12th IPWG Workshop

Microphysical Controls of High-Frequency Microwave Scattering

Implications for Radiance Simulations, O–B Biases, and MP Bias Correction

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ROADMAP

From Microphysical Sensitivity to MP Bias Correction

All-sky microwave DA hinges on unbiased O–B; conventional VarBC corrects only air-mass and scan bias, yet in cloudy scenes microphysical assumptions inject the TB variability.

1 Sensitivity to MP →

Brief Reviews on Paper Points

Kim et al. (2025), IEEE TGRS

"Sensitivity of Microwave RT Simulations to Cloud Microphysics Assumptions"

Frozen density & habit drive TB sensitivity at scattering channels.

2 Implication for O-B →

THIS WORK

Shin & Kim, IPWG-12 — this study

The predictors driving MP-injected TB variability: XGBoost + SHAP rank

3 Proposing MP bias correction

THIS WORK

Shin & Kim, IPWG-12 — this study (proposed)

Extend airmass / scan bias correction with MP-aware predictors.

Microphysics Changes Microwave TB

General RTM forward-simulation pipeline — from model state to top-of-atmosphere brightness temperature

NWP / WRF MP scheme
parameterizes cloud processes

→

Input atmospheric fields
T, q, N_{tot}, F_{rime}, ρ_{rime}

→

RTM scattering module
PSD + single-scatter
→ **bulk properties**

→

Simulated TB
top-of-atmosphere

- **MP enters the RT through two pathways:**
  - → **via NWP input fields**
  - → **via the RTM's PSD, particle density & habit**
- **Coupling problem:** both routes change together, so we isolate each with controlled RTM runs.
- **What we test:** TB sensitivity to individual MP factors — PSD, particle density & habit — at fixed water content.

Isolating each microphysical lever

EXP#1
Rainwater PSD

EXP#2
Frozen-particle PSD

EXP#3
Frozen density

EXP#4 (REF)
Full MP assumptions, but fixed fields

PSD — the Self-Limiting Lever

RTM pathway — particle-size distribution. Both rain & frozen PSD lose their grip at high frequency.

1 2 3

EXP#1 · RAINWATER PSD

6 K → 0.6 K

self-limiting (10 → 166 GHz)

- Large at 10 GHz — large-particle emission dominates rainwater extinction
- Collapses with frequency as small/large extinction and emission/scatter offset each other
- N_0 & μ matter more than the distribution family (EXPD ≈ DMD)

EXP#2 · FROZEN-PARTICLE PSD

2.6 – 5.3 K

comparable, then constrained

- Super-exponential Field PSDs push mass to small particles → weaker depression
- Forward-scatter cancels: high g (→ 0.78) at 166 GHz offsets extreme depression
- Net effect: variability shrinks at high frequency, like rainwater PSD

Bottom line: PSD shape is a second-order lever — pick a reasonable family and move on. The real levers are density & the input field.

Figures = TB sensitivity — the max–min spread of TB depression (ΔTB) across the swapped MP assumptions, shown by GMI channel (10–183 GHz).

1 2 3

Density & Field — What Matters

The dominant RTM lever (density) and the coupling NWP lever (input field) — where TB accuracy is won or lost.

EXP#3 · FROZEN-PARTICLE DENSITY

9.3 K · 49 K extreme

the dominant lever

- Controls Q_sca far more than any PSD choice (SPHERE / COX88 / MG08)
- Sets how strongly frozen hydrometeors scatter at high frequency
- **Get this right first — the single most important RTM assumption**

EXP#4 · INPUT FIELD × MODULE

up to 16.4 K

couples the whole chain

- Case A (WDM6 rain): RTM's DMD μ=1 suppresses dTB 9.3 → 7 K at 10 GHz
- **Case B (THOM frozen): MP + Input fields resonates → 166 GHz spread 7.7 → 16.4 K (>2×)**
- **NWP field & RTM module are not independent — consistency wins**

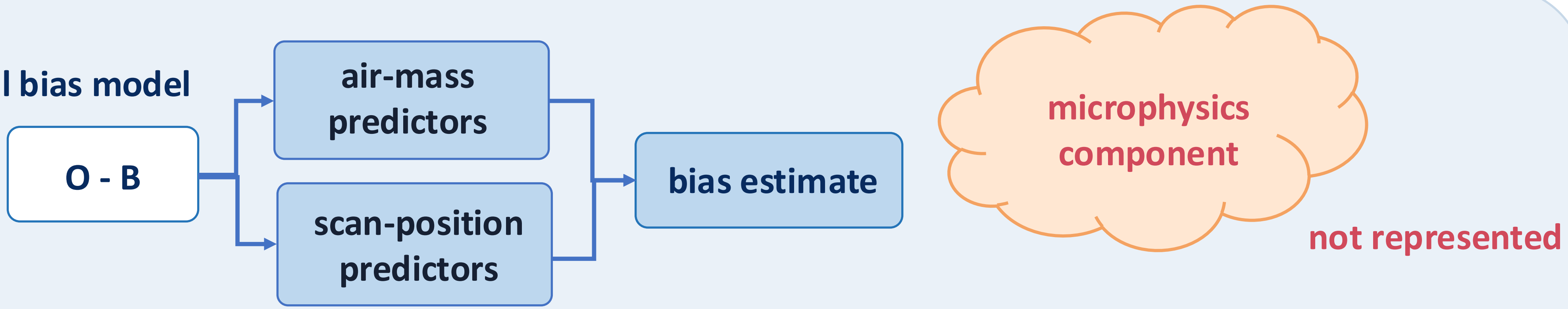
Bottom line: density dominates the module and the field can more than double the spread — accuracy comes from a physically consistent chain, not one 'realistic' component.

Figures = TB sensitivity — the max–min spread of TB depression (ΔTB) across the swapped MP assumptions, shown by GMI channel (10–183 GHz).

Implication for O-B biases

Motivation: all-sky O-B departures contains more than air mass and scan bias

Conventional bias model



$$b_o = \underbrace{\beta_0}_{\textit{offset}} + \sum_i \underbrace{\beta_i^{AM} P_i^{AM}}_{\textit{air-mass}} + \sum_j \underbrace{\beta_j^{SCAN} P_j^{SCAN}}_{\textit{Scan-geometry}}$$

Conventional VarBC predictors were designed mainly for slowly varying systematic errors.

air-mass predictors:

$$P^{AM} = \{TPW,\ T_s,\ \Gamma,\ T_{850},\ T_{200}\}$$

scan-position predictors:

$$P^{SCAN} = \{\theta,\ Scan\,Position,\ FOV\}$$

Key implication

- **If MP assumptions alter H(x), their effect can appear directly in O-B departures.**
- **Microphysics-induced TB variability — rain & ice PSD, habit, density — has no predictor of its own.**
- **It is aliased into the air-mass & scan coefficients, *quietly contaminating the correction.***

Finding the predictors driving MP-induced TB variability

Fixed-State RTM Experiments

Perturbing microphysical assumptions inside the radiative transfer — the atmospheric state is held fixed

INPUT

Fixed atmosphere

- WRF-P3 typhoon simulation supplies the cloud-resolving state.
- Temperature, humidity, and hydrometeor mass are held fixed across every run.

PERTURB

RTM assumptions only

- Within the RT scattering calculation we vary microphysical assumptions — particle shape, PSD, and density.
- The WRF microphysics scheme itself is unchanged.

OUTPUT

Simulated TB

- Brightness temperatures are computed on GPM/GMI channel geometry, 10–183 GHz, for each perturbed configuration.

"By holding the atmospheric input fields fixed, the experiment isolates the component of TB variability attributable to microphysical assumptions within the radiative-transfer simulation."

→ TB differences reflect RTM microphysics assumptions — not differences in dynamics or water content.

