

# Super-Droplet Method (and its Application to Mixed-Phase Clouds) Shin-ichiro Shima (U Hyogo/R-CCS)

### Abstract

Super-Droplet Method (SDM) is a particle-based scheme to simulate cloud-microphysics accurately. (S.S. et al. 2009)

Basic framework, advantages, and future directions of SDM will be presented

### Contents

- 1. Motivation
- 2. Basic Equations of Clouds and their Hierarchy
- 3. Super-Droplet Method
- 4. Demonstration
- 5. Computational cost
- 6. Advantages
- 7. Various Applications
- 8. Towards Further Acceleration
- 9. Code Availability

### **1. Motivation:** It is still difficult to simulate clouds accurately





**2.2. Mesoscopic Description of Cloud Microphysics** 

Introduce the basic equations of particles with stochastic coalescence (but no breakups)

Then, also derive the Smoluchowski eq.

### **State variables**

Particles (or Droplets): generic name for aerosol/cloud/precipitation particles

- x(t): the position of a particle
- $a(t) = \{a^{(1)}(t), a^{(2)}(t), \dots, a^{(d)}(t)\}$ : the state of a particle, that is specified by *d* number of attributes

 $N_r(t)$ : total number of particles at a time t

Then, the state of the cloud microphysical system is determined by

$$\{(\boldsymbol{x}_{i}(t), \boldsymbol{a}_{i}(t))|i = 1, 2, \dots, N_{r}(t)\}$$

#### **Individual dynamics of particles**

**Time evolution without particle-particle interaction** 

It is affected by the ambient atmosphere.

These can be expressed by the following form:

$$\frac{d\boldsymbol{x}_i}{dt} = \boldsymbol{v}_i, \quad \frac{d\boldsymbol{a}_i}{dt} = \boldsymbol{f}(\boldsymbol{a}_i), \quad i = 1, 2, \dots, N_r(t).$$

Here,  $v_i$  is the velocity of the particle.

 $\boldsymbol{v}_i$  is regarded as one of the attribute variables

In general, f is an atmosphere (fluid field) dependent function.

# Stochastic Coalescence of particles Interaction between particles

Assuming that the particles are well mixed by the atmospheric turbulence, coalescence can be regarded as a stochastic event

$$P_{jk} = C(\boldsymbol{a}_j, \boldsymbol{a}_k) |\mathbf{v}_j - \mathbf{v}_k| \frac{\Delta t}{\Delta V}$$
$$= K(\boldsymbol{a}_j, \boldsymbol{a}_k) \frac{\Delta t}{\Delta V}$$

=probability that droplet j and k

inside a small region  $\Delta V$  will coalesce

in a short time interval  $(t, t + \Delta t)$ .

All the pair (*j*,*k*) inside  $\Delta V$  have some possibility to coalesce In general *C* and *K* also depend on fluid field 7/96

These are the mesoscopic basic equations of cloud microphysics Another mesoscopic representation follows. **Smoluchowski eq. (Stochastic Coalescence Equation; SCE)** Let n(a,x,t) be the number density of particles at time t, at x, with attribute *a*. Under the decoupling assumption  $p(n_1, a_1, n_2, a_2) = p(n_1, a_1)p(n_2, a_2)$  etc., we can derive  $\frac{\partial n(\boldsymbol{a},\boldsymbol{x},t)}{\partial \boldsymbol{t}} + \nabla_{\boldsymbol{x}}\cdot\{\boldsymbol{v}n\} + \nabla_{\boldsymbol{a}}\cdot\{\boldsymbol{f}n\}$  $=\frac{1}{2}\int d^{d}a'n(\boldsymbol{a}')n(\boldsymbol{a}'')K(\boldsymbol{a}',\boldsymbol{a}'')$  $-n(\boldsymbol{a})\int d^d a' n(\boldsymbol{a}') K(\boldsymbol{a}, \boldsymbol{a}').$ 

Here,  $a' \rightarrow \leftarrow a'' = a$ .

Decoupling in not valid if the well-mixed volume is small

#### **2.3. Minimal Warm Cloud Microphysics**

As a concrete example, the most fundamental warm cloud microphysical processes are introduced.

**State variables** 

$$\{(\boldsymbol{x}_{i}(t), \boldsymbol{a}_{i}(t))|i=1, 2, \dots, N_{r}(t)\}$$

 $\boldsymbol{x}(t)$ : the position of the particle

State of a particle is described by 5 attribute variables: a(t)={velocity v, equivalent radius of water R, mass of ammonium sulfate M}

Typical size range

- Aerosols: 1nm to 1µm
- Cloud droplets: 1µm to 50µm
- Rain droplets: 50µm to 1mm

### **Individual dynamics of particles**

a). Advection by the wind and gravity

Adopt the terminal velocity approximation

 $\rightarrow$  Number of independent attributes reduces to 2

**Important for precipitation (rain droplets falling)** 

b). Condensation/evaporation of vapor

Depending on the saturation ratio, particles absorb/evolve vapor from the ambient atmosphere

**Important for converting aerosols to cloud drops** 

# **Coalescence of particles**

c). Coalescence by the gravitational settling

**Dominant for converting cloud droplets to rain droplets** 

#### a) Motion of particles by the wind and gravity

Let  $F_D$  be the air resistance. The motion eq. of a particle is  $m_i dv_i/dt = m_i g + F_D, \quad dx_i/dt = v_i.$ 

If particles are always moving with the terminal velocity,

$$\boldsymbol{v}_i(t) = \boldsymbol{U}_i^* - \hat{\boldsymbol{z}} v_\infty(R_i, T_i^*, P_i^*), \quad d\boldsymbol{x}_i/dt = \boldsymbol{v}_i,$$

