Investigating Vertical Precipitation Profiles Estimated from Passive Microwave Algorithms, Separated by Land Surface Conditions

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With acknowledgement to Ziad Haddad, Dave Marks, Pierre-Emmanuel Kirstetter, Sarah Ringerud and many others within the PMM Land Surface Working Group, and support from NASA-PMM

2019 PMM Science Team Meeting, 4-8 November 2019, Indianapolis

Overview of Presentation

- Even though some radiometer-based techniques provide an estimate of the condensed water vertical structure, nearly all validation studies to date examine only the "surface" precipitation rate.

- As concluded by a previous study[1] (Utsumi et al., 2019, JHM, see poster #213), the use of the vertical precipitation profile information can improve sub-hourly surface precipitation estimates.

- As highlighted in the recent NASA decadal survey, with emphasis on cloud-precipitation "processes", an improved depiction of the vertical structure is meaningful.

- Here, the **joint verification** of the vertical structure of the condensed water content and surface precipitation rate is examined for two radiometer algorithms, the GPROF V05 and the emissivity principal components (EPC) technique developed by the authors.

[1] Utsumi, N., H. Kim, F. J. Turk, and Ziad. S. Haddad, 2019: Improving Satellite-Based Subhourly Surface Rain Estimates Using Vertical Rain Profile Information. *J. Hydrometeor.*, **20**, 1015–1026

Background of the Emissivity Principal Components (EPC) Algorithm

- A main constraint on the interpretation of passive microwave TB is the "background" – the surface emissivity vector, or more generally, the joint surface and atmospheric moisture/temperature state.

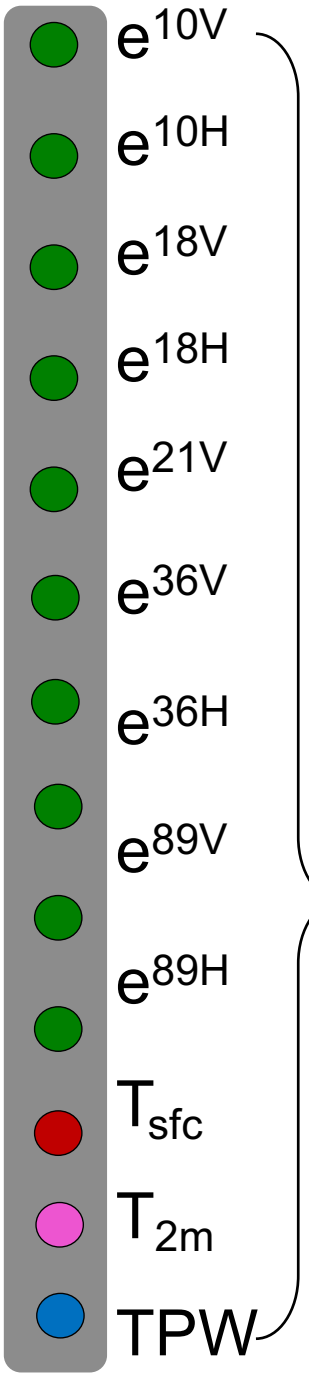
- Previous work[2] have demonstrated a Bayesian-based precipitation retrieval framework that is based on the principal components of the joint emissivity vector and the associated environmental state (emissivity principal components, or EPC).

- The EPC is used to index and guide the *a-priori* database searches, to isolate candidates that are most congruent to the observations.

[2] Turk, F. J., Z. S. Haddad, P.-E. Kirstetter, Y. You, and S. Ringerud, 2018: An observationally based method for stratifying a priori passive microwave observations in a Bayesian-based precipitation retrieval framework. Quarterly Journal of the Royal Meteorological Society, 144, 145–164

For GPM-GMI

- sfc class
- T_{sfc}
- T_{2m}
- TPW



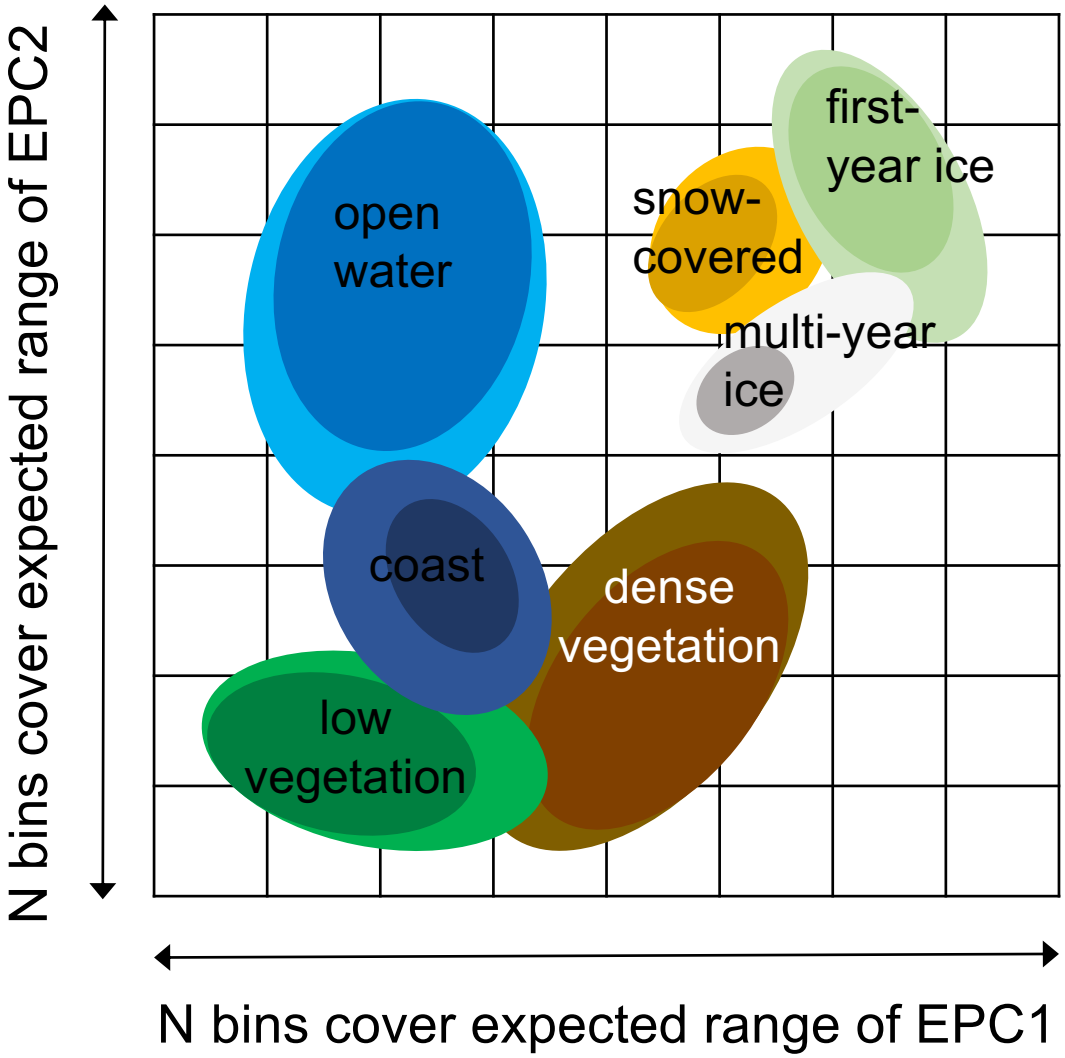
highly correlated

Principle

If we could obtain the emissivity vector at the observation time, this formulation would better accommodate **day-to-day (or shorter) changes** in the surface (land, ocean, mixed…) emissivity properties.

emissivity principal component analysis (EPC) → EPC1, EPC2, EPC3 → Used for indexing database

Surface, cloud, precipitation signatures in EPC space



(Note that EPC3 is not shown, this for illustrative and conceptual purposes only)

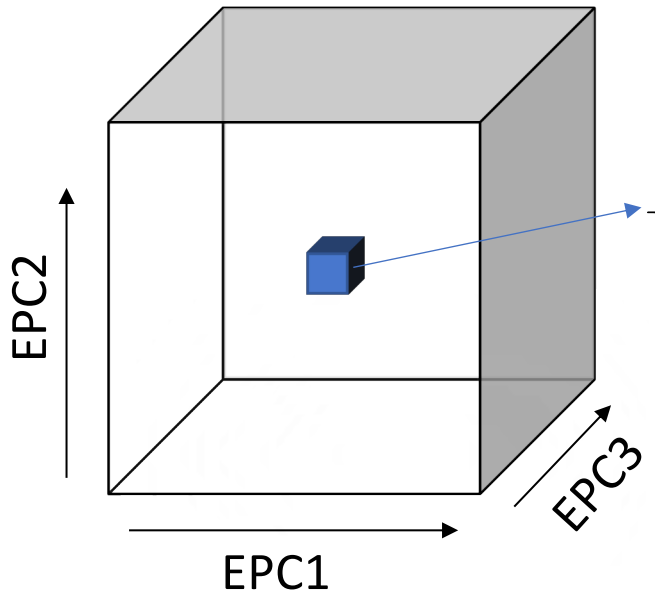
Different kinds of surfaces self-arrange into different areas of the EPC-binned database

While the clusters associated with typical surfaces are largely distinct, there is inherently some overlap

As increasing clouds/precipitation enters the scene, the EPC structure is gradually displaced from its ”no-cloud” clusters

a-Priori Database (DB) binned by EPC

A-Priori DB, indexed by EPC, was developed from DPR & each of the constellation of radiometer matching scenes.



- Surface precipitation rate DPRGMI Ku
- Condensed water content profile DPRGMI
- Storm top height Ku
- Precipitation type Ku

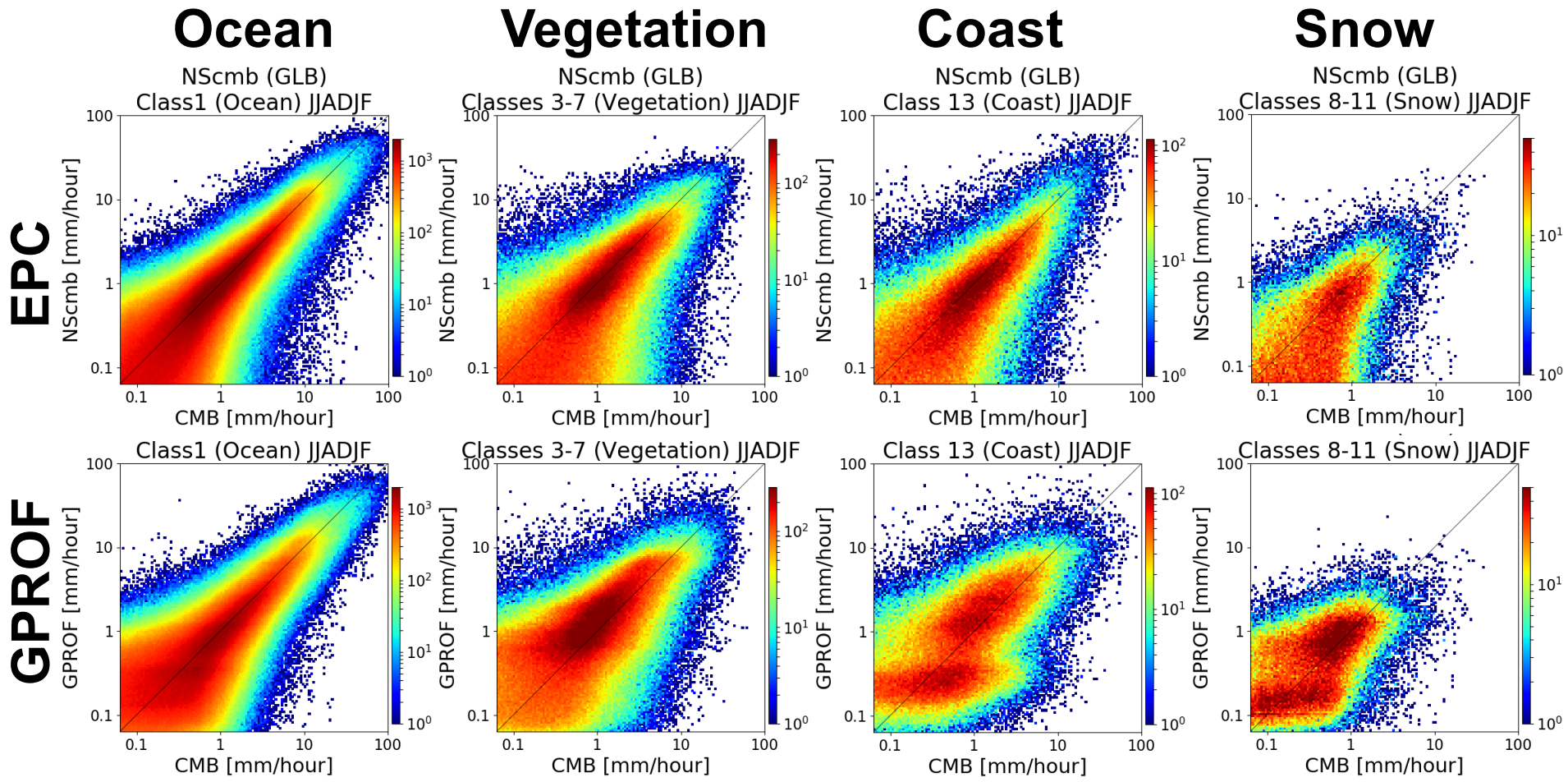
…. etc.

- EPC is calculated from TB at each observation time.

$$EPC = f(TB)$$ ← Predefined regression function relating TB combinations to each EPC

- Candidates that are most congruent to the observations are searched using EPC vector.

