Rain rate quantiles retrieved from GMI brightness temperatures

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Background

With the advent of GPM, we often deal with far more difficult and varied surfaces than was (usually) the case for TRMM:

- Variable snow cover
- Variable vegetation
- Variable sea ice
- Complex spatial mixtures of land, wetlands, open water

Background

More surface complexity and variability combined with generally weaker, shallower precipitation implies

- Less signal
- More noise
- Low overall radiometric sensitivity to precipitation and potentially large retrieval errors

Two distinct approaches to high-latitude retrievals

1. Try to *specify* or explicitly *retrieve* surface properties; OR
2. Design the algorithm to treat the background as *noise* and use channel combinations that *reduce sensitivity to that noise* while *retaining sensitivity to precip*.

Two distinct approaches to high-latitude retrievals

1. Try to *specify* or explicitly *retrieve* surface properties; OR
2. Design the algorithm to treat the background as *noise* and use channel combinations that reduce sensitivity to that noise while retaining sensitivity to precip.

The second approach is sometimes referred to as the “surface-blind” or “S0” approach.

The conceptual basis for S0 retrievals is not new!

- Weinmann and Guetter (1977) used an ad hoc linear combination of 19V and 19H channels to eliminate the strong contrast between land and ocean.
- Spencer et al. (1989) did essentially the same thing for SSM/I 85 GHz channels – *polarization corrected temperature* (PCT)
- Grody's "scattering index" (1990s) was a more elaborate (but still ad hoc) multifrequency method.

UW-Madison algorithm

- *Formalizes*, *generalizes*, and *optimizes* the S0 approach using objectively derived linear transformations of GMI channels (10–89 GHz, dual polarization).
- Requires only *statistical* information about temporal and spatial background TB variability (“noise”) in the form of channel means, covariances.
- Currently still a standalone algorithm, but methods could be seamlessly integrated into GPROF today.

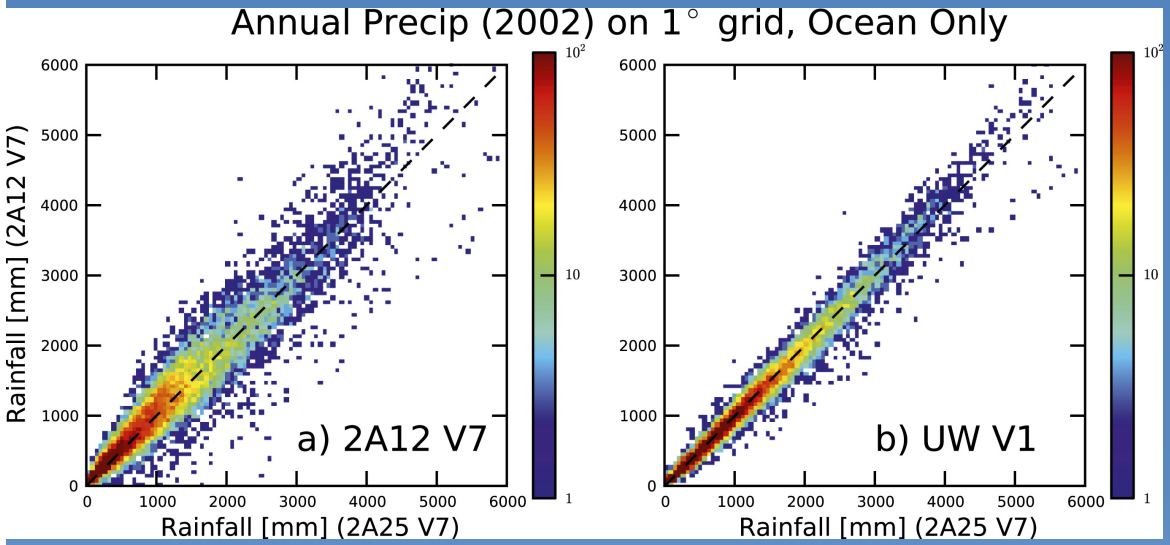
UW-Madison Algorithm

- Bayesian
- Trained on over two year's worth of matchups with near-nadir DPR Ku-band rain rate
- Uses resolution-matched GMI Tbs
- Employs dimensionality reduction (9 channels to 3 pseudochannels + 2 env. variables) based on covariance of background TB variability in 12 static surface classes, further stratified by surface skin temperature ("warm" or "cold")
- Automatic fallback if too few samples found in 5D space
- Completely objective implementation, no subjective channel weightings or match criteria; no ad hoc IF statements; no "screens."
- In most cases, 10^2–10^6 matches found for any given GMI scene
- Robust posterior CDFs (or quantiles) of rain rate

Recap for TMI

- Published in Petty and Li (2013), Parts I and II, *J. Atmos. Ocean. Tech.*
- Validated globally for 2012 and 2015
- Compared with GPROF / 2A12 v. 7
- Complete 17-year TMI record has been processed and will be posted on a suitable server soon.

TMI Validation



Class	Ratio			RMS error			Correlation		
	2A12 (2002)	UW (2002)	UW (2005)	2A12 (2002)	UW (2002)	UW (2005)	2A12 (2002)	UW (2002)	UW (2005)
Ocean	1.04	1.00	0.99	260	129	129	0.96	0.99	0.99
1w	1.09	1.01	1.00	602	309	298	0.73	0.91	0.92
2w	0.68	0.97	0.96	640	343	357	0.86	0.94	0.95
3w	0.75	1.04	0.98	150	90	94	0.75	0.79	0.82
4w	1.00	1.00	1.05	692	425	503	0.70	0.81	0.73
5w	2.38	1.02	1.09	676	85	77	−0.05	0.83	0.82
6w	8.56	0.67	0.70	4221	406	400	0.62	0.26	0.23
1c	3.06	1.11	1.00	1282	390	235	0.24	0.87	0.32
2c	0.43	1.13	2.23	334	180	267	0.84	0.85	0.16
3c	3.72	2.39	1.36	150	21	49	0.09	0.55	0.22
4c	11.09	1.05	0.70	3087	99	190	−0.63	0.99	0.33
5c	5.85	0.81	0.99	540	41	37	0.27	0.33	0.22
6c	3.02	0.52	0.52	1020	357	353	0.17	0.77	0.66

Adaptation to GMI

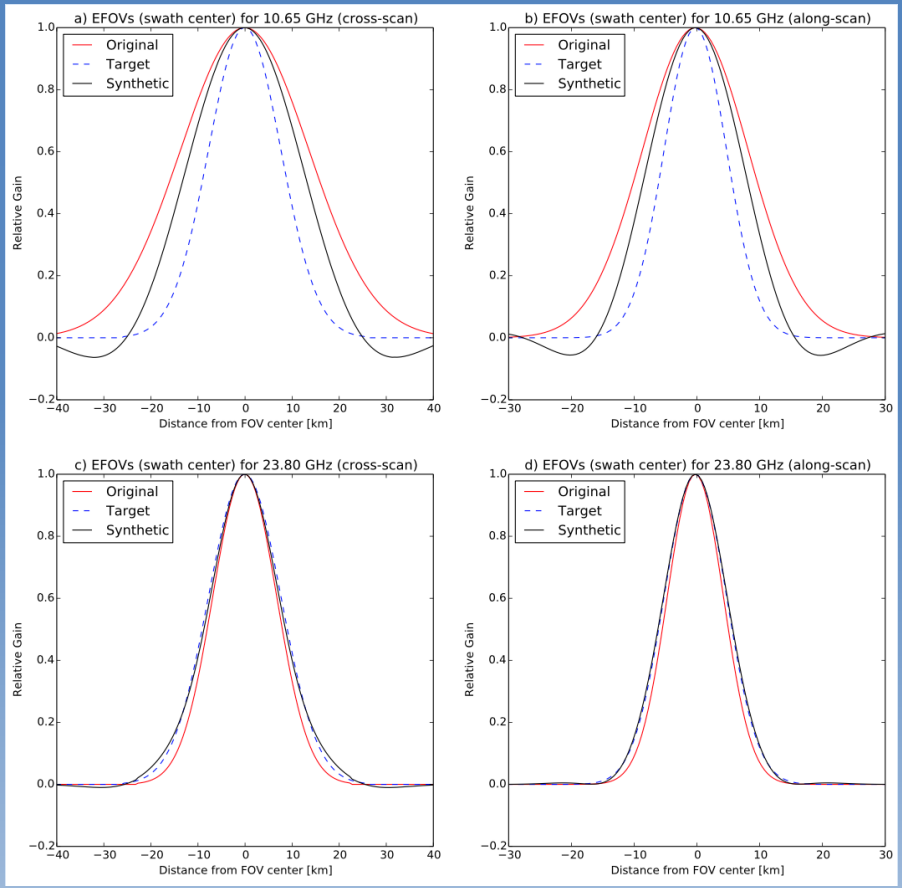
- Required resolution-matched channels
- Needed adequate GMI-DPR matchup dataset to objectively define land classes, derive channel transformations, and populate the *a priori* data base (5D lookup table for each surface class).
- Current version retrieves DPR near-surface rain rate.