 $U_i^*, T_i^*, P_i^*$  are the wind velocity, temperature, pressure



b) Condensation and evaporation of water from droplets
 When oversaturated, vapor condensates to droplets. When undersaturated, vapor evaporates from droplets.
 Here, the effective saturation vapor pressure is affected by the curvature effect and dissolution effect of aerosols

Based on Köhler's theory(1936), we can derive

$$R_{i}\frac{dR_{i}}{dt} = \frac{1}{F_{k}(T_{i}^{*}) + F_{d}(T_{i}^{*})} \left\{ S_{i}^{*} - \frac{e_{s}'(R_{i}, M_{i}, T_{i}^{*})}{e_{s}(T_{i}^{*})} \right\},$$
$$\frac{e_{s}'(R_{i}, M_{i}, T_{i}^{*})}{e_{s}(T_{i}^{*})} = 1 + \frac{a(T_{i}^{*})}{R_{i}} - \frac{b(M_{i})}{R_{i}^{3}},$$
$$F_{k}(T_{i}^{*}) = \left(\frac{L}{R_{v}T_{i}^{*}} - 1\right) \frac{L\rho_{\text{liq}}}{KT_{i}^{*}}, \quad F_{d}(T_{i}^{*}) = \frac{\rho_{\text{liq}}R_{v}T_{i}^{*}}{De_{s}(T_{i}^{*})}$$

#### ...cont. (Condensation and evaporation of water...)

- $S_i^*$ : saturation ratio at the position of the particle *i*
- $e_s'/e_s$ : ratio of effective saturation ratio and saturation ratio of the bulk
- $a(T_i^*)/R_i$ : expressing the increase of effective saturation ratio caused by the curvature effect of the droplet
- $b(M_i)/R_i^3$ : expressing the decrease of effective saturation ratio caused by the dissolution effect of ammonium sulfate
- $F_k$ : coefficient relating to the thermal conduction
- $F_d$ : coefficient relating to the vapor diffusion

#### ...cont. (Condensation and evaporation of water...)

Köhler curve for a droplet containing ammonium sulfate 10<sup>-16</sup>g at 293K is



Tiny droplet is stable even if it's unsaturated. Cloud droplets won't be created if oversaturation of some extent occurs  $_{14/96}$ 

# c) Coalescence of particles by the gravitational settling Bigger particles sweep smaller particles because of the difference of their terminal velocities Consider two particles *j* and *k* in a volume $\Delta V$ 2 particles sweep the volume $\pi (R_i + R_k)^2 |v_i - v_k| \Delta t$ during a small time interval $(t,t+\Delta t)$ If $\Delta V$ is small enough, particles are well mixed by the atmospheric turbulence Thus, the probability that the coalescence occurs is the ratio of sweep volume and $\Delta V$ $P_{jk} = \pi (R_j + R_k)^2 |\boldsymbol{v}_j - \boldsymbol{v}_k| \frac{\Delta t}{\Lambda \mathbf{V}}.$

However,

...cont. (Coalescence of particles by the gravitational settling) this evaluation is not good for small droplets Small droplet could swept aside, or bounce





collision and bounce of small droplet (35µm in radius) and large droplet (1.75mm in radius). (adapted from Whelpdale and List, 1971)

swept aside along the flow

bounce on the surface

Incorporate this by the coalescence efficiency  $E(R_j, R_k)$  $P_{jk} = E(R_j, R_k)\pi(R_j + R_k)^2 |\boldsymbol{v}_j - \boldsymbol{v}_k| \frac{\Delta t}{\Delta V}.$ 

e.g., theories of Davis(1972), Jonas(1972), Hall(1980)

...cont. (Coalescence of particles by the gravitational settling) Contour plot of  $P_{ik}$  as a function of  $R_i$  and  $R_k$  $\Delta V=1$  cm<sup>3</sup>,  $\Delta t=1$ s, 101.3kPa, 20°C. 1000 Same size droplets won't coalesce  $10^{-1}$ Droplet Radius  $R_k$  [ $\mu$ m] Small droplets seldom  $10^{-2}$ 100  $10^{-3}$ coalesce  $10^{\circ}$ Droplets larger than  $10^{-1}$  $10^{-7}$  $10^{-2}$ 10  $10^{-8}$ 10µm are  $10^{-3}$ 10<sup>-7</sup> 10<sup>-61</sup>  $10^{-9}$ necessary for rain  $10^{-10}$ · 10<sup>-8</sup> (10<sup>-10</sup>)10<sup>-9</sup> Clustering of inertia 10 100 1000 particles by turbulence Droplet Radius  $R_i$  [µm] could be important (e.g., Falkovich et al., 2002) 17/96

### 2.4. Basic Equations of the Cloud Dynamics

## **Compressible Navier-Stokes equation for moist air**

 $\rho \frac{D\vec{v}}{Dt} = -\nabla P - \rho \vec{g} + S_m, \text{ motion eq.} \\ P = \rho R_d T, \text{ eq. of state} \text{ coupling}$  $\frac{D\theta}{Dt} = -\frac{L}{c_p \Pi} S_v, \quad \text{ener}$   $\frac{D\rho}{Dt} = -\rho \nabla \cdot \vec{v},$ energy eq. continuity eq.  $\frac{Dq_v}{S} = \frac{S_v}{M} \text{ mass coupling}$ coupling term to  $S_m(\boldsymbol{r},t), S_v(\boldsymbol{r},t)$ microphysics process density of liquid water / unit space volume