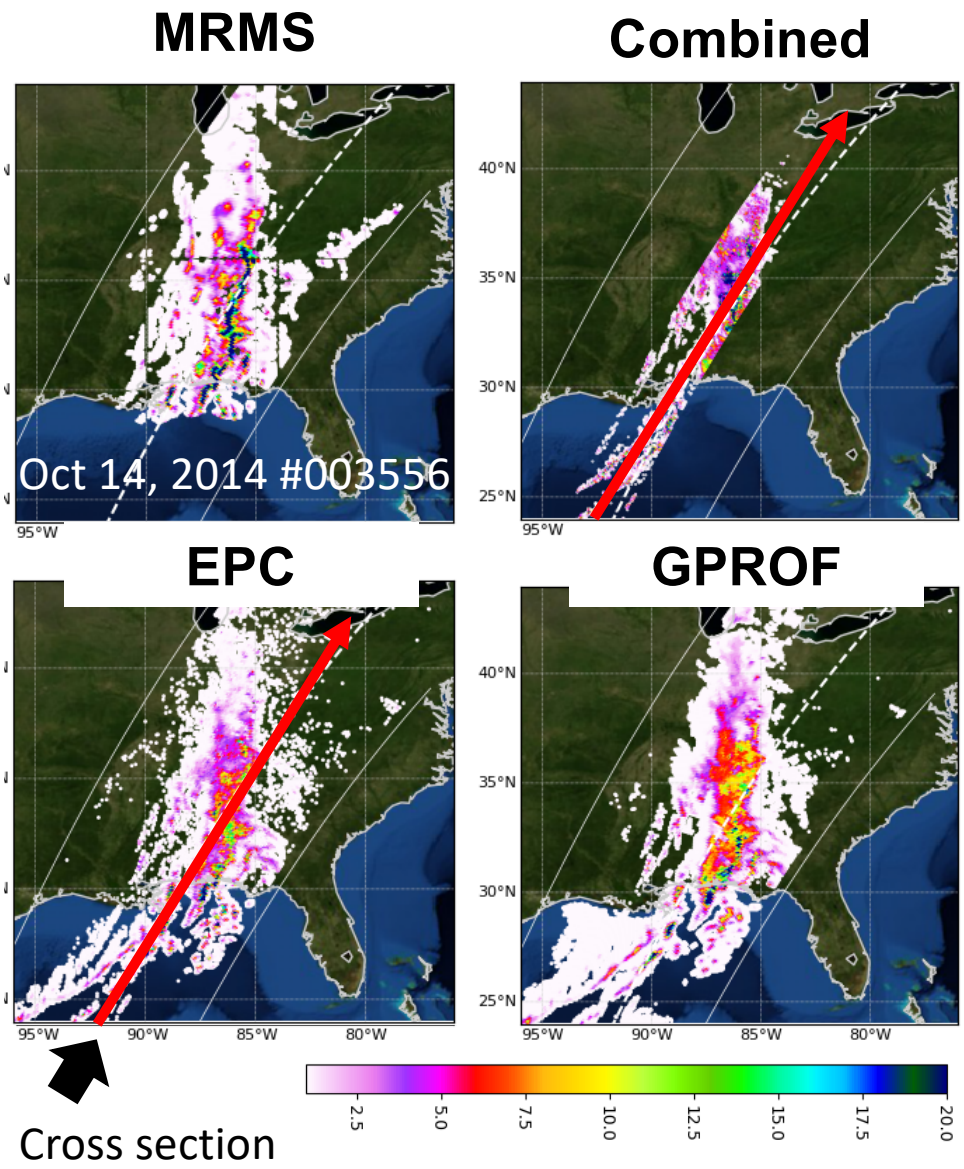
Overall performance (Relative to Combined algorithm) (JJA+DJF 2014)

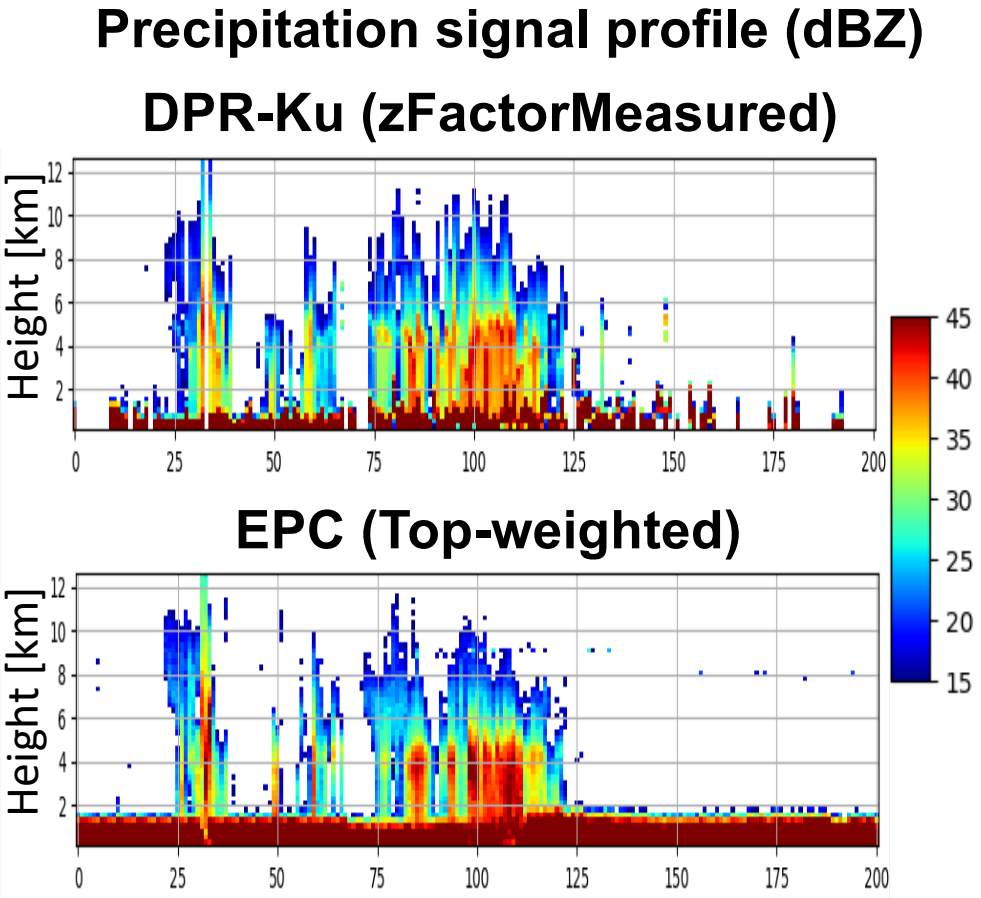


Surface precipitation is well estimated by PMW algorithms.

What about the precipitation profiles from PMW algorithms?

Frontal rain: Oct 14, 2014 #003556

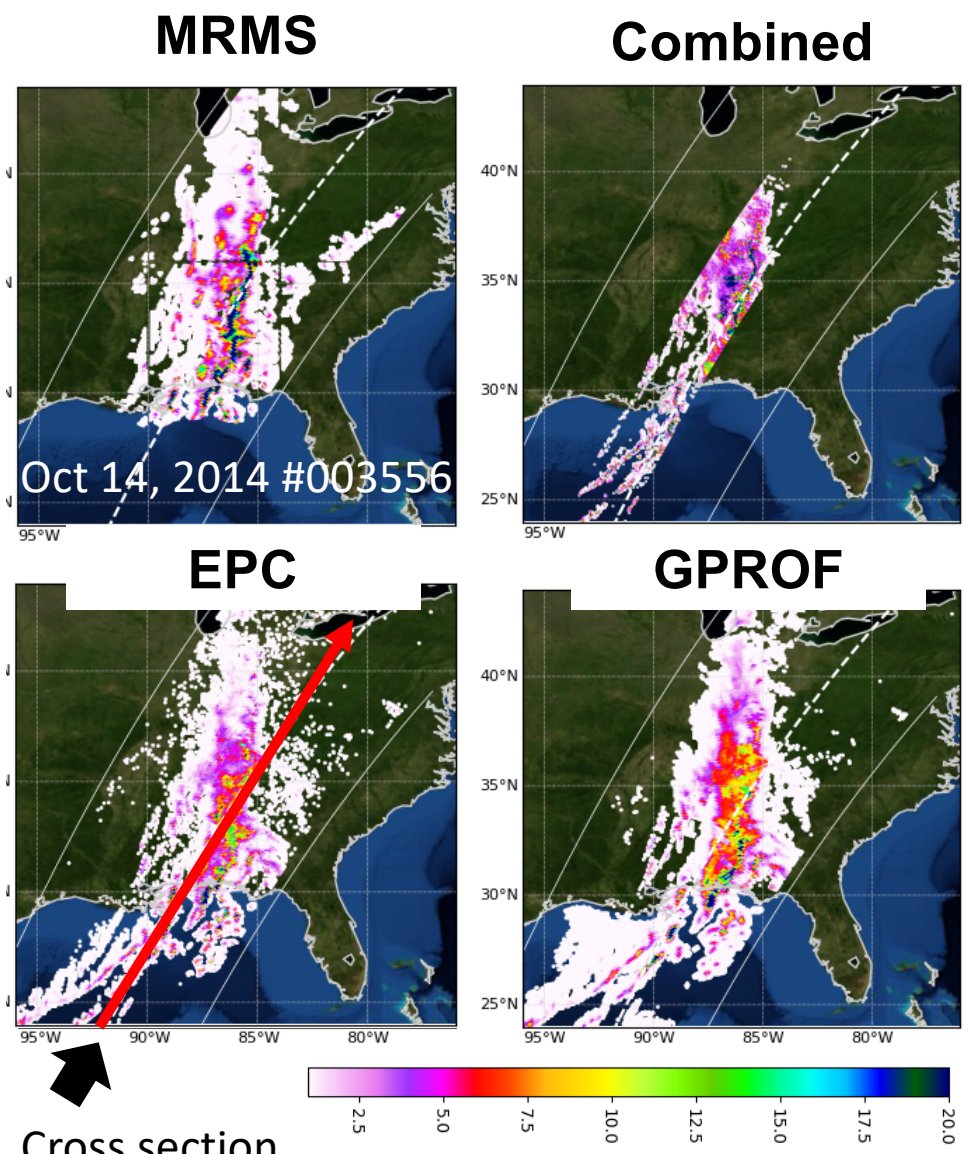




*Top-weighted:
Profile database entry that has the top-weight in Bayesian weighting

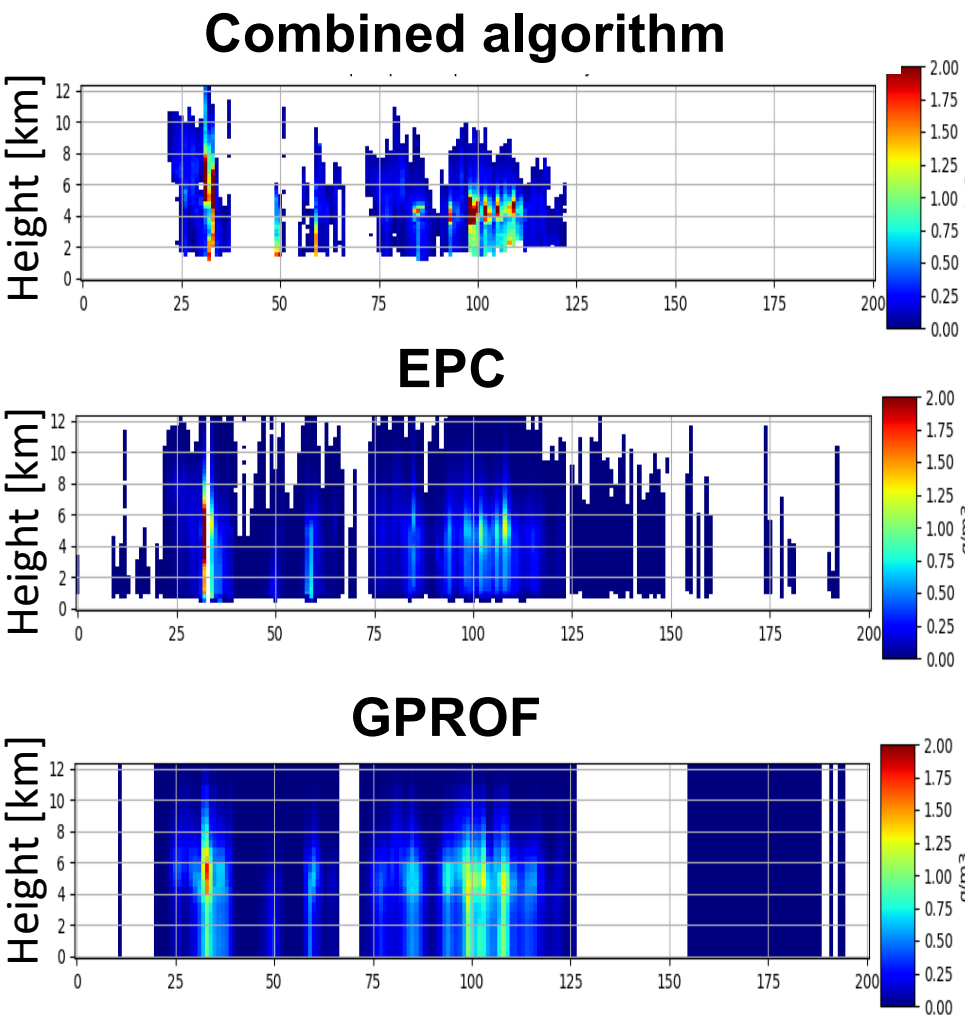
Precipitation profile signals are well captured by PMW algorithm