Microphysics-Perturbation Sets

Each set is a controlled perturbation of one MP factor — isolating which predictor family the bias model must include

Shape / habit

Default · ARTS-OPT · SSRGA-OPT · SSRGA-RIME

Poster 9.15

Rain PSD

RAIN_WSM6 · RAIN_WDM6

Ice PSD

ICE_PSDWSM6 · ICE_PSDTHOM · ICE_PSDMORR

Ice density

ICE_DENWSM6 · ICE_DENTHOM

CLW PSD

CLW_WSM6 · CLW_THOM · CLW_MORR

Two reference aggregates

MIE — all non-shape factors (shape variability excluded)

ALL — full MP-driven TB variability

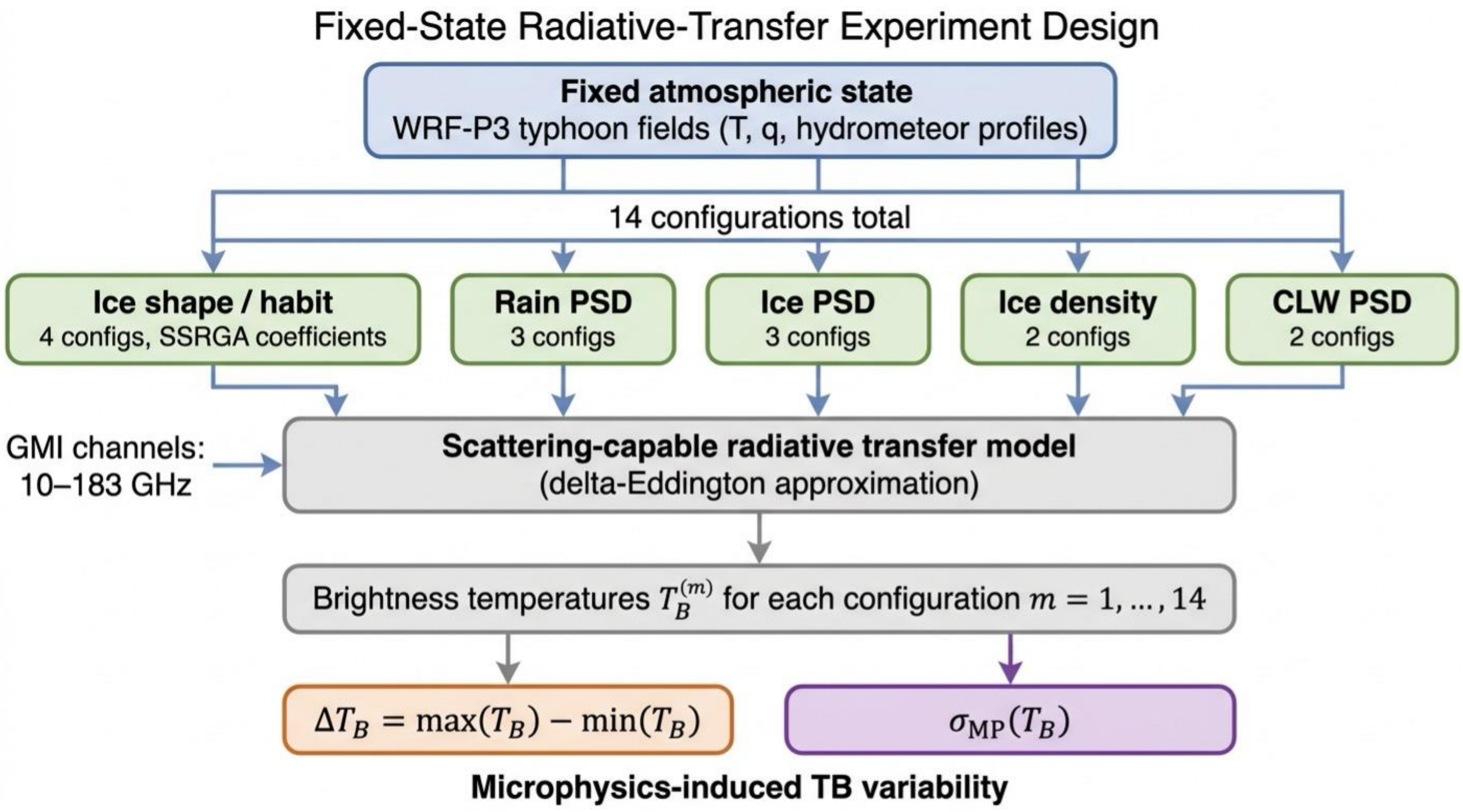
P9.15 (TR) Integration of optimal habit selection with DDA and SSRGA models for improved microwave radiative transfer simulations (Kim and Shin)

WRF-P3 typhoon simulation cases

15 typhoon cases — each applied to 14 MP-perturbed sets → 210 total simulations (15 × 14)

CASE#	Scene Name	Location [km]	MSLP [hPa]	MWS [m/s]
CASE#1	SURIGAE_041503	45.95	1.24	6.07
CASE#2	SURIGAE_041615	33.45	-1.13	1.82
CASE#3	SURIGAE_041815	19.48	1.6	-2.42
CASE#4	SURIGAE_042001	25.12	8.43	-7.13
CASE#5	SURIGAE_042300	33.23	0.27	-0.39
CASE#6	NIDA_080506	54.76	3.51	1.50
CASE#7	NIDA_080516	31.30	3.75	1.67
CASE#8	CHANTHU_090921	18.68	-1.91	3.26
CASE#9	CHANTHU_091121	31.55	7.69	-4.08
CASE#10	MINDULLE_092403	55.28	-5.91	5.07
CASE#11	MINDULLE_092902	22.11	11.90	-6.75
CASE#12	MINDULLE_092915	17.40	10.21	-5.91
CASE#13	MALOU_102617	22.43	-4.71	6.29
CASE#14	NYATOH_120207	26.76	-6.66	5.11
CASE#15	RAI_121717	33.38	-0.13	-0.58

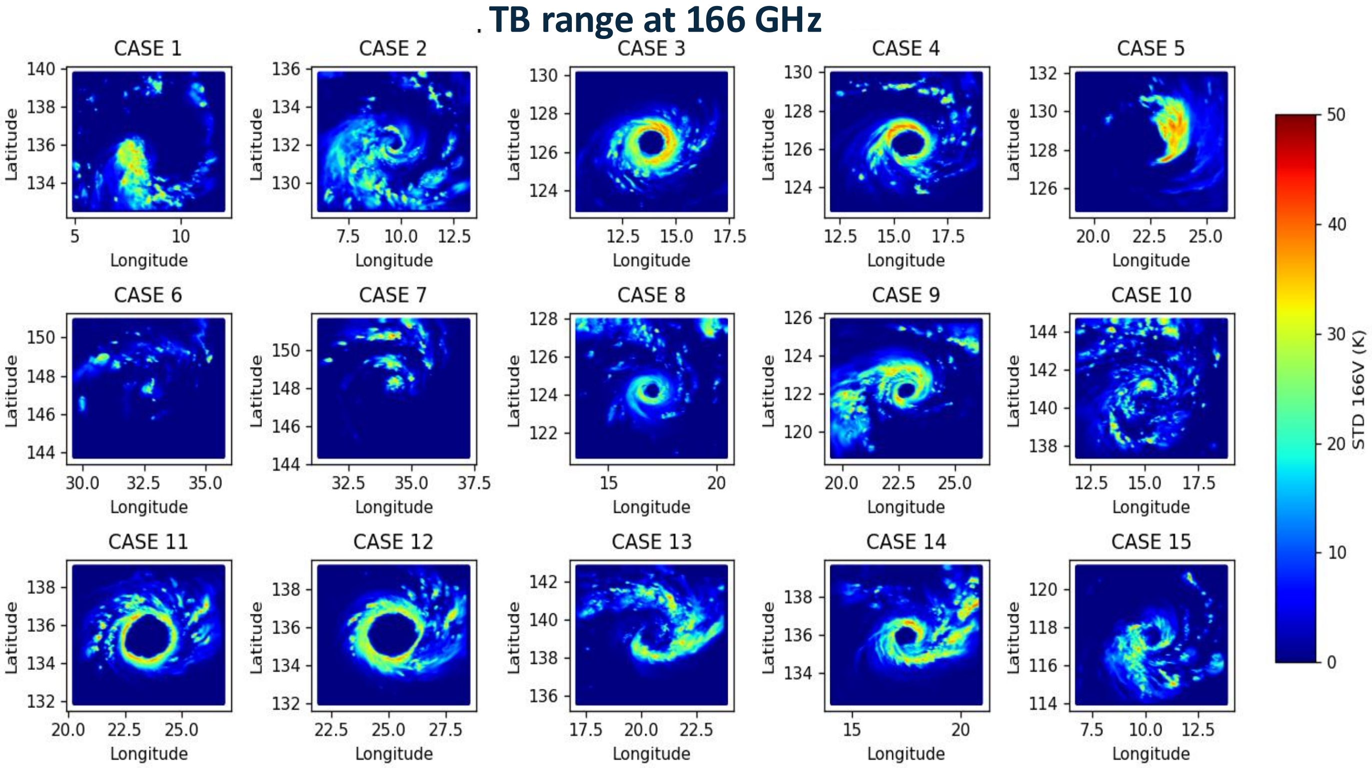
Workflow Summary



MP assumptions generate structured TB variability

Example: Full TB variability

Standard deviation across 14 MP-perturbed sets, shown for each of the 15 typhoon cases



What this shows

Same atmospheric fields, different MP settings → spatially organized TB spread.