 $\rho = \rho_d + \rho_v$ : densitiy of moist air  $q_v = \rho_v / \rho$ : mixing ratio of vapor  $\mathbf{\bar{v}}$ : wind velocity T: temperature  $\theta$ : potential temperature  $\Pi = (p / p_0)^{R_d / c_p}$  Exner function  $\rho_w$ : density of liquid water  $S_{v}$ : source term for vapor from liquid  $\mathbf{\tilde{g}}$ : gravitational constant  $R_d$ : gas constant for dry air  $c_p$ : isobaric specific heat *L*: latent heat of vapor

mass of evaporated liquid water/ unit space volume /unit time/p

# **3. Super-Droplet Method**

un

deco

assu

### Mesoscopic governing equation of the cloud microphysics

Dynamics of particles with stochastic coalescence

$$\frac{d\boldsymbol{x}_i}{dt} = \boldsymbol{v}_i, \quad \frac{d\boldsymbol{a}_i}{dt} = \boldsymbol{f}(\boldsymbol{a}_i), \quad i = 1, 2, \dots, N_r(t).$$
$$P_{jk} = K(\boldsymbol{a}_j, \boldsymbol{a}_k) \Delta t / \Delta V.$$

Smoluchowski eq. (for number density of particles)

$$\begin{array}{c} \begin{array}{c} \begin{array}{c} \displaystyle \operatorname{der} \\ \begin{array}{c} \displaystyle \operatorname{upling} \\ \displaystyle \operatorname{mption} \end{array} \end{array} \end{array} \\ \end{array} \end{array} \\ \begin{array}{c} \displaystyle \begin{array}{c} \displaystyle \frac{\partial n(\boldsymbol{a},\boldsymbol{x},t)}{\partial t} + \nabla_{\boldsymbol{x}} \cdot \{\boldsymbol{v}n\} + \nabla_{\boldsymbol{a}} \cdot \{\boldsymbol{f}n\} \\ \\ \displaystyle = \frac{1}{2} \int d^{d}a' n(\boldsymbol{a}') n(\boldsymbol{a}'') K(\boldsymbol{a}',\boldsymbol{a}'') \\ \\ \\ \displaystyle - n(\boldsymbol{a}) \int d^{d}a' n(\boldsymbol{a}') K(\boldsymbol{a},\boldsymbol{a}'). \end{array} \end{array}$$

SDM is a numerical scheme to solve this equation For simulating clouds, we need to mutually couple SDM with an LES (Large Eddy Simulation) model <sup>19/96</sup> Here after, SDM is introduced in 2 steps: concept of super-droplets and its numerical implementation

**3.1. Governing Law of the Super-Droplet World** 

**Basic idea** 

**Coarse-grain unnecessary degrees of freedom Super-droplet** 

SD has **multiplicity**  $\xi$ , position x, and attribute aEach SD represents  $\xi$  number of real-droplets (x,a)Population of real-droplets  $\{(x_i(t), a_i(t))|i=1,2,...,N_r(t)\}$  is represented by the SD population.  $(N_s(t)$  is the num of SDs)  $\{(\xi_i(t), x_i(t), a_i(t))|i=1, 2, ..., N_s(t)\}$ **SD can be regarded as a weighted sample of RDs** Note that  $\xi$  is time dependent (Detail follows)

#### **Dynamics of super-droplets**

Individual dynamics

Same as real-droplets, they obey

$$\frac{d\boldsymbol{x}_i}{dt} = \boldsymbol{v}_i, \quad \frac{d\boldsymbol{a}_i}{dt} = \boldsymbol{f}(\boldsymbol{a}_i), \quad i = 1, 2, \dots, N_s(t).$$

Coalescence

**Coalescence of SDs is also a stochastic event** 

 $P_{jk}^{(s)}$  =probability that super-droplets j and kinside a small region  $\Delta V$  will coalesce in a short time interval  $(t, t + \Delta t)$ . **SD # won't be decreased after the coalescence The expected results is consistent with RD** (Detail follows)

#### **Definition of how a pair of SDs coalesce**

Let  $\xi_1$  and  $\xi_2(>\xi_1)$  be the multiplicity of the two SDs

After the coalescence event, we define that a big SD with  $\xi_1$ , and a SD with  $(\xi_2 - \xi_1)$  with no size difference are created



**SD num is almost conserved though RD num decreases** When  $\xi_2 = \xi_1$ , we split the remaining SD We now adjust the probability to get a consistent results

### Definition of the coalescence probability of super-droplets Requiring that the expected num of coalesced RDs becomes the same, we get

 $P_{jk}^{(s)} \coloneqq \max(\xi_j, \xi_k) P_{jk}$ 

Check) Consider coalescence between  $\xi_j$  num of RD  $a_j$  and  $\xi_k$  num of RD  $a_k$ . Expected num of coalesced pairs is

 $E_{jk} = \xi_j \xi_k P_{jk} \quad \leftarrow \text{Real World}$ 

Coalescence of SDs  $(\xi_j, a_j)$  and  $(\xi_k, a_k)$  corresponds to coalescence of min $(\xi_j, \xi_k)$  pairs of RD  $a_j$  and  $a_k$ 

Thus, the expected num of coalesced RD num in the superdroplet world becomes

$$E_{jk}^{(s)} = \min(\xi_j, \xi_k) P_{jk}^{(s)} \leftarrow \text{Super-Droplet World}$$
  
$$= \min(\xi_j, \xi_k) \max(\xi_j, \xi_k) P_{jk}$$
  
$$= \xi_j \xi_k P_{jk}$$
  
$$= E_{jk}$$
  
23/96

# **3.2. Numerical Implementation of the SDM**

Outlook

Cloud microphysics (= Super-Droplet Method) Individual dynamics

$$\frac{d\boldsymbol{x}_i}{dt} = \boldsymbol{v}_i, \quad \frac{d\boldsymbol{a}_i}{dt} = \boldsymbol{f}(\boldsymbol{a}_i), \quad i = 1, 2, \dots, N_s(t).$$

Solve these ODEs for each SD

Coalescence

A novel Monte Carlo scheme is developed to solve this stochastic process of SDs (Detail later)

Cloud Dynamics Solve the Navier-Stokes eq. for atmospheric fluid When simulating a whole cloud, we need to resort to some sub-grid scale turbulence model.

