Development and applications of benchmarking aerosol models on the regional scale using a stochastic particle-resolved approach

Jeffrey H. Curtis, Nicole Riemer and Matthew West

University of Illinois at Urbana-Champaign

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Atmospheric modeling: A multiscale challenge



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How do models represent aerosol composition?



- Simplifying assumptions regarding the aerosol composition
 - Sectional model: aerosols in a bin are fully internally mixed.
 - Modal model: aerosols in a mode are fully internally mixed.

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Alternative representation: Particle-resolved



Use a discrete representation of particles

- Representation of processes are straight-forward to model
- No bins or modes
- No assumption made regarding how particles are mixed

N. Riemer, M. West, R. A. Zaveri, and R. C. Easter, Journal of Geophysical Research, 2009

Model verification of aerosol representation

We need approximations at the regional and global scales. But approximations cause error and uncertainties.



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Particle-resolved modeling technique

What is composition space? Each particle is uniquely represented as an *A*-dimensional vector with mass composition components $\{\mu_1^i, \mu_2^i, \dots, \mu_A^i\}$



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Benefits of particle-resolved models

- No approximation need for representing mixing state
 - Coarse graining tool: deriving parameters for more approximate models
 - Benchmark and error quantification for more approximate models
 - Detailed studies on the particle scale and experimental intercomparison.
- Scales efficiently for high-dimensional data (number of aerosol species)
 - Avoids curse of dimensionality
- Efficient algorithms make particle-resolved modeling feasible
 - Accelerated binned coagulation (Riemer et al. 2009, Michelotti et al. 2013)
 - Particle weighting methods to reduce statistical error (DeVille et al. 2011, 2019)
 - Accelerated particle removal algorithms (Curtis et al. 2016)

Benchmarking approximate models

Simulation inputs and processes should be as similar as possible

- Same meteorological model
- Same chemical mechanisms
- Consistency in emissions
- Identical particle removal processes
- Identical transport algorithms

Only change the aerosol microphysics

Particle-resolved modeling on the regional scale

- PartMC coupled with WRF allows regional simulations with highly-detailed mixing state.
- Each grid cell simulates 10 000 computational particles - billions of particles for the domain.
- Many levels of detail from the large-scale to population level to single-particle details of composition and emission source.
- Computational expense: 300 000 core hours for 2 day simulation from the domain to right





Curtis, Riemer and West, Geoscientific Model Development, 2017

How do we move vectors of particle composition?

Transport PDE \rightarrow Discretize in space, time, and particles \rightarrow Determine probabilities \rightarrow Sample particle sets

Replicates deterministic finite volume method to isolate importance of representation

Testcase: 1D constant positive *u* advection (third order)



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Results: Simulating stochastic aerosol transport



Odd orders perform better (implicit diffusion)

Converges to FV method in particle number

Curtis, Riemer and West, Geoscientific Model Development (in prep)

Transport performance in real-world case

Complex terrain, complex and evolving wind field



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Stochastic algorithm applied to third order monotonic advection scheme in WRF



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First step: CCN error quantification for a sectional projection



Concluding thoughts