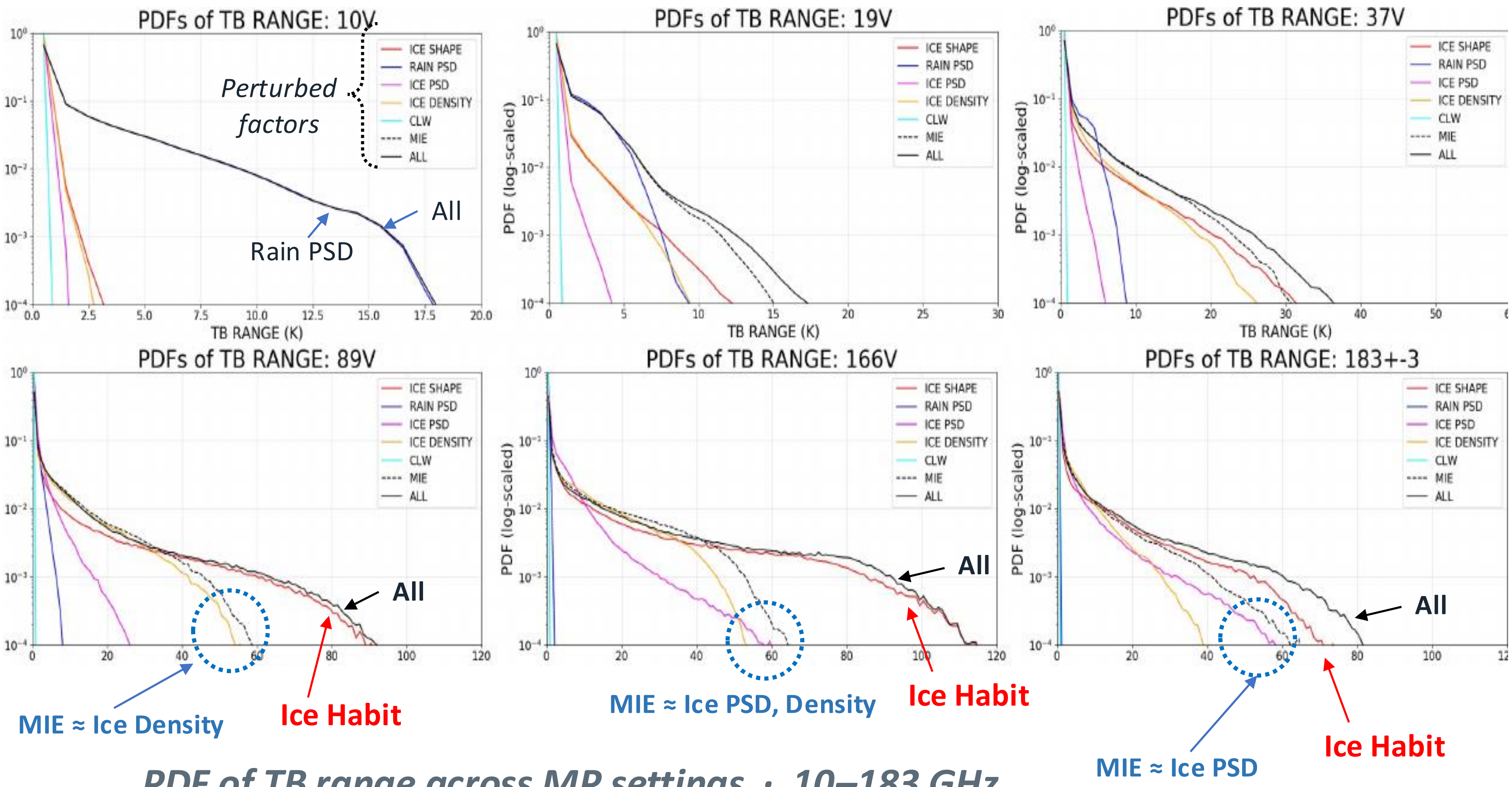
- not random noise
- channel dependent
- cloud-regime dependent

Bias-correction implication again

A correction model that lacks MP information may absorb this variability into unrelated predictors.

How Much Spread, and From What?

PDFs of TB range by perturbed factors — the dominant factor shifts with frequency



PDF of TB range across MP settings · 10–183 GHz

10 GHz

ALL ≈ MIE ≈ **RAIN PSD** — no shape effect; rain PSD dominates

Higher freq (89-183GHz)

ALL > MIE ≈ **ICE HABIT** — habit becomes the big lever

Shape off (Mie case)

89 GHz: MIE ≈ **ICE DENSITY** dominates
166 GHz: MIE ≈ **ICE PSD+ DENSITY** dominates
183 GHz: MIE ≈ **ICE PSD** dominates

Predictor Diagnosis

***XGBoost** learns the MP-driven TB variability from 22 model-based predictors;*
***SHAP** attributes it — organized into five physical families*

Hydrometeor amount

Column-integrated paths

IWP
LWP
RWP
CWP

Thermodynamic / moisture

Temperature & vapor

TPW
T2
Z_FREEZE
TPWFRZ

Vertical structure

Layer heights & tops

Z_ICE
Z_RAIN
ZTOP_ICE
ZTOP_RAIN
IWPFRZ

Microphysical property

Size · density · rime state

D_RAIN_COL
D_ICE_COL
RHO_ICE_COL
RF_ICE_COL

Dynamical

Surface & updraft flow

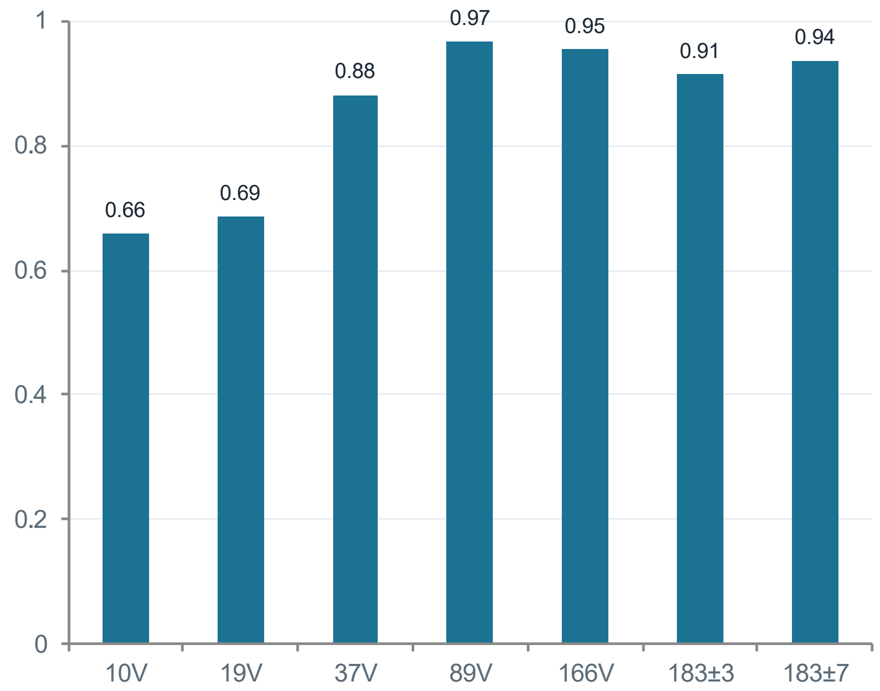
WSPD10
WMAX

22 model-based predictors → XGBoost per channel → SHAP attribution → which family drives TB variability at each frequency

