

Assessing Ice-Phase Microphysical Parameterizations for Winter Storms in the United States using In-Situ Observations

Brian Filipiak¹, Adrian Loftus², Stephen Lang²,
Diego Cerrai¹, and Marina Astitha¹

¹School of Civil and Environmental Engineering, University of Connecticut, CT, USA

²Mesoscale Modeling Group, NASA Goddard Space Flight Center, Greenbelt MD, USA

Funding Source: NASA FINESST 80NSSC24K1602



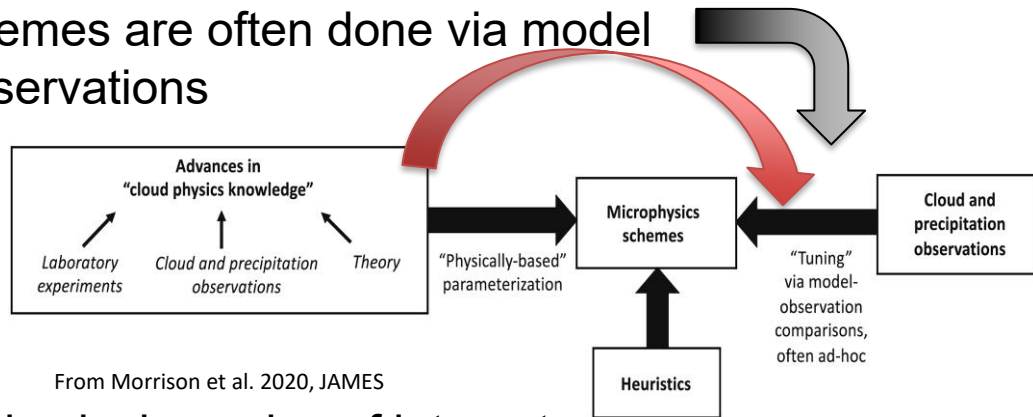
Research Goal

- Motivation:
 - Parameterizations for hydrometeor species can impact microphysical and radiative processes
 - How can in-situ observations be utilized to evaluate and refine parameterizations?
- Objective:
 - Validate key microphysical parameterizations by using a fully observation-based dataset that is representative of global conditions
 - Understand and identify biases or limitations, so tuning can be a more physically-based process
 - Allows for direct, offline evaluations and refinement

Initial Focus on Snow

Incorporating Observations

- Testing and refinements of schemes are often done via model sensitivity experiments with observations



Methodology

1. Constrain datasets to fit microphysical species of interest
 - Isolate specific periods where microphysical species is dominant
2. Extract parameterizations from model code, and compute using observed state quantities as input
 - No model data required

Observation Requirements

1-Moment MP Scheme

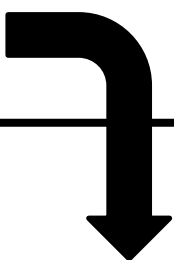
- State variables
 - T, RH, P, ρ_{air}
- Mixing ratios (Q)

Observations

- Weather Station- T, RH, P

$$\rho_{air} = \frac{P - e}{R_d T} + \frac{e}{R_v T}$$

- PSD

$$Q_{snow} = \frac{SWC}{\rho_{air}}$$


Snow Water Content (SWC, g/m³)

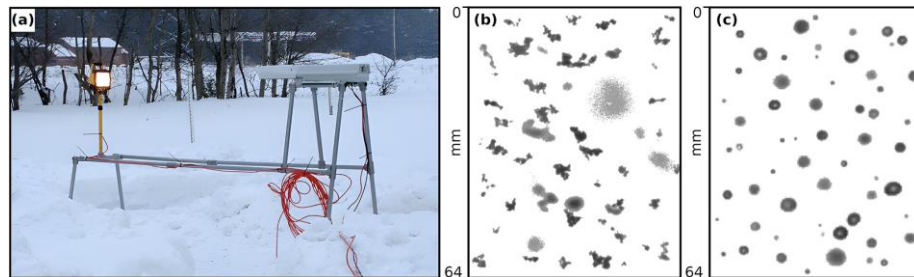
- $SWC = \frac{10^{-3} * \pi}{6} * \int \rho_s(D) * D^3 * N(D) * dD$ (Yu et al. 2020, Hong et al. 2024)
- $SWC = \int m_s(D) * N(D) * dD$ (Heymsfield et al. 2004)

