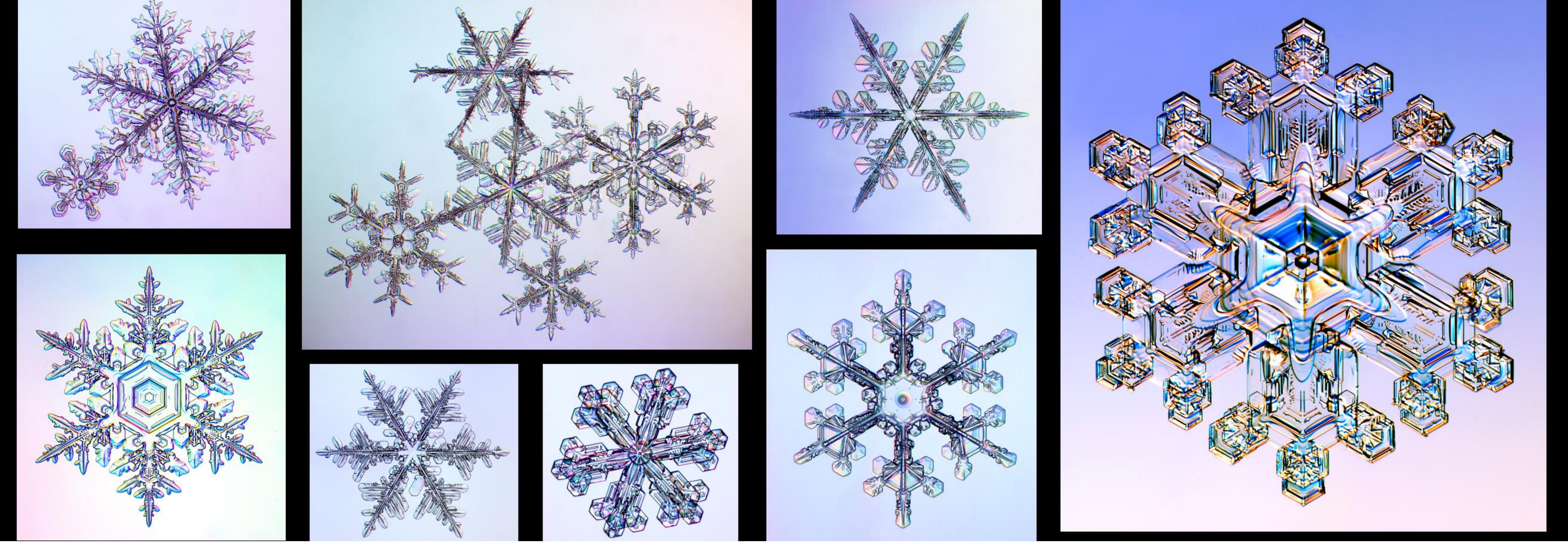


K. Libbrecht, snowcrystals.com

FRAGILE

SPP PROM Meeting Kiel

Simone Wald, Jan-Niklas Welß, Axel Seifert, Christoph Siewert
Deutscher Wetterdienst

19.07.23

Current status of microphysical modeling

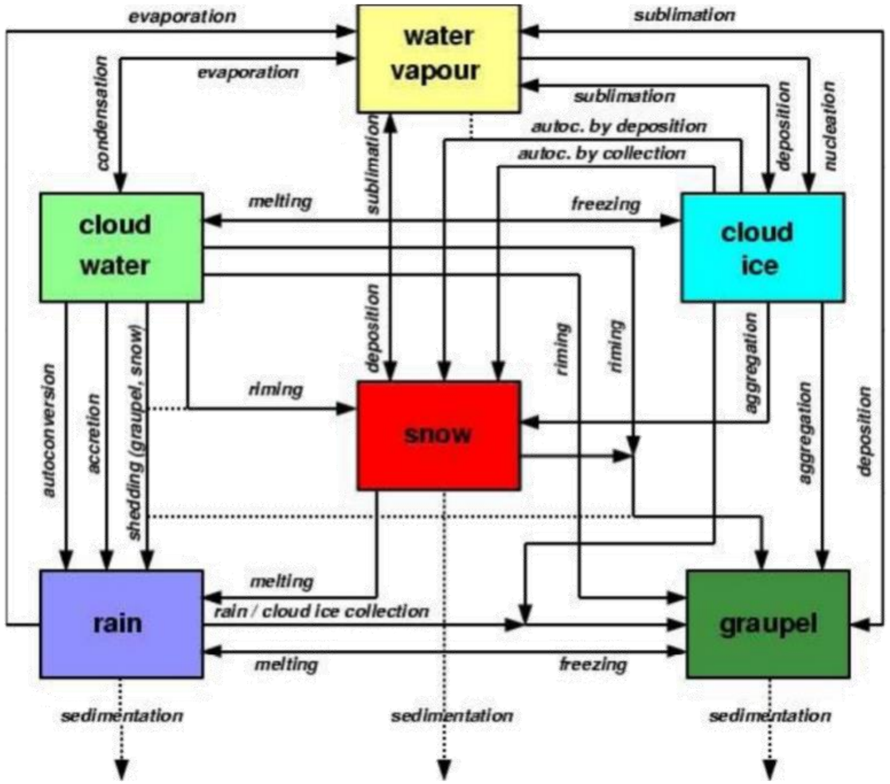
- Current simplifications:
  - Fixed form of size distribution

