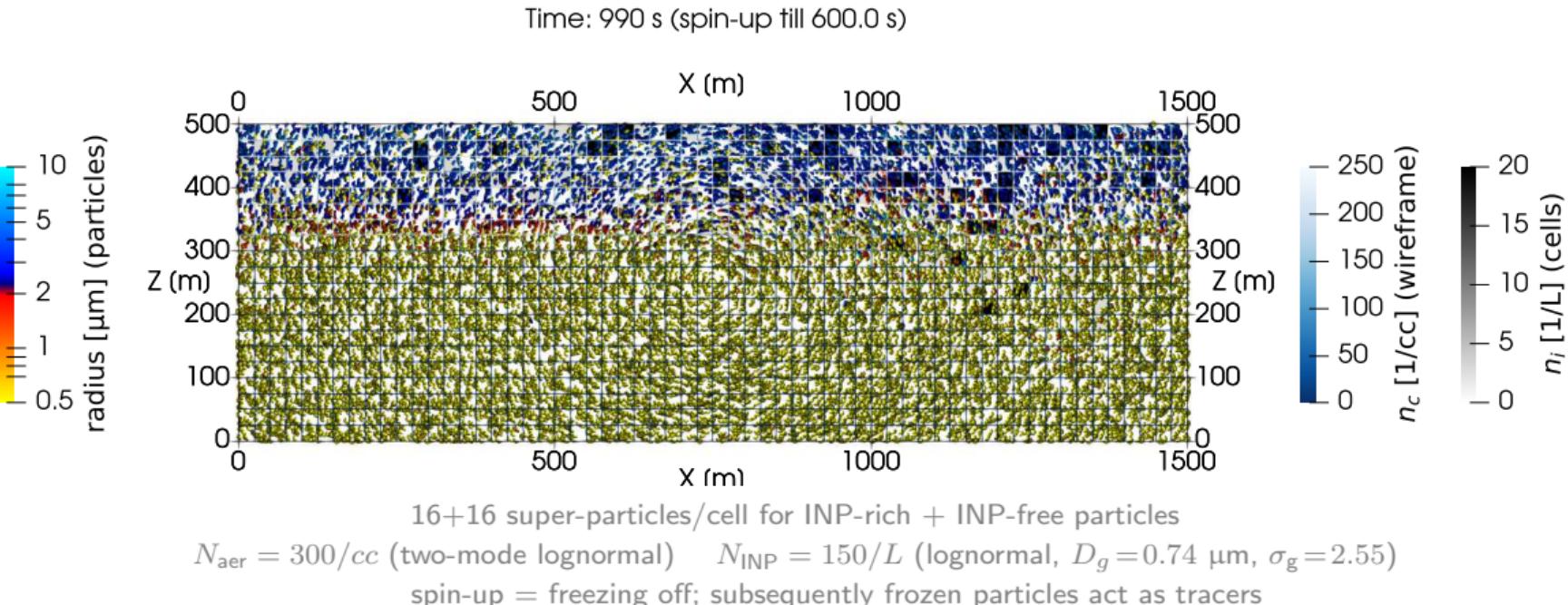


16+16 super-particles/cell for INP-rich + INP-free particles

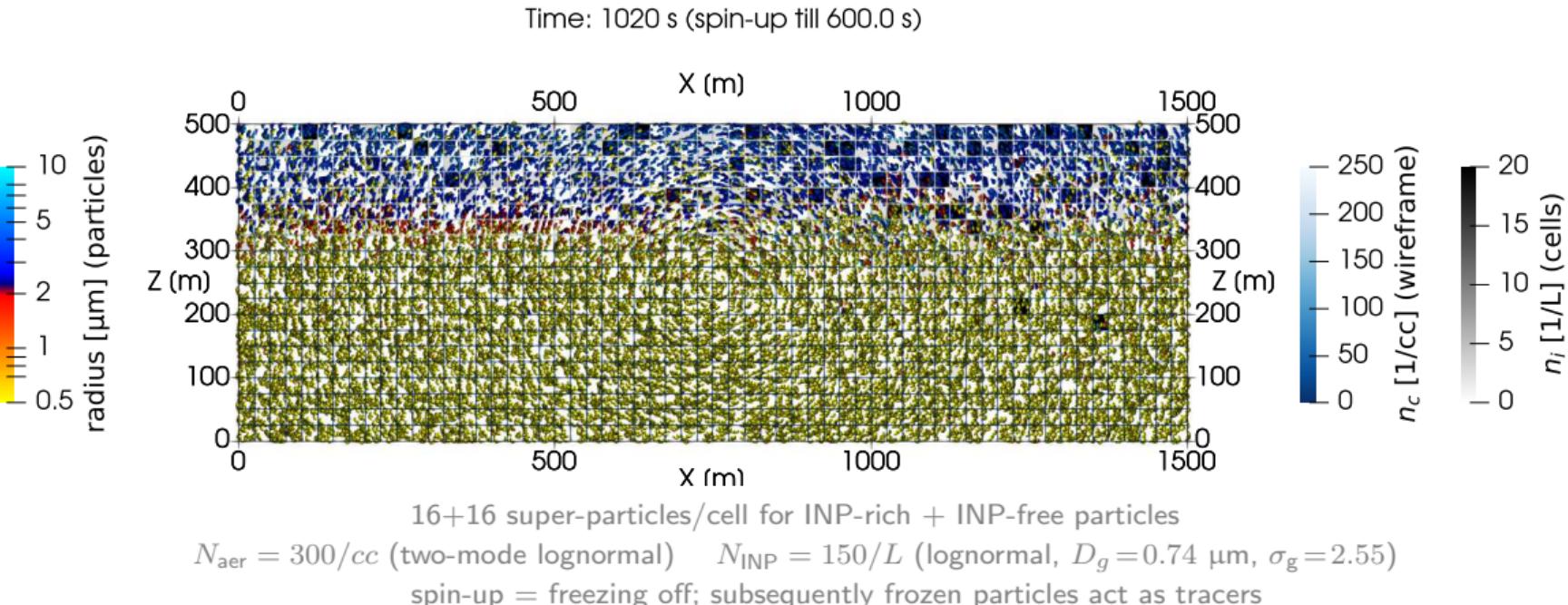
$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \text{ }\mu\text{m}$ ,  $\sigma_g = 2.55$ )

