Uncertainty in model representations of microphysics...

...or: Airing the dirty laundry of microphysics schemes



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Microphysics parameterization schemes in cloud, weather, and climate models



The parameterization problem:



There are *two* critical aspects for microphysics:

- <u>Inability to resolve relevant scales</u> (i.e., the traditional "parameterization problem" in models)
- <u>Uncertainty in microphysics at its native scale</u> (e.g., drop breakup or ice crystal growth rates)

A (very) brief history of <u>cloud microphysics</u> schemes...

- Bulk schemes \rightarrow 1960's to present
 - 1970's-1980's... inclusion of ice microphysics
 - 1980's-2000's... 2-moment schemes
 - 2000's-2010's... 3-moment schemes
 - 2000's-2010's.... ice particle property based schemes
- Bin schemes \rightarrow 1960's to present
 - 1980's-2000's... inclusion of ice microphysics
 - 1980's-2000's... multi-moment (in each bin) schemes
 - 2000's-2010's.... multi-dimensional (in bin space)



Bulk schemes remain the workhorses of weather and climate models because they are simple and cheap. Lots of complexity has been added in recent years (e.g., 1moment to 2-moment schemes...).



State-of-the-art 2-moment scheme

Added <u>complexity</u> (more detailed process formulations, more moments, more prognostic variables) means more degrees of freedom and (presumably) better realism in representing cloud evolution. *Has this actually resulted in <u>better forecasts</u>?* Added <u>complexity</u> (more detailed process formulations, more moments, more prognostic variables) means more degrees of freedom and (presumably) better realism in representing cloud evolution. *Has this actually resulted in <u>better forecasts</u>?*

Ummm... maybe? For specific cases or well-constrained processes (e.g. size sorting) yes, but overall the picture is less clear...

Moreover, <u>solution spread</u> generally is *not* reduced by adding complexity.



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Bin schemes are expensive but widely used now as computer power keeps increasing.

- Process level microphysical studies
- Developing/testing bulk schemes

Have a <u>more detailed</u> representation of process rates than bulk schemes, but <u>face challenges</u> (*Grabowski et al.* 2018, BAMS in review):

- Drop size distribution broadening may often be dominated by unphysical vertical numerical diffusion.
- Impact of statistical fluctuations on collision-coalescence neglected.
- Expensive to add rigorous treatment of *N* particle properties (scales as number of bins to power of *N*).
- Doesn't address fundamental process rate uncertainty.

There is NOT better convergence using different bin schemes compared to bulk schemes...



<u>Lagrangian particle-based schemes</u> (e.g., *super-droplet method*) address many difficulties facing bin schemes.



Cloud water mixing ratio (g/kg)

DSDs in the boxes indicated

Shallow cumulus simulations using the University of Warsaw Lagrangian Cloud Model (led by Dziekan, Pawlowska)

Grabowski et al. (2018), *in review, BAMS*

However, there is still fundamental process rate uncertainty.

Where things stand...

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- There is a constant march toward increasing complexity of schemes.
- Progress has been made over the decades, but fundamentally microphysics is <u>highly uncertain</u> and will remain so into the foreseeable future:
 - → We have poor understanding of the underlying physics, especially for ice microphysics, and thus <u>no benchmark</u>! (this is fundamentally different from dynamics, turbulence, and radiation but perhaps similar to e.g. land surface processes...)
 - → Thus, there is generally NOT convergence using different schemes as schemes become more complex...



A microphysics scheme developer?

As a community, we as microphysics scheme developers have *not* adequately confronted this uncertainty! As a community, we as microphysics scheme developers have *not* adequately confronted this uncertainty!

On the other hand, we now have a wealth of cloud/precip <u>observations</u> for constraining schemes...



The BIG question:

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How to use these observations to constrain schemes?

- Very <u>challenging</u> because we generally cannot measure microphysical processes directly, only their net effects on clouds and precipitation.
- As more complex schemes are developed this makes constraint with observations even more difficult!

 Continue developing better process models (e.g. Lagrangian particle based schemes) and constraining process rates (e.g. lab studies).

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- Focus on the role of microphysics <u>uncertainty</u>, and leverage this to develop novel approaches that facilitate constraint by observations (e.g., statistical-physical schemes).



- Continue developing better process models (e.g. Lagrangian particle based schemes) and constraining process rates (e.g. lab studies).
- Focus on the role of microphysics <u>uncertainty</u>, and leverage this to develop novel approaches that facilitate constraint by observations (e.g., statistical-physical schemes).

Simply stated: we want to incorporate (somewhat uncertain) observations into uncertain models in a <u>rigorous</u> way, and quantify model uncertainty.