$$f(x) = A x^{\nu} e^{-\lambda x^{\mu}}$$

  - Categorization

Locatelli & Hobbs 74

- Idea: continuous particle-based model



T. Reinhardt, A. Seifert 2005

particle-based mixed-phase microphysics McSnow

S. Brdar and A. Seifert 2017, *McSnow – A Monte-Carlo particle model for riming and aggregation of ice particles in a multidimensional microphysical phase space*, Journal of Advances in Modeling Earth Systems 10, 10.1002/2017MS001167

Processes

- nucleation
- vapor diffusion
- sedimentation
- coalescence
- riming
- rime splintering
- riming
- melting & shedding
- hydrodynamic breakup
- collision breakup

Locatelli & Hobbs 74

Prognostic Variables

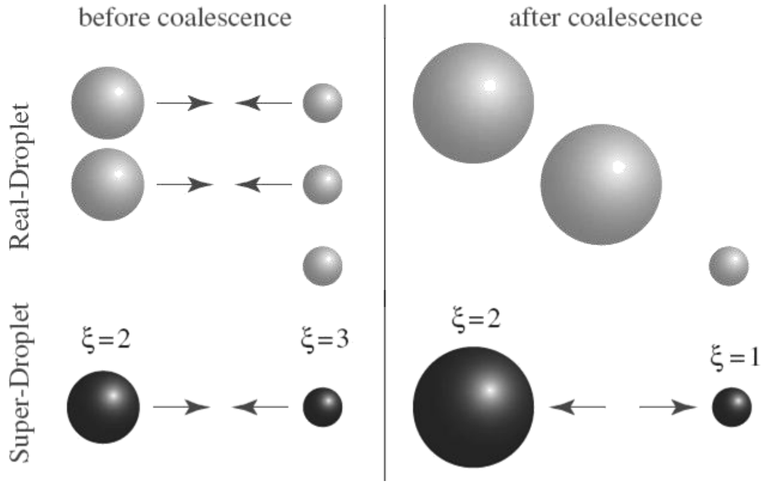
- ice mass m_i
- number of monomers N_m
- rime mass m_r
- rime density ρ_r
- liquid mass m_w

Diagnose geometry
→ fall velocity

- aspect ratio Φ
- ice volume V_i

PROM 1 → monomer geometry prognostic
PROM 2 → aggregate geometry prognostic

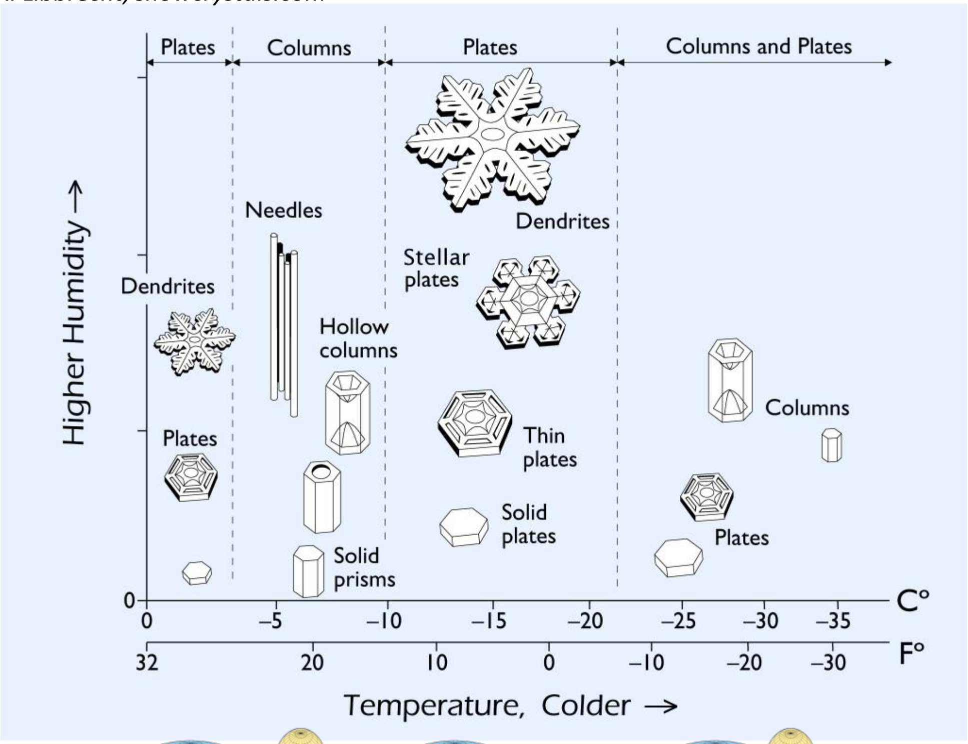
Too many particle
ξ similar particles = 1 representative super-particle
→ interaction stochastic