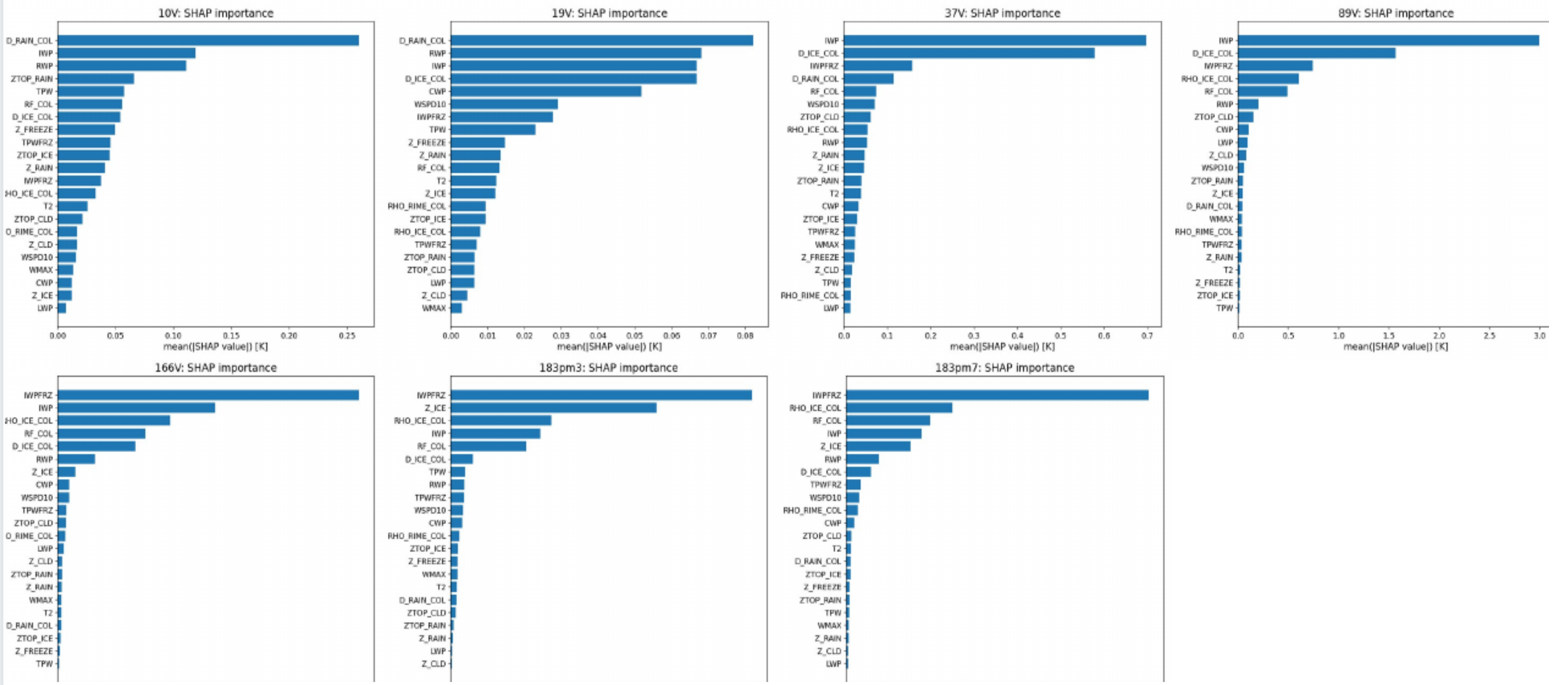
Which Variables Drive the Spread?

XGBoost predicts TB STD from 22 model-based predictors; SHAP attributes each predictor's contribution

XGBoost skill (R^2) — best in scattering channels



Mean |SHAP| importance per channel



10 & 19 GHz

DRAIN_COL *rain drop size*

37 & 89 GHz

IWP *ice water path*

166 & 183 GHz

IWPFRZ *ice mass above freezing level*

The Predictors That Matter

Ranked WRF-output predictors of TB variability — ice mass quantities lead, esp. at scattering channels

Rank	10 & 19 GHz	37 & 89 GHz	166 & 183 GHz
1	**D_RAIN_COL** *rain drop size*	**IWP** *ice water path*	**IWPFRZ** *IWP above freezing level*
2	**RWP** *rain water path*	**D_ICE_COL** *ice particle size*	**RHO_ICE_COL** *ice density*
3	**IWP** *ice water path*	**IWPFRZ** *ice mass aloft*	**RF_ICE_COL** *rime fraction*
4	**D_ICE_COL** *ice particle size*	**RHO_ICE_COL** *ice density*	**IWP** *ice water path*
5	**TPW** *water vapor path*	**RF_ICE_COL** *rime fraction*	**Z_ICE** *ice centroid height*

Note: RF_ICE_COL, RHO_ICE_COL, D_ICE_COL are available only from WRF-P3 (predicted ice properties) — the physics that six-class schemes cannot expose.

A Missing Term in Bias Correction

Correcting only air-mass and scan bias lets MP variability alias onto them
*— **We need to add an explicit MP term.***

Proposed Microphysics-aware Observation Bias Model

$$b_o = \beta_0 + \sum_i \beta_i^{AM} P_i^{AM} + \sum_j \beta_j^{SCAN} P_j^{SCAN} \boxed{+ \sum_k \beta_k^{MP} P_k^{MP}}$$

offset *air-mass* *Scan-geometry* *Microphysics*

$$P^{AM} = \{TPW,\ T_s,\ \Gamma,\ T_{850},\ T_{200}\}$$

$$P^{SCAN} = \{\theta,\ Scan\,Position,\ FOV\}$$

$$P^{MP} = \{IWP,\ IWP_{FRZ},\ D_{ice},\ \rho_{ice},\ F_{rime},\ \rho_{rime},\ \cdots\}$$

Problem*: Microphysical Aliasing*

Conventional basis has no **MP bias** term → it aliases onto air-mass and scan biases .

Extension of the Observation Bias Model

- **Treat MP assumptions and inconsistency as a structured bias source.**
- **Use predictors with physical meaning**
- **Estimate adaptively by channel**
  - more investigation for surface, cloud regime.

Thank you

Microphysics-aware RT — from per-channel drivers to smaller, better-targeted O–B biases

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Yonsei University | 12th IPWG Workshop

Questions welcome

APPENDIX

Supporting Detail

Backup slides for Q&A — full setup and per-experiment results.

Forward simulation · Experimental design · EXP#1–#4 · REF vs GMI

Summary: Kim, Shin and Kim (2025), IEEE TGRS: Sensitivity of Microwave Radiative Transfer Simulations to Cloud Microphysics Assumptions.

Methods at a Glance

WRF cloud-resolving runs

12 / 4 / 1.3 km nested, vortex-following; 6 MP schemes (WSM6, WDM6, THOM, MORR, P3-1ICE, P3-2ICE)

5 GPM-GMI typhoon overpasses

Surigae & Mindulle (2021); location error < 120 km at 54 h

Fast plane-parallel RTM

delta-Eddington two-stream; Mie soft-sphere + Maxwell-Garnett; pre-computed bulk-scattering LUTs

Metrics on dTB_x PDFs

$dTB_x = TB_x - TB\_clear$; PDF-weighted mean & extreme tail; sensitivity = max–min range across assumptions

Five GMI V-pol channels analyzed: 10 · 19 · 37 · 89 · 166 GHz

Experimental Design

Fix the input field (WRF-P3 1ICE), vary one MP assumption at a time in the RTM

EXP#1
Rainwater PSD

Exponential vs double-moment gamma; vary N_0, μ

EXP#2
Frozen-particle PSD

EXPD/DMD + temperature-dependent (Houze, Field)

EXP#3
Frozen density

SPHERE vs COX88 vs MG08 (riming-based)

EXP#4
REF assumptions, fixed field

Six WRF MP schemes in the RTM; isolates the module

REF (reference) = physically consistent: each WRF scheme paired with its own RTM assumptions. **EXP#4 vs REF** isolates the effect of varying input fields.