### **Operator Splitting**

- Evaluate each process individually, based on Trotter's factorization formula
- Let X(t) be the state of our system (Everything included)

Let  $\Delta t$  be the least common multiple time step and repeat

 $X^{(1)}(t + \Delta t) = A(\Delta t)X(t)$ , (update fluid)

 $X^{(2)}(t + \Delta t) = B(\Delta t)X^{(1)}(t + \Delta t), \text{ (coalescence)}$ 

 $X^{(3)}(t + \Delta t) = C(\Delta t)X^{(2)}(t + \Delta t)$ , (condensation / evaporation)

 $X(t + \Delta t) = D(\Delta t)X^{(3)}(t + \Delta t)$ , (advection / sedimentation)

Here, A,B,C,D denote their time propagation operators The global error is  $O(\Delta t)$ 

Employing higher order formula, accuracy can be improved

#### **Cloud Dynamics**

**Basic** equations

$$\rho \frac{D\mathbf{U}}{Dt} = -\nabla P - (\rho + \rho_w)\mathbf{g} + \lambda \nabla^2 \mathbf{U},$$
$$P = \rho R_d T,$$
$$\frac{D\theta}{Dt} = \left(-\frac{L}{c_p \Pi} S_v\right) + \kappa \nabla^2 \theta,$$
$$\frac{D\rho}{Dt} = -\rho \nabla \cdot \mathbf{U},$$
$$\frac{Dq_v}{Dt} = S_v + \kappa \nabla^2 q_v.$$

Numerical scheme

Evaluate all the terms except pink terms with  $\Delta t_f$ Green term is calculated from the super-droplets e.g., Space: 2nd order center difference+LES, Time: 4th order Runge-Kutta

# Advection and Sedimentation in Terminal Velocity

Basic eq.

$$m_i \frac{d\mathbf{v}_i}{dt} = m_i \mathbf{g} + \mathbf{F}_D(\mathbf{v}_i, \mathbf{U}(\mathbf{x}_i), R_i), \quad \frac{d\mathbf{x}_i}{dt} = \mathbf{v}_i,$$

#### Numerical scheme

$$\mathbf{v}_i(t) = \mathbf{U}_i^* - \hat{\mathbf{z}}v_\infty(R_i(t))$$
$$\mathbf{x}_i(t + \Delta t_m) = \mathbf{x}_i(t) + \Delta t_m \mathbf{v}_i(t)$$

#### **Condensation/Evaporation**

Basic eqs.

$$R_{i}\frac{dR_{i}}{dt} = \frac{(S-1) - \frac{a}{R_{i}} + \frac{b}{R_{i}^{3}}}{F_{k} + F_{d}},$$

$$F_{k} = \left(\frac{L}{R_{v}T} - 1\right)\frac{L\rho_{\text{liq}}}{KT}, \quad F_{d} = \frac{\rho_{\text{liq}}R_{v}T}{De_{s}(T)}.$$

$$\frac{D\theta}{Dt} = \left(\frac{L}{c_{p}\Pi}S_{v} + \kappa\nabla^{2}\theta, \frac{D}{Dt}\right)$$

$$S_{v}(\mathbf{x}, t) := \frac{-1}{\rho(\mathbf{x}, t)}\sum_{i=1}^{N_{r}}\frac{dm_{i}(t)}{dt}\delta^{3}(\mathbf{x} - \mathbf{x}_{i}(t)).$$

$$\frac{Dq_{v}}{Dt} = S_{v} + \kappa\nabla^{2}q_{v}.$$

Numerical scheme (Implicitly for SDs, explicitly for fluids)  $\frac{R_i^2(t + \Delta t_g) - R_i^2(t)}{2\Delta t_g} = \frac{(S_i^* - 1) - \frac{a(T_i^*)}{R_i(t + \Delta t_g)} + \frac{b(M_i(t))}{R_i^3(t + \Delta t_g)})}{F_k(T_i^*) + F_d(T_i^*)},$   $S_v(\mathbf{x}_{lmn}, t) = \frac{-1}{\rho(\mathbf{x}_{lmn}, t)} \sum_{i=1}^{N_s} \xi_i \frac{m_i(t + \Delta t_g) - m_i(t)}{\Delta t_g} w(\mathbf{x}_{lmn} - \mathbf{x}_i(t)).$   $\theta(\mathbf{x}_{lmn}, t + \Delta t_g) = \theta(\mathbf{x}_{lmn}, t) - \Delta t_g \frac{LS_v(\mathbf{x}_{lmn}, t)}{c_p \Pi(\mathbf{x}_{lmn}, t)},$ (also update fluid)  $q_v(\mathbf{x}_{lmn}, t + \Delta t_g) = q_v(\mathbf{x}_{lmn}, t) + \Delta t_g S_v(\mathbf{x}_{lmn}, t).$ (also update fluid)

#### **Momentum Transfer from Microphysics**

Basic eq.  $\rho \frac{D\mathbf{U}}{Dt} = -\nabla P - (\rho + \rho_w)\mathbf{g} + \lambda \nabla^2 \mathbf{U},$   $\rho_w(\mathbf{x}, t) := \sum_{i=1}^{N_r} m_i(t)\delta^3(\mathbf{x} - \mathbf{x}_i(t)),$ 

Numerical scheme

$$\rho_w(\mathbf{x}_{lmn}, t) = \sum_{i=1}^{N_s} \xi_i m_i(t) w(\mathbf{x}_{lmn} - \mathbf{x}_i(t)).$$

#### **Stochastic Coalescence**

Basic eq.