PIP

- Precipitation Imaging Package (PIP)
 - Video Disdrometer w/ open FOV^{1,2}
 - Size range: 0.3 to 25.9mm, 0.2mm bin width
 - Observed Quantities (1 minute resolution)
 - Particle size distribution
 - Mean fall velocity distribution
 - Equivalent density distribution
 - Bulk equivalent density
- Co-located Surface Met Station
 - T, RH, WS, WD, and P

Name	Lat (°N), Lon (°E)	Elevation (m)	Coverage	Met Resolution
Finland (FIN)	61.845, 24.287	170	2017/09/01 - 2022/05/19	Res= 3-11s, resampled to 1min
Marquette, MI (MQT)	46.532, -87.548	426	2015/01/01 - 2023/08/31	Res= 5min
North Slope, AK (NSA)	71.323, -156.612	8	2018/10/24 - 2023/07/18	Res=1min
ICE-POP, South Korea (ICP)	37.665, 128.7	789	2018/01/07 - 2018/04/24	Res= 10s, resampled to 1min
UConn, CT (UCN)	41.807, -72.294	78	2021/09/15 - 2024/05/01	Res=1min

From King et al. 2024, ESS

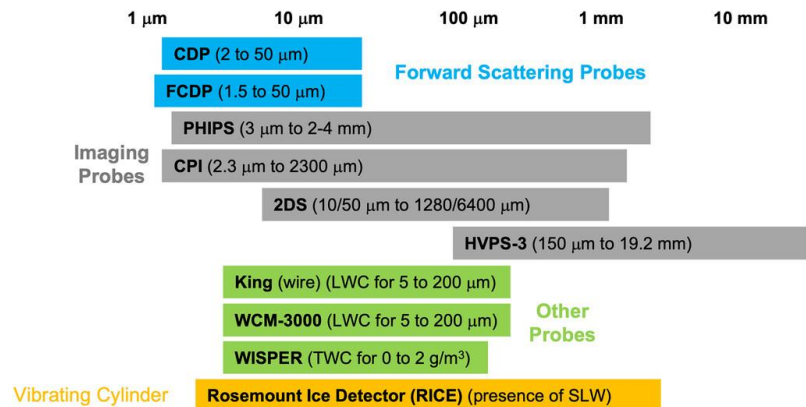


¹ Pettersen et al. 2020, Atmosphere

² King et al. 2024, ESS

Aircraft Probes

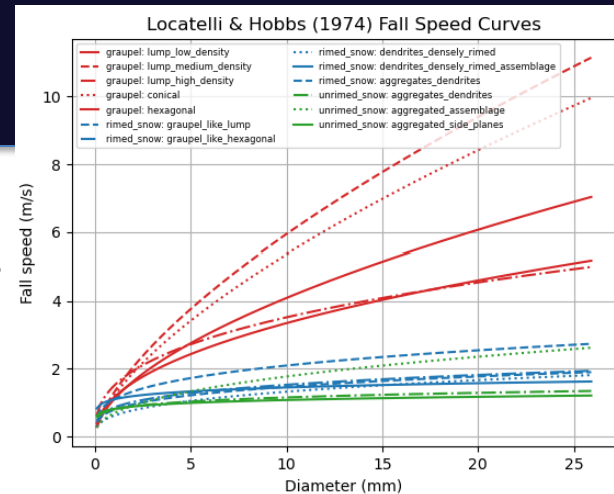
- IMPACTS- NASA P-3 Aircraft
 - 22 flights over 3 winter deployments (2020, 2022, 2023) over Midwest/Eastern US
 - PSD from 2D-S and HVPS-3
- Co-located Meteorological observations
 - Standard measurements: T, RH, P
 - Other useful instruments/probes for identifying SCLW, Cloud LWC, and particle habit/shape



From Yorks et al. 2025, BAMS

Identifying Snow

- PIP
 - Bulk equivalent density $< 0.4 \text{ g/cm}^3$ – remove non-ice species
 - Observed size (0.3-25.9mm)- assume no cloud ice remains
 - Snow and Graupel separated using fall speed distribution
 - Curves from Locatelli and Hobbs 1974
 - Match to curve via least squares
- Aircraft
 - Removed periods with large amounts of liquid water
 - $\text{CDP } N_t > 10$, $\text{CDP LWC} \geq 0.1$, $\text{King LWC} > 0.1$, $\text{RICE frequency change} > 2 \text{ Hz}$ (only at temperatures < -4)¹
 - Minimum size of 0.1 mm from 2D-S and HVPS-3 (assume no significant cloud ice ... for now)
- Additional Thresholds
 - Use only Good QA/QC Flags
 - $N_t > 100 \text{ m}^{-3}$ – ensure a minimum number of species exist