spin-up = freezing off; subsequently frozen particles act as tracers

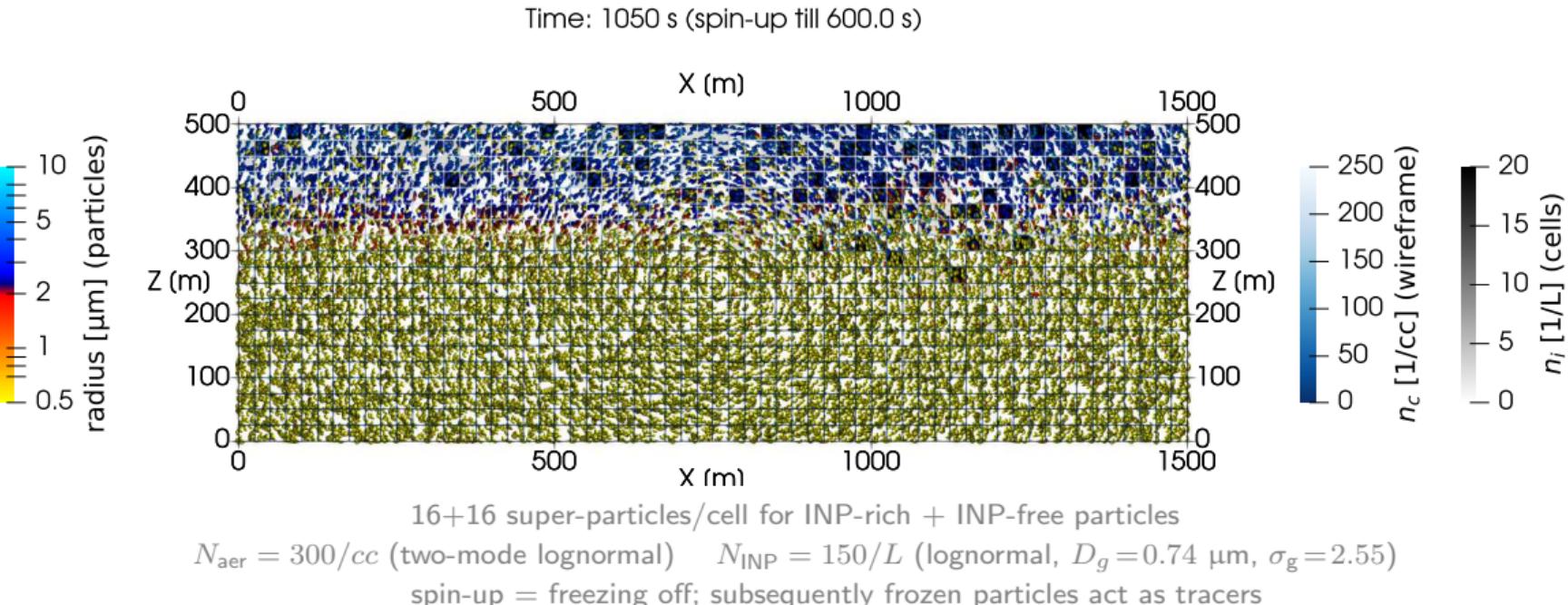
# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



