Uncertainty in model representations of microphysics…

…or: Airing the dirty laundry of microphysics schemes

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Thanks to: Marcus van Lier-Walqui, Wojciech Grabowski

OU/CIMMS Workshop on Uncertainty in Radar Retrievals, Model Parameterizations, Assimilated Data and In-situ Observations: Implications for the Predictability of Weather

October 31, 2018
Microphysics parameterization schemes in cloud, weather, and climate models

**Dynamical Core**
(dynamics, advection)

Thermodynamic, Cloud State Variables
($T, Q_v, Q_c, Q_i$, etc.)

Dynamic, Thermodynamic, Cloud State Variables
($w, T, Q_v, Q_c, Q_i$, etc.)

**Microphysics Scheme**
(cond, evap, freezing, melting, etc.)

Cloud state variables
Precip rates
Convective detrainment

**Other Physics Schemes**
(cloud, radiation, PBL, SGS mixing, convection, land/ocean/ice surface, etc.)
There are two critical aspects for microphysics:

- **Inability to resolve relevant scales** (i.e., the traditional “parameterization problem” in models)
- **Uncertainty in microphysics at its native scale** (e.g., drop breakup or ice crystal growth rates)
A (very) brief history of cloud microphysics schemes...

- Bulk schemes → 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 → 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)

Bin (explicit)

Bulk

Size distribution discretized into bins

Size distribution assumed to follow functional form
**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., 1-moment to 2-moment schemes...).

**State-of-the-art 2-moment scheme**
Added complexity (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 better forecasts?
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Ummm… maybe? For specific cases or well-constrained processes (e.g. size sorting) yes, but overall the picture is less clear…

Moreover, solution spread generally is *not* reduced by adding complexity.

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**Observations**

WRF squall line simulations of June 20, 2007 OK case.

Morrison et al. (2015), JAS
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WRF squall line simulations of June 20, 2007 OK case.

Morrison et al. (2015), *JAS*
Bin schemes are expensive but widely used now as computer power keeps increasing.

- Process level microphysical studies
- Developing/testing bulk schemes

Have a more detailed representation of process rates than bulk schemes, but face challenges (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...

Intercomparison of *bin* microphysics schemes in WRF

Xue et al. (2017), *MWR*

Intercomparison of LES of shallow precipitating convection from RICO

vanZanten et al. (2011), *JAMES*
Lagrangian particle-based schemes (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…

• There is a constant march toward increasing complexity of schemes.
Where things stand…

• There is a constant march toward increasing complexity of schemes.

• Progress has been made over the decades, but fundamentally microphysics is highly uncertain and will remain so into the foreseeable future:

  → We have poor understanding of the underlying physics, especially for ice microphysics, and thus no benchmark! (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…
As a community, we as microphysics scheme developers have *not* adequately confronted this uncertainty!
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On the other hand, we now have a wealth of cloud/precip observations for constraining schemes...

- Ground-based remote sensing
- Aircraft in-situ
- Surface in-situ (e.g. disdrometer)
- Satellite
- Etc.

...
The BIG question:

How to use these observations to constrain schemes?
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*How to use these observations to constrain schemes?*

- Very challenging 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!
Some ideas for moving forward…
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- Continue developing better process models (e.g. Lagrangian particle based schemes) and constraining process rates (e.g. lab studies).
Some ideas for moving forward…

• 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 **uncertainty**, and leverage this to develop novel approaches that facilitate constraint by observations (e.g., statistical-physical schemes).
Some ideas for moving forward...

• 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 uncertainty, 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 rigorous way, and quantify model uncertainty.

→ this is a Bayesian 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)
Posterior parameter PDFs from “obs” constraint

Forward simulated from joint PDFs with independent randomly selected IC’s
Concluding Remarks

• The parameterization of microphysics is currently dominated by *uncertainty*, and will be into the foreseeable future → *no benchmark!!!*
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→ Reducing uncertainty will require continued advances in *observing* clouds and precip (including lab studies)
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→ 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

  ➢ *statistical methods* and *automated learning* to rigorously constrain schemes using observations and to characterize uncertainty (e.g., BOSS)
Thank you!
Questions?
Unphysical size distribution broadening from vertical numerical diffusion may often dominate bin model solutions!

Parcel

Morrison et al.
(2018), in press JAS

1D
The role of **uncertainty** in microphysics schemes

• Fundamentally, microphysics is *highly uncertain* and will remain so into the foreseeable future:

  ➔ We have poor understanding of the underlying physics, especially for ice microphysics, and thus *no benchmark*! (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...

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Intercomparison of *bin* microphysics schemes in WRF

Xue et al. (2017), *MWR*
The BIG question:

How to use these observations to constrain schemes?

- Very challenging 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!

Simply stated: we want to incorporate (somewhat uncertain) observations into uncertain models in a rigorous way.