¹Lance et al. 2010, Finlon et al. 2019, Wanget al. 2020, Varcie et al. 2023, Nicholls et al. 2025

Example Snow Application

- Thompson Scheme (1 moment for snow)
 - Based on Field et al. 2005, used aircraft data to parameterized PSD through moments and temperature
 - Moment 2 is the basis for most of the snow parameterizations

$$\text{Moment 2: } M_2 = \frac{q_s}{0.069} \left[\frac{0.622P}{287.04 * T(q_v + 0.622)} \right]$$

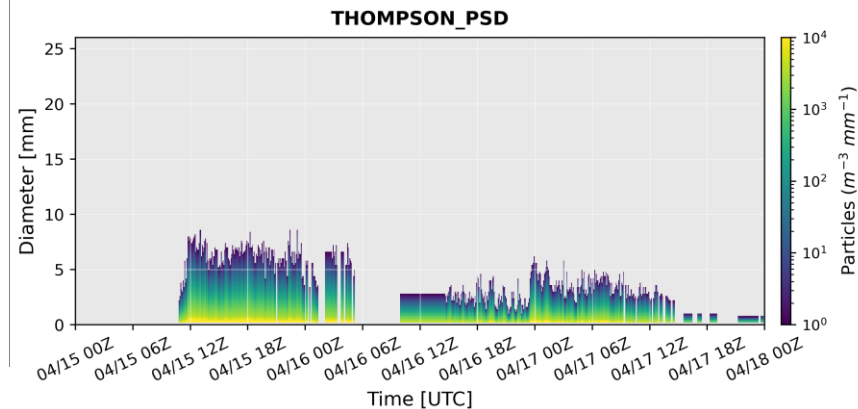
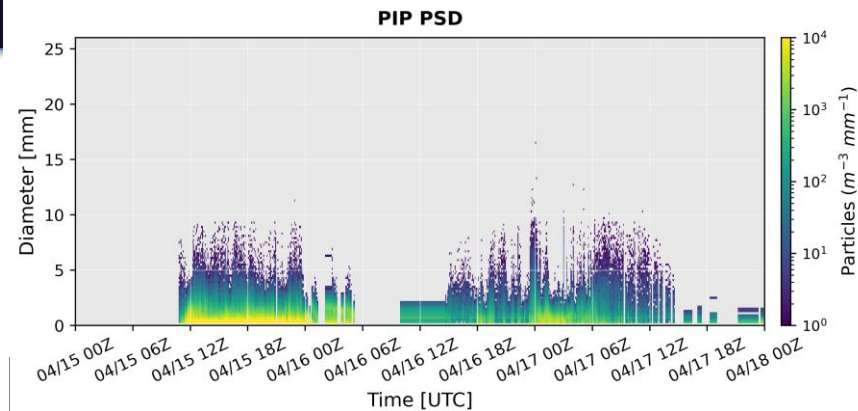
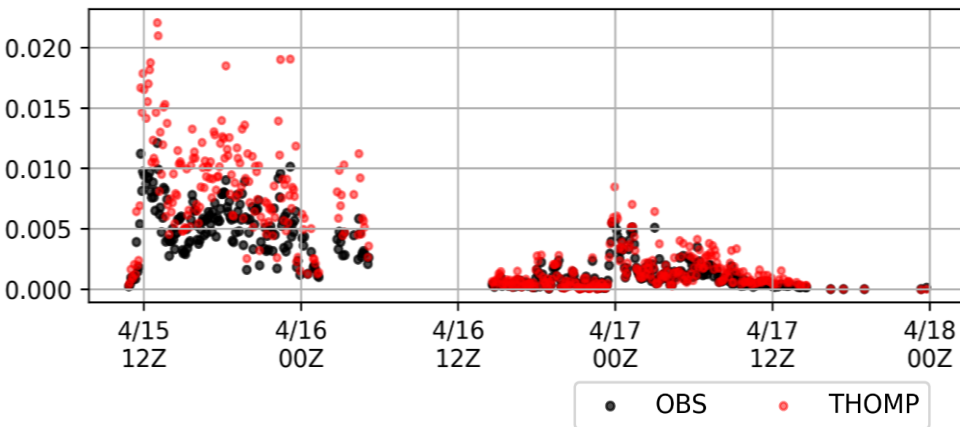
$$\text{PSD: } N(D) = \frac{M_2^4}{M_3^3} \left[490.6 * e^{-\frac{M_2}{M_3} 20.78D} + 17.46 * \left(\frac{M_2}{M_3} D \right)^{0.6357} * e^{-\frac{M_2}{M_3} 3.29D} \right]$$