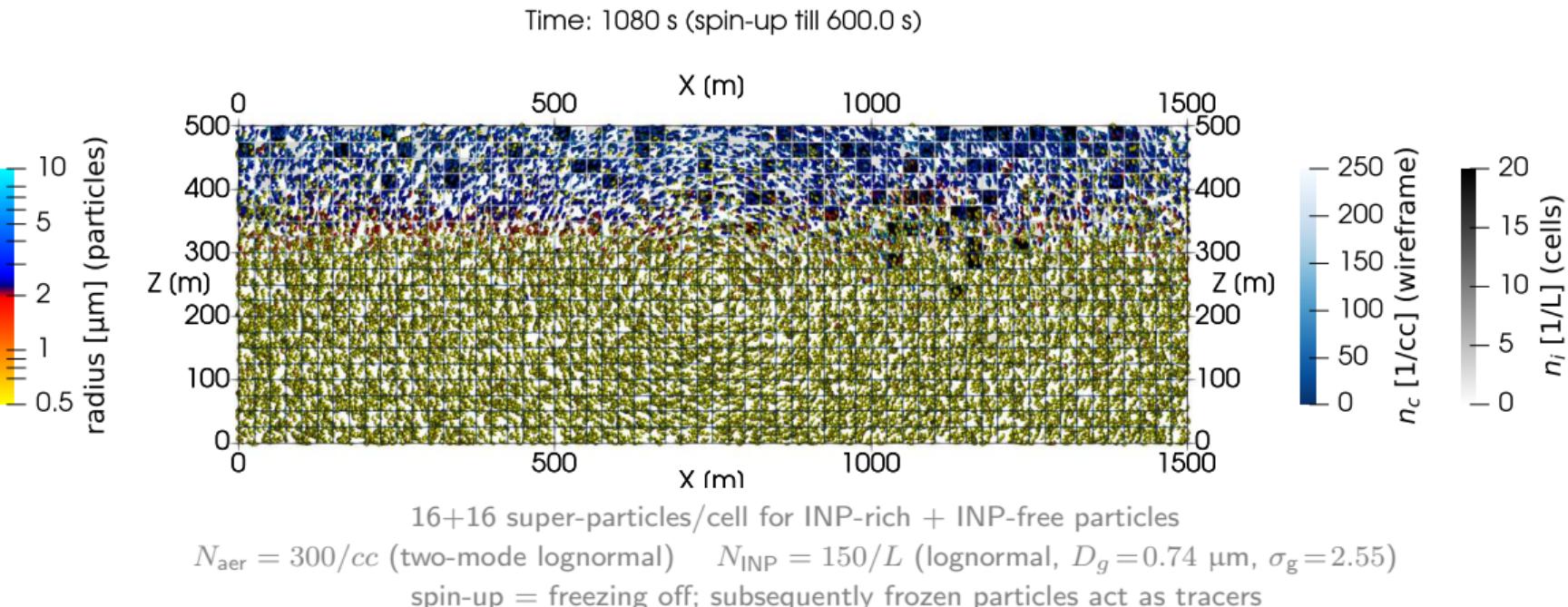
# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



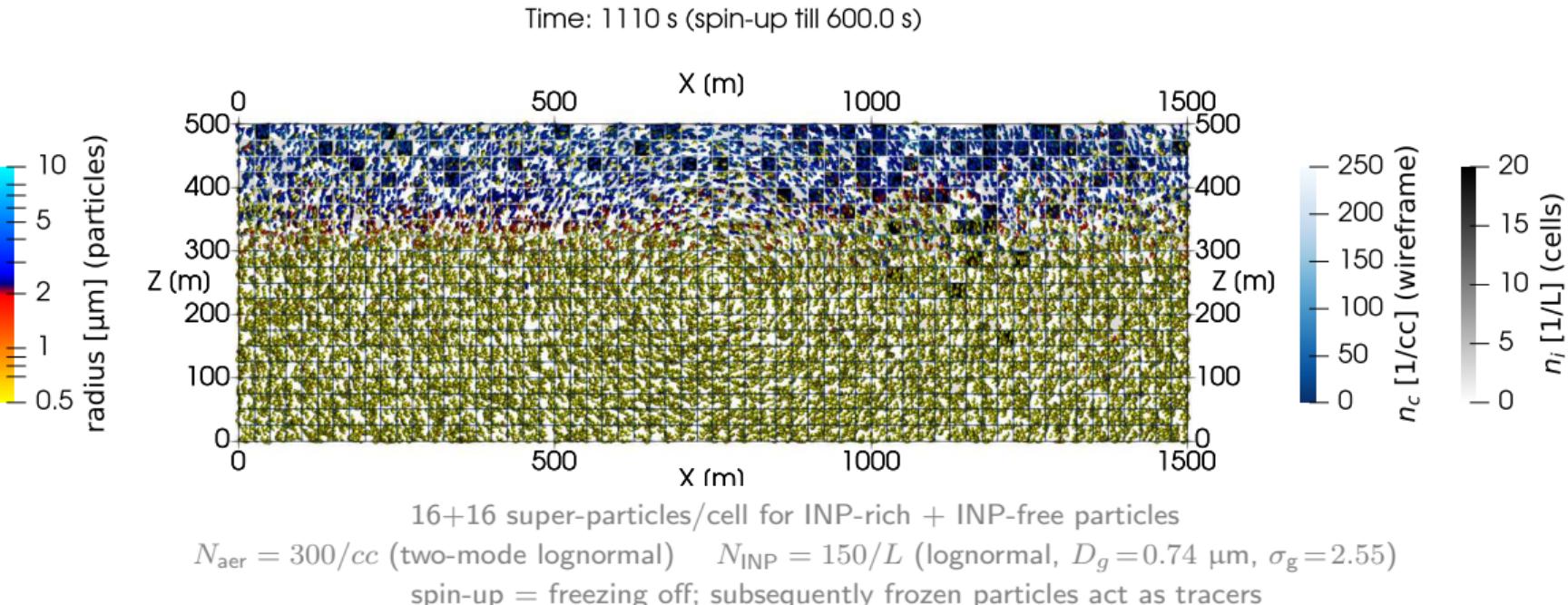
# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