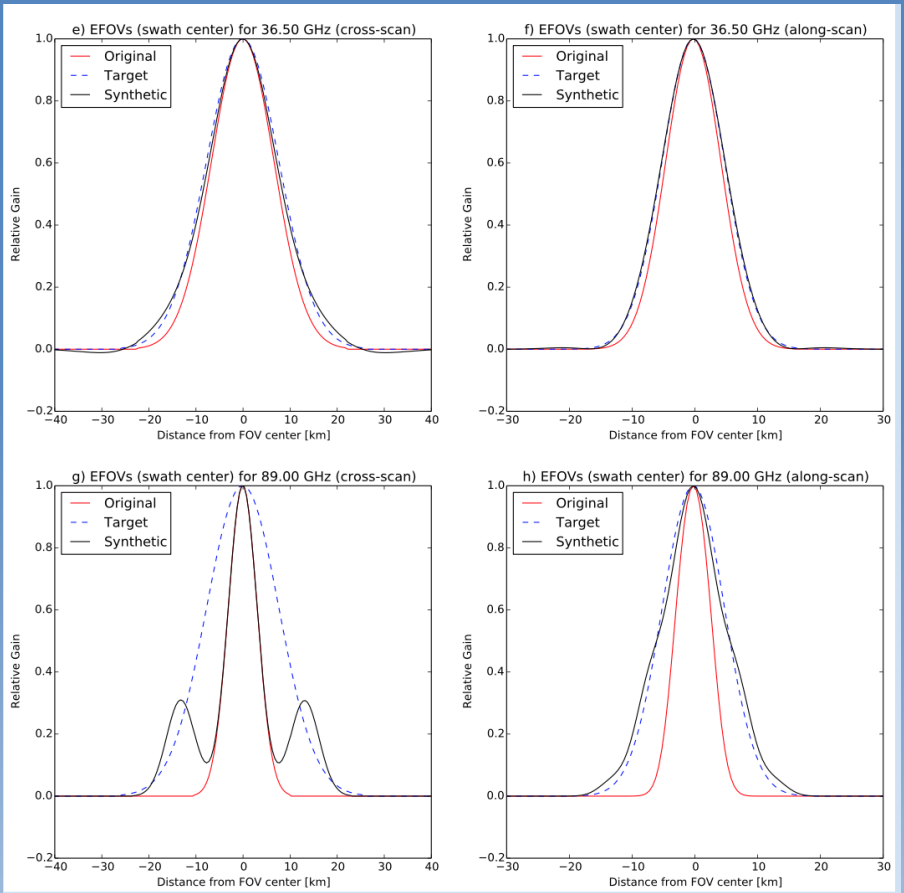
GMI Field-of-View matching

Why do we care?

- Mismatched footprints introduce severe noise in the vicinity of sharp spatial gradients (e.g., coastlines)
- Worse: that noise is non-linearly correlated between channels so it *cannot* be completely removed via principal component transformations.

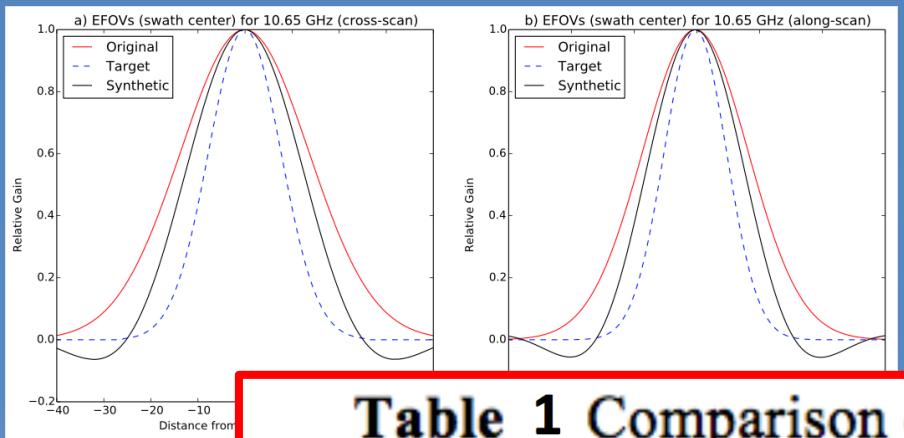
GMI Field-of-View matching

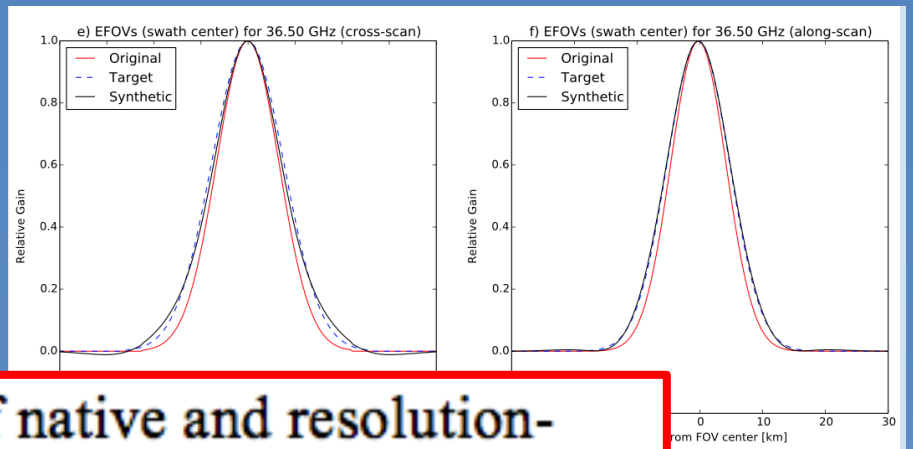


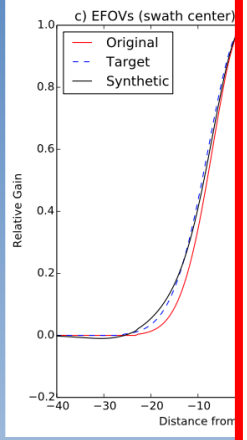


Petty, G. W. and Bennartz, R. (2017): Field-of-view characteristics and resolution matching for the Global Precipitation Measurement (GPM) Microwave Imager (GMI), Atmos. Meas. Tech., 10, 745-758

GMI Field-of-View matching







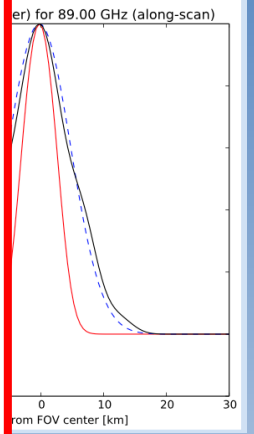
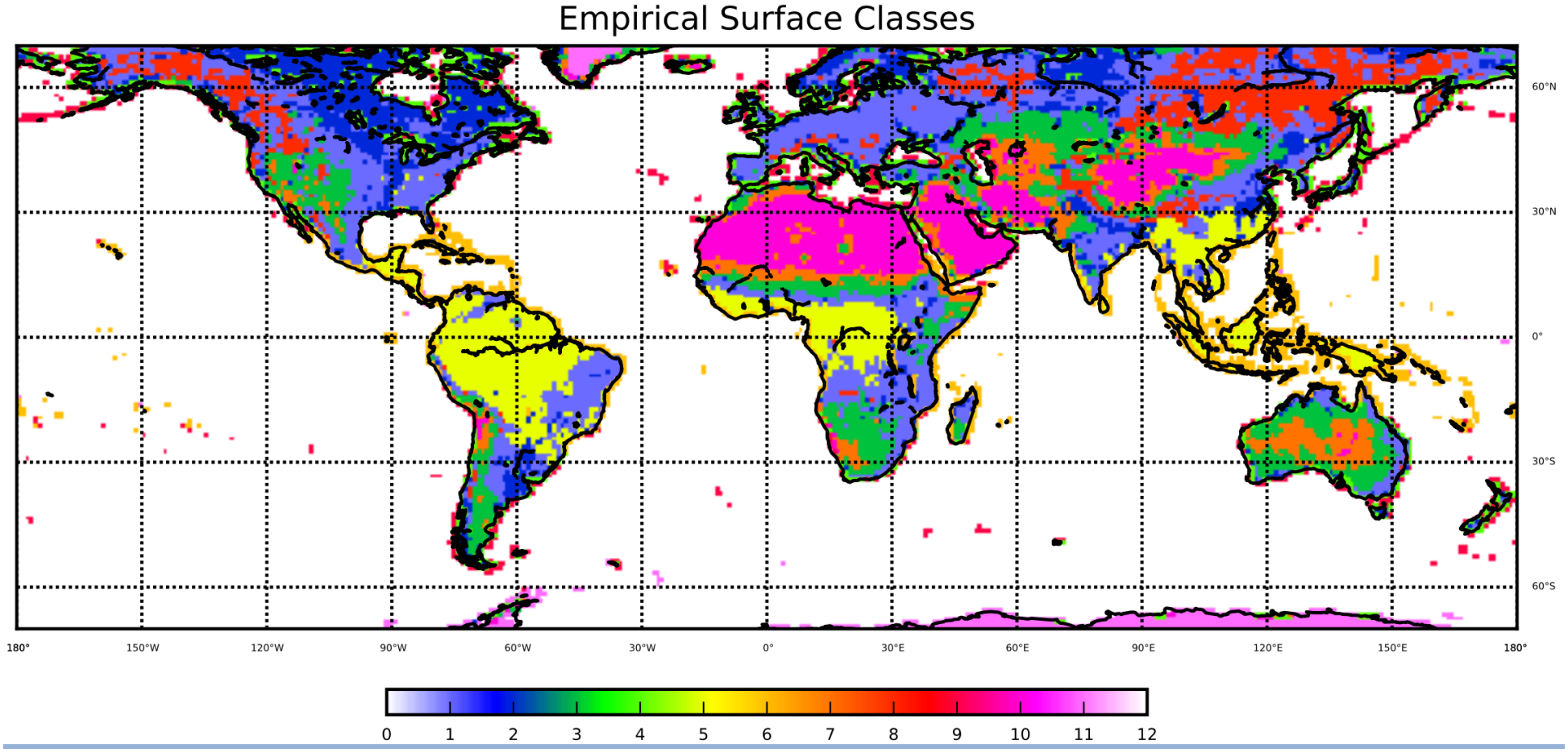


Table 1 Comparison of native and resolution-matched EFOV 3 dB widths [km].