EXP#1–2 · PSD

$$N(D) = N_0 D^{\mu} e^{-\lambda D}$$

vary N_0, μ

EXP#3 · density

$$\rho_{\mathrm{eff}}(D) = \frac{6a}{\pi} D^{b-3}$$

$b < 3 \Rightarrow \rho$ falls with D

Metric — dTB & sensitivity range

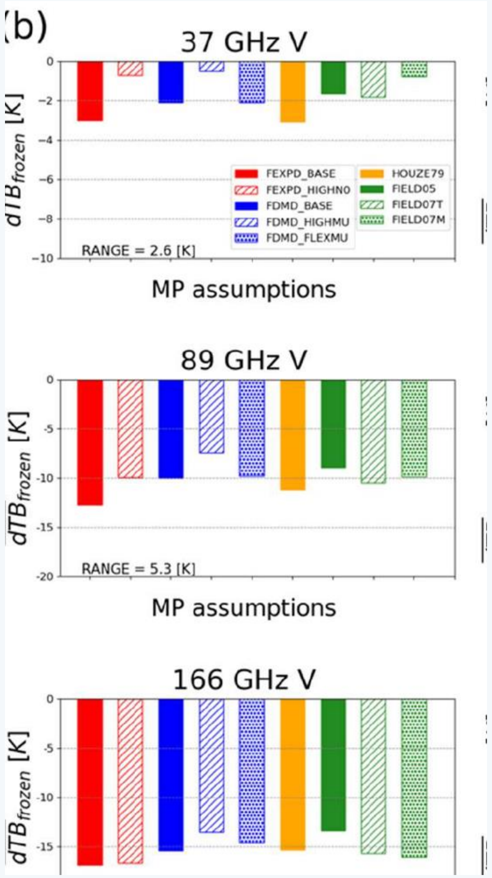
$$dTB_x = TB_x - TB_{\mathrm{clear}}$$

$$\mathrm{Range} = \max_m(\overline{dTB_x}) - \min_m(\overline{dTB_x})$$

TB depression vs clear-sky; **Range** = spread across MP schemes

EXP#2 Frozen-particle PSD — comparable, then constrained

dTB_frozen by MP assumption



Paper Fig. 8(b): dTB_frozen with RANGE labels (9 MP assumptions)

PSD families (color = PSD form):

FEXPD *(exponential)*
solid / hatched = BASE / HIGHN0
large particles → strongest depression

FDMD *(double-moment γ)*
BASE(μ=0) / HIGHMU(μ=8) / FLEXMU
higher μ → smaller particles → weaker

HOUZE79 *(empirical)*
N(D) compensates low/high-T
moderate depression

FIELD *(empirical (Field))*
05 / 07T / 07M — super-exponential
strong shift to small → weakest depression

Range 2.6 – 5.3 K
Comparable in magnitude to rainwater PSD (EXP#1)

Small particles win
Super-exponential Field PSDs shift mass to small sizes → weak depression

Forward-scatter cancels
At 166 GHz high g (→0.78) offsets extreme depression

Net effect: constrained
Variability shrinks at high frequency, like rainwater

REF vs GMI Observations

Even the most realistic configuration can give the worst fit

Low frequency (10–37 GHz)

REF under-estimates TB enhancement → points to too-weak WRF rainwater fields.

High frequency (89–166 GHz)

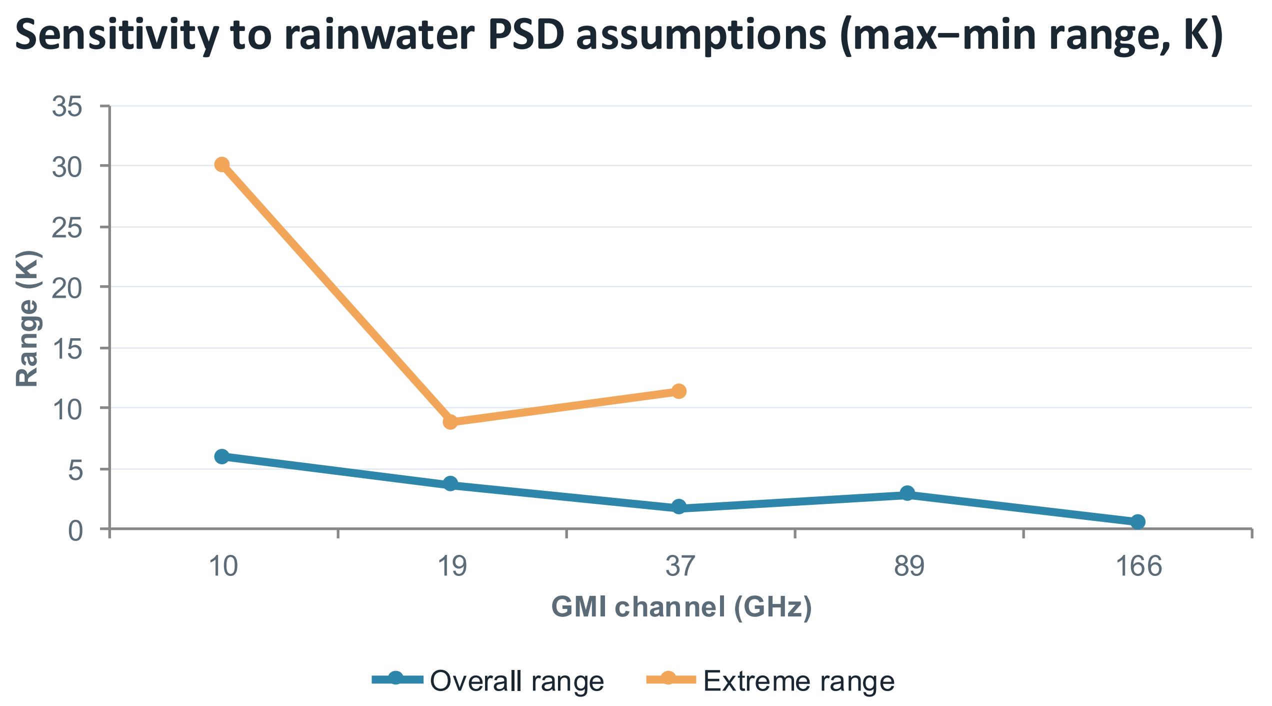
REF under-estimates TB depression → Mie soft-sphere over-estimates g and over-modifies Q_sca for non-spherical ice.

The surprise. P3-1ICE / P3-2ICE — with the **most sophisticated density scheme (MG08)** — give the worst high-frequency JSD. A partially realistic component, fed through an unrealistic Mie soft-sphere model, degrades the result more than a simpler but consistent one.

Best Jensen–Shannon match to OBS (case-dependent):

10 GHz	19 GHz	37 GHz	89 GHz	166 GHz
MORR	P3-2ICE	P3-2ICE	MORR	THOM

PSD: The Self-Limiting Lever



Largest at 10 GHz
6 K overall — large-particle emission dominates rainwater extinction

Collapses with frequency
Down to 0.6 K at 166 GHz

Two offsets at work
Small- vs large-particle extinction + emission vs scattering cancel

EXPD vs DMD ≈ minor
Changing N_0 / μ matters more than the distribution family

Density:

Frozen-particle density assumptions produce the largest, most robust TB variations

9.3 K
overall range at 166 GHz
≈3× the PSD effect

49 K
extreme range at 89 GHz
≈250% of the PSD effect

Q_sca
the mechanism
density reshapes scattering efficiency

COX88 (non-spherical, b<3)

↓ Q_sca for large particles → weaker depression at 37/89 GHz; ↑ Q_sca for small particles boosts 166 GHz when paired with flexible DMD.

MG08 (riming-based, P3)

Most realistic density; but P3 fields rarely rime (F_rime<0.5) → weakest scattering of all — a realism-vs-consistency warning revisited later.

Key points: of all MP choices in the scattering module, **density is the one to get right** — it controls Q_sca more than the self-limiting PSD levers. **Realism ≠ accuracy:** the most "realistic" setup can give the worst fit to GMI (REF vs obs).

EXP#4 vs REF — Fields interact with the module

Varying the input atmospheric field adds variability and can reinforce or suppress signals

Case A — WDM6 rainwater

WRF-WDM6 makes abundant mid-level rainwater → expected strong 10–19 GHz enhancement.

Suppressed by the RTM's DMD μ=1 assumption, which shifts N(D) to small particles.
dTB drops 9.3 → 7 K at 10 GHz.