→ this is a <u>Bayesian</u> problem, and we can therefore use Bayesian statistics to address it rigorously... Example: A *statistical-physical* microphysics parameterization framework (BOSS):

Bayesian (we treat uncertainty robustly)

Observationally-constrained (scheme is rigorously informed by observations using MCMC)

Statistical-physical (we don't want just a statistical scheme or rely solely on standard machine learning, but we will use statistics and automated learning)

Scheme (bulk microphysics parameterization scheme, currently warm cloud-rain only)

Morrison et al., in prep. (scheme description) van Lier-Walqui et al., in prep. (application of MCMC)

BOSS schematic



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- The parameterization of microphysics is currently dominated by <u>uncertainty</u>, and will be into the foreseeable future → <u>no benchmark!!!</u>
 - → Reducing uncertainty will require continued advances in observing clouds and precip (including lab studies)
 - → Confronting uncertainty may also require a re-thinking of scheme design:
 - simplification, reducing the number of poorly constrained parameters, i.e., the level of complexity should match our fundamental knowledge of the physics and our ability to inform schemes with observations
 - <u>statistical methods</u> and <u>automated learning</u> to rigorously constrain schemes using observations and to characterize uncertainty (e.g., BOSS)

Thank you! Questions?

Unphysical size distribution broadening from vertical <u>numerical diffusion may often dominate bin model solutions!</u>



The role of <u>uncertainty</u> in microphysics schemes

- Fundamentally, microphysics is <u>highly uncertain</u> and will remain so into the foreseeable future:
 - → We have poor understanding of the underlying physics, especially for ice microphysics, and thus <u>no benchmark</u>! (this is fundamentally different from dynamics, turbulence, radiation but perhaps similar to e.g. land surface processes...)
 - → There is NOT convergence using different schemes as schemes become more complex...





The BIG question:

How to use these observations to constrain schemes?

- Very <u>challenging</u> because we generally cannot measure microphysical processes directly, only their net effects on clouds and precipitation.
- As more complex schemes are developed this makes constraint with observations even more difficult!

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Some potential applications:

- Microphysical process "fingerprinting"
- Quantification of process uncertainty/sensitivity in system-wide context
- Quantifying information content from observations
- Stochastic microphysics (stochastic sampling from the parameter PDFs) → ensemble prediction

Stay tuned for Marcus's seminar on April 5!

Liquid Phase

"Warm rain" coalescence process:

 \rightarrow 2-moment, 2-category bulk schemes model this process well



Ice Phase

Traditional bulk approach:



← abrupt / unphysical conversions

Problems with pre-defined ice categories:

- **1. Real ice particles have complex shapes**
- 2. Conversion between categories is ad-hoc
- 3. Conversion leads to large, discrete changes in particle properties
- NOTE: Bin microphysics schemes have the identical problem

Observed crystals:



c/o Alexi Korolev

The simulation of ice-containing cloud systems is often <u>very sensitive</u> to how ice is partitioned among categories



Morrison and Milbrandt (2011), MWR

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Recent shift (in parameterization of ice phase):

Representation by fixed hydrometeor <u>categories</u> to Prediction of hydrometeor <u>properties</u>

- Predicted rime/axis ratio (bin scheme) Hashino and Tropoli (2007)
- Predicted rime fraction Morrison and Grabowski (2008), Lin and Colle (2011) (diagnostic F_r)
- Predicted crystal axis ratio and density Harrington et al. (2013), Jensen et al. (2017)

• Predicted Particle Properties (P3) - Morrison and Milbrandt (2015)

2. Overview of the P3 microphysics scheme

New Bulk Microphysics Scheme:

Predicted Particle Properties (P3)

NEW CONCEPT

"free" ice category – predicted properties, thus freely evolving type

VS.

"pre-defined" ice category – traditional; prescribed properties
 (e.g. "ice", "snow", "graupel", etc.)

Compared to traditional schemes (for ice phase), P3:

- avoids <u>some</u> necessary evils (ad-hoc category conversion, fixed properties)
- is better linked to observations
- is more computationally efficient

Morrison and Milbrandt (2015), JAS- Part 1Morrison et al. (2015), JAS- Part 2Milbrandt and Morrison (2016), JAS- Part 3

Overview of P3 Scheme

Prognostic Variables: (advected)

LIQUID PHASE:	2 categories, 2-moment:		
	$oldsymbol{Q}_{oldsymbol{c}}$ – cloud mass mixing ratio	[kg kg⁻¹]	
	Q _r – rain mass mixing ratio	[kg kg⁻¹]	
	$m{N_c}$ – cloud number mixing ratio	[#kg ⁻¹]	
	N_r – rain number mixing ratio	[#kg ⁻¹]	

nCat categories, 4 prognostic variables each:		
$Q_{dep}(n)$ – deposition ice mass mixing ratio	[kg kg⁻¹]	
Q_{rim} (<i>n</i>) – rime ice mass mixing ratio	[kg kg ⁻¹]	
$N_{tot}(n)$ – total ice number mixing ratio	[# kg ⁻¹]	
B _{rim} (n) – rime ice volume mixing ratio	[m ³ kg ⁻¹]	
	$nCat \text{ categories, 4 prognostic variables eac}$ $Q_{dep}(n) - \text{ deposition ice mass mixing ratio}$ $Q_{rim}(n) - \text{ rime ice mass mixing ratio}$ $N_{tot}(n) - \text{ total ice number mixing ratio}$ $B_{rim}(n) - \text{ rime ice volume mixing ratio}$	