Frequency	Cross-Scan		Along-Scan	
	Native	Matched	Native	Matched
10.65	32.1	26.5	19.8	16.5
18.70	18.1	18.1	11.8	11.8
23.80	16.0	18.0	10.6	11.8
36.50	15.6	18.0	10.3	11.8
89.00	7.2	(7.2)	6.3	11.8

GMI land surface classes



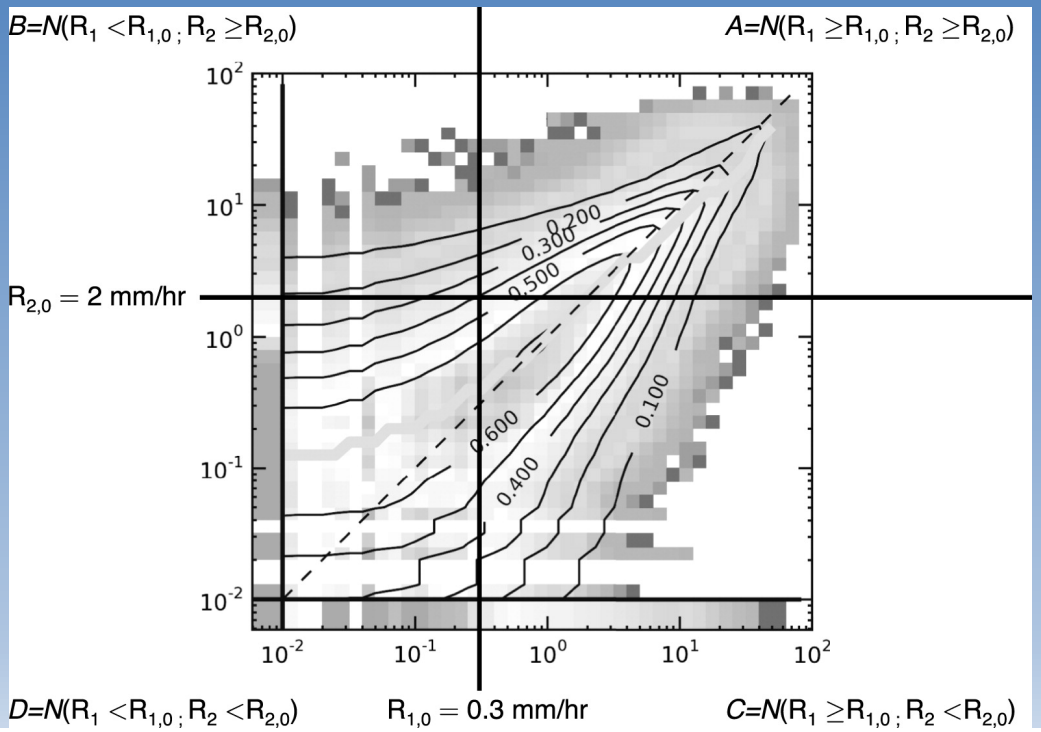
Based on novel unsupervised classification scheme applied to a pairwise “similarity” metric applied to annual multichannel brightness temperature means & covariances from precipitation-free scenes.

Current status

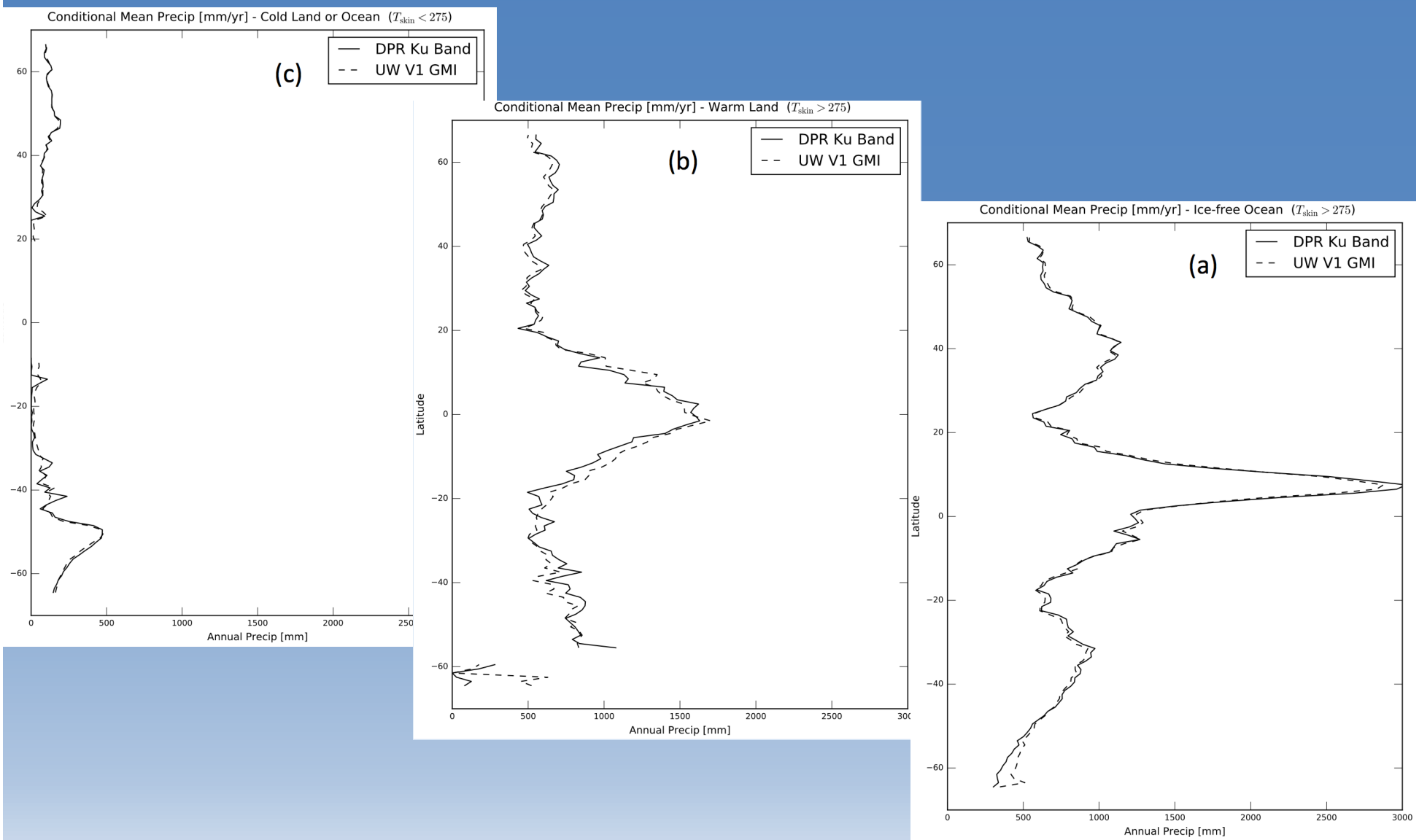
- Pre-distilled lookup table based on one-half of the available near-nadir DPR-GMI matchups since launch.
- Approximately 340 million matches
- Validation is underway using the other half of the matchups.

Preliminary validation for GMI

- Pixel by pixel skill for all land classes, warm and cold surfaces.
- Annual totals compared between GMI and DPR (near-nadir only) on 1 degree grid.
- No comparisons yet with GPROF.



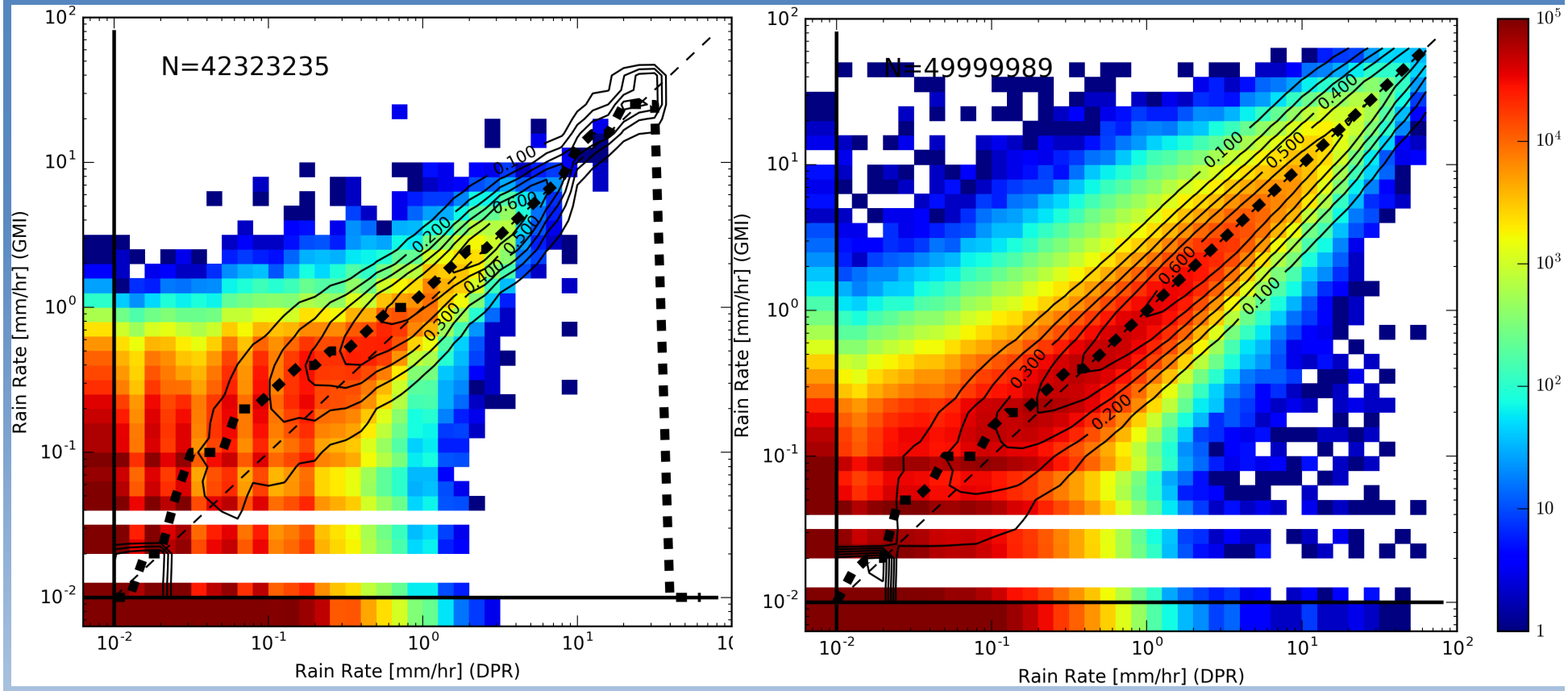
Latitudinal profiles – first year



Class 0 (ocean)