Case B — THOM frozen

WRF-THOM makes abundant snow; FIELD05 PSD adds small particles; COX88 boosts their Q_sca.

Reinforced — the trio compounds into a strong 166 GHz depression.
dTB spread 7.7 → 16.4 K (REF), more than double EXP#4.

Lesson: MP assumptions in the NWP field and in the RTM module are not independent — **physical consistency across the whole chain matters.**

Key Takeaways

PSD impact is self-limiting

Rainwater & frozen PSD effects shrink at high frequency via extinction compensation and forward-scatter cancellation.

Density is the dominant lever

Frozen-particle density drives the largest TB variations (up to 9.3 K overall, 49 K extreme) through Q_sca.

Consistency over isolated realism

Keep PSD & density assumptions consistent across field, RTM, and scattering DB (DDA databases) — relevant to all-sky DA & cloud-property retrievals.

Microphysics systematically shapes TB

→ but does our DA bias correction even account for it?

Does DA bias correction account for microphysics?

1 2 3

TB VARIABILITY DRIVERS

The predictor set was designed for air-mass and scan errors — not for microphysics.

CONVENTIONAL OBSERVATION-BIAS MODEL (VarBC)

$$b_o = \underbrace{\beta_0}_{\text{offset}} + \sum_i \underbrace{\beta_i^{AM} P_i^{AM}}_{\text{air-mass}} + \sum_j \underbrace{\beta_j^{SCAN} P_j^{SCAN}}_{\text{Scan-geometry}}$$

air-mass predictors: $P^{AM} = \{TPW,\ T_s,\ \Gamma,\ T_{850},\ T_{200}\}$

scan-position predictors: $P^{SCAN} = \{\theta,\ Scan\,Position,\ FOV\}$

Microphysics-induced TB variability — rain & ice PSD, habit, density — has no predictor of its own.

Captured? No — yet not gone: it is aliased into the air-mass & scan coefficients, quietly contaminating the correction.

Adding Microphysics (MP) correction: $+\sum_k \beta_k^{MP} P_k^{MP}$? → **then the predictors?**

01. Calculating TB variability arising from various MP assumptions

Various MP settings

*Default: P3 settings

*MGD: Modified-Gamma dist.

	MP name	CLW	RAIN	ICE PSD	ICE Density	ICE shape
1	Default	Single-moment MGD (Martin *et al.*, 1994)	Double-moment MGD ($\mu = 0$)	Double-moment MGD ($\mu = f(\lambda)$)	Morrison and Grabowski (2008)	MIE
2	ARTS-OPT	Default	Default	Default	Default	ARTS-OPT (Kim *et al.* 2024)
3	SSRGA-OPT	Default	Default	Default	Default	SSRGA-OPT (See poster 9.15)
4	SSRGA-RIME	Default	Default	Default	Default	SSRGA-RIME (See poster 9.15)
5	RAIN_WSM6	Default	Single-moment MGD	Default	Default	Default
6	RAIN_WDM6	Default	Double-moment MGD ($\mu = 1$)	Default	Default	Default
7	ICE_PSDWSM6	Default	Default	Houze *et al.* (1979)	Default	Default
8	ICE_PSDTHOM	Default	Default	Field *et al.* (2005)	Default	Default
9	ICE_PSDMORR	Default	Default	Double-moment MGD ($\mu = 0$)	Default	Default
10	ICE_DENWSM6	Default	Default	Default	Spherical	Default
11	ICE_DENTHOM	Default	Default	Default	Cox (1988)	Default

01. Calculating TB variability arising from various MP assumptions

Various MP settings

***Default: P3 settings**

*MGD: Modified-Gamma dist.

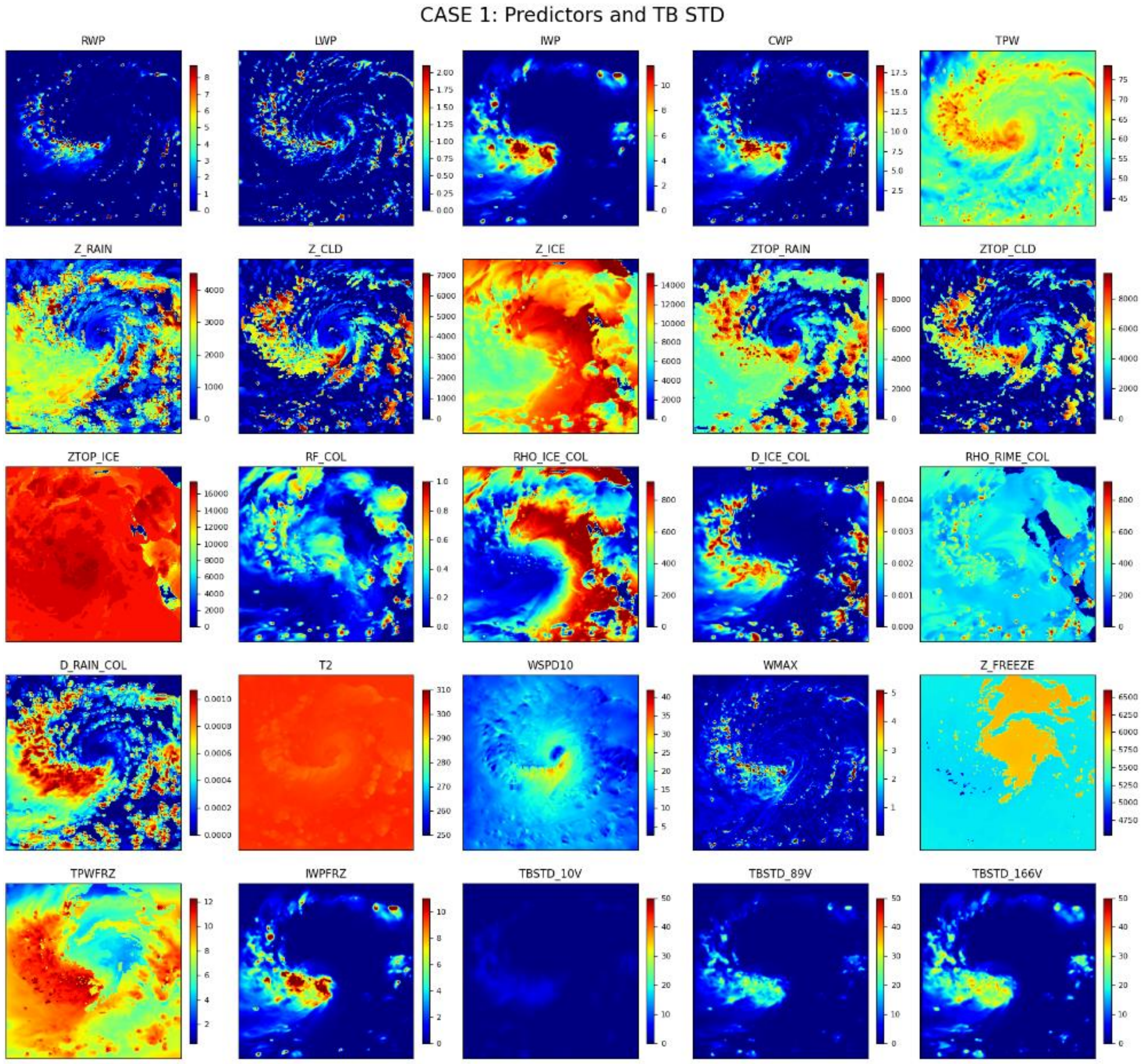
	MP name	CLW	RAIN	ICE PSD	ICE Density	ICE shape
#1	Default	Single-moment MGD (Martin *et al.*, 1994)	Double-moment MGD ($\mu = 0$)	Double-moment MGD ($\mu = f(\lambda)$)	Morrison and Grabowski (2008)	MIE
12	CLW_WSM6	Monodisperse	Default	Default	Default	Default
13	CLW_THOM	Thompson *et al.* (2008)	Default	Default	Default	Default
14	CLW_MORR	Curry (1999)	Default	Default	Default	Default