Frontal rain: Oct 14, 2014 #003556



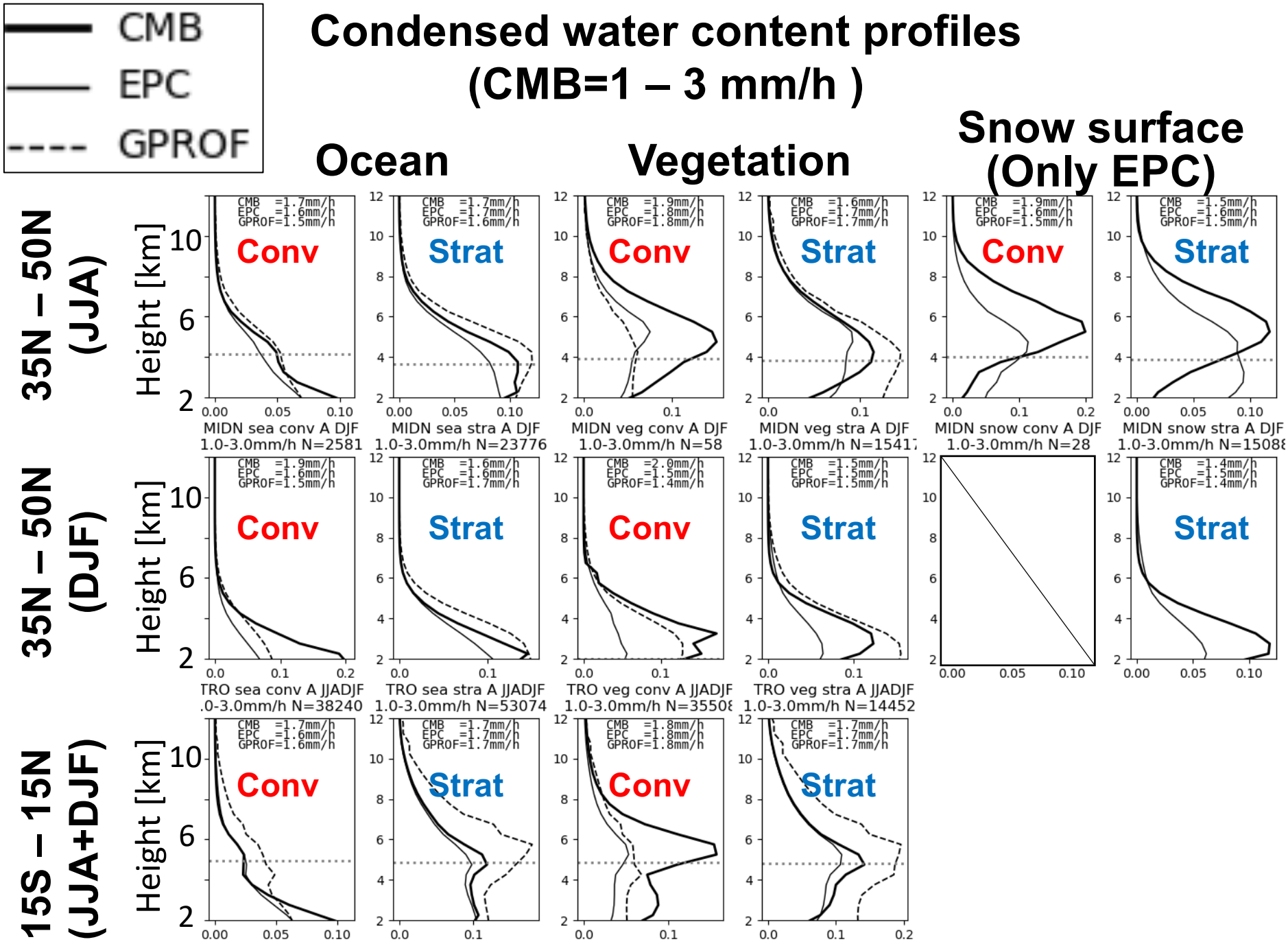
Cross section

Condensed water content profile (g/m3)



Precipitation water content profiles are also estimated by PMW (with bias).

Condensed water content profiles (CMB=1 – 3 mm/h)



Condensed water content profiles (CMB=1 – 3 mm/h)

CMB
EPC
GPROF

Ocean

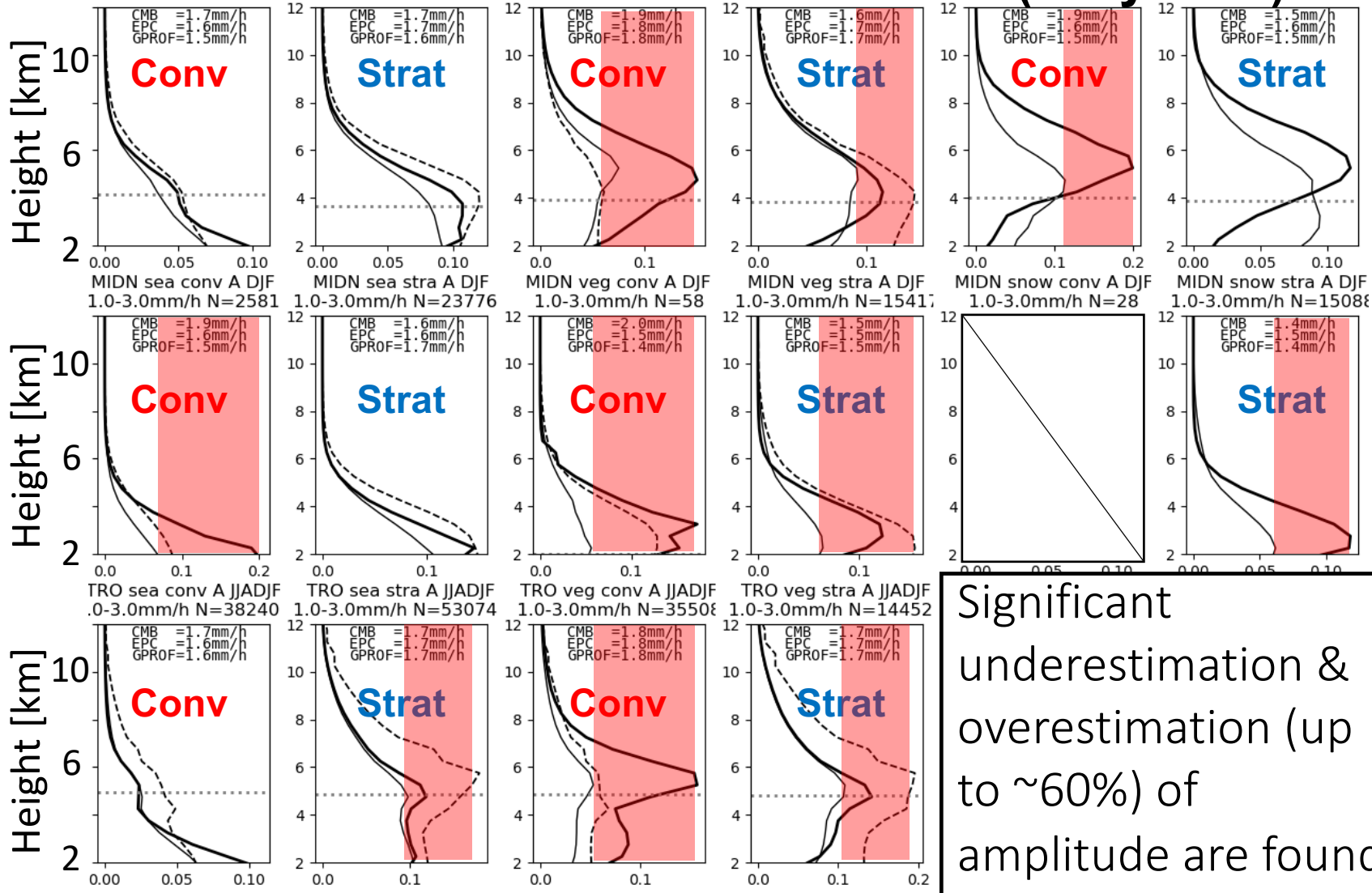
Vegetation

Snow surface (Only EPC)

35N – 50N (JJA)

35N – 50N (DJF)

15S – 15N (JJA+DJF)



Significant underestimation & overestimation (up to ~60%) of amplitude are found (vegetation & snow)

Condensed water content profiles (CMB=1 – 3 mm/h)

Ocean

Vegetation

Snow surface (Only EPC)

35N – 50N (JJA)

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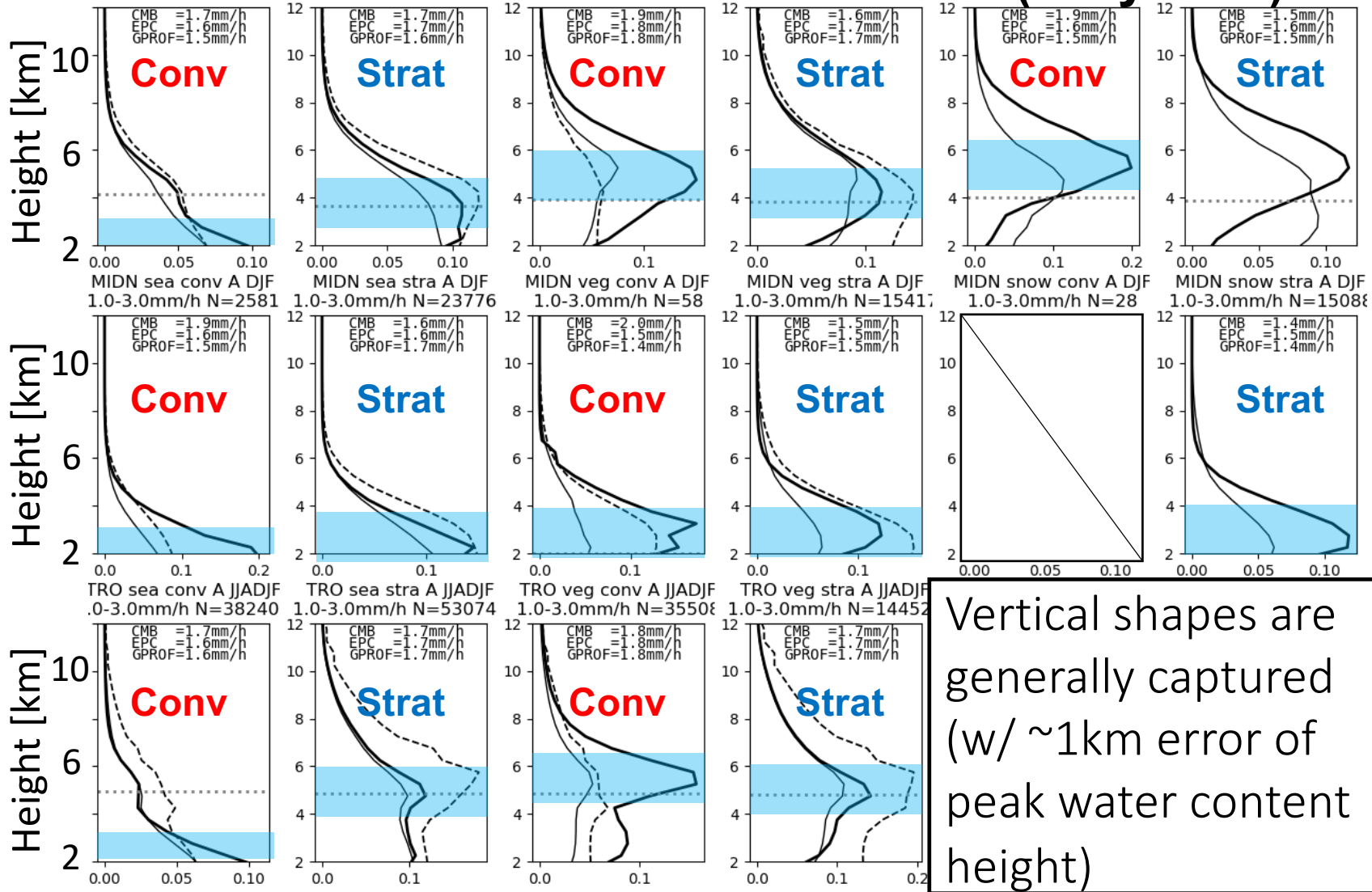
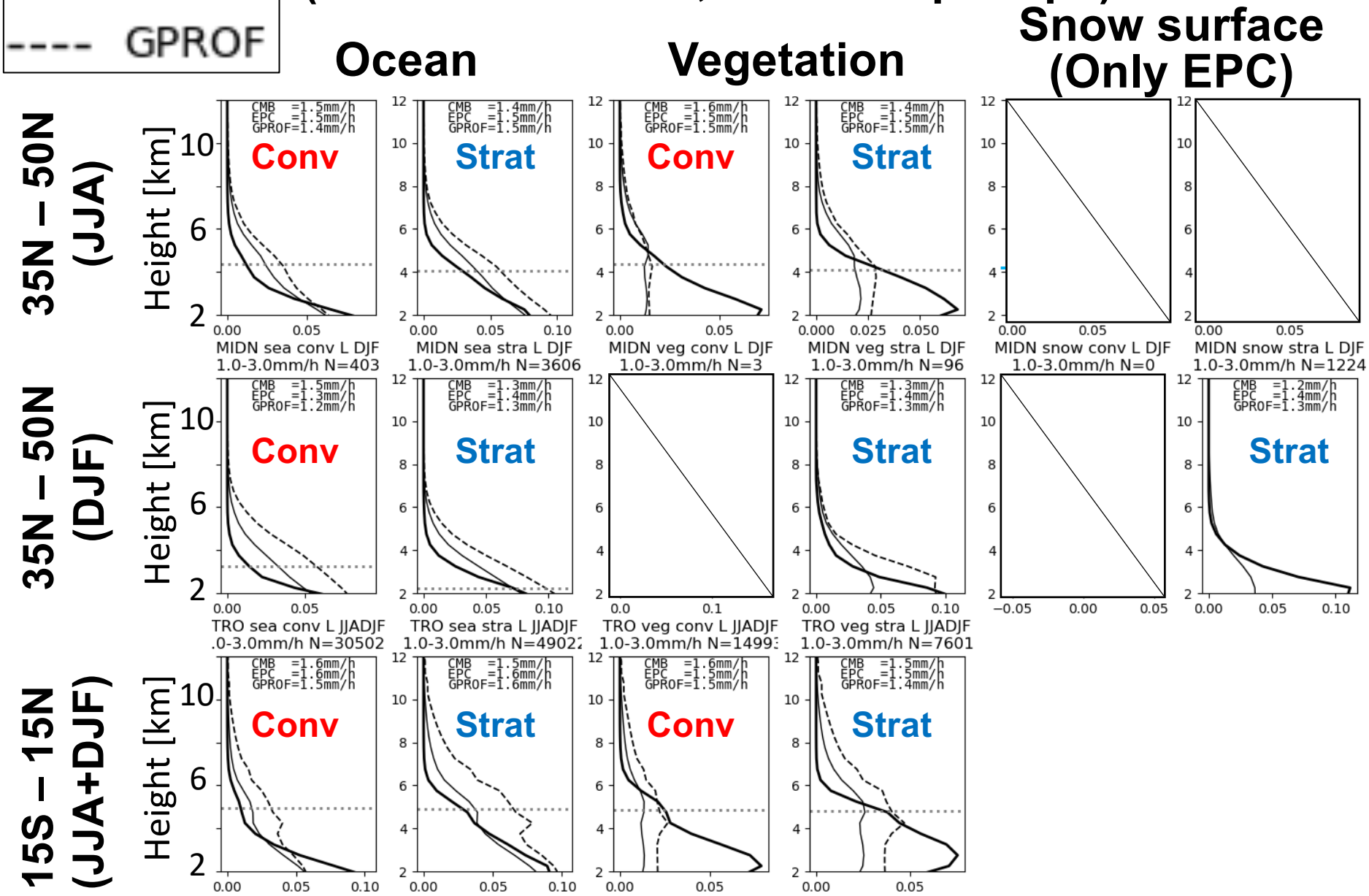


Vertical shapes are generally captured (w/ ~1km error of peak water content height)

CMB
EPC
GPROF

Condensed water content profiles (CMB=1 – 3 mm/h, Shallow* precip.)