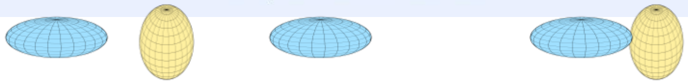


Shima et al. 2009

Habit prediction in McSnow

K. Libbrecht, snowcrystals.com





→ additional prognostic variables:

Φ aspect ratio (particle shape),

V_i ice volume/density (branching/hollowing)

→ prognostic monomer geometry

Approximate monomer shapes with oblate & prolate spheroids

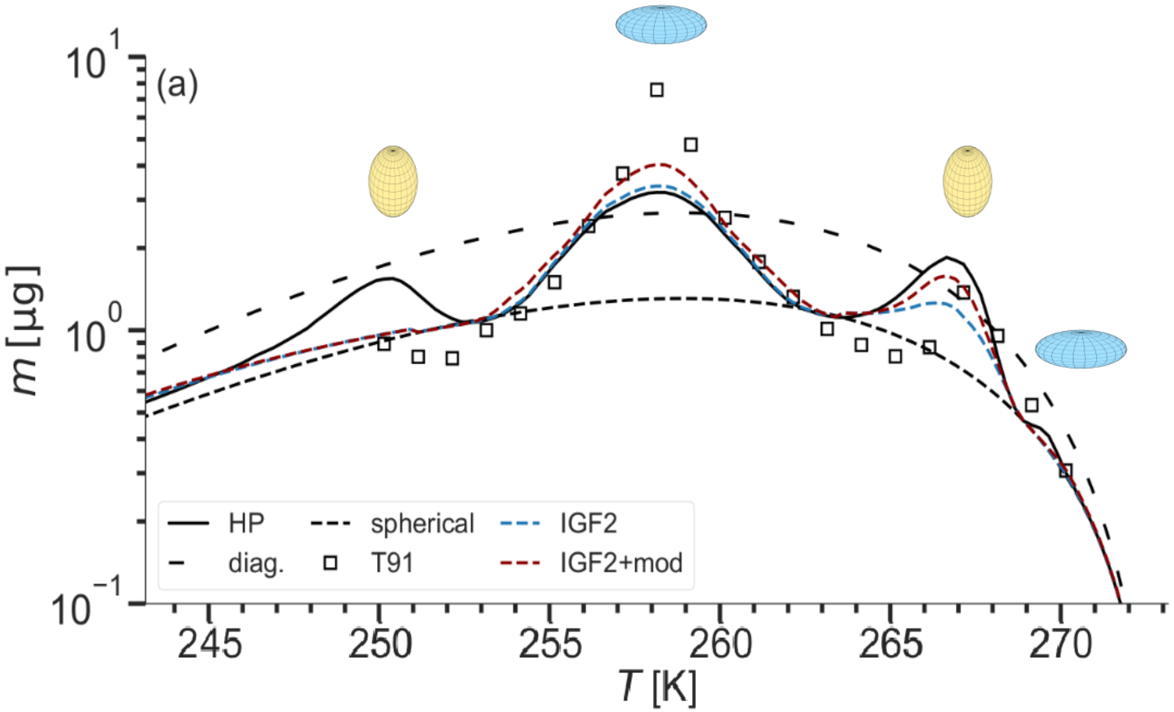
Ice habit growth feedback loop

Ice mass m_i $\quad \frac{\mathrm{d}m_i}{\mathrm{d}t} \sim C(V,\phi) \sim D_{max}$