- Set#1: [Default, #2-4] => Shape effect
  Set#2: [Default, #5-6] => RAIN PSD effect
- Set#3: [Default, #7-9] => ICE PSD effect
- Set#4: [Default, #10-11] => ICE Density effect
- Set#5: [Default, #12-14] => CLW PSD effect
- MIE: [Default, #5-14] => Exclude Shape-related variability (assume MIE)
- ALL => represent full TB variability

Predictors of TB variability

Model-based predictors

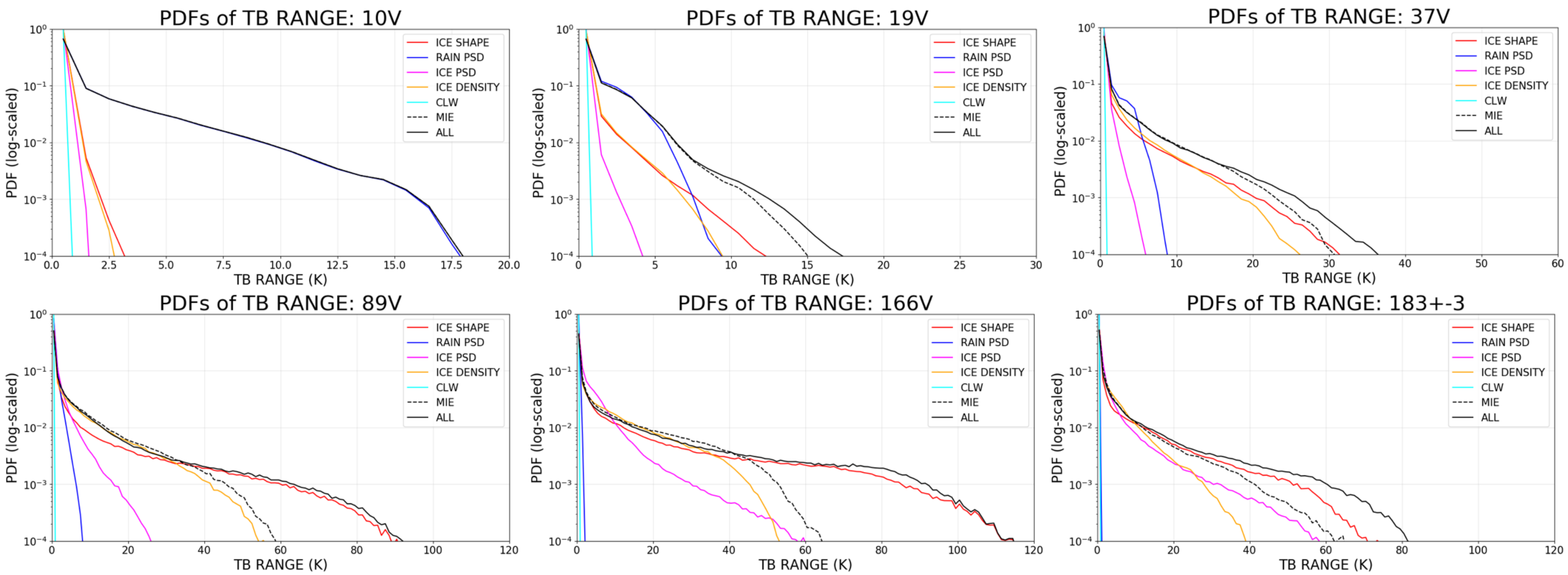
22 Possible predictors of TB variability (*i.e.,* TBSTD)



- IWP: ICE Water Path
- LWP: CLW Path
- RWP: RAIN Water Path
- CWP: IWP+LWP+RWP
- TPW: Water Vapor Path
- Z_X: mass-weighted average altitude of hydrometeor X
- ZTOP_X: top altitude of hydrometeor X
- RF_ICE_COL: mass-weighted average F_{rime}
- RHO_ICE_COL: mass-weighted average ρ_{ice}
- D_ICE_COL: mass-weighted average D_{ice}
- RHO_ICE_COL: mass-weighted average ρ_{rime}
- *F_{rime} , ρ_{ice}, D_{ice}, ρ_{rime} are only available from WRF-P3 simulations
- D_RAIN_COL: mass-weighted average proxy of rain diameter
- T2: 2-m Temperature
- WSPD10: 10-m Wind Speed
- WMAX: maximum vertical velocity
- Z_FREEZE: Freezing level height
- TPWFRZ: TPW above Z_FREEZE
- IWPFRZ: IWP above Z_FREEZE

01. Calculating TB variability arising from various MP assumptions

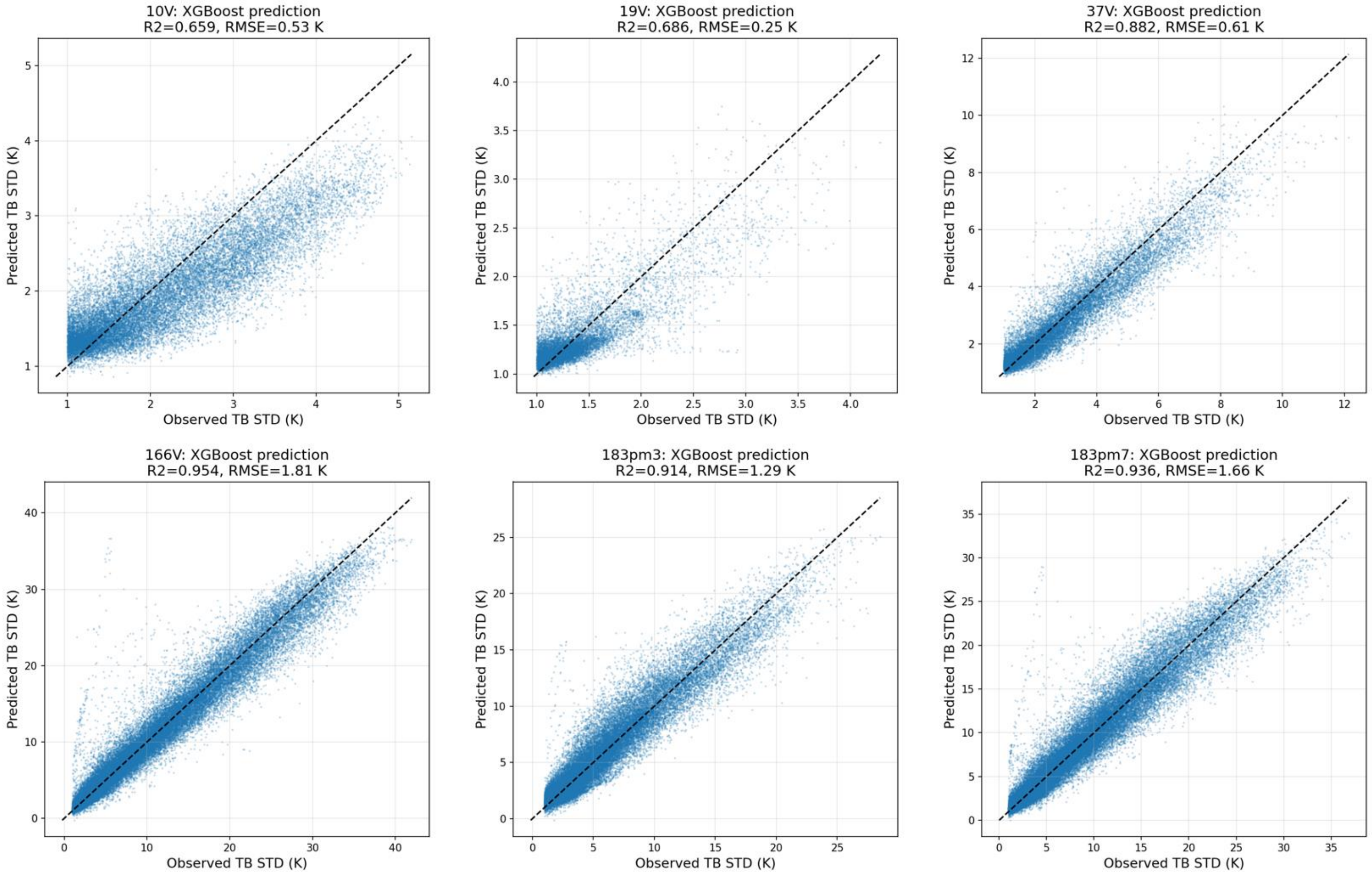
Distribution of TB range



- 10 GHz: TB range in ALL = MIE ~ RAIN PSD => No shape effect, large RAIN PSD effect
- Higher frequency: TB range in ALL > MIE ~ ICE SHAPE => large shape effect
- 89 GHz: TB range in MIE ~ ICE Density => when shape effect excluded, large Density effect
- 89 => 183 GHz: TB range in MIE ~ ICE PSD => when shape effect excluded, large PSD effect