T_{skin} < 275 K

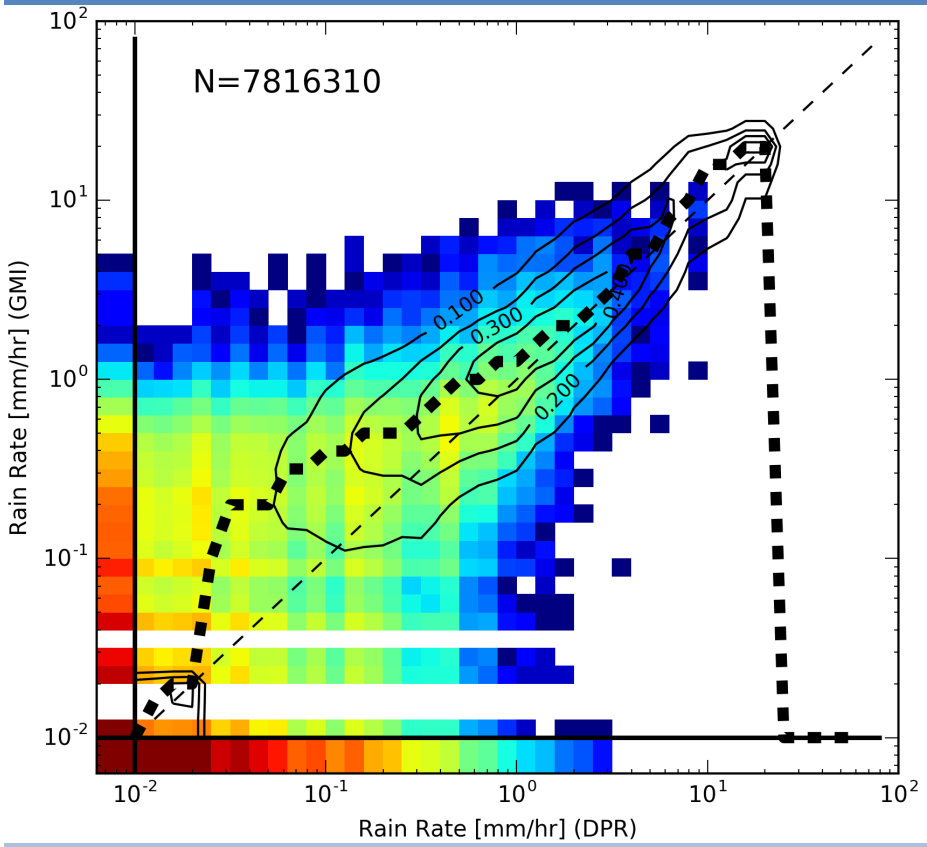
T_{skin} > 275 K

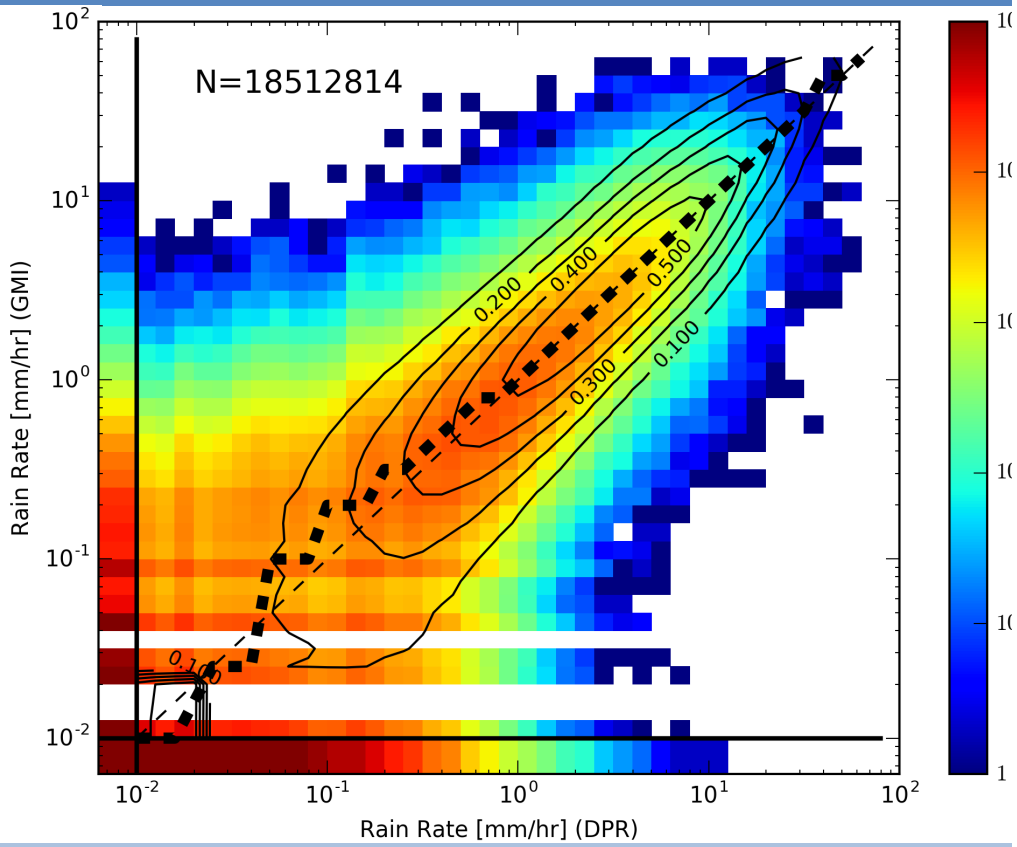


Class 1

T_{skin} < 275 K

T_{skin} > 275 K

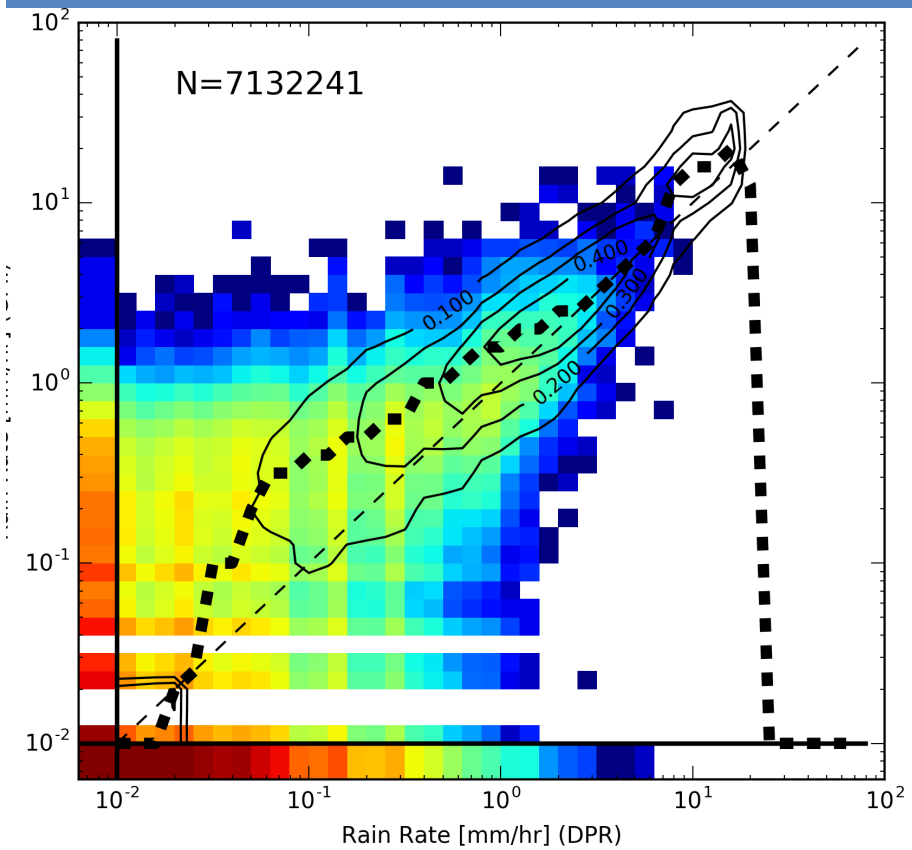


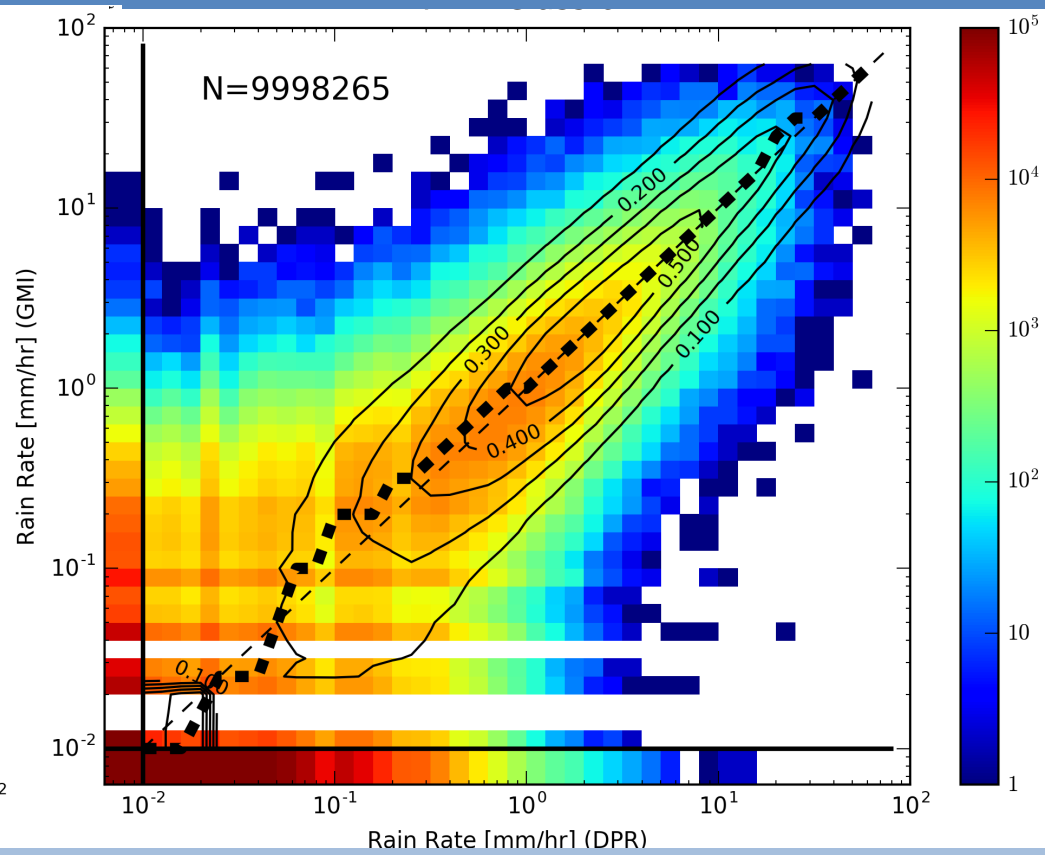


Class 2

T_{skin} < 275 K

T_{skin} > 275 K

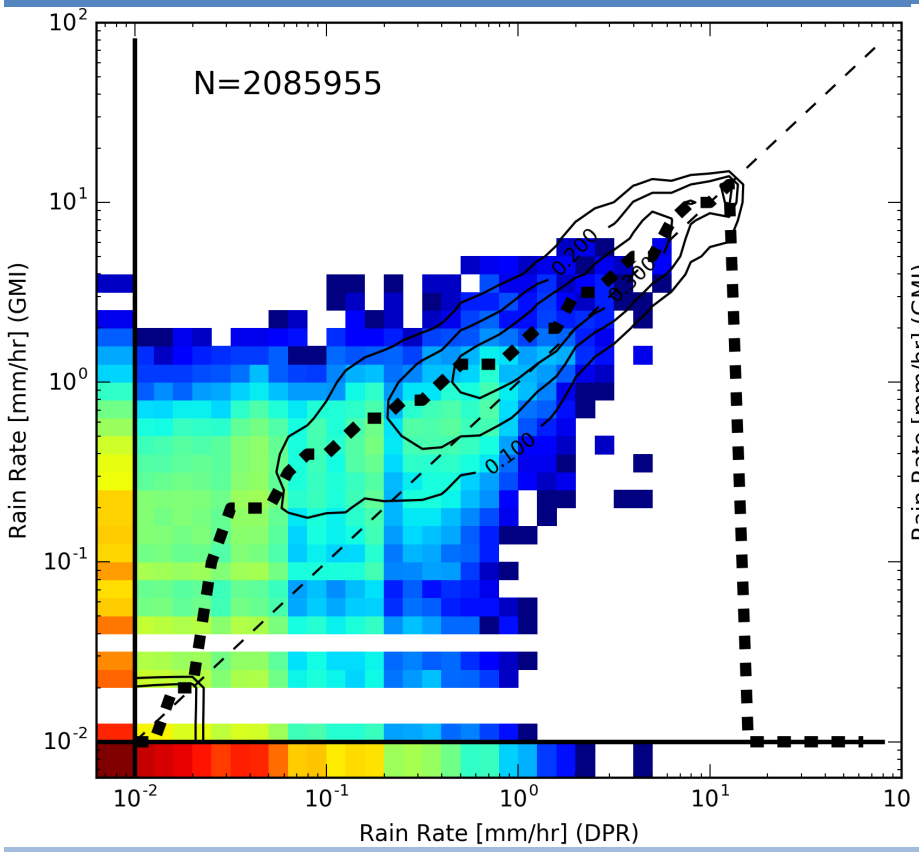


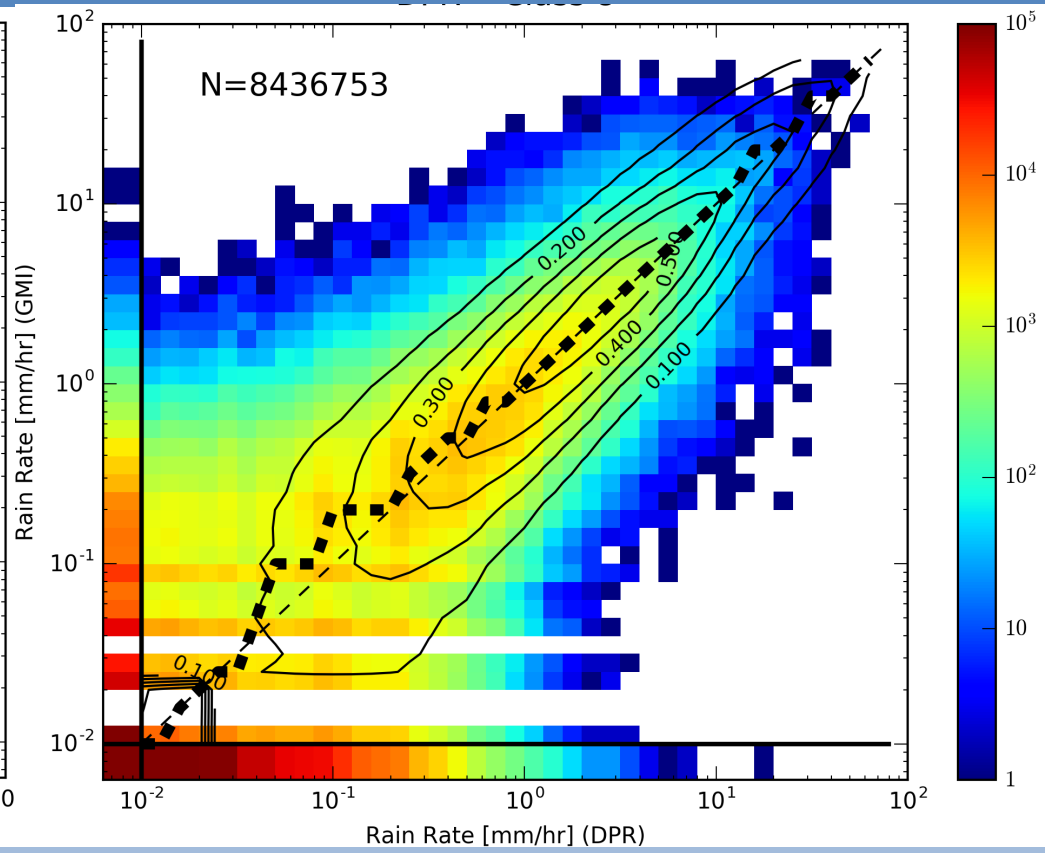


Class 3

T_{skin} < 275 K

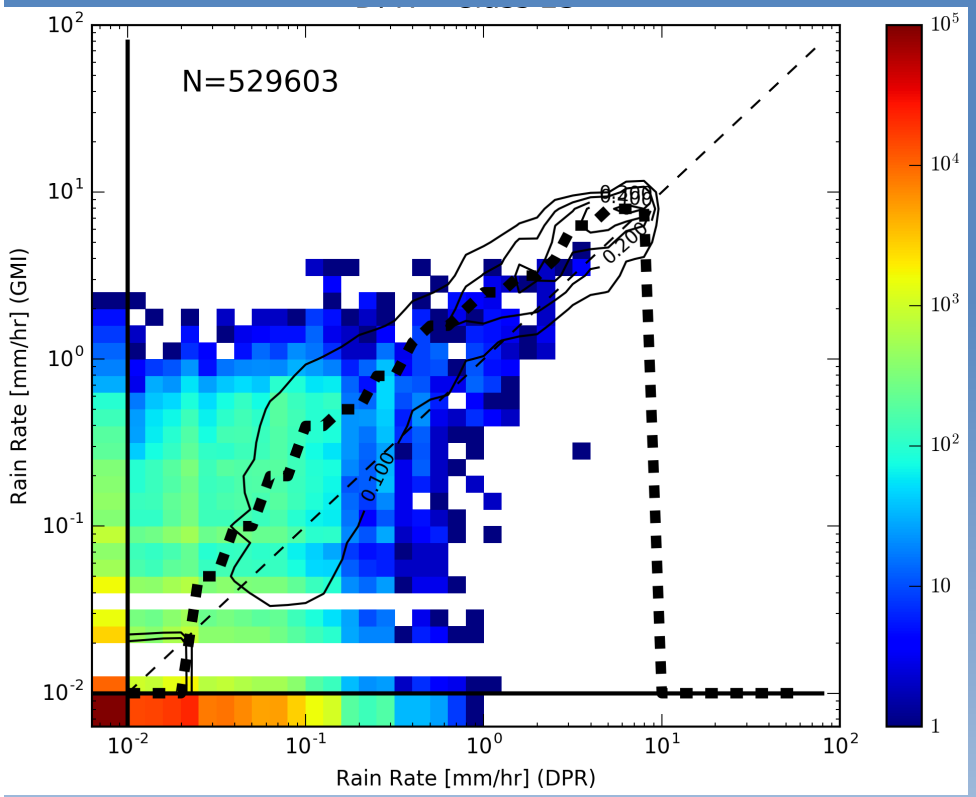
T_{skin} > 275 K



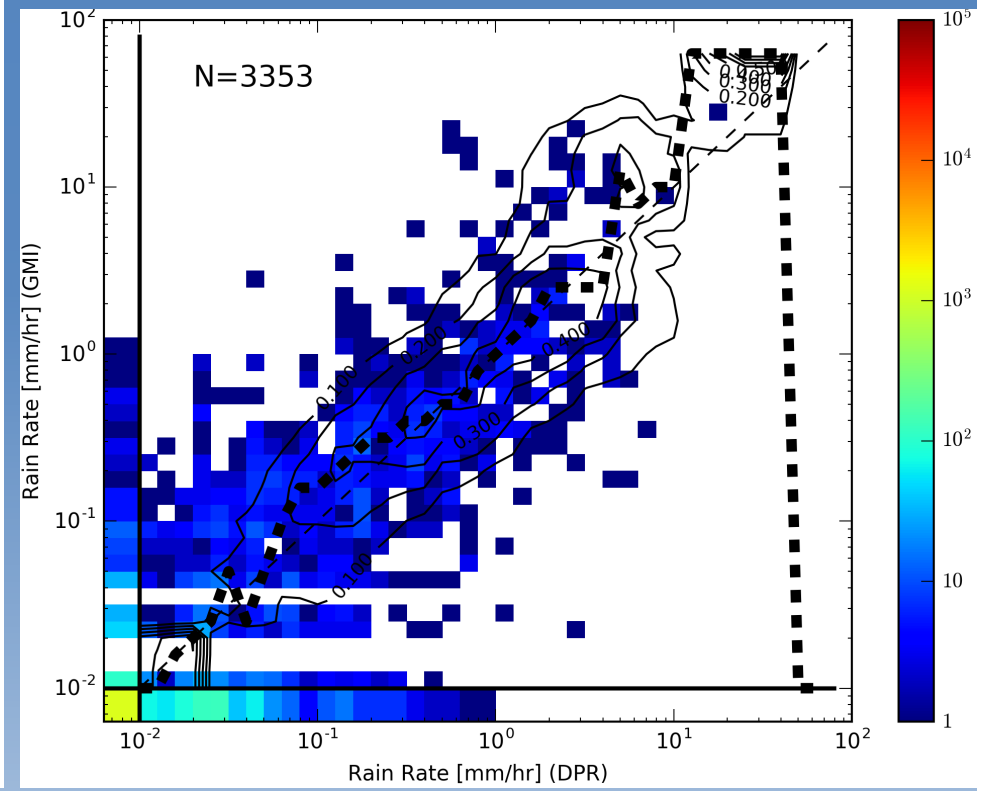