- Observations (PIP and P-3 Probe data)
 - PSD is observed
 - $M_2 = \int (D)^2 * N(D) * dD$

Case Study

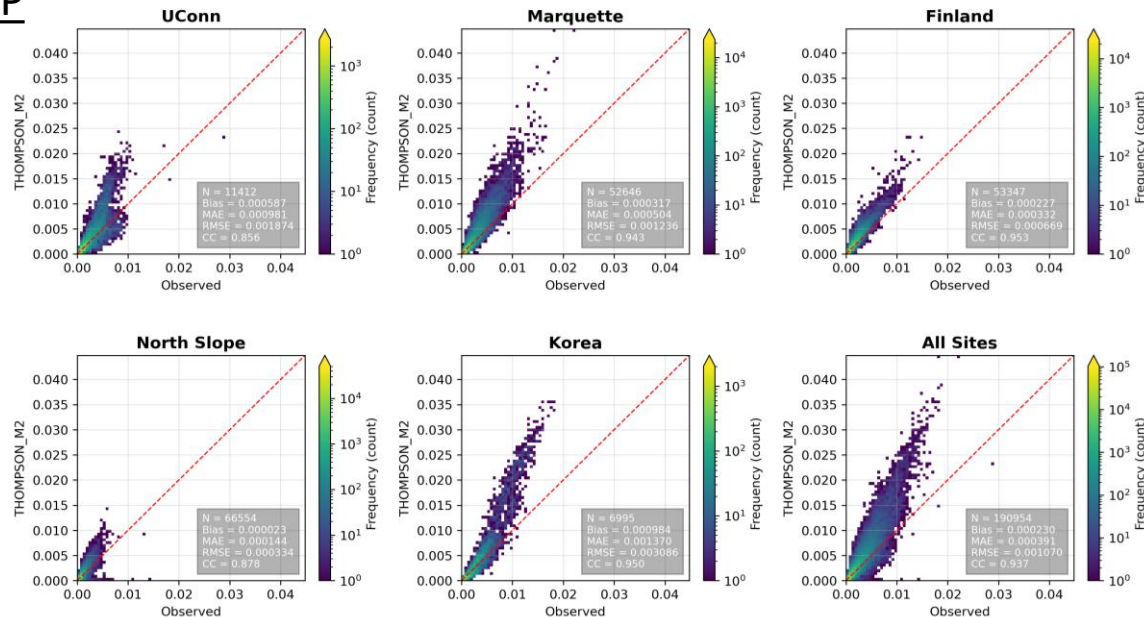
Example Event: Marquette, MI
synoptic snowfall followed by LES

Moment 2 (m^{-1})