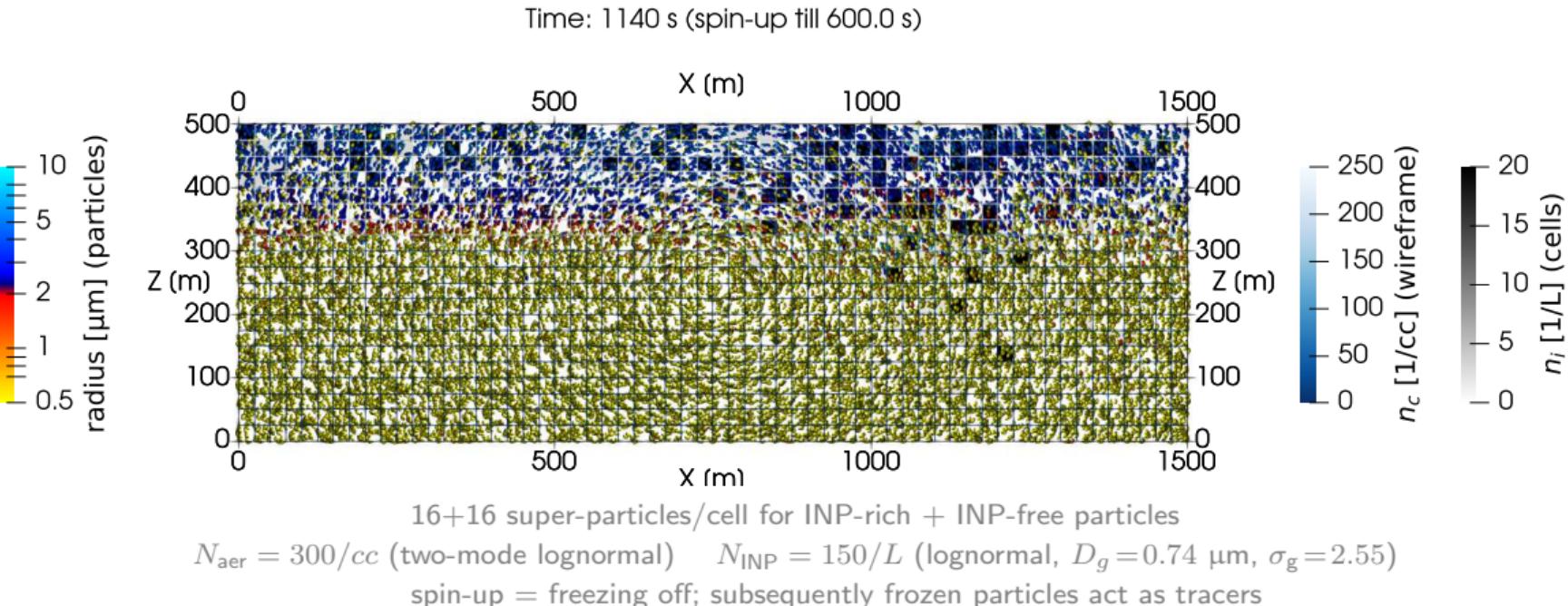
# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



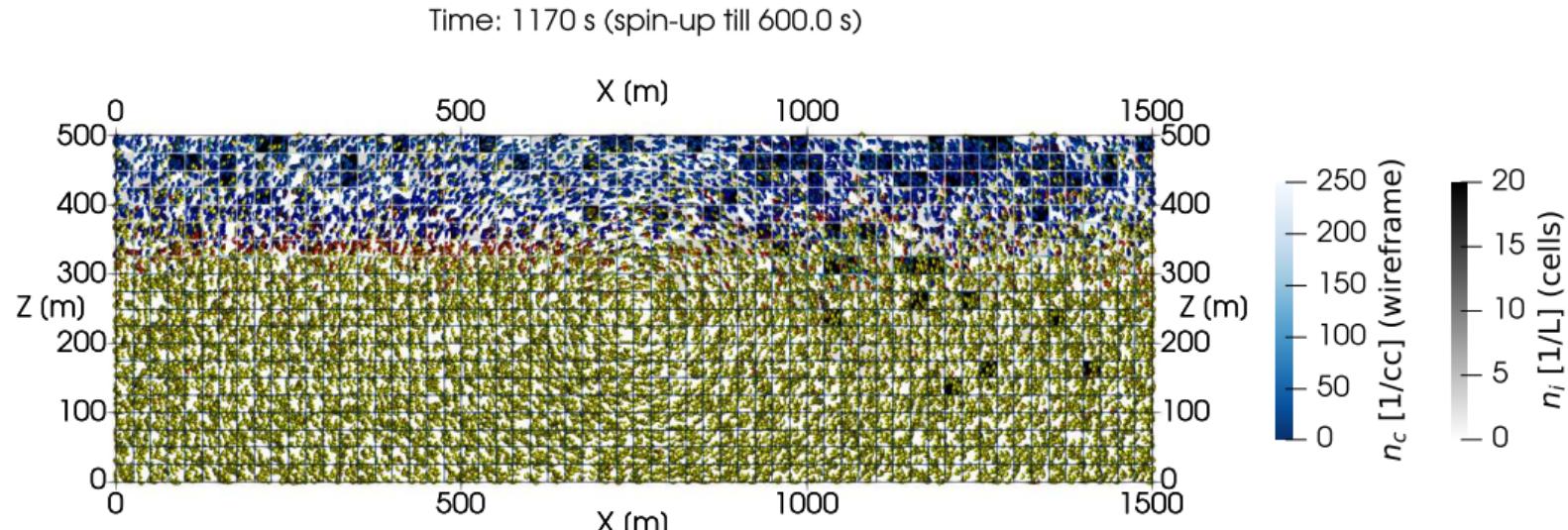
# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)