Class 11

T_{skin} < 275 K



T_{skin} > 275 K



So much for run-of-the-mill rain rate retrievals…

Let's talk about *quantiles*, which is the *unique* feature of the UW-Madison algorithm

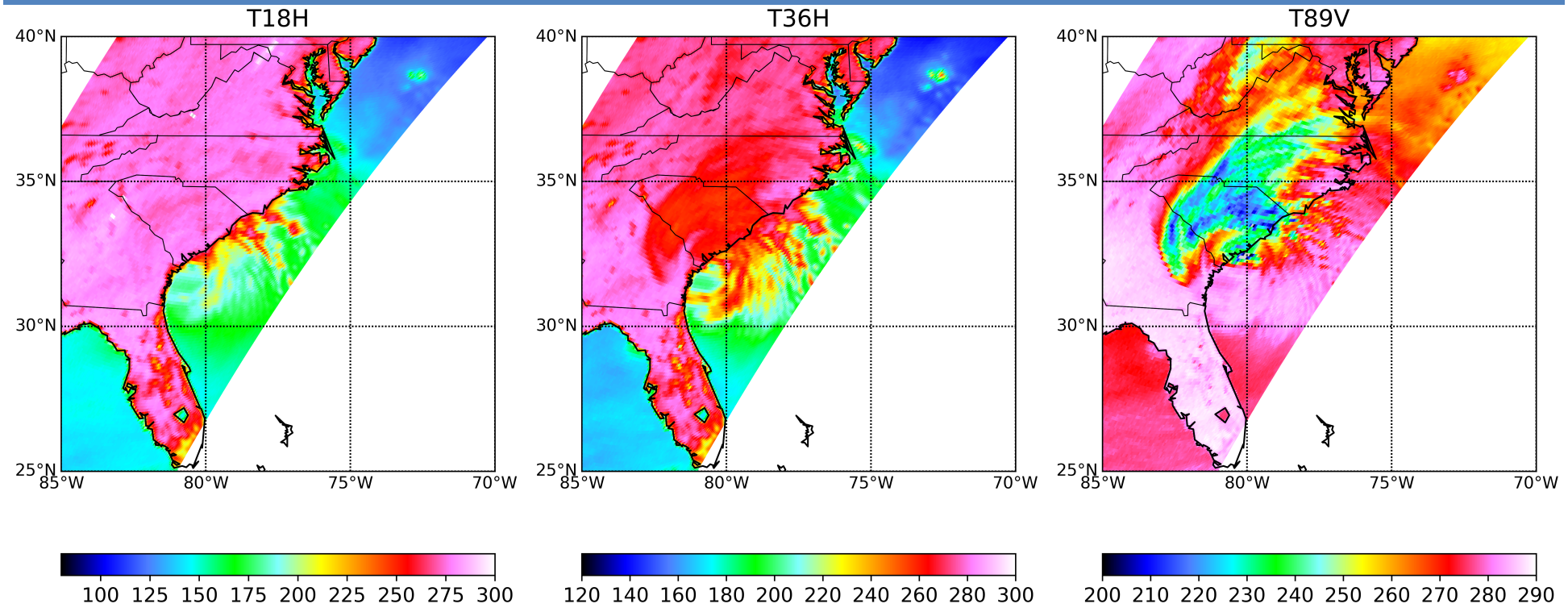
We're able to retrieve quantiles only because the S0 methodology (and associated dimensional reduction) yields very large numbers of DPR matches for most scenes.

What good are quantiles?

- Error bars! They answer the age-old question: What is the *range* of plausible rain rates associated with *this* pixel?