Aspect ratio Φ $\quad dln\phi = \frac{\Gamma(T)-1}{\Gamma(T)+2} dlnV$

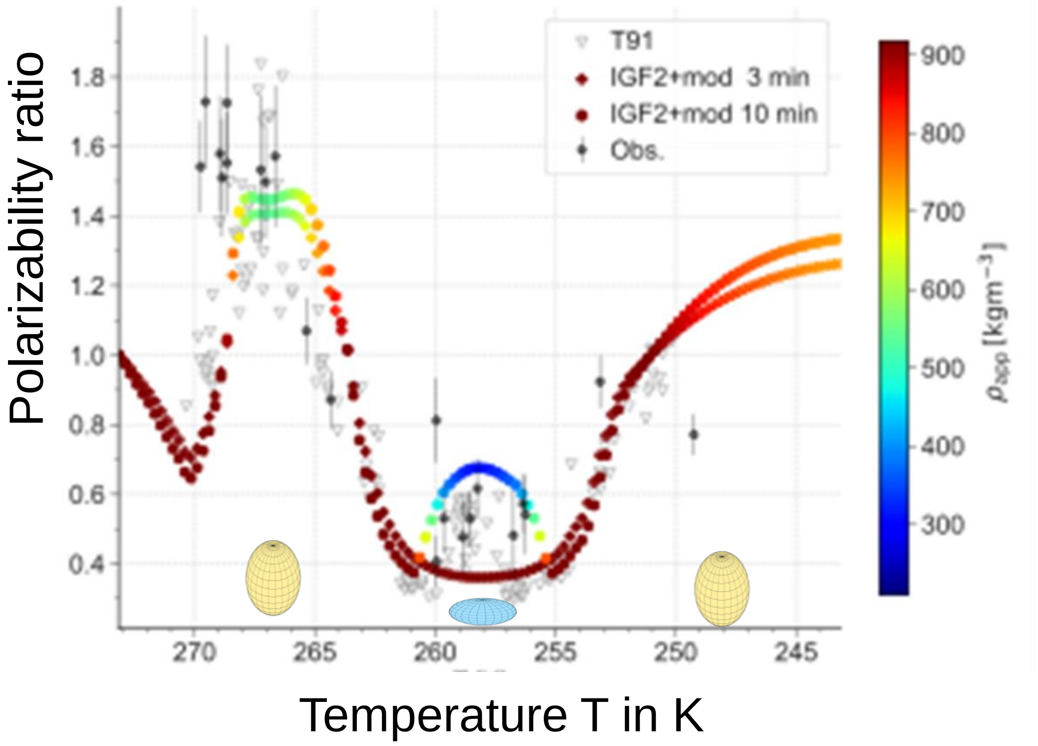
C : Capacitance
Γ : Inherent Growth Function

- Takahashi et al. (1991) ice growth at const T (symbols)
- Solid sphere model underestimates mass (short dashed)
- Empirical m-D misses T dependencies (long dashed)
- McSnow captures the habit dependent mass growth (lines)



Polarizability ratio

- Observed polarizability ratio from 35 GHz cloud radar based on algorithm of Myagkov et al. (2016) using cloud top data (dots with error bars).
- Takahashi et al. (1991) lab data (m_i, V_i, Φ) converted to polarizability ratio (triangles).
- McSnow simulations with habit prediction (colors).
- McSnow captures the qualitative behaviour well



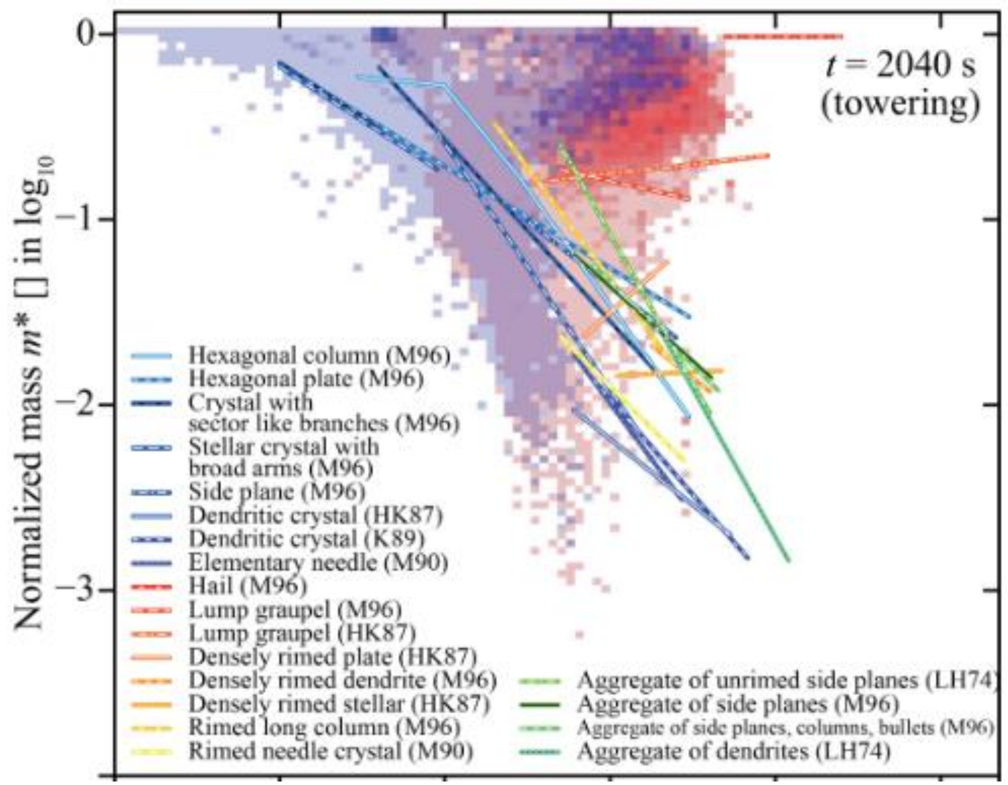
Paper submitted to JAMES, see preprint: J.-N. Welss, C. Siewert, A. Seifert. *Explicit habit-prediction in the Lagrangian super-particle ice microphysics model McSnow*. Authorea. 2023. DOI: 10.22541/essoar.168614461.18006193/v1

Prognostic aggregate geometry

Shima et al. 2020 deterministic approach

Assumptions:

1. maximum dimension constant (fill-in) 
2. density interpolated



Maximum dimension D [m] in log10

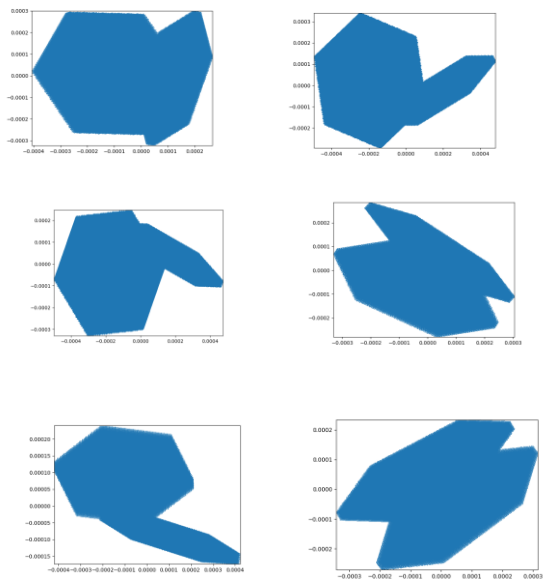
How to build an aggregate

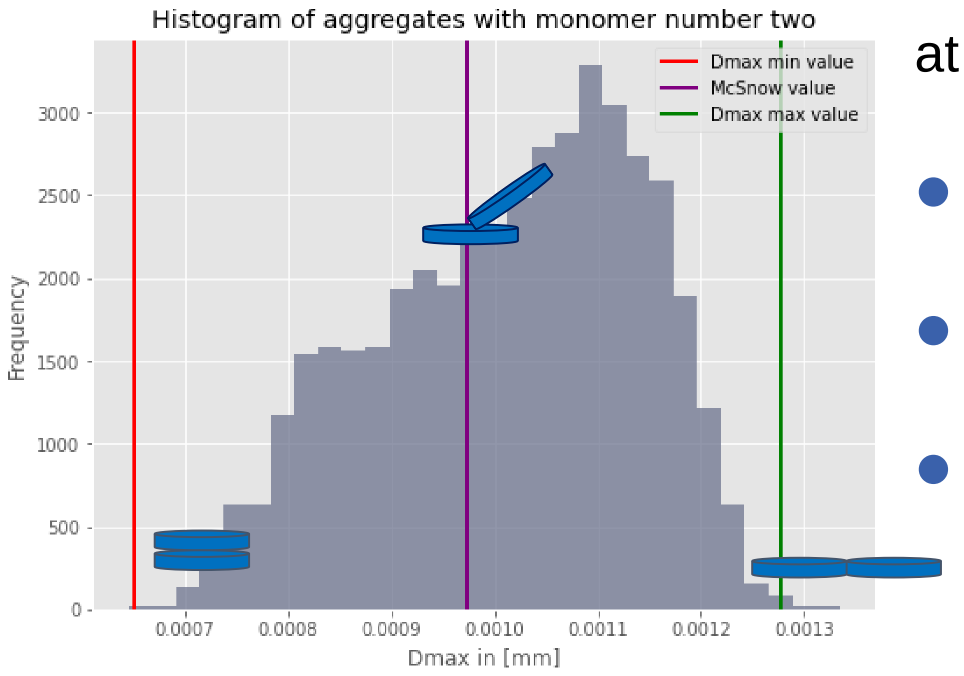
Leinonen and Moisseev (2015)

- realistic monomers geometries (plates, dendrites, columns, and needle)
- monomers drawn from size distribution
- pairs selected according to collision probability
- 40° orientation variance relative to maximum drag

M. Karrer, A. Seifert, C. Siewert, D. Ori, A. von Lerber, S. Kneifel. *Ice Particle Properties Inferred From Aggregation Modelling*. Journal of Advances in Modeling Earth Systems 12. 2020. DOI: 10.1029/2020MS002066

Distribution of aggregates (number of monomers = 2)