* Storm top (Ku)
< Freezing level



CMB
EPC
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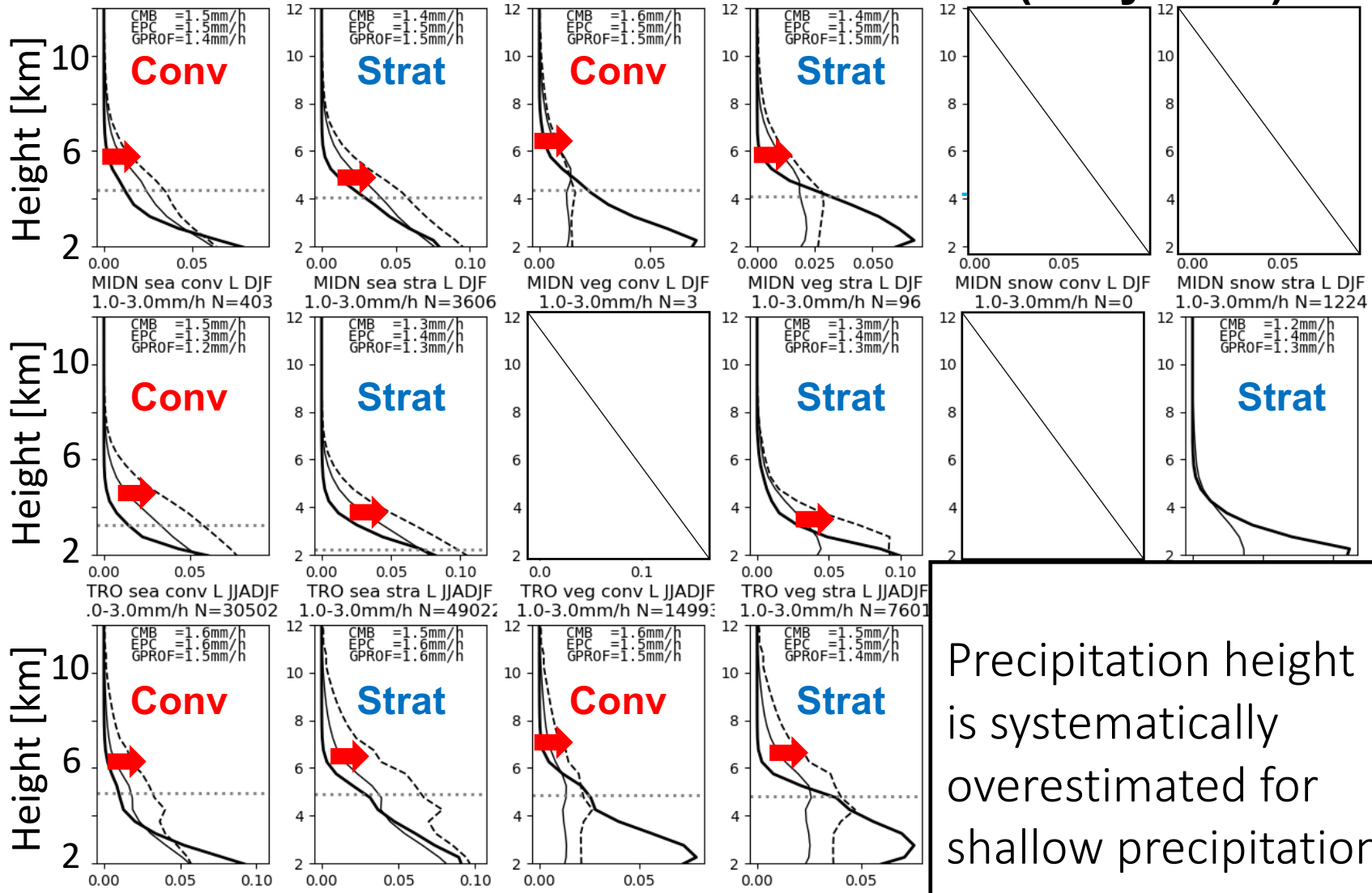
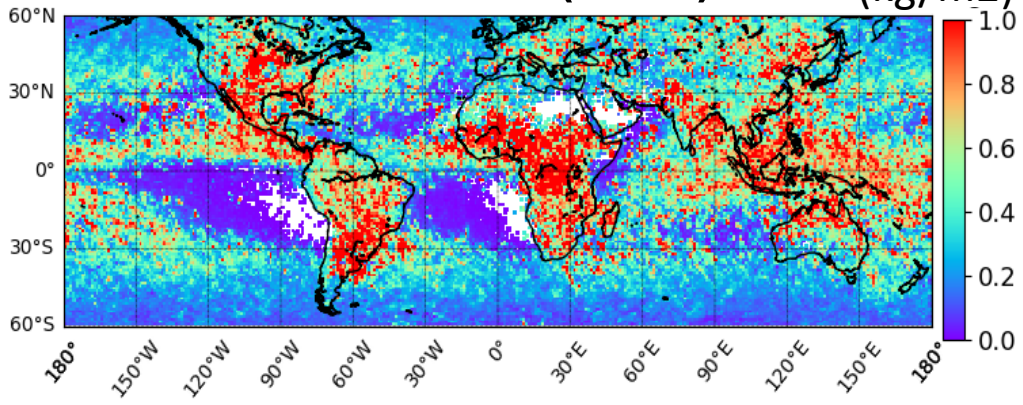


Precipitation height is systematically overestimated for shallow precipitation

Total condensed water content (kg/m2) (>2km)

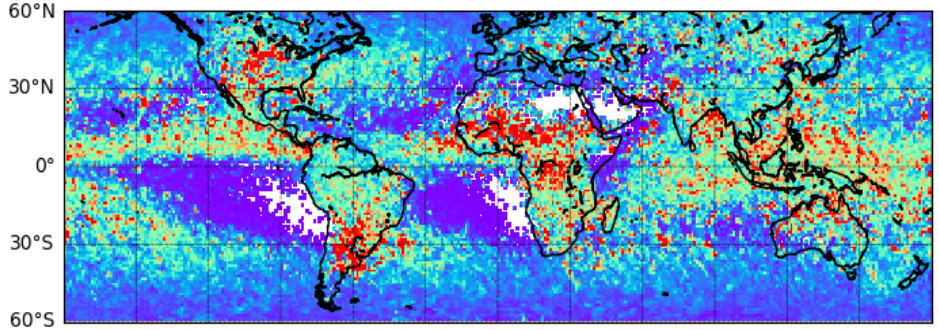
Combined (CMB) (kg/m2) (JJA+DJF, surface >0.5mm/h)



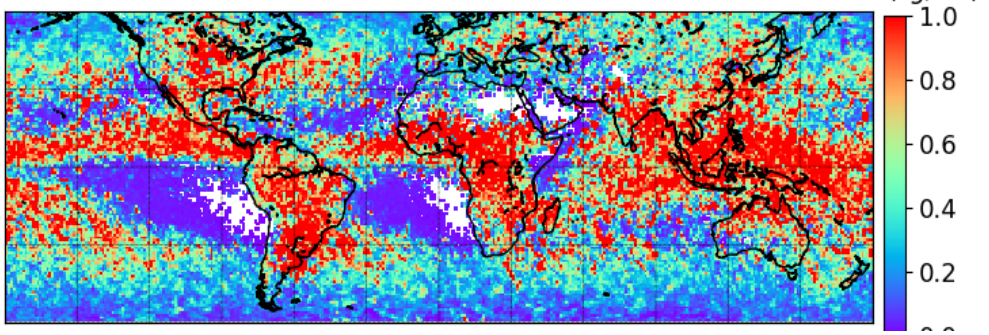
EPC
Underestimation (land)

GPROF
Overestimation (ocean)

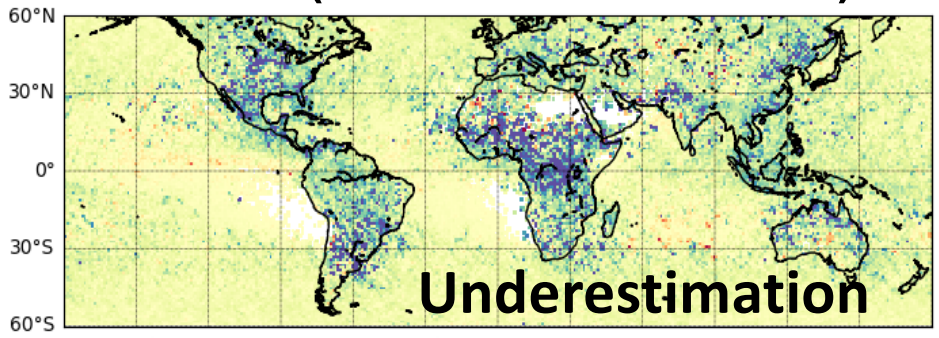
EPC



GPROF (kg/m2)

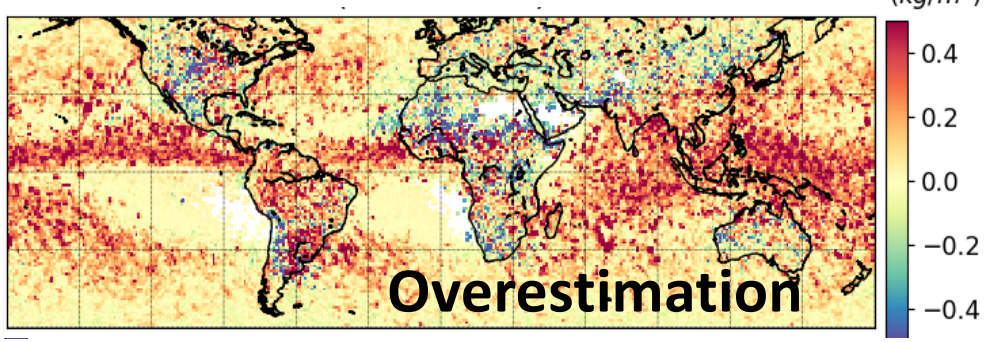


EPC (bias relative to CMB)



(Over land)

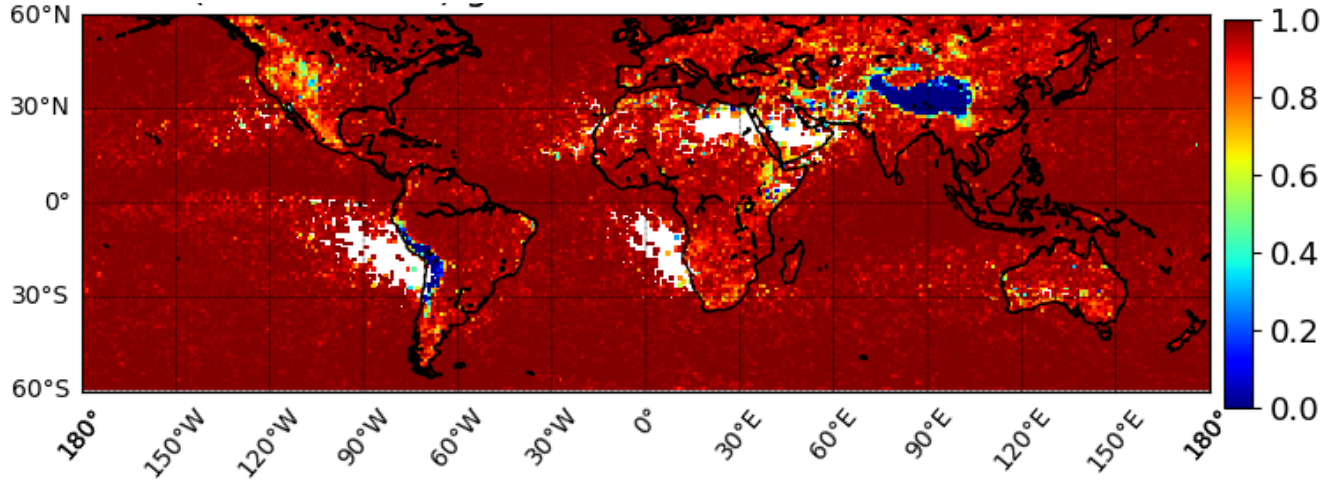
GPROF (bias relative to CMB) (kg/m2)