- Quantiles (or percentiles) tell you the fraction of DPR rain rates for a given scene below a particular value. For example:
  - 10%-ile: Ten percent of DPR matchups fall below this value.
  - 50%-ile (median): half of DPR matchups fall below this value; the other half above
  - 90%-ile: Ten percent of DPR matchups fall above this value

Hurricane Matthew

October 8, 2016



Hurricane Matthew

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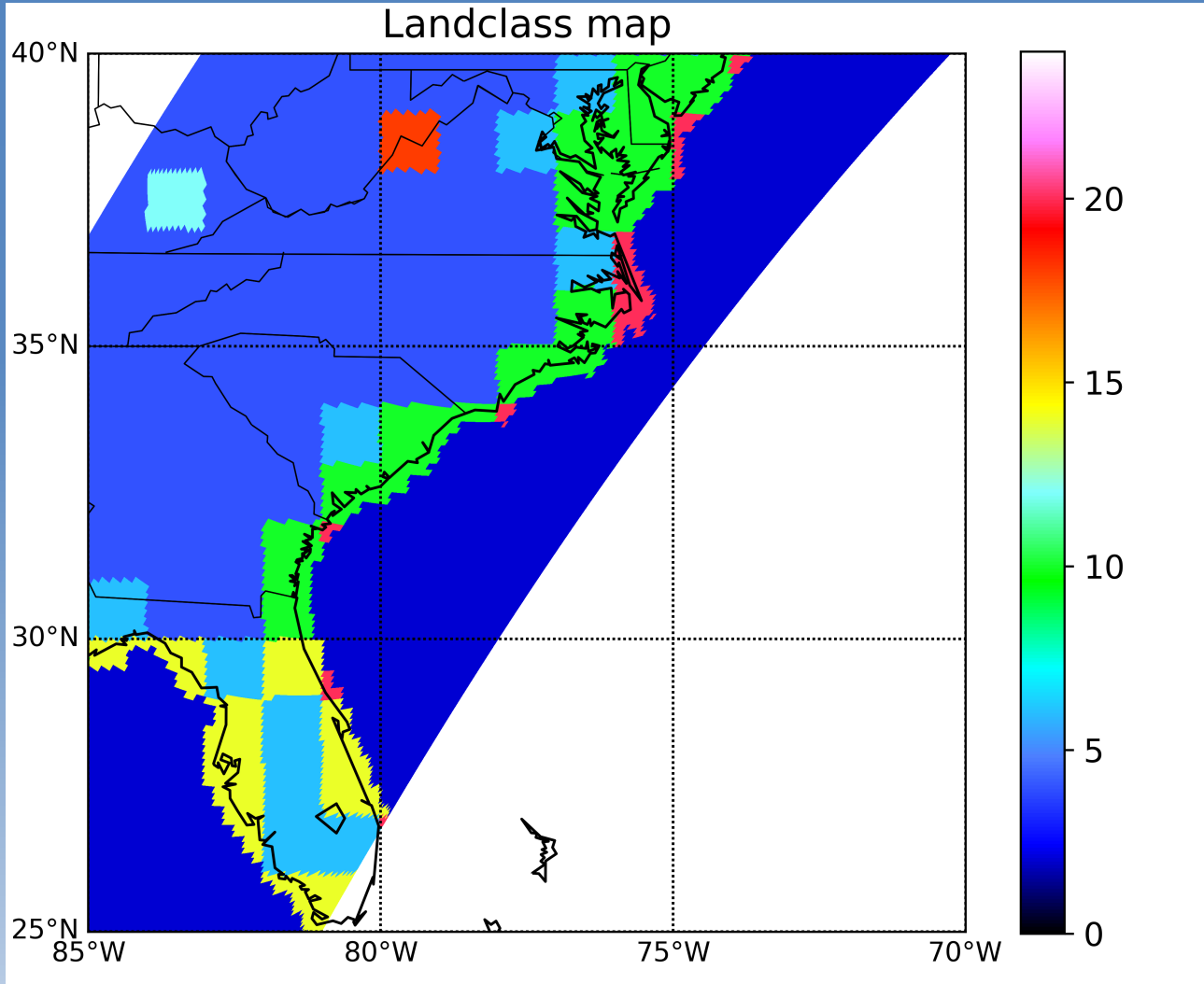