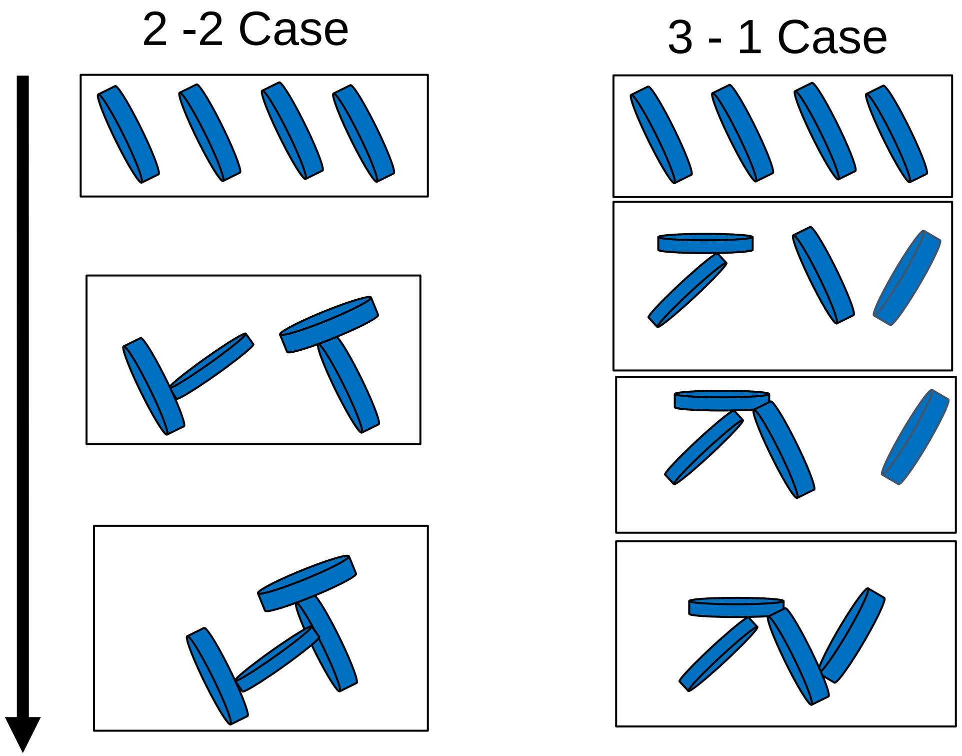


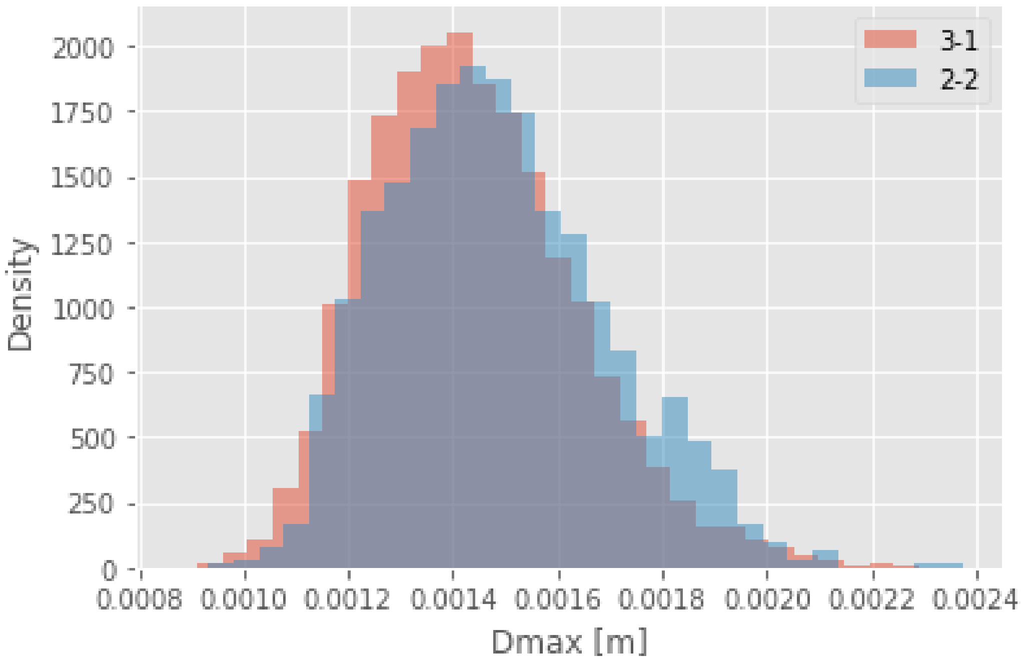


at constant mass:

- Shima et al. 2020: lower limit
- empirical m-D: reasonable mean
- significant geometrical spread