2 techniques here (Detail follows)

$$P_{jk} = E(R_j, R_k)\pi(R_j + R_k)^2 |\boldsymbol{v}_j - \boldsymbol{v}_k| \frac{\Delta t}{\Delta V}.$$

All the pair (j,k) in  $\Delta V$  have some possibility to coalesce **Translation into a dynamics of SDs**  $P_{jk}^{(s)} := \max(\xi_j, \xi_k) P_{jk}$ Numerical scheme: **DSMC-like Monte Carlo scheme** 

- 1. Make a list of SDs in each cell.  $(O(N_s) \text{ cost})$  (The space is divided by a grid.)
- 2. In each cell, create candidate pairs randomly
- 3. For each candidate pair, draw a random number and judge whether the coalescence occurs or not.
- 4. Update of SDs from t to  $t+\Delta t_c$

#### Tech A) Pair num reduction and correction to the probability

- Let  $N_s$ ' be the num of SDs in this cell.
- Instead of checking all the pairs  $_{Ns'}C_2$  honestly, we reduce the num of candidate pairs to  $[N_s'/2]$
- Making a random permutation of SD indices and paring from the front, we create a non-overlapping pairs(costs  $O(N_s')$ )

e.g.,  $(1,2,3,4,5,6,7) \rightarrow (2,4),(3,5),(7,6),1$ 

With this trick the cost reduces from  $O(N_s'^2)$  to  $O(N_s')$ 

In compensation, we scale up the probability of each pair

$$p_i := P_{j_i k_i}^{(s)} \frac{N'_s(N'_s - 1)}{2} / \left[\frac{N'_s}{2}\right], \quad i = 1, 2, ..., \left[\frac{N'_s}{2}\right].$$

This assures the consistency of expectation value

$$E[N_{coal}] = \sum_{j=1}^{N's} \sum_{k=1}^{N's} \frac{1}{2} \min(\xi_j, \xi_k) P_{jk}^{(s)} = E\left[\sum_{i=1}^{[N's/2]} \min(\xi_{ji}, \xi_{ki}) p_i\right].$$

#### **Tech B) Handling of Multiple Coalescence**

To be exact,  $p_i > 1$  is not allowed, but we accept this. Let *Ran* be a (0,1) uniform random number

$$q = \begin{cases} [p_i] + 1 \text{ if } Ran \langle p_i - [p_i] \\ \\ [p_i] \text{ if } Ran \geq p_i - [p_i] \end{cases}$$

Coalescence occurs q times

**3.3. Characteristics of the SDM** Super-Droplet represents multiple  $\zeta_1$ 

Suitable for detailed cloud microphysics

Applicable if particles collide and coalesce repeatedly



Star formation, Spray combustion, bubbles, volcanic fumes, population dynamics etc.

before  $\xi_2=3$ 

after

 $\xi_1 = 2$ 

## 4. Demonstration (Isolated shallow cumulus, 2D)

T = 1590 sec



# Shallow cumulus $(3D, \Delta z = 8 m)$

grid: 624x1024x1024, particles: #10^10, ES 256 nodes

#### photo realistic visualization:

 $\Delta z = 16 \text{ m}$ 

Photon-mapping method is used to simulate the radiation transfer
## **5.** Computational Cost of SDM

## **5.1. Asymptotic Behavior of SDM as** $N_s \rightarrow N_r$

### **Scaling Law of Number Density of SDs** $q(\xi, a; N_s)$

Assuming that

 $q(\xi, \bar{a}, t; \alpha N_s) = \alpha^{k_1} q(\alpha^{k_2} \xi, \bar{a}, t; N_s)$  Scaling law of this form exists  $\sum_{\xi=0}^{\infty} \xi q(\xi, \bar{a}, t; N_s) = n(\bar{a}, t)$  SDs expected to reproduce RD num density

$$\int d^d a \sum_{\xi=0}^{\infty} q(\xi, \bar{a}, t; N_s) = N_s \stackrel{\leftarrow}{\Rightarrow} const. \text{ in time} \qquad \text{Conservation of } N_s$$

 $\sum_{\xi=0,\alpha,2\alpha,\ldots}^{\infty} = \frac{1}{\alpha} \sum_{\xi=0}^{\infty}$ 

q is smooth enough with respect to  $\xi$ 

Then, we can derive  $(k_1, k_2) = (2, 1)$ , i.e.,

$$q(\xi, \bar{a}, t; \alpha N_S) = \alpha^2 q(\alpha \xi, \bar{a}, t; N_S)$$
<sup>37/96</sup>

### **Scaling Relation Between Error and Cost**

RD num density n(a,t) can be estimated from SD population  $\{(\xi_i, a_i) \mid i=1, ..., Ns\}$ . Let's evaluate the error of this.