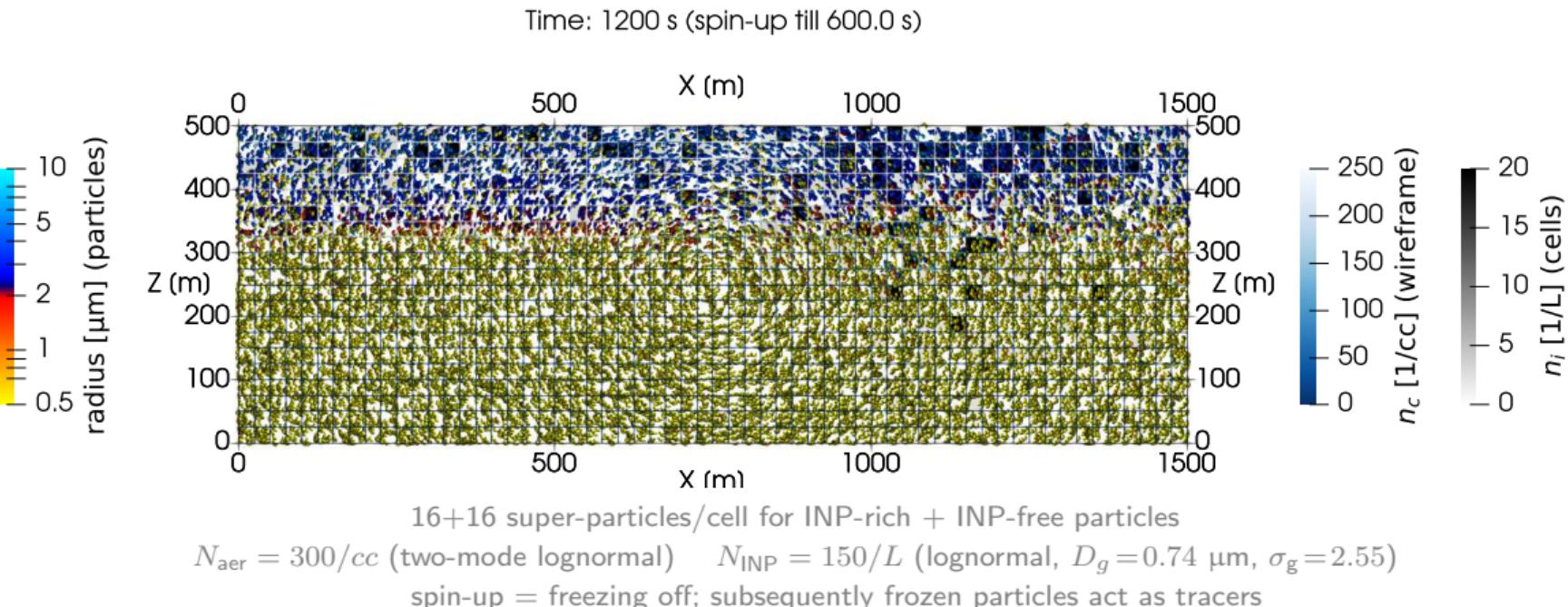


16+16 super-particles/cell for INP-rich + INP-free particles

$N_{\text{aer}} = 300/\text{cc}$  (two-mode lognormal)     $N_{\text{INP}} = 150/L$  (lognormal,  $D_g = 0.74 \mu\text{m}$ ,  $\sigma_g = 2.55$ )

spin-up = freezing off; subsequently frozen particles act as tracers

# PySDM: particle-based $\mu$ -physics + prescribed-flow test (PyMPDATA)



<https://github.com/open-atmos>

The screenshot shows the GitHub organization page for `open-atmos`. The top navigation bar includes links for Overview, Repositories (8), Projects, Packages, and People. Below this, a "Pinned" section displays four repositories:

- camp** (Public) - Multi-phase chemistry treatment for atmospheric models. Languages: Fortran, C++. Stars: 7, Forks: 2.
- PyPartMC** (Public) - Python (and C++) interface to PartMC with Jupyter/Python and Julia examples. Languages: C++, Python. Stars: 9, Forks: 5.
- PySDM** (Public) - Pythonic particle-based (super-droplet) warm-rain/aqueous-chemistry cloud microphysics package with box, parcel & 1D/2D prescribed-flow examples in Python, Julia and Matlab. Languages: Python. Stars: 35, Forks: 21.
- PyMPDATA** (Public) - Numba-accelerated Pythonic implementation of MPDATA with examples in Python, Julia and Matlab. Languages: Python. Stars: 18, Forks: 10.