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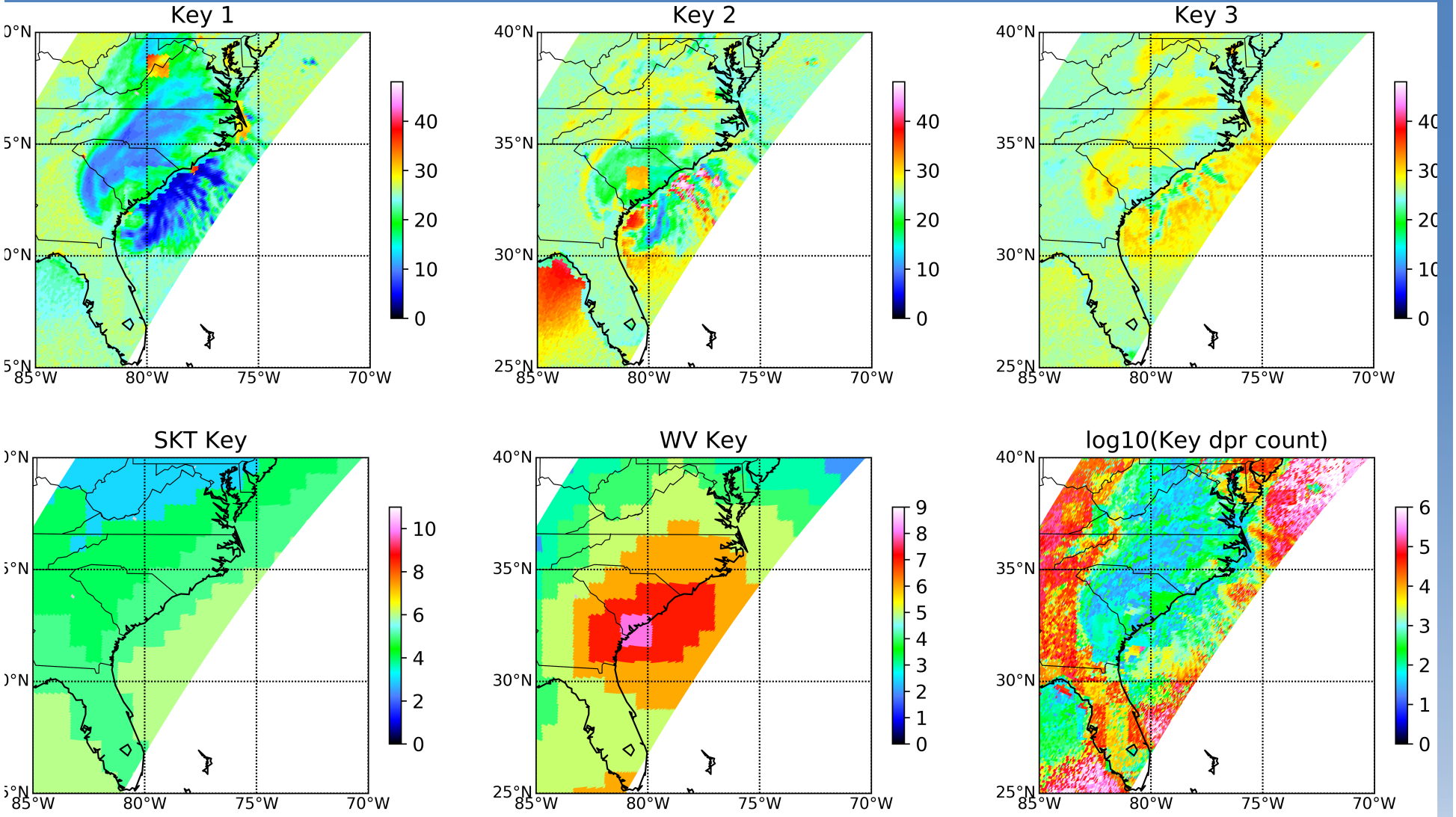

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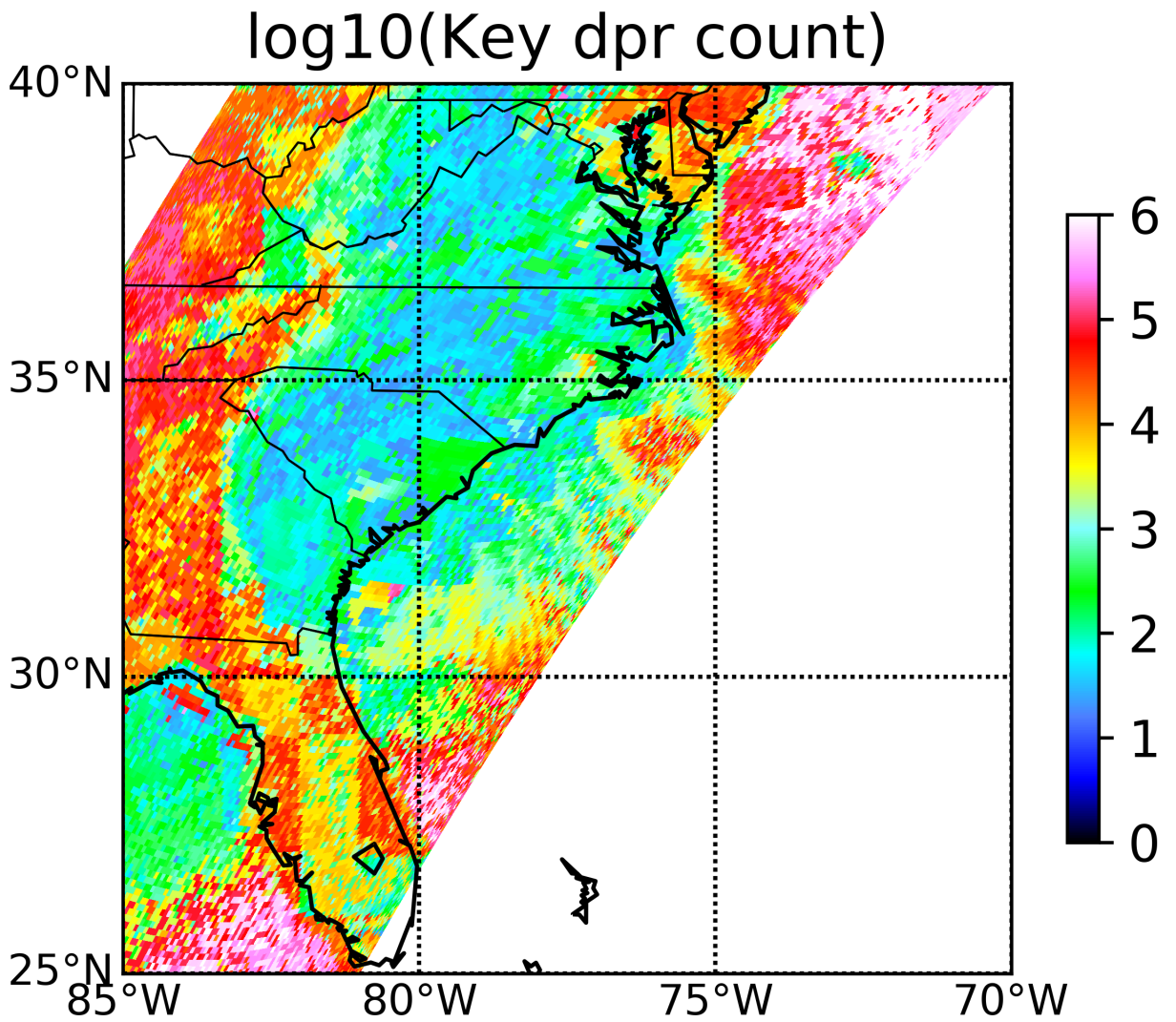