Applying kernel density estimation (Terrell and Scott 1992),

 $\tilde{n}(\boldsymbol{a}) := \sum_{i=1}^{N_s} \xi_i W_{\sigma}^{(d)}(\boldsymbol{a} - \boldsymbol{a}_i). \qquad \tilde{\boldsymbol{n}} \qquad \tilde{$ 

Evaluate the error by Mean Integrated Squared Error (MISE)  $C(\sigma) = E\left[\int d^{d}a \{n(\boldsymbol{a}) - \tilde{n}(\boldsymbol{a})\}^{2}\right].$ Combined with the scaling law of *q*, we can derive the

relation between error  $C(\sigma^*)$  and cost Ns

$$operation \sim N_s \sim \left(\frac{1}{\sqrt{C(\sigma^*)}}\right)^{(d+4)/2}, \qquad m$$

$$memory \sim N_s \sim \left(\frac{1}{\sqrt{C(\sigma^*)}}\right)^{(d+4)/2}$$

### **Computational Cost of Bin method**

- Eulerian scheme to solve SCE separating n(a,t) into grids. Let the error of Bin method be  $O(N_b^{-k})$
- Then, we can derive

operation ~  $N_b^{2d} \sim \left(\frac{1}{\sqrt{C}}\right)^{2d/k}$ , memory ~  $N_b^d \sim \left(\frac{1}{\sqrt{C}}\right)^{d/k}$ . here, *C* is the error defined by  $C = \int d^d a \{n(a) - n_b(a)\}^2$ .

### **Comparison between SDM and Bin**

If $d > \frac{4k}{4-k}$  and k < 4,SDM is faster than Bin. (less operation)If $d > \frac{4k}{2-k}$  and k < 2,SDM needs less memory than Bin.

### **Exponential Flux Method (Bott 1998, 2000)**

Numerically measured k is 1.5.

If d>2.4 SDM is faster, if d>12 SDM needs less memory.

### Comment

In general, in high dimensional space, random sampling is efficient than regular grid.

Regular grids have "curse of dimensionality"

Perhaps **"discrepancy"** of random sampling is lower in high dimension

To derive the scaling of q, we didn't use any detail of SDM Similar analysis can be applied for any particle-based method

Cost is evaluated using the kernel density estimation method Kernel density estimation itself is not part of SDM Maybe our analysis gives just a lower bound In practice, how many num of SDs are necessary?? 5.2. Coalescence of Particles in a Small Box

Particles are confined to a small box and coalesce forever Golovin's Kernel

Analytical solution is known for this coalescence probability



## Hydrodynamic Kernel (Initial Mean Radius <r0>=30um) Much more realistic kernel for simulating clouds



Hydrodynamic Kernel (Initial Mean Radius <r0>=10um) Starting from a smaller size distribution Coalescence seldom occurs, and two peaks are created More difficult to simulate



### Comments

### **8000 SDs could be sufficient for** *d*=1?

There are arbitrariness how to initialize SDs

This time we used "uniform sampling" method

Initialize SDs uniformly from [log  $r_{min}$ , log  $r_{max}$ ], and assign a multiplicity as follows

$$\xi_i = \frac{n_0(\log r_i)\log\left(r_{\max}/r_{\min}\right)}{n_s}$$

here  $n_s = N_s / \Delta V$ ,  $n_0(\log r)$ : initial num density of RDs

This reduces sampling error and improve the convergence In S.S. et al (2009) we employed "constant multiplicity" method.

This is not be recommended. (Unterstrasser et al. 2017; Dziekan and Pawlowska 2017)

5.3. Isolated Shallow Cumulus (2D, 30min)

### Initially Very Clean Case (10<sup>7</sup>/m<sup>3</sup>)

Particle size distribution in the square region and precipitation amount are investigated for various SD num





#### Initially clean case NaCl aerosol n=10^8/m^3









5.4. Shallow Trade Wind Cumuli Field (3D, 24h)

Simulation of precipitating cumuli field is performed based on RICO setup (Arabas and Shima, 2011)

Rain droplet size distribution below cloud based



49/96

## ...cont. (RICO simulation using the SDM) SDM: $(\Delta x = \Delta y, \Delta z) = (100\text{m}, 40\text{m}), (50\text{m}, 20\text{m}), (25\text{m}, 10\text{m}).$



### **Summary of the computational cost of SDM**

- Asymptotically, SDM could be faster than Bin when  $d \ge 3$ In practice, if d=2,
  - Even SDs #8/cell can produce a qualitative results,
  - To produce a quantitative results, SDs at least #64/cell to at most #8000/cell is needed

## 6. Advantages of SDM

### (Recap) Mesoscopic governing equation of the cloud microphysics

Dynamics of particles with stochastic coalescence

$$\frac{d\boldsymbol{x}_{i}}{dt} = \boldsymbol{v}_{i}, \quad \frac{d\boldsymbol{a}_{i}}{dt} = \boldsymbol{f}(\boldsymbol{a}_{i}), \quad i = 1, 2, \dots, N_{r}(t).$$

$$P_{jk} = K(\boldsymbol{a}_{j}, \boldsymbol{a}_{k})\Delta t/\Delta V.$$
Smoluchowski eq. (for number density of particles)
$$\frac{\partial n(\boldsymbol{a}, \boldsymbol{x}, t)}{\partial t} + \nabla_{\boldsymbol{x}} \cdot \{\boldsymbol{v}n\} + \nabla_{\boldsymbol{a}} \cdot \{\boldsymbol{f}n\}$$

$$= \frac{1}{2} \int d^{d}\boldsymbol{a}' n(\boldsymbol{a}') n(\boldsymbol{a}'') K(\boldsymbol{a}', \boldsymbol{a}'')$$

Here, n(a,x,t) is the number density;  $a=(a_1,a_2,...)$  is the attribute of particles; x is the position in real space; t is time; v is the velocity; f(a) is the velocity in attribute space, i.e., da/dt=f(a); K(a,a') is the coalescence kernel

SDM is not the only way to solve this equation.