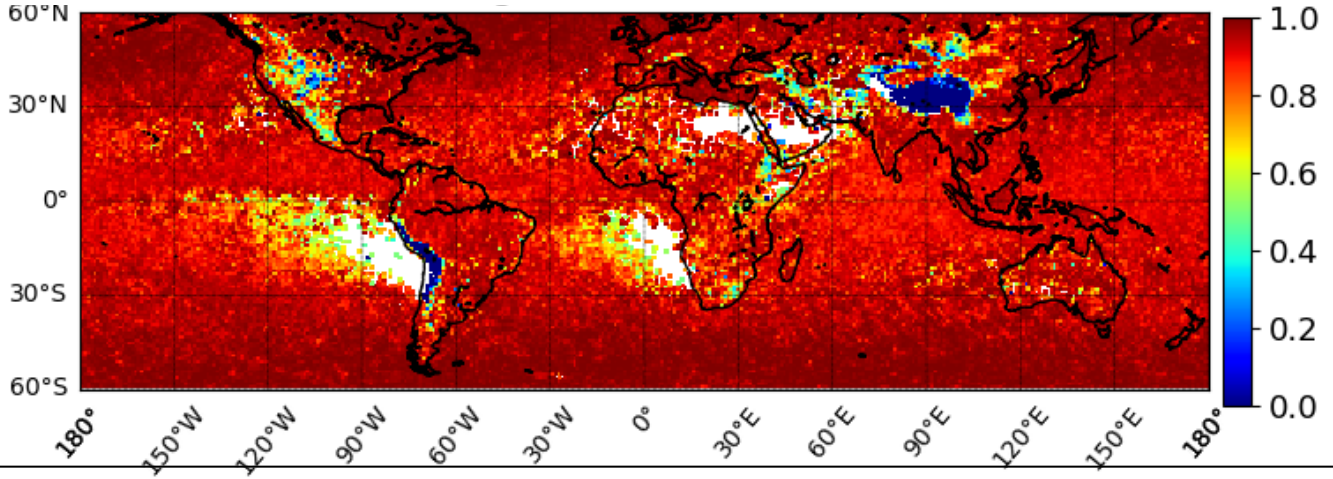
(Over ocean)

Profile shape correlation coefficient (relative to combined algorithm)

EPC



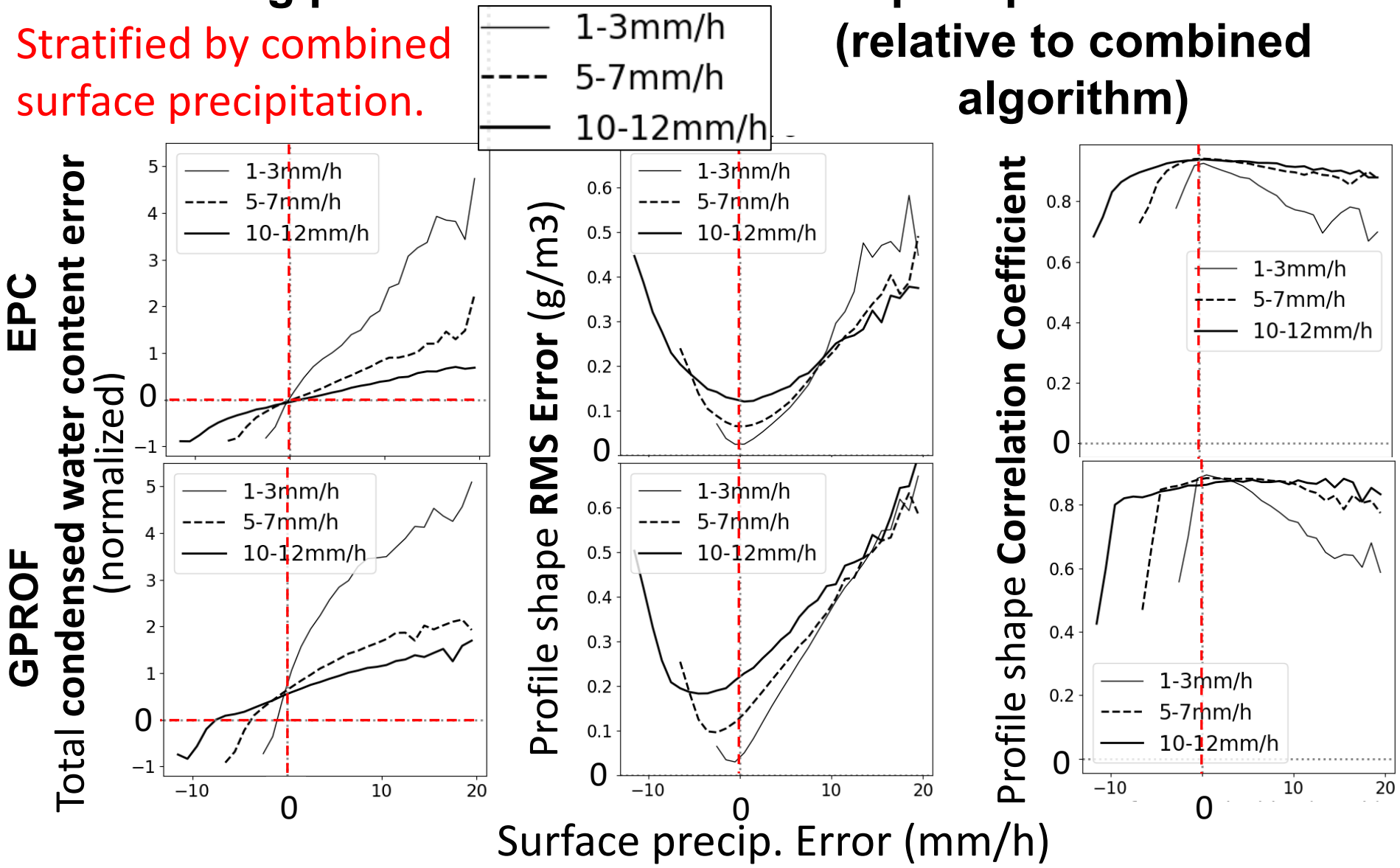
GPROF



Although there are bias for profile amplitude, the shapes of the profiles are well captured by PMW algorithms.

Profiling performance and surface precipitation error (relative to combined algorithm)

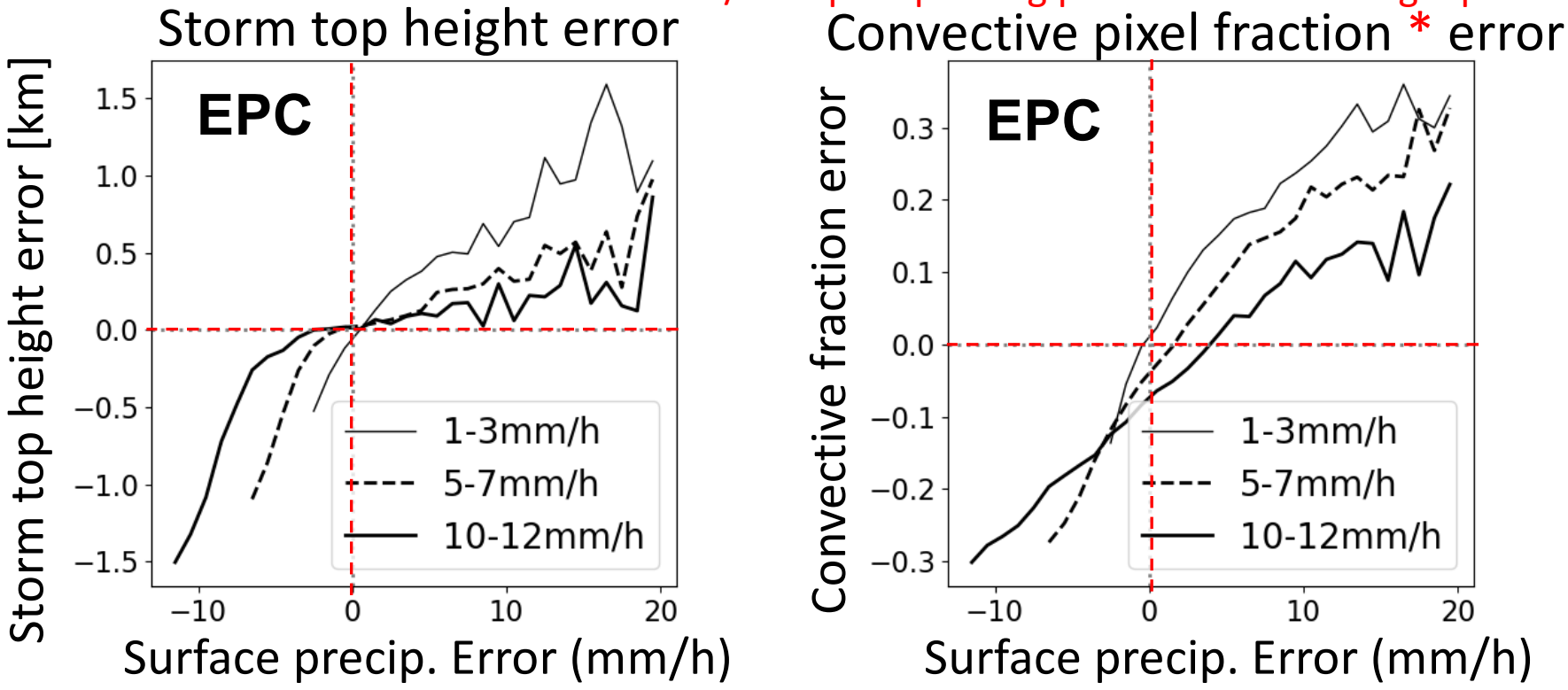
Stratified by combined surface precipitation.



The error in the estimation of the surface precipitation rate and its corresponding profile are strongly related

Profiling performance and surface precipitation error

* # of conv / # of precipitating pixels in surrounding 9 pixels



- Errors in storm top height & convective fraction are strongly correlated with errors in surface precipitation.
- This suggests that if these or related parameters could be successfully constrained in the algorithm, it would reduce the error in the surface precipitation estimates. (consistent with previous studies; e.g., Petković et al., 2018)

Summary

Background questions

- How well do PMW algorithms represent vertical structures of precipitation?
- Is there a connection between the performances for surface precipitation estimates and vertical structure estimates?

- PMW algorithms can represent average shapes of precipitation profiles.

- But there are some biases for the condensed water content by current implementation of the algorithms.
  - There are significant bias for the amplitude (up to ~60%, underestimation & overestimation) over vegetation & snow surfaces.
  - Precipitation height for shallow precipitation is systematically overestimated by PMW algorithms

- Error in surface precipitation rate is strongly related to:
  - the error in its profile
  - the error in storm top height and convective pixel fraction.

Suggestions and future work

- The strong correlations between surface precipitation error and storm top height & convective fraction errors suggest a proper constraint on these parameters in the algorithms would improve surface precipitation estimates.

- This study assumes the combined algorithm as a reference. Future work will include dense ground-based radar coverage (e.g., MRMS over SE. United States).

- Further investigation for cold season and snow profile using collection of FMI C-band radar data.

- This study was only for GPM-GMI. Similar validation of other constellation radiometers products is in progress.

Backup slides

Precipitation water content profiles (CMB=8 – 12 mm/h)

Ocean

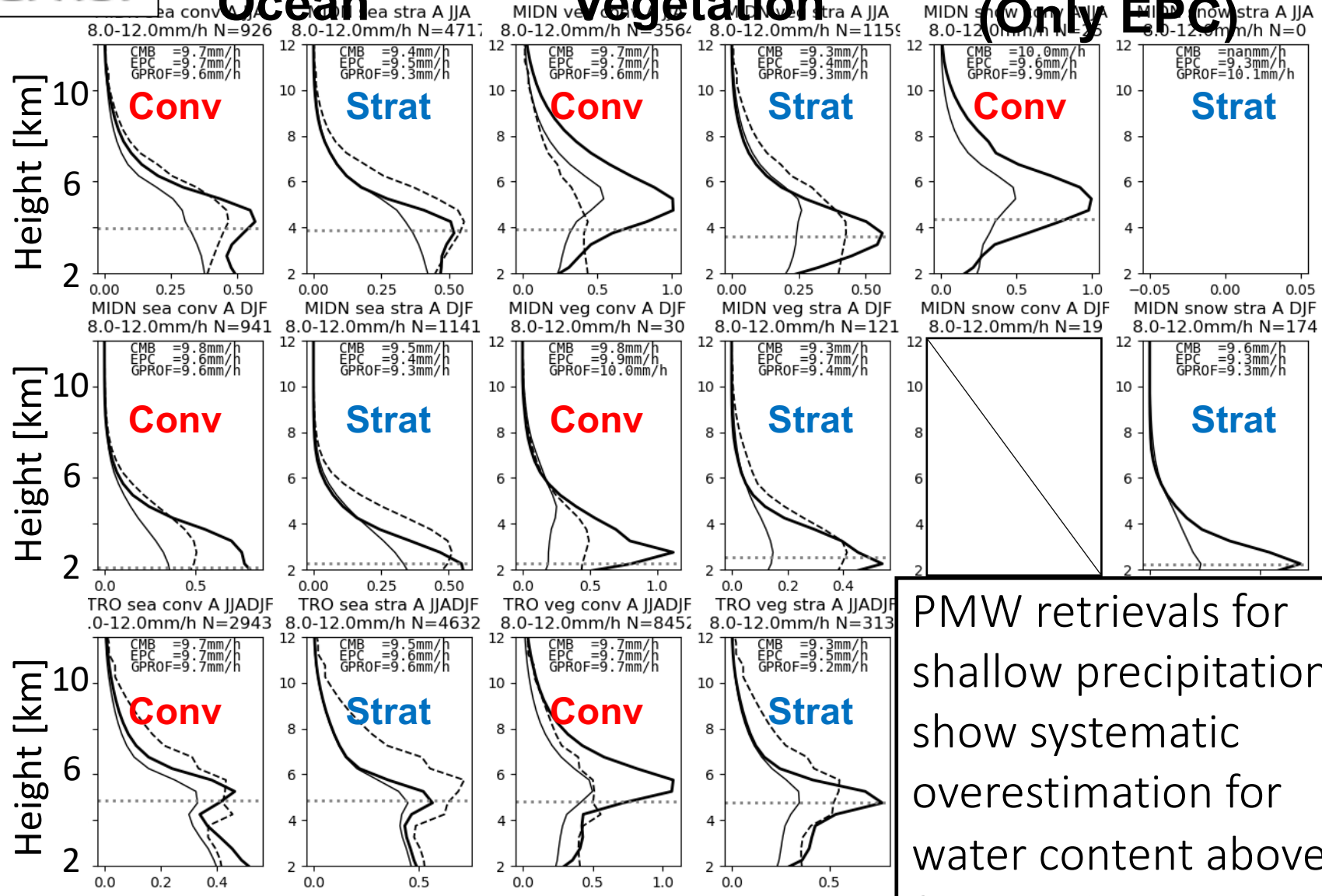
Vegetation

Snow surface (Only EPC)