03. Finding drivers of TB variability

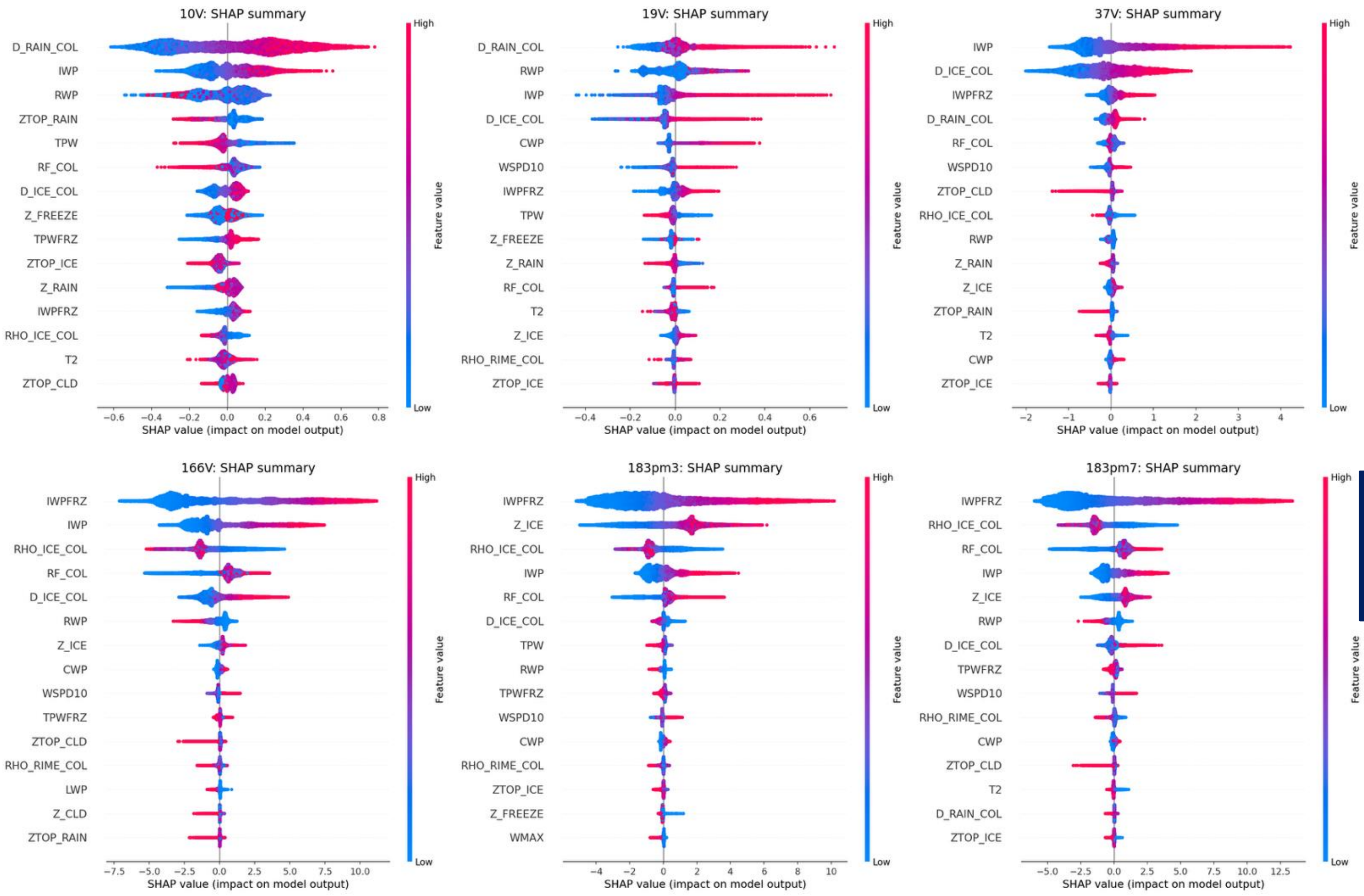
XGBoost Prediction



Better performance at scattering channels (Best at 89 GHz V)

03. Finding drivers of TB variability

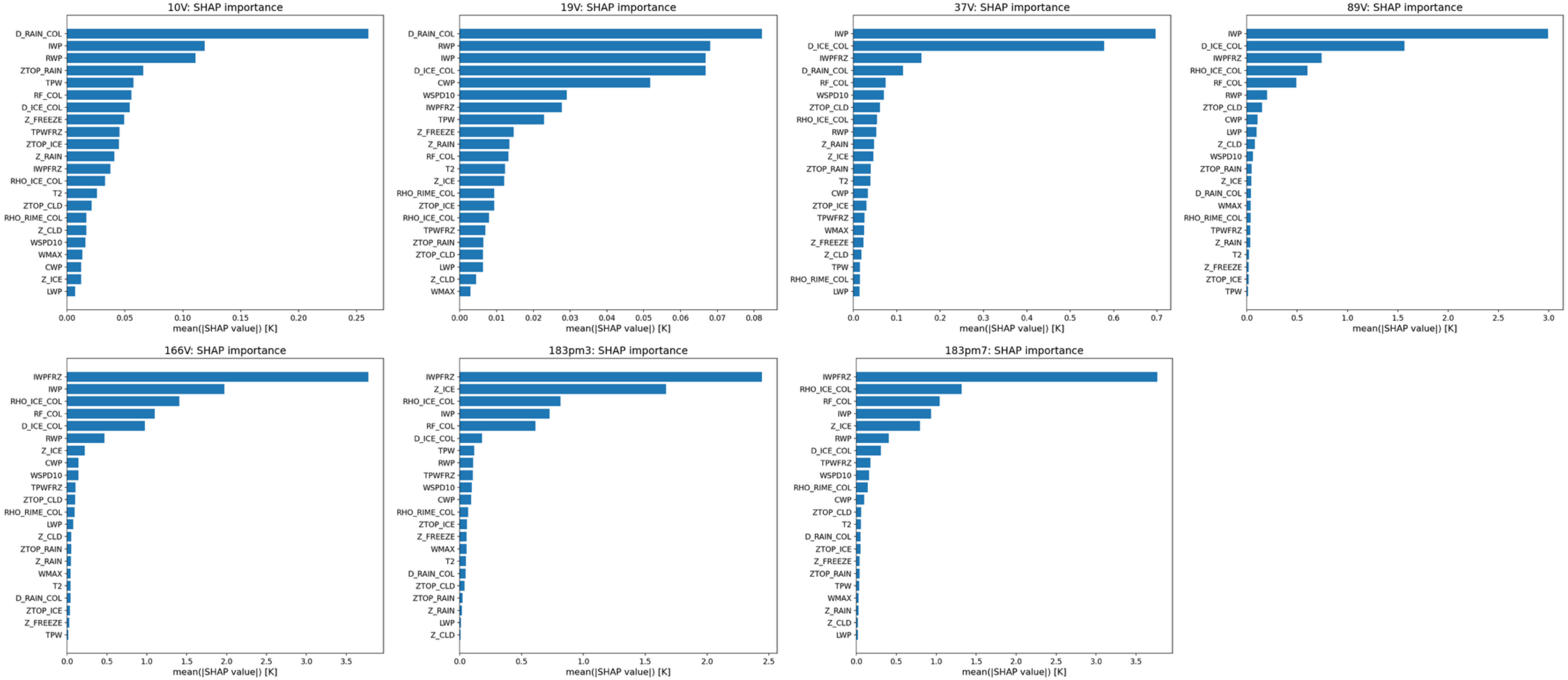
SHAP values



IWP, IWPFRZ are important drivers of TB variability

03. Finding drivers of TB variability

Mean SHAP values



DRAIN_COL (10 and 19 GHz), IWP (37 and 89 GHz), IWPFRZ (166 and 183 GHz), are primary drivers of TB variability