History of aggregates with number of monomers of 4





- 3-1 Case more compact
- history might be important

Expanding the parameter space

McSnow

Prognostic Variables

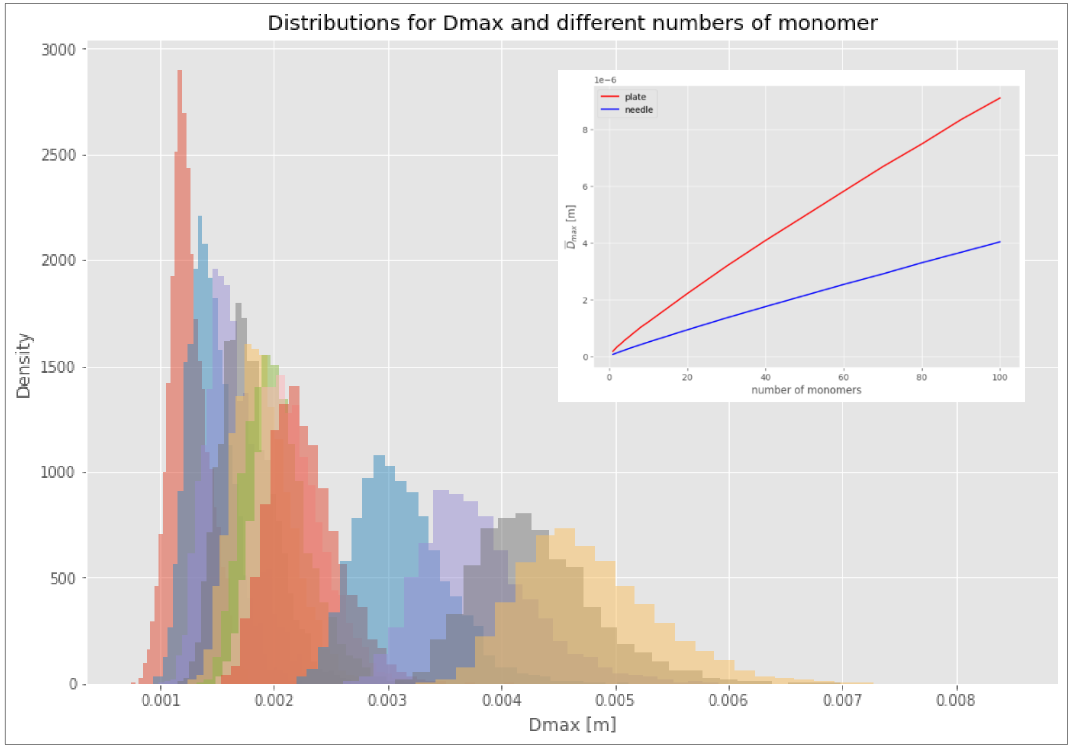
Locatelli & Hobbs 74

- ice mass m_i
- ice volume V_i
- aspect ratio Φ
- number of monomers N_m
- rime mass m_r
- rime density ρ_r
- liquid mass m_w

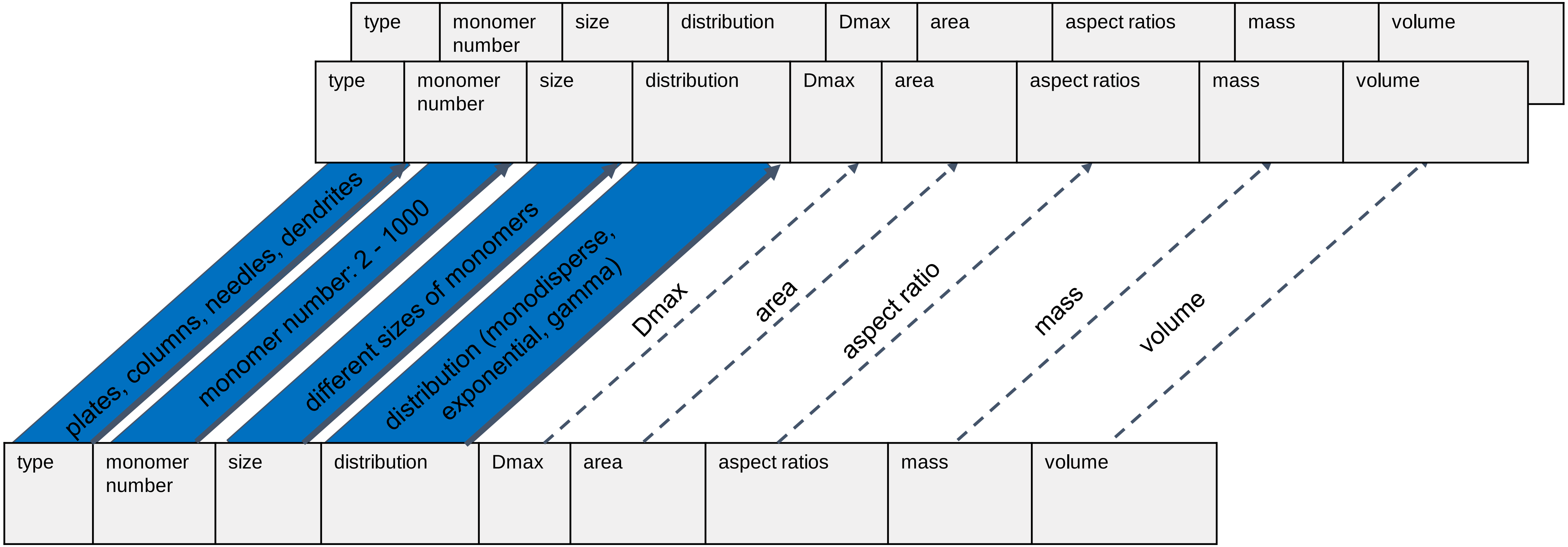
- each particle 7 prognostics
- 2 particles 14 prognostics