A given (free) category can represent any type of ice-phase hydrometeor

Prognostic Variables: Q_{dep} - deposition ice mass mixing ratio[kg kg⁻¹] Q_{rim} - rime ice mass mixing ratio[kg kg⁻¹] N_{tot} - total ice number mixing ratio[# kg⁻¹] B_{rim} - rime ice volume mixing ratio[m³ kg⁻¹]Predicted Properties:

F_{rim} – rime mass fraction, $F_{rim} = Q_{rim} / (Q_{rim} + Q_{dep})$	[]
${oldsymbol ho}_{rim}$ – rime density, ${oldsymbol ho}_{rim}$ = Q_{rim} / B_{rim}	[kg m ⁻³]
$m{D}_{m{m}}$ – mean-mass diameter, $m{D}_{m} \propto m{Q}_{tot}$ / $m{N}_{tot}$	[m]
V_m – mass-weighted fall speed, V_m = f(D_m , ρ_{rim} , F_{rim})	[m s ⁻¹]
etc.	

Diagnostic Particle Types:

Based on the predicted properties (rather than pre-defined)

P3 SCHEME – Determining $m(D) = \alpha D^{\beta}$ for regions of *D*: Similar for A(D); V(D) calculated from *m* and *A*...

Conceptual model of particle growth following Heymsfield (1982):



3D Squall Line case: (June 20, 2007 central Oklahoma)

- WRF_v3.4.1, $\Delta x = 1$ km, $\Delta z \sim 250-300$ m, 112 x 612 x 24 km domain
- initial sounding from observations
- convection initiated by *u*-convergence
- no radiation, surface fluxes



10 -5 0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 Reflectivity (dB2)



WRF Results: Line-averaged Reflectivity (t = 6 h)





Morrison et al. (2015), JAS

Frontal/orographic case: IMPROVE-2, 13-14 December 2001

• WRF_v3.4.1, $\Delta x = 3$ km, 72 stretched vertical levels



Simulated lowest level **REFLECTIVITY** (00 UTC December 14)

Accumulated **PRECIPITATION** (14 UTC Dec 13 - 08 UTC Dec 14)

Morrison et al. (2015), JAS



Timing Tests for 3D WRF Simulations

Scheme	Squall line case	Orographic case	# prognostic variables
P3 – 1 Cat	1.043	1.013	7
MY2	1.485	1.495	12
MOR-H	1.203	1.200	9
ТНО	1.141	1.174	7
WSM6	1.000	1.000	5
WDM6	1.170	1.148	8

• Times relative to those of WSM6 are indicated parenthetically.

\rightarrow P3 in WRF is relatively fast...

Issues with advection and microphysics...

- Much of the cost of microphysics schemes is advecting hydrometeor variables (a few % total run time per scalar in WRF).
- A new method called <u>Scaled Flux Vector Transport</u> can reduce the cost of advection for multi-moment bulk schemes including P3 (Morrison et al. 2016, *MWR*).
 - → advects the mass mixing ratio variables using the unmodified scheme and the "secondary" variables (e.g. number mixing ratios) by appropriately scaling the mass mixing ratio fluxes.
 - → Total model run time for P3 reduced by ~10% while producing very similar solutions and retaining accuracy in analytic benchmark tests.

So far – despite using only 1 ice-phase category, P3 performs well compared to detailed, established (well-tuned), traditional bulk schemes

However – with 1 category, P3 has some *intrinsic limitations*:

- it cannot represent more than one bulk type of particle in the same point in time and space
- As a result, there is an inherent "*dilution problem*"; the properties of particle populations from different origins get averaged upon mixing



Single-Category Version

All ice-phase hydrometeors represented by a single category, with Q_{dep} , Q_{rim} , N_{tot} , B_{rim}

Processes:

- 1. Initiation of new particles
- 2. Growth/decay processes
 - interactions with water vapor
 - interactions with liquid water
 - self-collection
- 3. Sedimentation

Multi-Category Version

Milbrandt and Morrison (2016) [P3, part 3]

All ice-phase hydrometeors represented by a *nCat* categories, with $Q_{dep}(n)$, $Q_{rim}(n)$, $N_{tot}(n)$, $B_{rim}(n)$ [n = 1..nCat]