On the right side, there are sections for "Top languages" (Python, Jupyter Notebook, C++, Fortran) and "Most used topics" (#python #pypi-package, #atmospheric-modelling, #monte-carlo-simulation #research).

**CAMP**: BSC, NCAR, UIUC, UCI

**PySDM**: Jagiellonian, Caltech, UIUC

**PyPartMC**: UIUC

**PyMPDATA**: Jagiellonian

<https://github.com/open-atmos>

The screenshot shows the GitHub repository page for `open-atmos`. The page has a light gray header and a white main content area. At the top left is a large gray square placeholder for a profile picture. Below it, the repository name `open-atmos` is displayed in a bold black font. The navigation bar at the top includes links for Overview (which is underlined in red), Repositories (8), Projects, Packages, and People.

The main content area is titled "Pinned" and contains four project cards:

- `camp` (Public)**  
Multi-phase chemistry treatment for atmospheric models  
Languages: Fortran, C++  
Stars: 7, Forks: 2
- `PyPartMC` (Public)**  
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To the right of the pinned projects, there are two sections:

- Top languages**: Python (blue dot), Jupyter Notebook (orange dot), C++ (red dot), Fortran (purple dot).
- Most used topics**: #python #pypi-package, #atmospheric-modelling, #monte-carlo-simulation #research.

**CAMP**: BSC, NCAR, UIUC, UCI

**PySDM**: Jagiellonian, Caltech, UIUC

**PyPartMC**: UIUC

**PyMPDATA**: Jagiellonian

# compdyn/partmc: Particle-resolved stochastic atmospheric aerosol model



PartMC: Particle-resolved Monte Carlo code for atmospheric aerosol simulation

version v2.6.1 docker build automated CI passing license GPL-2.0 DOI 10.5281/zenodo.6144610