→ this is a Bayesian problem, and we can therefore use Bayesian statistics to address it rigorously…
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:

→ 2-moment, 2-category bulk schemes model this process well

Bin microphysics coalescence model
Berry and Reinhardt (1974)
Ice Phase

Traditional bulk approach:

CLOUD ICE
\[ \rho_i = 500 \, \text{kg m}^{-3} \]
\[ m = (\pi/6 \, \rho_i)D^3 \]
\[ V = a_i D^{bi} \]

“SNOW”
\[ \rho_s = 100 \, \text{kg m}^{-3} \]
\[ m = cD^2 \]
\[ V = a_s D^{bs} \]

GRAUPEL
\[ \rho_g = 400 \, \text{kg m}^{-3} \]
\[ m = (\pi/6 \, \rho_g)D^3 \]
\[ V = a_g D^{bg} \]

HAIL
\[ \rho_h = 900 \, \text{kg m}^{-3} \]
\[ m = (\pi/6 \, \rho_h)D^3 \]
\[ V = a_h D^{bh} \]

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:

\[ \text{c/o Alexi Korolev} \]
The simulation of ice-containing cloud systems is often very sensitive to how ice is partitioned among categories.

- idealized 1-km WRF simulations (em_quarter_ss)
- base reflectivity

Microphysics Schemes:
**MOR**: Morrison et al. (2005, 2009)
**MY2**: Milbrandt and Yau (2005)

Morrison and Milbrandt (2011), *MWR*
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**Microphysics Schemes:**
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Recent shift (in parameterization of ice phase):

Representation by fixed hydrometeor categories to Prediction of hydrometeor properties

- 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 some necessary evils (ad-hoc category conversion, fixed properties)
• is better linked to observations
• is more computationally efficient

Morrison and Milbrandt (2015), JAS - Part 1
Morrison et al. (2015), JAS - Part 2
Milbrandt and Morrison (2016), JAS - Part 3
# Overview of P3 Scheme

## Prognostic Variables: (advected)

### LIQUID PHASE:

- 2 categories, 2-moment:
  - \( Q_c \) – cloud mass mixing ratio \([\text{kg kg}^{-1}]\)
  - \( Q_r \) – rain mass mixing ratio \([\text{kg kg}^{-1}]\)
  - \( N_c \) – cloud number mixing ratio \([\#\text{kg}^{-1}]\)
  - \( N_r \) – rain number mixing ratio \([\#\text{kg}^{-1}]\)

### ICE PHASE:

- \( n\text{Cat} \) categories, 4 prognostic variables each:
  - \( Q_{dep}(n) \) – deposition ice mass mixing ratio \([\text{kg kg}^{-1}]\)
  - \( Q_{rim}(n) \) – rime ice mass mixing ratio \([\text{kg kg}^{-1}]\)
  - \( N_{tot}(n) \) – total ice number mixing ratio \([\#\text{kg}^{-1}]\)
  - \( B_{rim}(n) \) – rime ice volume mixing ratio \([\text{m}^3 \text{kg}^{-1}]\)
A given \textit{(free)} category can represent any type of ice-phase hydrometeor.

### Prognostic Variables:

- $Q_{dep}$ – deposition ice mass mixing ratio \ [kg kg\textsuperscript{-1}]
- $Q_{rim}$ – rime ice mass mixing ratio \ [kg kg\textsuperscript{-1}]
- $N_{tot}$ – total ice number mixing ratio \ [# kg\textsuperscript{-1}]
- $B_{rim}$ – rime ice volume mixing ratio \ [m\textsuperscript{3} kg\textsuperscript{-1}]

### Predicted Properties:

- $F_{rim}$ – rime mass fraction, $F_{rim} = \frac{Q_{rim}}{Q_{rim} + Q_{dep}}$ \ [-]
- $\rho_{rim}$ – rime density, $\rho_{rim} = \frac{Q_{rim}}{B_{rim}}$ \ [kg m\textsuperscript{-3}]
- $D_m$ – mean-mass diameter, $D_m \propto \frac{Q_{tot}}{N_{tot}}$ \ [m]
- $V_m$ – mass-weighted fall speed, $V_m = f(D_m, \rho_{rim}, F_{rim})$ \ [m s\textsuperscript{-1}]
- \textit{etc.}

### Diagnostic Particle Types:

Based on the \textit{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):

1. **ICE INITIATION**
   - spherical ice
   - \( \alpha = \pi/6 \rho_{\text{bulk\_ice}} \)
   - \( \beta = 3 \)

2. **VAPOR GROWTH**
   - unrimed crystals
   - \( \alpha = \text{const} \)
   - \( \beta \sim 2 \)

3. **AGGREGATION**
   - partially rimed crystal
   - \( \alpha = f(F_{\text{rim}}, \rho_{\text{rim}}) \)
   - \( \beta \sim 2 \)

4. **RIME COLLECTION IN CRYSTAL INTERSTICES**
   - spherical graupel
   - \( \alpha = f(F_{\text{rim}}, \rho_{\text{rim}}) \)
   - \( \beta = 3 \)
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

Morrison et al. (2015), JAS
WRF Results: Line-averaged Reflectivity ($t = 6\text{ h}$)