Processes:

- 1. Initiation of new particles → determine destination category
- 2. Growth/decay processes
 - interactions with water vapor
 - interactions with liquid water
 - self-collection
 - collection amongst other ice categories
- 3. Sedimentation

WRF Results: Line-averaged Reflectivity* (t = 6 h)



Morrison et al. (2015), JAS

*Hallet-Mossop rime splintering \rightarrow generation of new crystals splintering of rimed ice

**Uses WRFV3.9.1 instead of V3.5.1 in earlier slides.

Current Status of P3 (in WRF)

WRF >> THE WEATHER RESEARCH & FORECASTING MODEL



Spring 2017: Released in WRFV3.9

- *MP option* 50 (Single category P3 with specified cloud droplet number)
- *MP option* 51 (Single category P3 with prognostic cloud droplet number and simple coupling with aerosols)

August 2017: P3 code updated for WRFV3.9.1 release

Spring 2018: To be released in WRFV4.0

- MP option 52 (Two-category P3 with prognostic cloud droplet number and simple coupling with aerosols)
- Updates to single-category P3 options

Status for real-time NWP

NOAA NSSL Spring Hazardous Weather Testbed



• Run in the OU CAPS WRF ensemble since 2014

Operational NWP in Canada



Environment and Climate Change Canada Environnement et Changement climatique Canada

- Currently (as of Jan 2018) running in ECCC's operational high-resolution 3 km pan-Arctic system in support of the International Year of Polar Prediction (YOPP) experiment
- To be implemented (summer 2018) into ECCC's operational high-resolution 2.5 km pan-Canadian NWP system
- Currently being adapted for planned use in coarser grid ECCC operational NWP systems

Climate modeling...

Community Atmosphere Model version 5 (CAM5)

www.nasa.gov

Simplified P3 implemented in CAM5



3. Current developments and broader outlook + commentary

(a.k.a. the part of the talk I will say controversial things...)

Broader outlook

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 - greater cost which could be used for other modeling aspects (e.g., increased grid resolution)

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There will be a role for simple microphysics schemes in the future...

P3 and BOSS were developed in this spirit.





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EXTRA

What we want in advection schemes (for clouds/precip):

- Positive definite for mass (needed for water conservation), or even better monotonic, but <u>not</u> as critical for *non-mass* microphysical variables
- Preserves initial linear relationships between advected quantities
- Accurate
- Efficient

There are trade-offs!

WRF Results: Base Reflectivity (1 km AGL, t = 6 h)



Morrison et al. (2015) [P3, part 2]



1D analytic test cases

Mean error as a function of Courant number

Issues with advection and microphysics...

- The traditional approach is to advect each cloud/precipitation prognostic variable independently.
- Potential problems:
- Slow
- Derived quantities (e.g., ratios) may not be monotonic even if each scalar is advected using a monotonic scheme

New method: Scaled Flux Vector Transport

Morrison et al. (2016, *MWR*)

Scales mass mixing ratio fluxes to advect "secondary" microphysical scalars:

- 1) Mass mixing ratio (Q) quantities are advected using the unmodified scheme
- 2) "Secondary" non-mass scalars (*N*, *Z*, *V*, etc.) then advected by scaling of *Q* fluxes using higher-order <u>linear</u> weighting

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Retains features of applying unmodified scheme to ALL scalars, but at a reduced cost..

 \rightarrow Accurate (for analytic test cases), <u>fast</u>, and preserves initial linear relationships



WRF 2D squall line test

t = 4 h

WRF-PD (5th order horizontal 3rd order vertical)

WRF-PD w/ SFVT

11% reduction in *total* model run time

Morrison et al. (2016), MWR

 The <u>efficiency</u> of SFVT increases as the number of secondary scalars increases relative to the number of mass variables.

• Thus SFVT works well with P3 because there are 3 secondary variables for each "free" ice category.

 It is particularly well-suited for <u>bin schemes</u> using the total bulk mass as the "lead" variables and the individual bin masses/numbers as the secondary scalars.

P3-like modifications to CAM5

- Modification of Morrison-Gettelman version 2 (MG2) scheme to combine "*cloud ice*" and "*snow*" in a single ice category and use physical representations of masssize (m-D) and projected area-size (A-D) relationships.
- Allows consistent linkages between fallspeed and effective radius (both depending on m-D and A-D), and removes the need for cloud ice to snow autoconversion.
- Two methods for specifying m-D and A-D:

- *P3:* constant m-D and A-D parameters, follows original P3 except representation of rimed ice is neglected

- EM16: varying m-D and A-D parameters from Erfani and Mitchell (2016) Eidhammer et al. (2017), J. Climate

WRF Results: Line-averaged precipitation rate at 1 km height