 $-n(\boldsymbol{a})\int d^d a' n(\boldsymbol{a}') K(\boldsymbol{a}, \boldsymbol{a}').$ 

Exact Monte Carlo method (Gillespie1975, Seebelberg1996) Calculate the waiting time when the next one pair of coalescence occurs using random numbers Most exact Enormous cost in computation

Bulk parameterization method (e.g., Kessler 1969)
Solve a semi-empirical closure equation in lower moments of num density (e.g., number and mass of particles)
(Fluid dynamics limit of the Smoluchowski eq.)
Less accurate
Very low cost
Deriving a reliable bulk model is mathematically challenging but should be pursued

**Spectral (Bin) method (Grabowski et al. (submitted to BAMS))** Eulerian scheme for Smoluchowski eq. using a regular grid 3 issues of Bin

## 1. Numerical diffusion (Morrison et al. 2018)

### No numerical diffusion in SDM

2. Curse of dimensionality

Estimated that SDM is faster if num of attributes *d* is large (S.S. et al. 2009)

Li et al. (2017) confirmed that SDM is indeed faster

3. Breakdown of Smoluchowski eq.

If the well-mixed volume is small, decoupling cannot be assumed (Alfonso, 2015)

SDM does not assume decoupling.

 $\xi \rightarrow 1$  is a exact limit. (SD $\rightarrow$ RD)

Dziekan and Pawlowska (2017) confirmed SDM works even when decoupling is not valid 54/96 Monte Carlo Spectral (Bin) method (Sato et al., JGR, 2009)
Monte Carlo scheme is developed to reduce the cost of evaluating the *d*-multiple coalescence integral Pair reduction technique very similar to SDM (Indeed they inspired by SDM)
Accurate, but need to cope with numerical diffusion
Cost is reduced at least to some extent Maybe another good direction to pursue?

Lagrangian Particle based Method

Deterministic: e.g., Andrejczuk et al. 2010; Riechelmann et al. 2012.

# Unterstrasser et al. (2017) elucidated that probabilistic method is more efficient

- Probabilistic: e.g.,
  - SDM (S.S. et al. 2009)
  - O'Rourke (1981): for spray combustion
  - No-Time Counter (NTC) for Smoluchowski eq. (Schmidt and Rutland 2000): for spray combustion
  - DeVille et al. 2011 (Weighted Flow Algorithm): for aerosol dynamics. Implemented on PartMC (Riemer and West)

**SDM faster than NTC and O'Rourke (in preparation)** WFA vs. SDM is remaining Some more schemes in astrophysics area?

## 6.1. SDM vs. NTC and O'Rourke method

### Characteristics

O'Rourke scheme (O'Rourke 1981): Check all SD pairs  $_NC_2$ . Cost  $O(N^2)$ NTC(No-Time Counter) (Schmidt and Rutland 2000): Check  $_NC_2 \cdot P^{(s)}_{max}$  pairs. Cost O(N)Does not allow multiple coalescence. Accurate but costly Parallelization is not easy SDM (Super-Droplet Method) (S.S. et al. 2009): Check [N/2] pairs. Cost O(N)Allow multiple coalescence to reduce the cost. Parallelization is easy. (No dependence between pairs)

### **Test with Golovin kernel**



58/96

### **Comparison (SDM is way faster)**

SDM													
Time [s]		SD num											
		80			800			8000			80000		
		all	spray	10	all	spray	10	all	spray	10	all	spray	10
dt [s]	10	2	0	2	3	1	1	13	6	6	104	60	37
	1	21	0	8	28	9	10	77	35	24	884	546	291
	0.1	193	8	71	276	62	99	759	382	220	8508	5284	2770
NTC													
Time [s]		parcel num											
		80			800			8000			80000		
		all	spray	Ю	all	spray	10	all	spray	10	all	spray	10
dt [s]	10	4	0	1	11	9	0	669	668	1	143512	143474	31
	1	20	0	6	84	59	10	4529	4479	30	-		
	0.1	196	7	81	367	140	103	41384	41004	217	-		
O'Rourke	e collisi	on											
Time [s]		parcel num											
		80			800			8000			80000		
		all	spray	10	all	spray	10	all	spray	10	all	spray	10
dt [s]	10	4	0	4	13	11	1	955	949	2	more than 38h		
	1	23	1	12	126	104	8	9524	9472	30	-		
	0.1	207	19	63	1242	1025	87	94985	94538	242			

## 7. Various Applications of the SDM

### Warm clouds

- Shallow cumulus (e.g., Arabas and Shima 2013 (RICO); Sato, Shima, and Tomita 2017, 2018 (BOMEX))
  - Comparison to observations, and bulk model
  - Check the numerical convergence (SD num, grid, dt)

Time evolution of cloud pattern (LWP[g/m<sup>2</sup>])



 $\Delta x = \Delta y = 1.25 \Delta z$ 

(Sato et al. 2018, Fig.6)

### (Flatter turbulence kinetic energy spectrum)



(Sato et al. 2017, Fig.4)

## **The spectrum in cloud layer is flatter than –5/3 power law** Various size cumuli produce and dissipate energy at various scales?

Not consistent with measurement? (Siebert et al. 2006)

Stratocumulus

# 2D simulation based on DYCOMS-II RF02 setup (Ackerman et al. 2009)

62/96

Proceed to 3D. Can be applied also to fog.