35N – 50N (JJA)

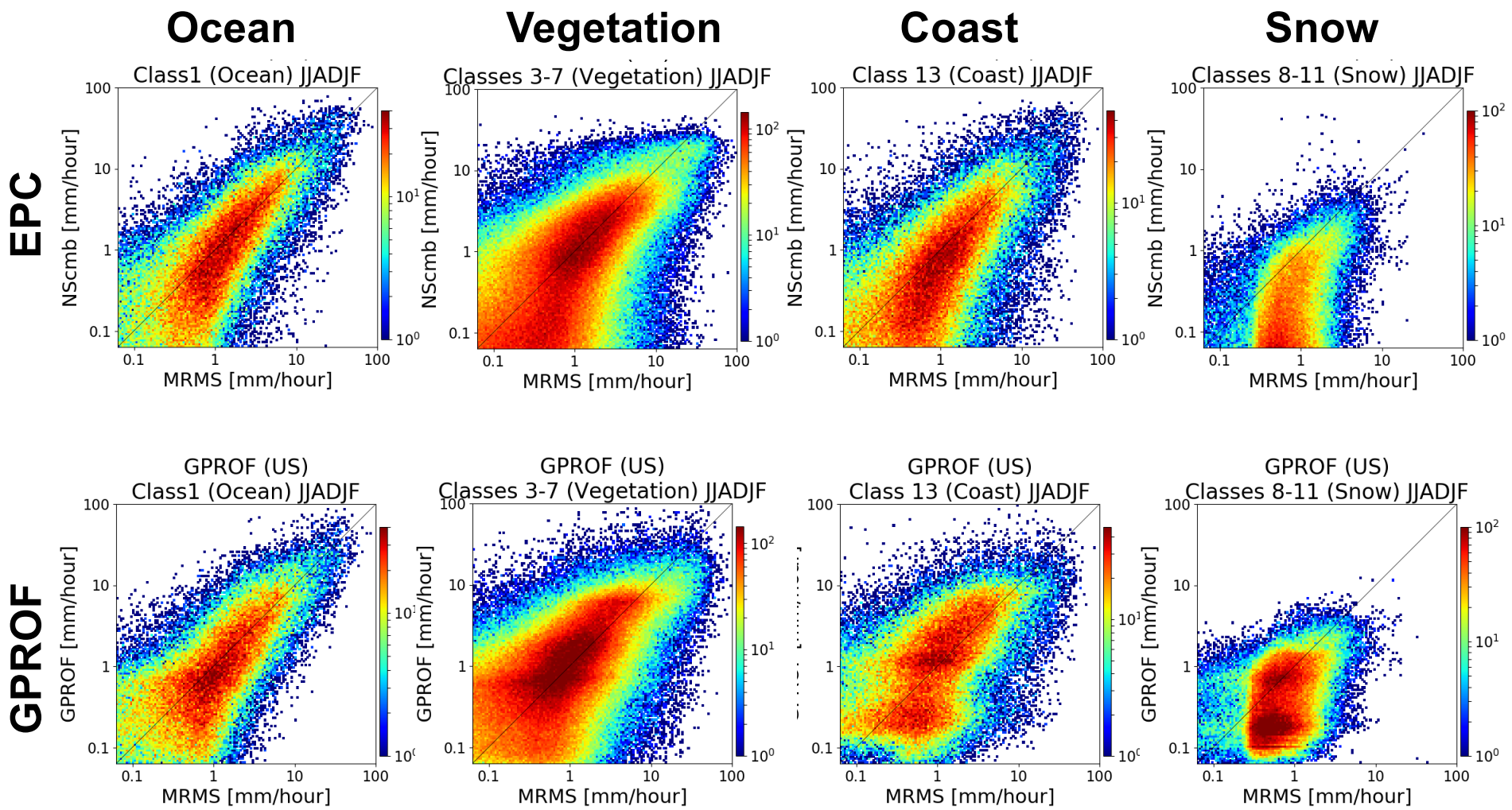
35N – 50N (DJF)

15S – 15N (JJA+DJF)



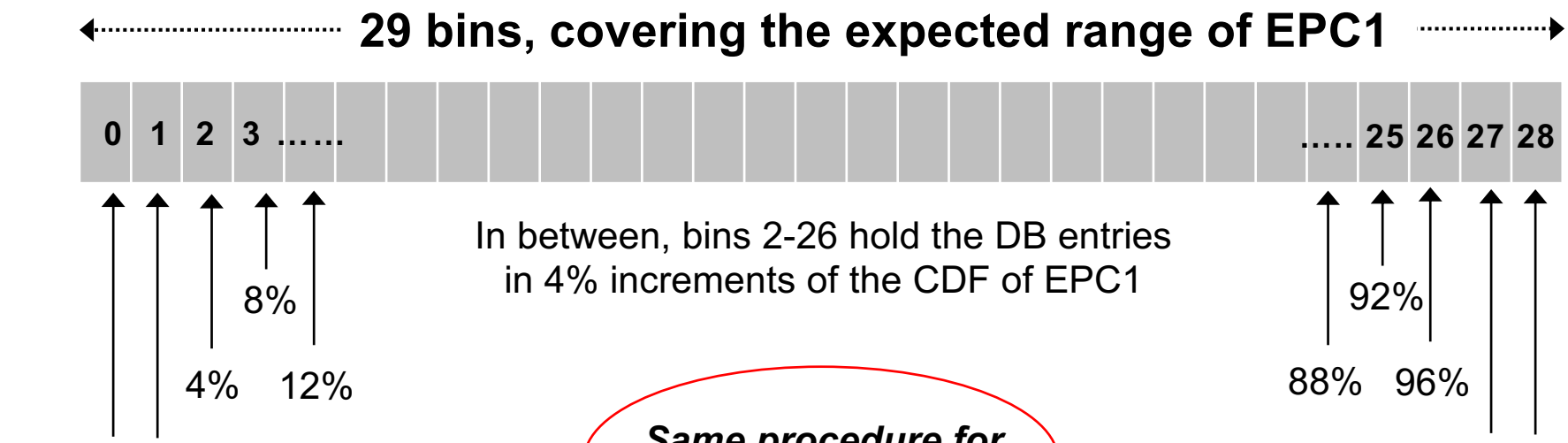
PMW retrievals for shallow precipitation show systematic overestimation for water content above freezing level

Overall Performance (Relative to MRMS) (JJA+DJF 2017)



MRMS surface precipitation rate [mm/hour]

Binning the a-Priori Database (DB)



In between, bins 2-26 hold the DB entries in 4% increments of the CDF of EPC1

Bins 0 and 1 hold the DB entries when the CDF of EPC1 reaches the 0.001% and 0.1% level

Same procedure for EPC2 and EPC3

Bin 27 and 28 hold the DB entries when the CDF of EPC1 reaches the 99.9% and 99.999% level

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Example: For a given TB, its EPC1, EPC2 and EPC3 fall into bins 10, 8, and 25.

DB index= $(29)^2\ EPC_1 + (29)^1\ EPC_2 + (29)^0\ EPC_3$
= $(29)^2\ 10 + (29)^1\ 8 + (29)^0\ 25 =$ **8667**

The DB index ranges from 0 to $(29)^3$-1

This is important for two reasons (next slide)

Binning the a-Priori Dataset

The database is sparsely populated in some of the 3-D areas.

Example: An observed TB falls in DB index 10000, but there are only 20 entries (insufficient). The database search can be expanded outward (9999, 10001, 9998, 10002, etc.) until a sufficient number of DB entries are reached.

Since this changes the smaller EPC3 bin (EPC2 if needed), *the database expansion search moves smoothly through the joint variability in surface emissivity and environmental conditions*.

The extreme cold 89 GHz TB (corresponding to the extreme precipitation observations) tend to cluster in the first (0, 1) or last (27, 28) EPC bins.

Using logarithmic bin spacing at the end bins isolates the extreme precipitation events. When the EPC computed from an observed TB falls in one of these bins, it gets associated with more extreme precipitation (ie, *fewer non-extreme events are included in the Bayesian weighting*).

Nomenclature

CMB-NS: EPC-based estimate, where the combined (CMB) radar-radiometer algorithm (CORRA) Ku-band normal scan (NS) retrievals are weighted by distance in EPC space

DPR-NS: EPC-based estimate, where the radar-only (DPR) Ku-band normal scan (NS) retrievals are weighted by distance in EPC space

CMB-MS: Same as CMB-NS but using the (CORRA) Ku+Ka-band matched scan (MS) retrievals

DPR-MS: Same as DPR-NS, but using the radar-only (DPR) Ku+Ka-band band matched scan (MS) retrievals

Precipitation content profiles (CMB=8 – 12 mm/h, Shallow* precip.)

* Storm top (Ku) < Freezing level

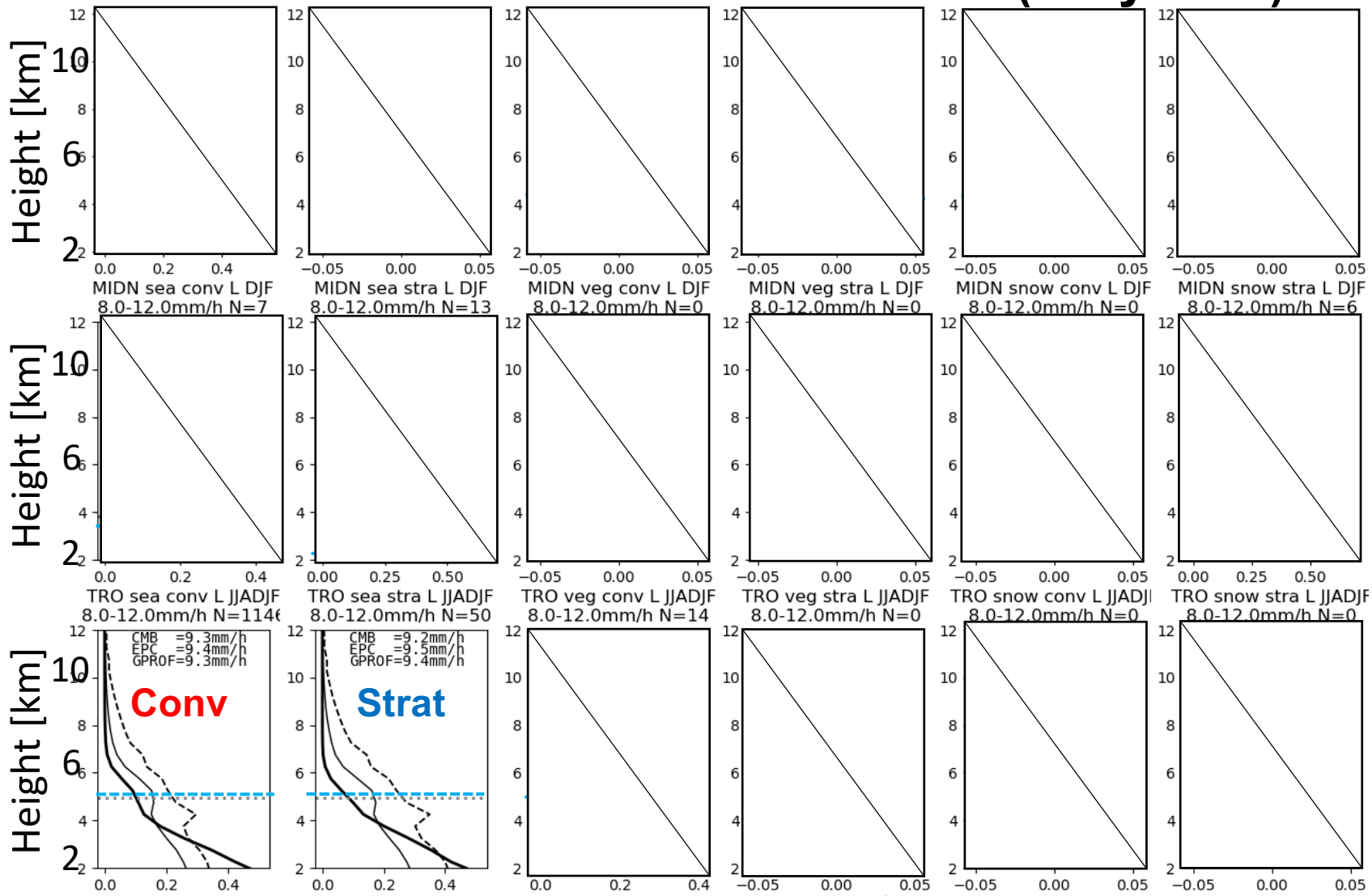
CMB
EPC
GPROF

Ocean | Vegetation | Snow surface (Only EPC)

35N – 50N (JJA)

35N – 50N (DJF)

15S – 15N (JJA+DJF)



Condensed water content (g/m3)

Precipitation content profiles (CMB=8 – 12 mm/h, Tall* precip.)