MOR-G

MOR-H

WDM6

P3

THO

MY2

WSM6

Observations

Line average KOUN reflectivity at 0759 UTC

Morrison et al. (2015), JAS
Ice Particle Properties:

- $F_r \sim 0-0.1$
- $\rho \sim 900 \text{ kg m}^{-3}$
- $V \sim 0.3 \text{ m s}^{-1}$
- $D_m \sim 100 \mu\text{m}$ → small crystals

- $F_r \sim 0$
- $\rho \sim 50 \text{ kg m}^{-3}$
- $V \sim 1 \text{ m s}^{-1}$
- $D_m \sim 3 \text{ mm}$ → aggregates

- $F_r \sim 1$
- $\rho \sim 900 \text{ kg m}^{-3}$
- $V > 10 \text{ m s}^{-1}$
- $D_m > 5 \text{ mm}$ → hail

Note – only one (free) category

Vertical cross section of model fields ($t = 6 \text{ h}$)

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 \textbf{REFLECTIVITY}
(00 UTC December 14)

Accumulated \textbf{PRECIPITATION}
(14 UTC Dec 13 - 08 UTC Dec 14)

Morrison et al. (2015), JAS
Low-density, unrimed snow
Low-density graupel
Small, dense ice
Low-density, unrimed snow
Low-density graupel
### Timing Tests for 3D WRF Simulations

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Squall line case</th>
<th>Orographic case</th>
<th># prognostic variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>P3 – 1 Cat</td>
<td>1.043</td>
<td>1.013</td>
<td>7</td>
</tr>
<tr>
<td>MY2</td>
<td>1.485</td>
<td>1.495</td>
<td>12</td>
</tr>
<tr>
<td>MOR-H</td>
<td>1.203</td>
<td>1.200</td>
<td>9</td>
</tr>
<tr>
<td>THO</td>
<td>1.141</td>
<td>1.174</td>
<td>7</td>
</tr>
<tr>
<td>WSM6</td>
<td>1.000</td>
<td>1.000</td>
<td>5</td>
</tr>
<tr>
<td>WDM6</td>
<td>1.170</td>
<td>1.148</td>
<td>8</td>
</tr>
</tbody>
</table>

- Times relative to those of WSM6 are indicated parenthetically.

→ **P3 in WRF is relatively fast…**

Morrison et al. (2015), JAS
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 *Scaled Flux Vector Transport* 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

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**Diagram**:

- **LARGE GRAUPEL** + **INITIATION** (of small crystals) = **SMALL GRAUPEL**

*The large (mean) sizes have been lost due to dilution*
Single-Category Version

Morrison and Milbrandt (2015) [P3, part 1]

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 $\rightarrow$ 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\(^*\) \((t = 6 \text{ h})\)

- **P3 - 1 category**
  - w/o H-M\(^*\)

- **P3 - 2 category**
  - w/ H-M\(^*\)

\*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.**

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**Observations**

Line average KOUN reflectivity at 0759 UTC

Morrison et al. (2015), JAS
Current Status of P3 (in WRF)

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**

- 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)
The physical basis of ice microphysics is improved while not “breaking” the simulated climate...

Eidhammer et al. (2017), J. Climate
3. Current developments and broader outlook + commentary

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

• There is a steady march towards *greater complexity* in microphysics schemes in weather and climate models. *Does this always make sense?*
Broader outlook

- There is a steady march towards greater complexity in microphysics schemes in weather and climate models. *Does this always make sense?*

- With increased scheme complexity comes:
  - larger number of parameters that are often poorly constrained
  - greater challenge in systematically constraining with observations
  - greater cost which could be used for other modeling aspects (e.g., increased grid resolution)
There will be a role for simple microphysics schemes in the future…

P3 and BOSS were developed in this spirit.

There is a steady march towards greater complexity in microphysics schemes in weather and climate models. Does this always make sense?

- larger number of parameters that are often poorly constrained
- greater challenge in systematically constraining with observations
- greater cost which could be used for other modeling aspects (e.g., increased grid resolution)

Broader outlook
Thanks!

Funding:

DOE ASR DE-SC0008648
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DOE ASR DE-SC0016579
DOE ASR DE-SC0016476
NASA NNX12AH90G
NASA ROSES
NSF base funding
EXTRA
What we want in advection schemes (for clouds/precip):

- Positive definite for mass (needed for water conservation), or even better monotonic, but not 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 linear weighting
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2) “Secondary” non-mass scalars ($N, Z, V$, etc.) then advected by scaling of $Q$ fluxes using higher-order linear weighting

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

→ Accurate (for analytic test cases), fast, and preserves initial linear relationships
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 efficiency 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 bin schemes 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 mass-size (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)
WRF Results: **Line-averaged precipitation rate at 1 km height**

![Graph showing line-averaged precipitation rate at 1 km height with various model comparisons.](image)

- **P3**
- **MOR-H**
- **MOR-G**
- **MY2**
- **THO**
- **WSM6**
- **WDM6**
- **RADAR**

Time-averaged from 6-7 h

Morrison et al. (2015), JAS