**Aerosol processing and aqueous/surface chemistry** Indispensable when discussing cloud-aerosol interaction We can incorporate it directly using SDM Jaruga and Pawlowska (2018) reproduced the formation of Hoppel gap from the first princple



typical composition and distribution of maritime aerosols

**Mixed-phase Clouds** (Ice and Liquid water) Sölch and Kärcher (2010), Brdar and Seifert (2018), Shima et al. (to be submitted to GMDD)



From "Precipitation Mechanisms" in

### Various morphology of ice particles

http://www.mrijma.go.jp/Dep/fo/fo3/araki/snowc rystals.html#sample photo by K. Araki





かくすい
角錐 針の 組み合わせ ほうだん 角柱の 針 角柱 針のたば 砲弾の組み合わせ 砲弹型 組み合わせ 枝の付いた 角板 角板の 樹枝の 角板 扇形 広幅六花 星状六花 樹枝状六花 シダ状六花 付いた樹枝 付いた角板 上下組み シダ状 三花 四花 広幅十二花 形の整わない六花 立体六花 立体放射状 合わせ六花 十二花 つづみ型 樹枝の 不規則な 交差した 形が定まらない雪 つづみ型 つづみ型 角柱の (角柱と角板) (角柱と樹枝) 付いた砲弾 角板 (段々つづみ) 付いた砲弾 集合(粉雪) (氷のかけら状) (雲粒付き) あられ あられ状雪 あられ状雪 あられ あられ 雲粒の付いたいろいろな結晶 雲粒の付いた厚い板 (かたまり状) (円錐状) (六花状) (六花状) (かたまり状) 中谷宇吉郎 Snow Crystals (1954)による <u>Araki (2014)「雲の中では何が起こっているのか</u> Following the idea of the multicomponent bin model (Chen and Lamb 1994, Misumi et al. 2010, Jensen and Harrington 2015)

Ice particles are represented by porous spheroids



IN: Freezing temperature strategy

Can account for homogeneous/condensation/immersion freezing





### More result of cumulonimbus simulation is available from

https://ams.confex.com/ams/15CLOUD15ATRAD/webprogram/Han dout/Paper346467/poster076.Shima.pdf

### SGS turbulence modeling

- Turbulence affects cloud microphysics in various ways
- Influence onto collision-coalesce can be incorporated by modifying the kernel. (e.g., Wang et al. 2008, Onishi et al. 2015, Chen et al. 2018)
- Supersaturation and velocity fluctuation through eddyhopping and entrainment can be incorporated using the SDM
  - By adding 4 new attributes (S',U',V',W') (Grabowski and Abade 2017, Abade et al. 2018)
  - By introducing Linear Eddy Model (Hoffman et al., under review)

## 8. Towards Further Acceleration

SDM is computationally demanding

Can we simulate much faster? without losing accuracy??

- Use SDM only for rain droplets (Naumann and Seifert 2015)
- Twomey SDM: use SDM only for cloud/rain droplets (Grabowski et al. 2018)

Derive reliable bulk model from Smoluchowski eq.?

Not like Boltzmann eq., no stable equilibrium solution But self-similar solutions exists for some kernels (Menon and Pego, 2004)

**Regarding those self-similar solutions as the** reference, maybe we can derive a bulk model through perturbation expansion or renormalization

## 9. Code Availability

Dr. Sylwester Arabas made a comprehensive list See p.11 of <u>http://slayoo.home.staszic.waw.pl/talk-houghton-20180719.pdf</u> recent research software (re)developments:

- INC/LCM from LLNL/Leeds,
- EULAG-LCM (http://www.mmm.ucar.edu/eulag/) from NCAR/DLR,
- PALM-LES (http://palm.muk.uni-hannover.de/) from Univ. Hannover,
- CReSS (http://www.rain.hyarc.nagoya-u.ac.jp/) from Univ. Nagoya,
- UCLA-LES (http://github.com/uclales) from UCLA/MPI-M,
- Pencil-Code (http://pencil-code.nordita.org) from Nordita/UC,
- SCALE (http://scale.aics.riken.jp/) from RIKEN,
- UWLCM (http://github.com/igfuw/UWLCM) from Univ. Warsaw,
- ICON/McSnow (http://gitlab.com/sbrdar/mcsnow) from DWD.

## **10. Summary**

Super-Droplet Method (SDM) is a particle-based scheme to simulate cloud-microphysics accurately. (S.S. et al. 2009) Basic framework and its advantages were presented Should be accurate and faster than bin schemes Various applications Warm clouds Aerosol processing and aqueous/surface chemistry Mixed-phase clouds (ice and liquid water) SGS turbulence modeling Possibility of further acceleration Twomey SDM Showed a list of various available codes
## Thank you for your attention!

## Acknowledgement

## **Computers and Funds**

This research used computational resources of the K computer and FX10 of the HPCI system provided by the RIKEN AICS and Kyushu University through the HPCI System Research Project (Project ID: hp140094, 150153). ES provided by JAMSTEC was also used.

This research is supported by JSPS KAKENHI Grant-in-Aid for Scientific Research(B): (26286089). and by the JSPS Grant-in-Aid for Young Scientists (B) (15K17756).

This research was supported by the Center for Cooperative Work on Computational Science, University of Hyogo. Y.S is supported by RIKEN special postdoctoral researcher program.

## Contributors

- Y. Sato (AICS)
- S. Arabas (Warsaw Univ.)
- K. Hasegawa (Chuden CTI Co. Ltd.)
- K. Kusano (Nagoya U)
- A. Sakakibara (Chuden CTI Co. Ltd.)
- K. Tsuboki (Nagoya U)
- W. Ohfuchi (JAMSTEC)

F. Araki (JAMSTEC) S. Kawahara (JAMSTEC) M. Kajino (MRI) A. Hashimoto (MRI) M. Deushi (MRI) H. Tomita (AICS)