Version 2.6.1

Released 2022-02-18

**Source:** <https://github.com/compdyn/partmc>

**Homepage:** <http://lagrange.mechse.illinois.edu/partmc/>

**Cite as:** M. West, N. Riemer, J. Curtis, M. Michelotti, and J. Tian (2022) PartMC, version v2.6.1,

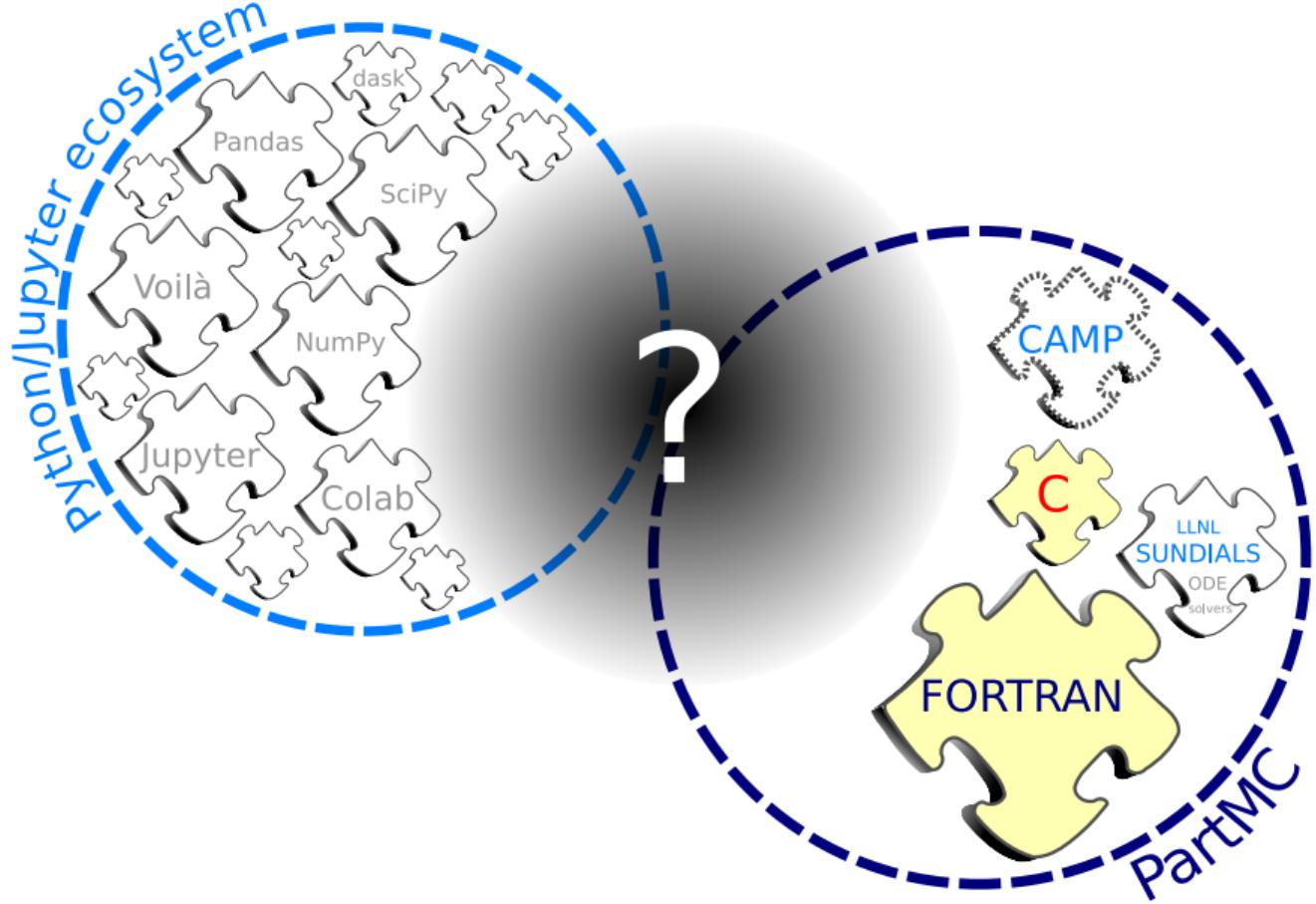
DOI 10.5281/zenodo.6144610

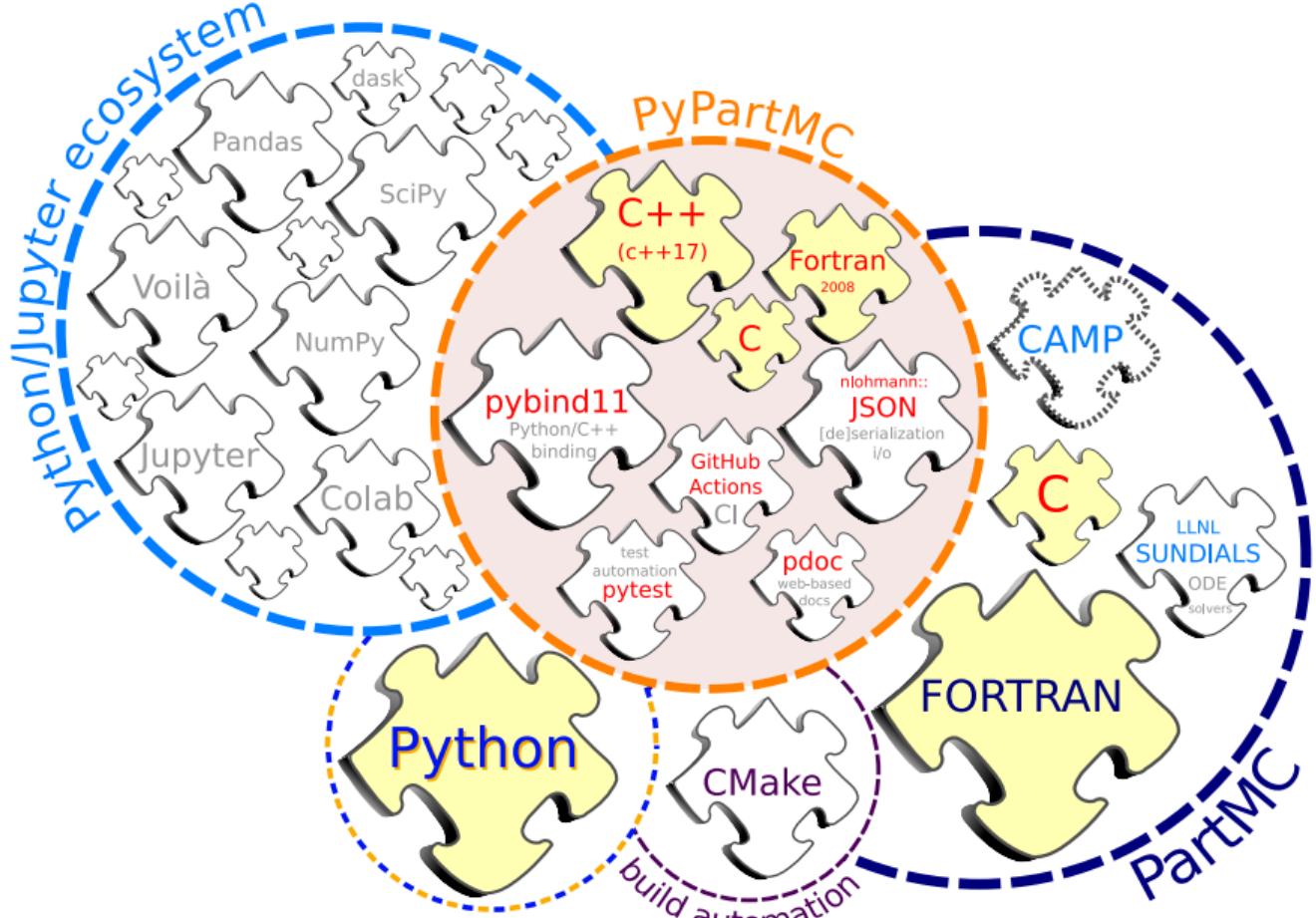
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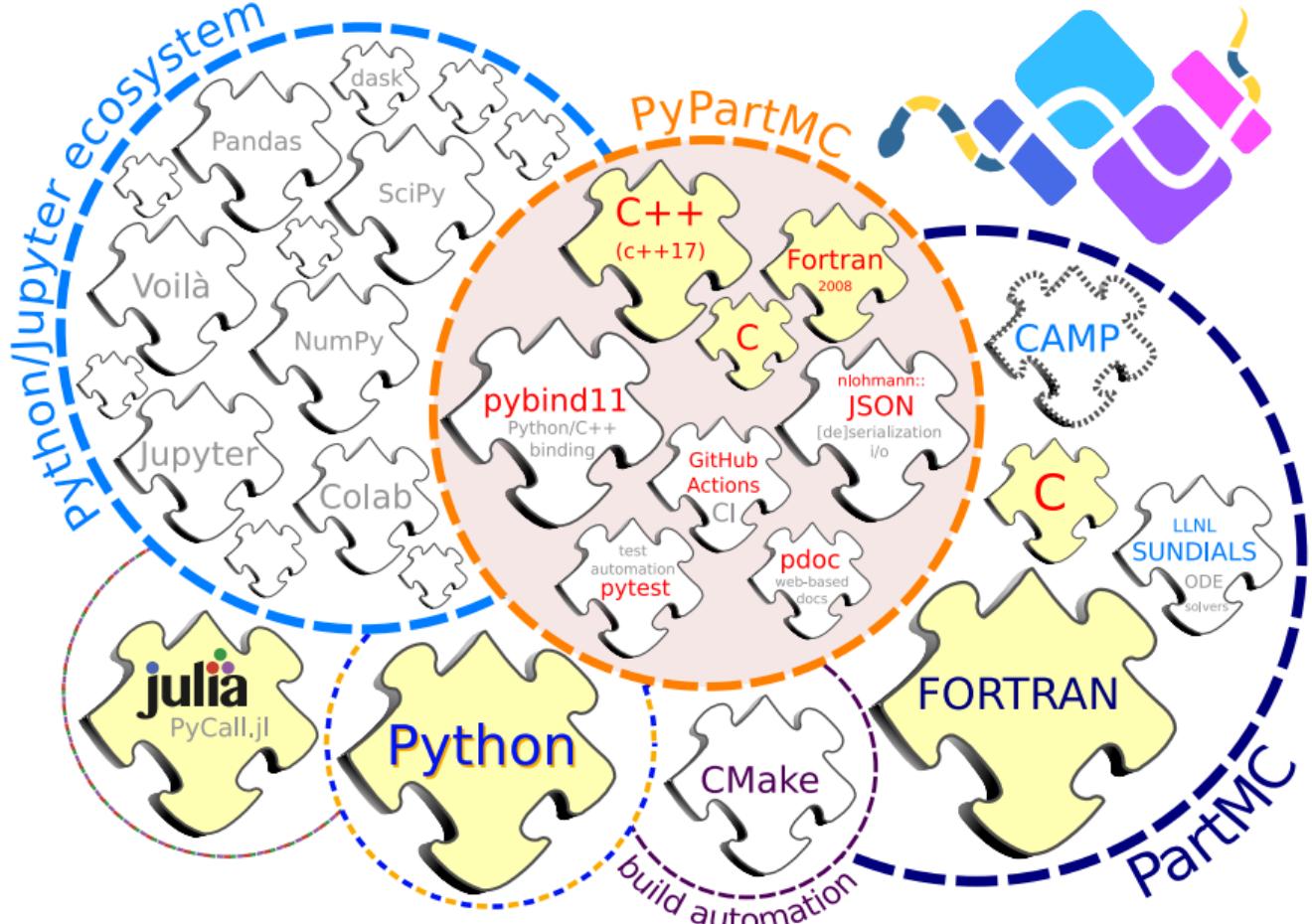
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# PyPartMC 0.0.25