→ high-dimensional space

- started sampling the space



Database of aggregates from aggregation model



Coupling McSnow with aggregation model

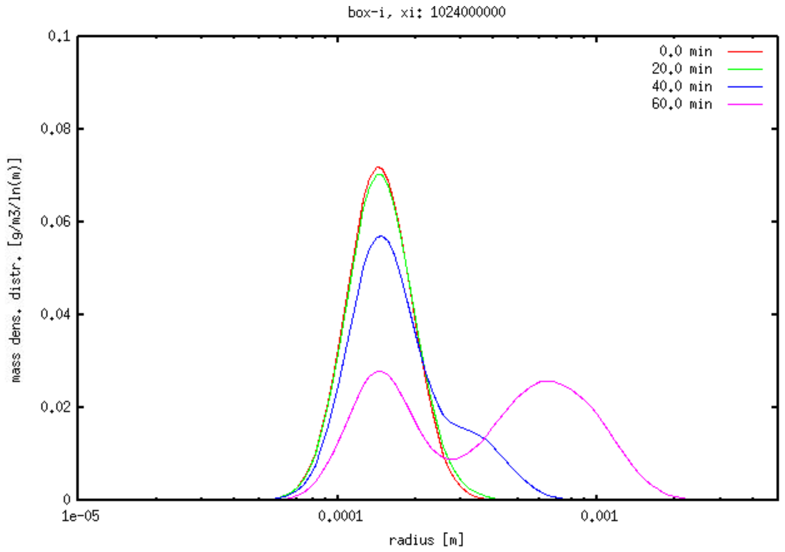
McSnow
(empirical m-D relation)

⇋
couple

Aggregation Model
simulated aggregate geometry (D_{max}, A, and Φ)

begin with simple toy model (box model, initially monodispers), compare:

- empirical m-D relation
- read precalculated values from aggregation model

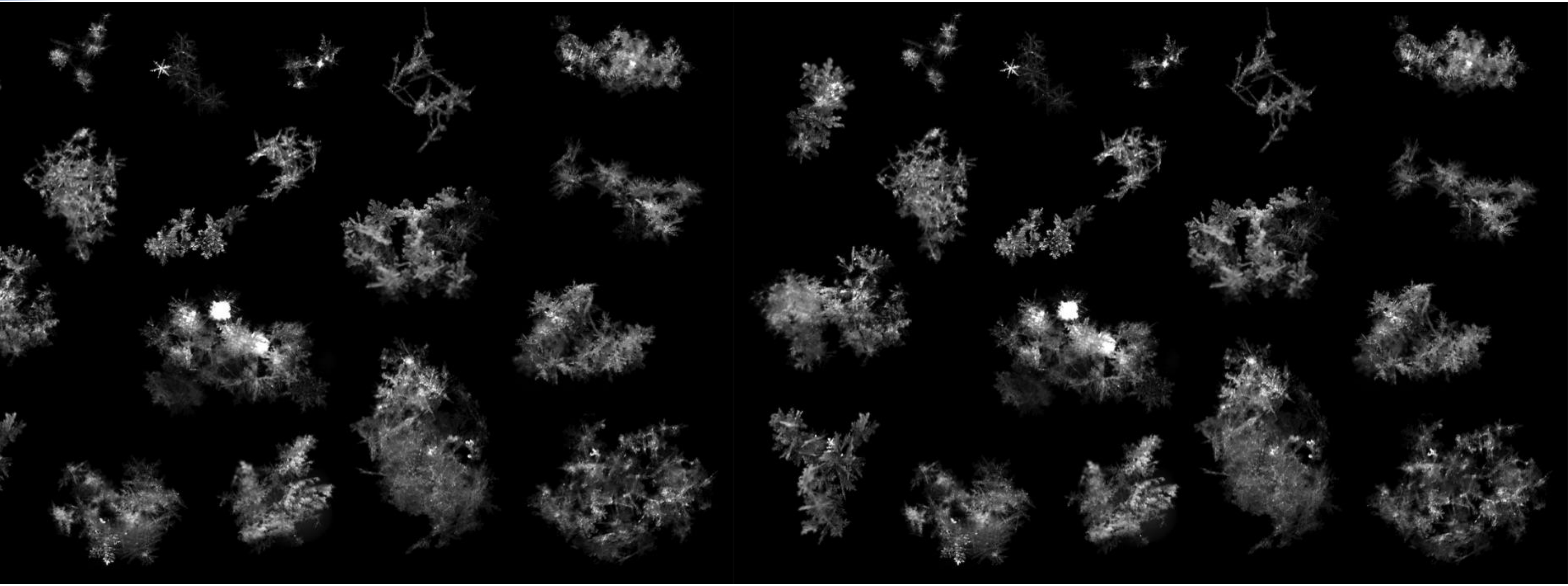


→ parameterization, interpolation or even machine learning

Outlook

- Aggregate geometry: (interesting for other projects: Soumi, PRISTINE)
  - Data Driven – parametrize, interpolate or use machine leanrning
  - prognostic aggregate geometry in McSnow → compare with observations (Leonie, FRAGILE)
- experimental data available → parametrization of fragmentation (Sudha, FRAGILE)
- 3d simulations in McSnow hardly feasible → training data for „ML“ bulk microphysics model

Seifert, Axel, and Stephan Rasp. "Potential and Limitations of Machine Learning for Modeling Warm-Rain Cloud Microphysical Processes." Journal of Advances in Modeling Earth Systems 12.12 (2020): e2020MS002301.



Grazioli et al. 2022

Thank you for your attention!