* Storm top (Ku) > Freezing level

CMB
EPC
GPROF

Ocean

Vegetation

Snow surface (Only EPC)

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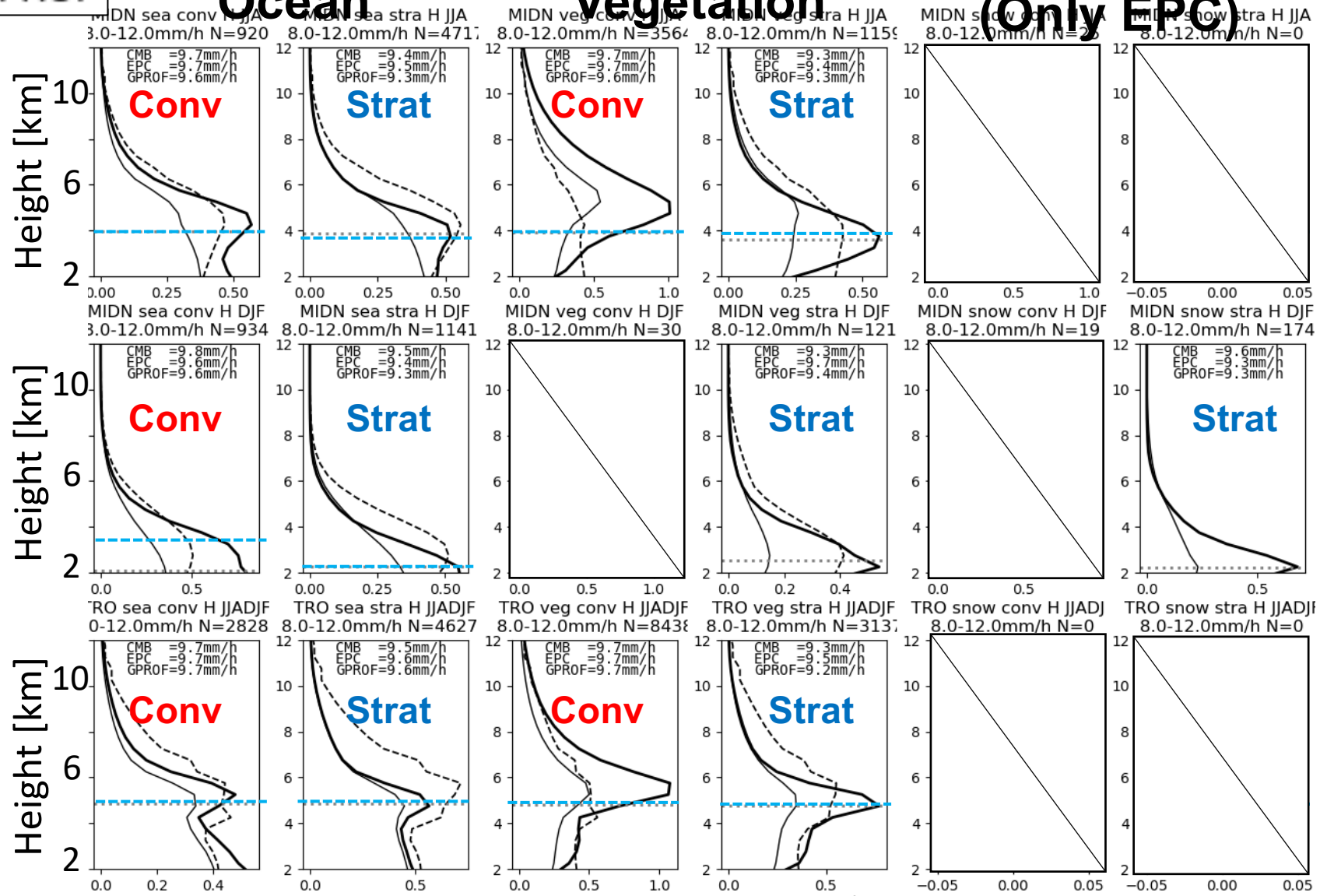
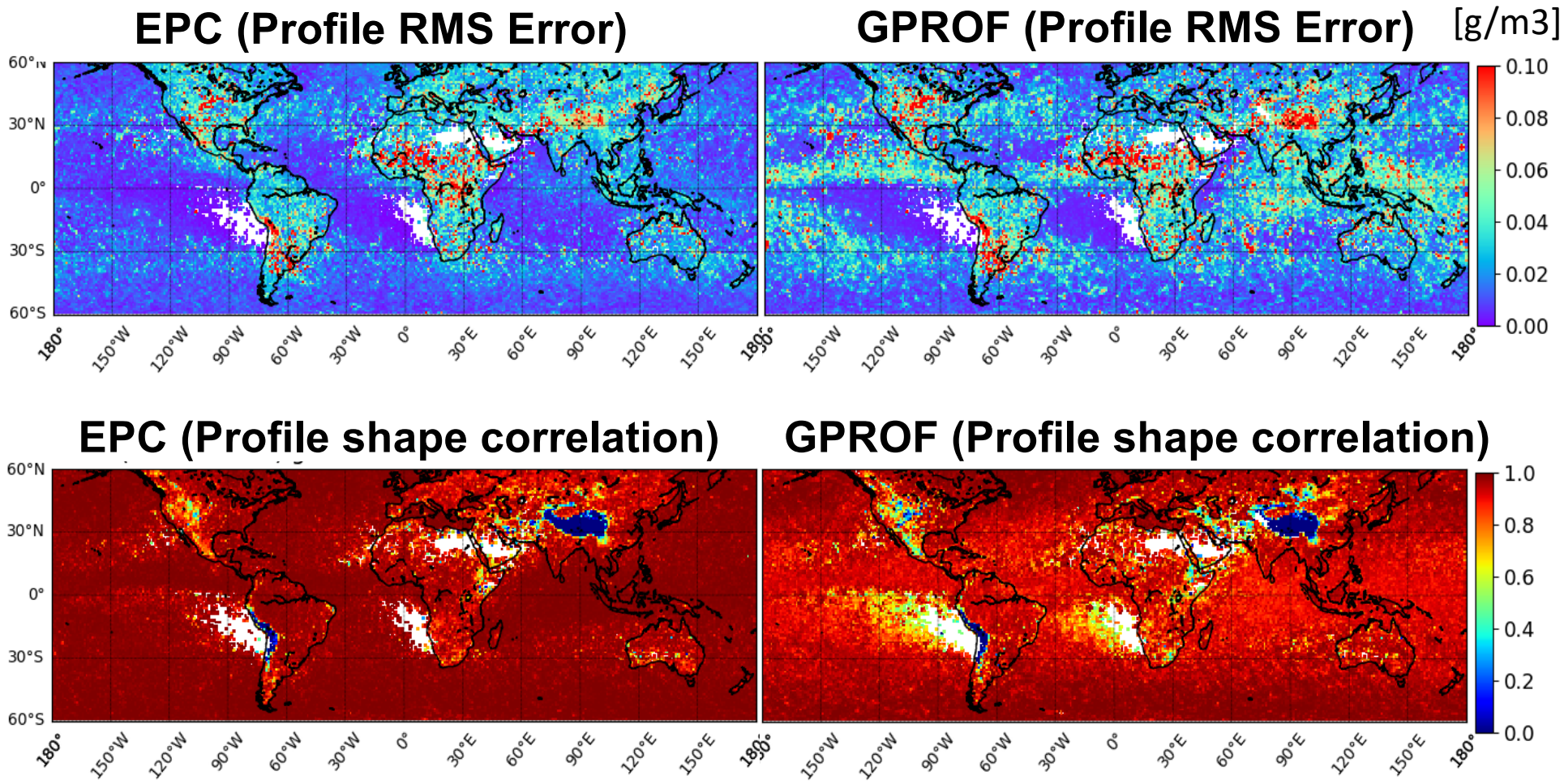
35N – 50N (DJF)

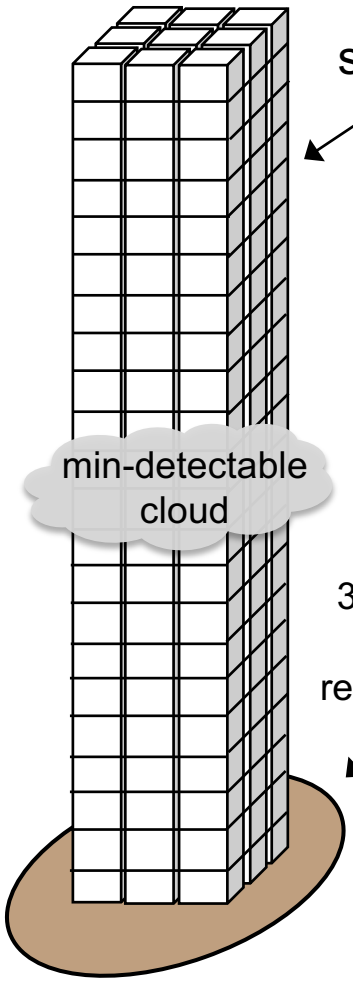
15S – 15N (JJA+DJF)



Profiling performances (relative to combined algorithm)



* Performances are estimated for average profile at each pixel



Z(Ku-NS) < 15 dB and
Z(Ka-MS) < 15 dB and
Z(Ka-HS) < 15 dB
(all bins)

➔ **"no cloud"**

+ MERRA2 interpolation

Compute 10-89 GHz emissivities

PC analysis

Calculate regression coefficients relating nonlinear TB combinations to each EPC*

$$EPC = f(TB)$$

One-time process

End result is a transformation between TB and EPC space

Has been done for other MW sensors with DPR coincidences (see poster)

*Turk, F.J., Haddad, Z.S. & You, Y., 2016, Estimating Non-Raining Surface Parameters to Assist GPM Constellation Radiometer Precipitation Algorithms, *J. Atmos. Oceanic Technol.*, 33(2016), pp. 1333-1353.

Surface precipitation error and profiling performance

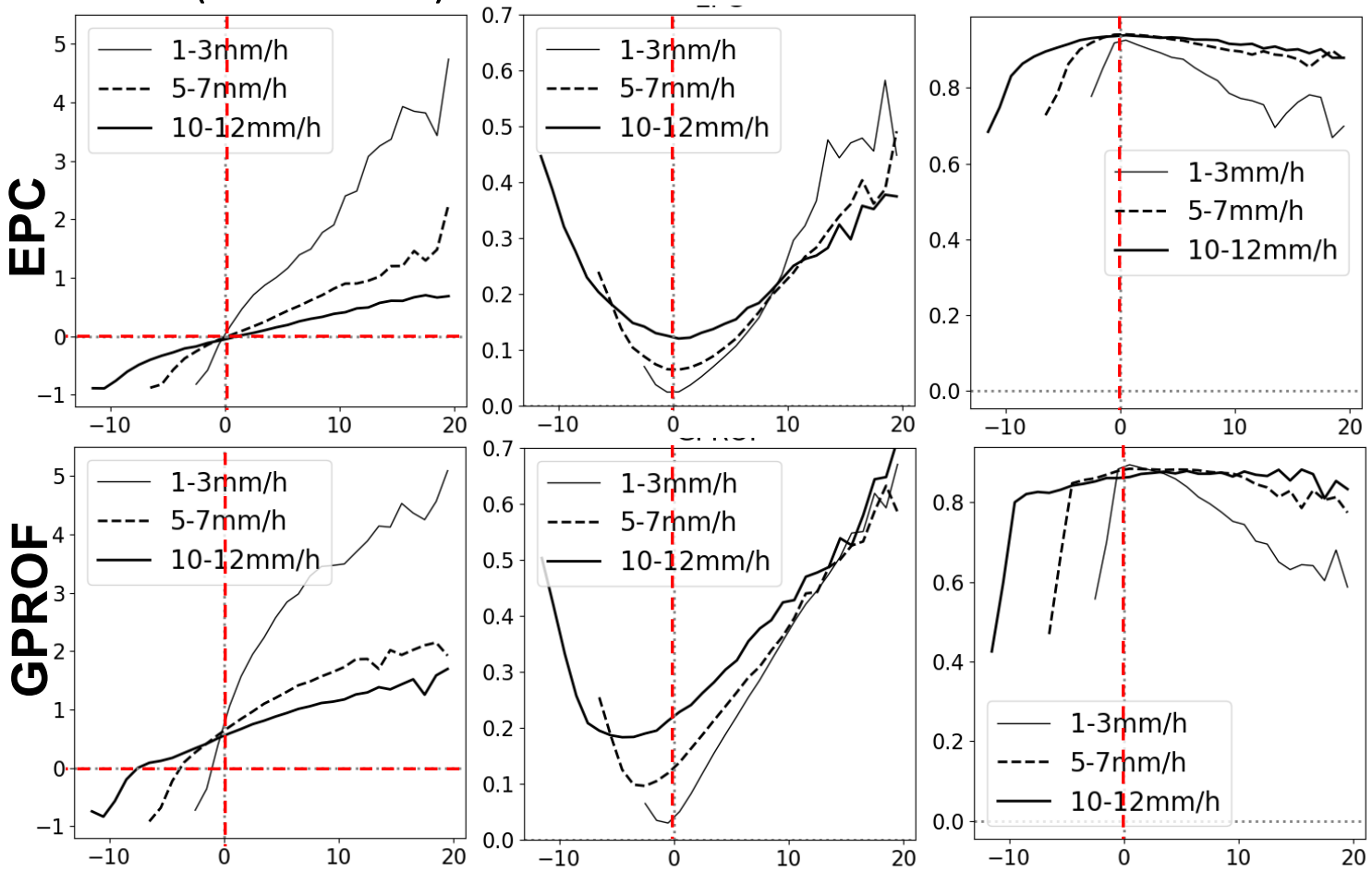
Stratified by DPRGMI surface precipitation.