pip install PyPartMC



Latest version

Released: Feb 21, 2023

Python interface to PartMC

## Navigation

Project description

Release history

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## Project links

Documentation

Source

## Project description



### PyPartMC (pre-alpha!)

PyPartMC is a Python interface to [PartMC](#), a particle-resolved Monte-Carlo code for atmospheric aerosol simulation. Since PyPartMC is implemented in C++, it also constitutes a C++ API to the PartMC Fortran internals; the Python API can be used from other environments - see, e.g., Julia example below.

US DOE Funding by ASR | License GPL v3 | Copyright UIUC | Maintained? yes | tests passing | API docs pdoc3

## doctoral network links/prospects

- super-particle-count conserving probabilistic collisional breakup (Emily de Jong @Caltech)  
~~ <https://doi.org/10.5194/egusphere-2022-1243>

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- where turbulence needs to be parameterised:
  - condensation/evaporation vs. supersaturation fluctuations
  - (super-)particle advection and sedimentation
  - collision kernel (mixed-phase!)

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- where turbulence needs to be parameterised:
  - condensation/evaporation vs. supersaturation fluctuations
  - (super-)particle advection and sedimentation
  - collision kernel (mixed-phase!)
- Python/Jupyter ecosystem in coursework/workshop context – PySDM already used at:
  - “Modelling of Atmospheric Clouds” course at the Jagiellonian Univ.
  - “ESE 134. Cloud and Boundary Layer Dynamics” course at Caltech
  - “High-Performance Computing Summer School” at Univ. Kobe

**Merci de votre attention**

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...

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