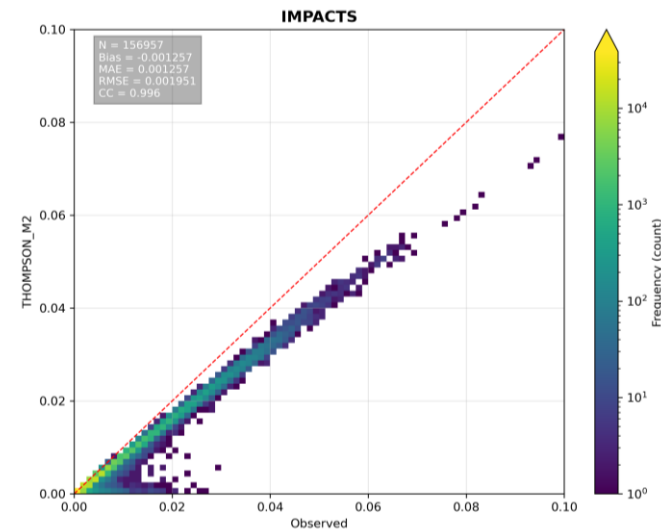


Global Evaluation

PIP



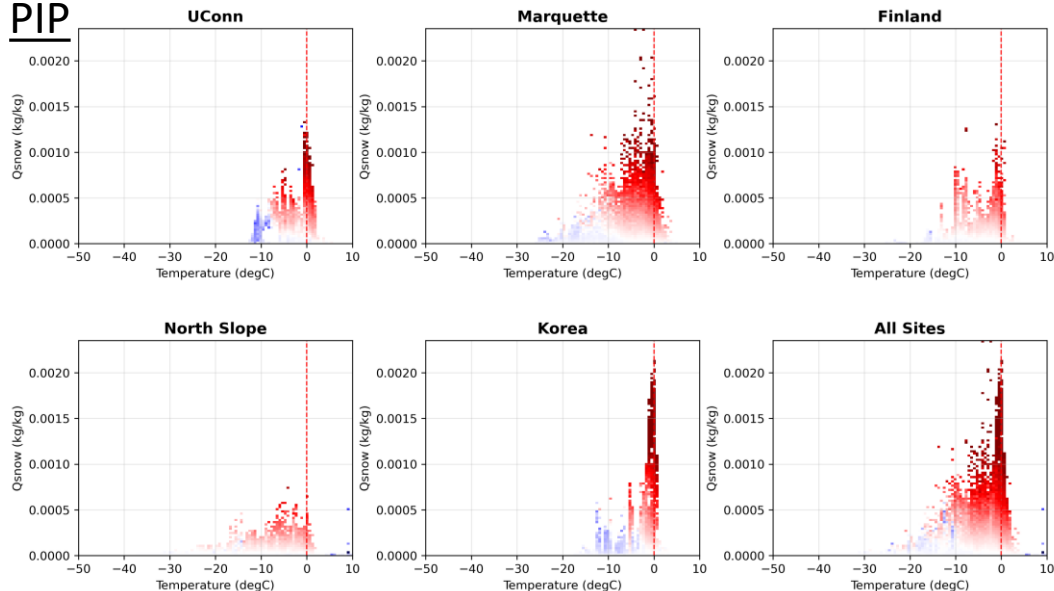
P-3



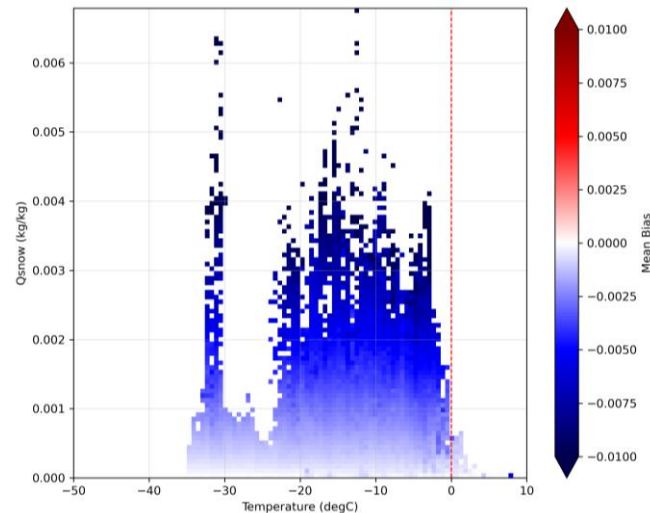
- ✓ PIP comparison shows broad overestimation
- ✓ P-3 comparison shows slight underestimation
- ✓ Instruments used impacts evaluation (but also the derived relationship!)

Understanding Biases

PIP



P-3



- ✓ PIP biases occur as function of both increasing Temperature and Qsnow
- ✓ P-3 biases are mostly dependent on Qsnow magnitude

Generalizability

- The methodology presented can be applied to most microphysics schemes and parameterizations and use different observational datasets
- Can be tuned to scheme-specific assumptions (min/max hydrometeor size)
- Identification of hydrometeor species
 - Can be separated by size, fall speed, or image classification
- Limitations
 - Not applicable to all parameterizations (e.g., process rates)
 - Hard to evaluate periods with combinations of hydrometeors
 - Instrumentation can limit the types of hydrometeors to be evaluated

Future Work

- Focus on ensuring generalizability and understanding evaluation limitations
- Improving separation of ice phase species in aircraft probes
- NASA Goddard Microphysics
 - Currently evaluating all snow parameterizations
 - N_0 , λ , PSD, N_t , ρ_{snow} , effective radius, fall speed
- Starting point for data-driven applications

Summary

- Developed an offline methodology for improving refinements of microphysical parameterizations through only observational datasets
- Highlighted the requirements of observational datasets and provided examples of processing for PIP and P-3 probe data
- Evaluated the Thompson Moment 2 and PSD parameterizations
 - Found that Moment 2 biases occurred in both PIP and P-3 but in different ways
- The method presented is flexible and generalizable to both other observational datasets and microphysical parameterizations