1-3mm/h
5-7mm/h
10-12mm/h

Total **condensed water error** (normalized)

Profile shape **RMS Error** (g/m3)

Profile shape **Correlation Coefficient**



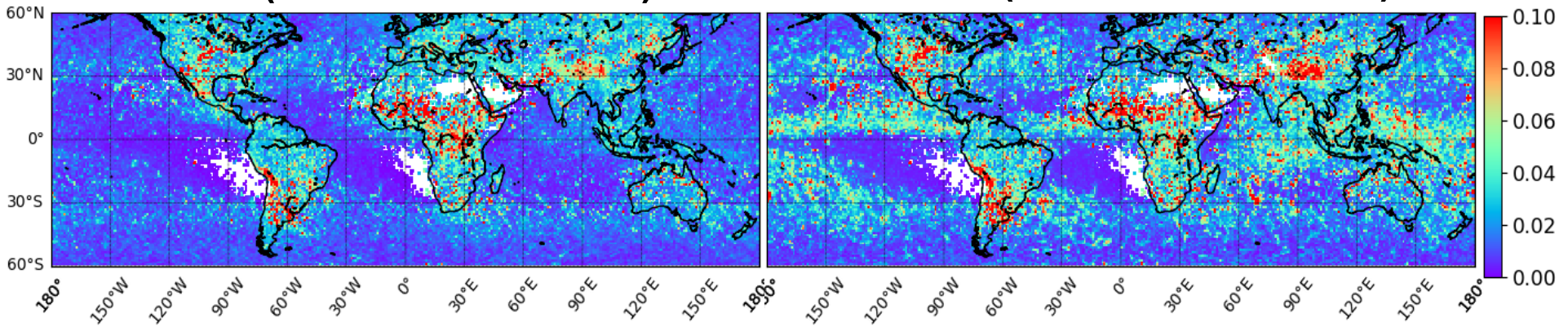
*For all surface are mixed in this analysis

The error in the estimation of the surface precipitation rate and its corresponding profile are strongly related

Estimation performances (relative to combined algorithm)

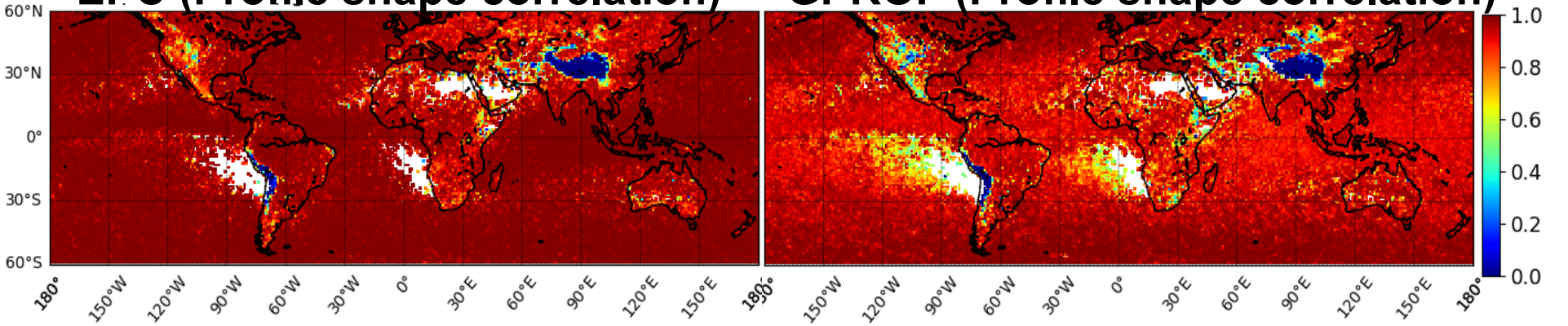
EPC (Profile RMS Error)

GPROF (Profile RMS Error)



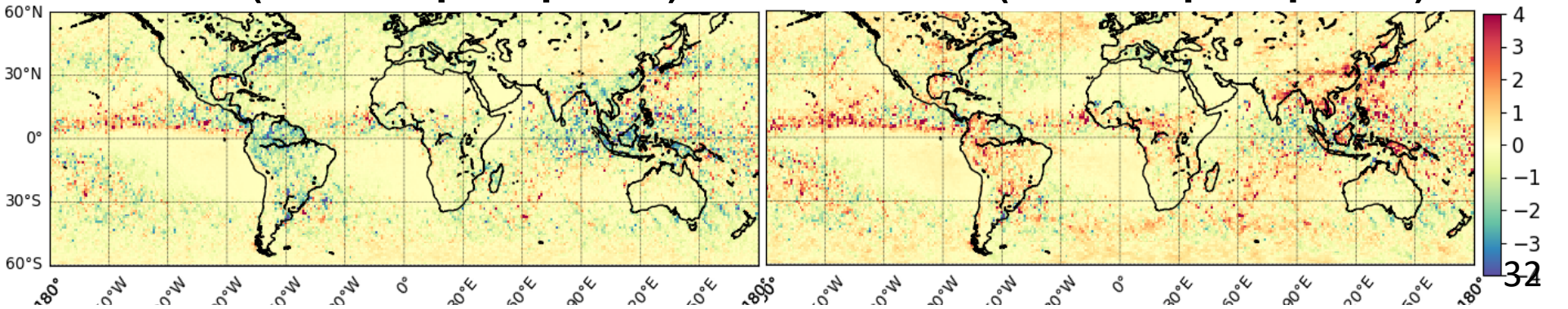
EPC (Profile shape correlation)

GPROF (Profile shape correlation)



EPC (Surface precip bias)

GPROF (Surface precip bias)



Design of this study

JJA (2014) & DJF (2014-2015) for GPM/GMI

Profiles higher than 2km above reference level are investigated.

PMW retrievals

Surface precip rate | Condensed water profile

- EPC retrieval
- GPROF V05

Reference data

- Combined algorithm product (CMB) V06

Surface precip rate | Condensed water profile

Other data

- Surface type: obtained from GPROF V05 product.
- Radar reflectivity, storm top height, precipitation type: obtained from GPM.Ku product

Condensed water content profiles (CMB=1 – 3 mm/h, Tall* precip.)

* Storm top (Ku) > Freezing level

Ocean

Vegetation

Snow surface (Only EPC)

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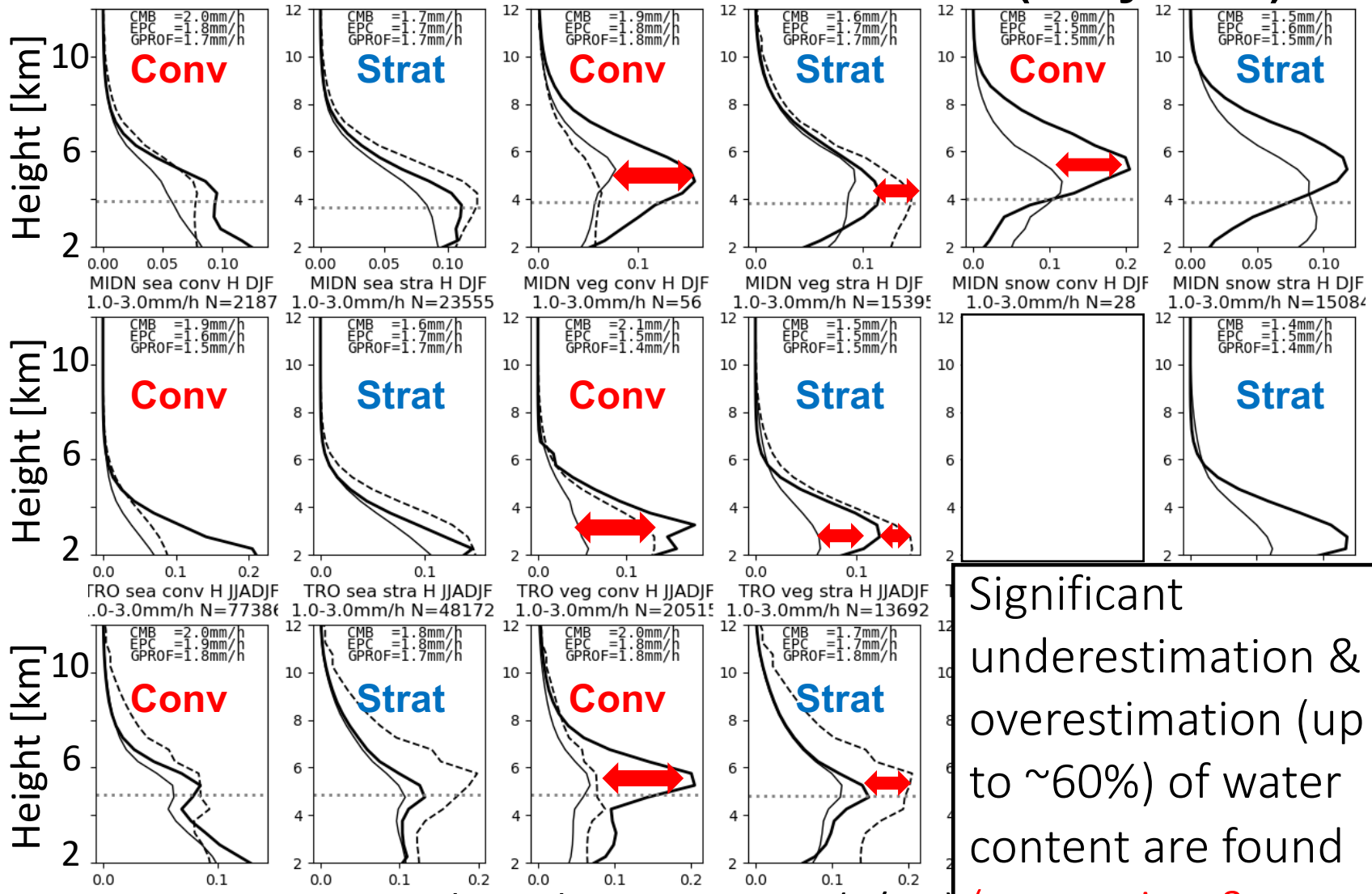

Significant underestimation & overestimation (up to ~60%) of water content are found (vegetation & snow)

CMB
EPC
GPROF

Condensed water content profiles (CMB=1 – 3 mm/h, Tall* precip.)

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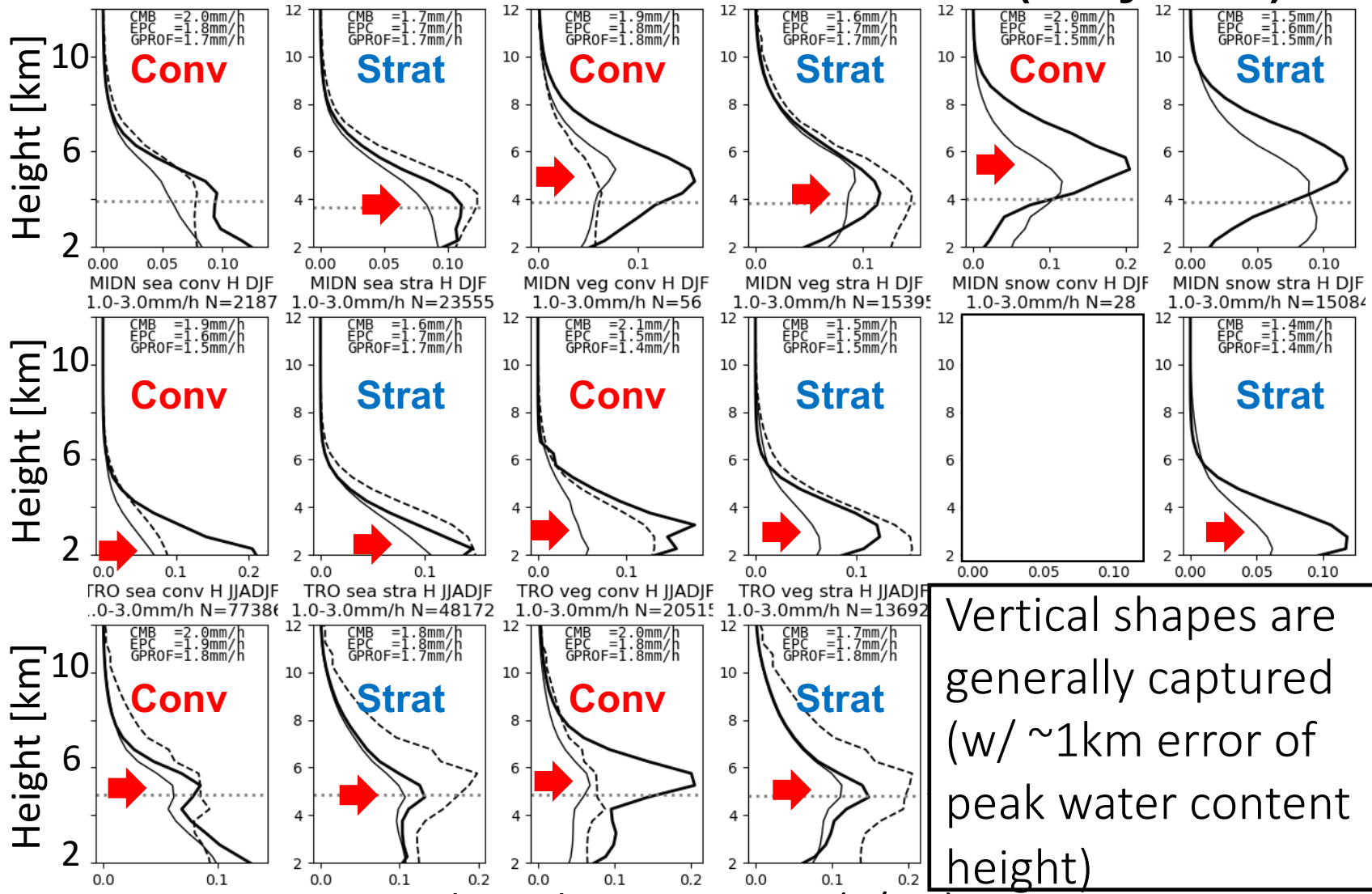
35N – 50N (JJA)

35N – 50N (DJF)

15S – 15N (JJA+DJF)



Vertical shapes are generally captured (w/ ~1km error of peak water content height)