Hurricane Matthew

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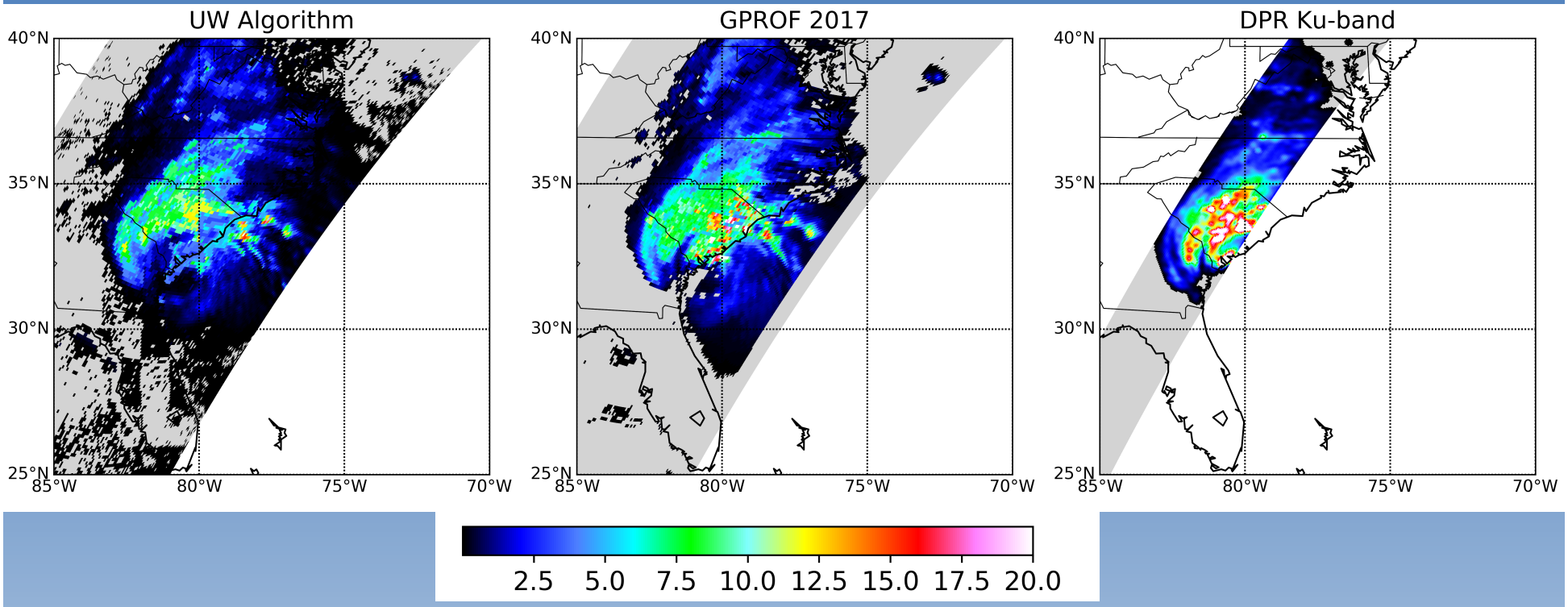

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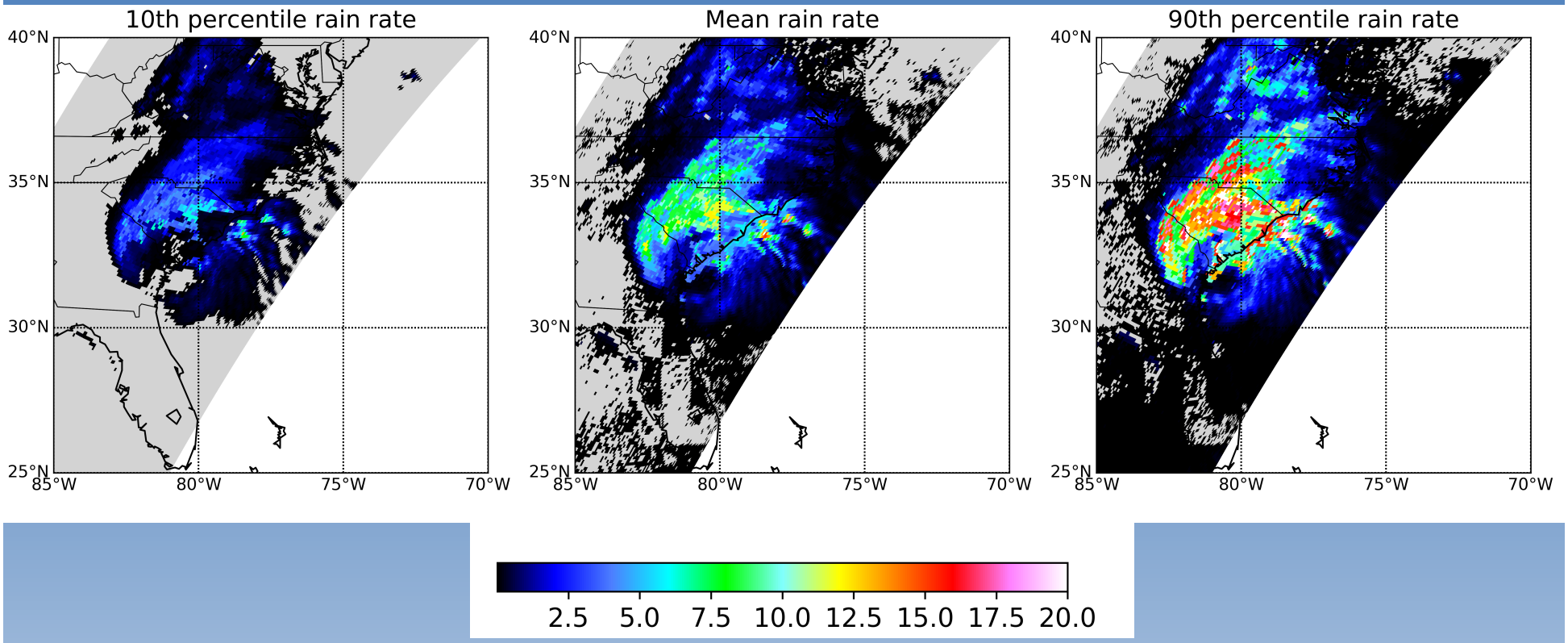
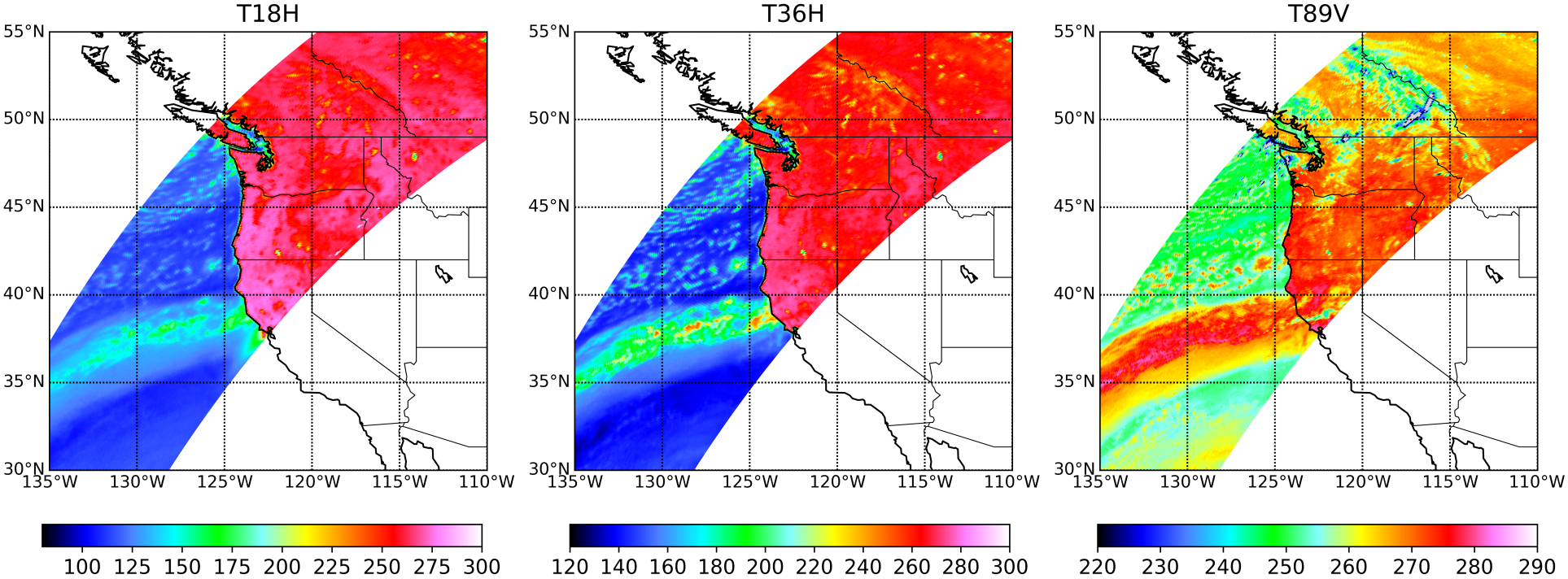
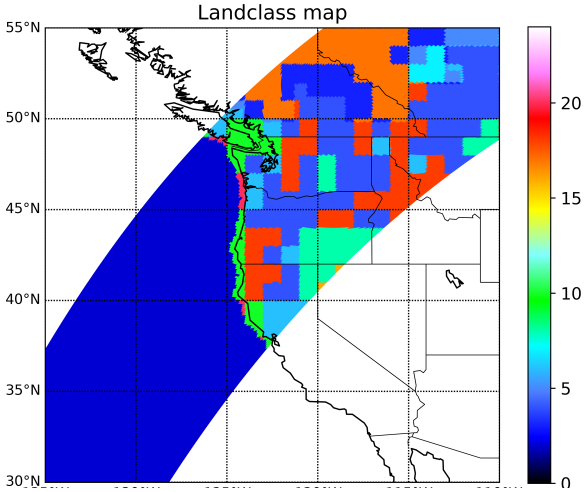
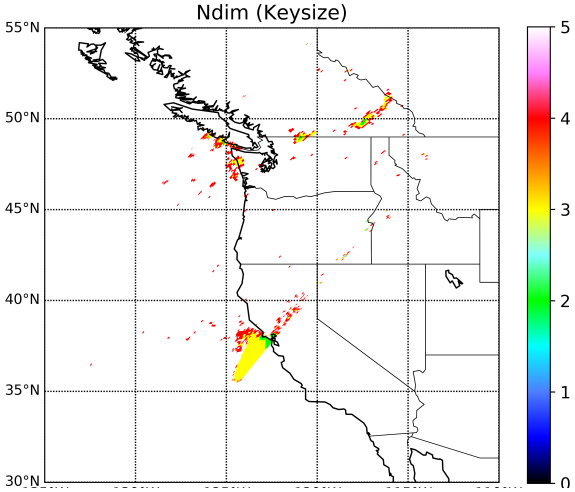


Pacific Northwest

Nov. 1, 2015







Pacific Northwest

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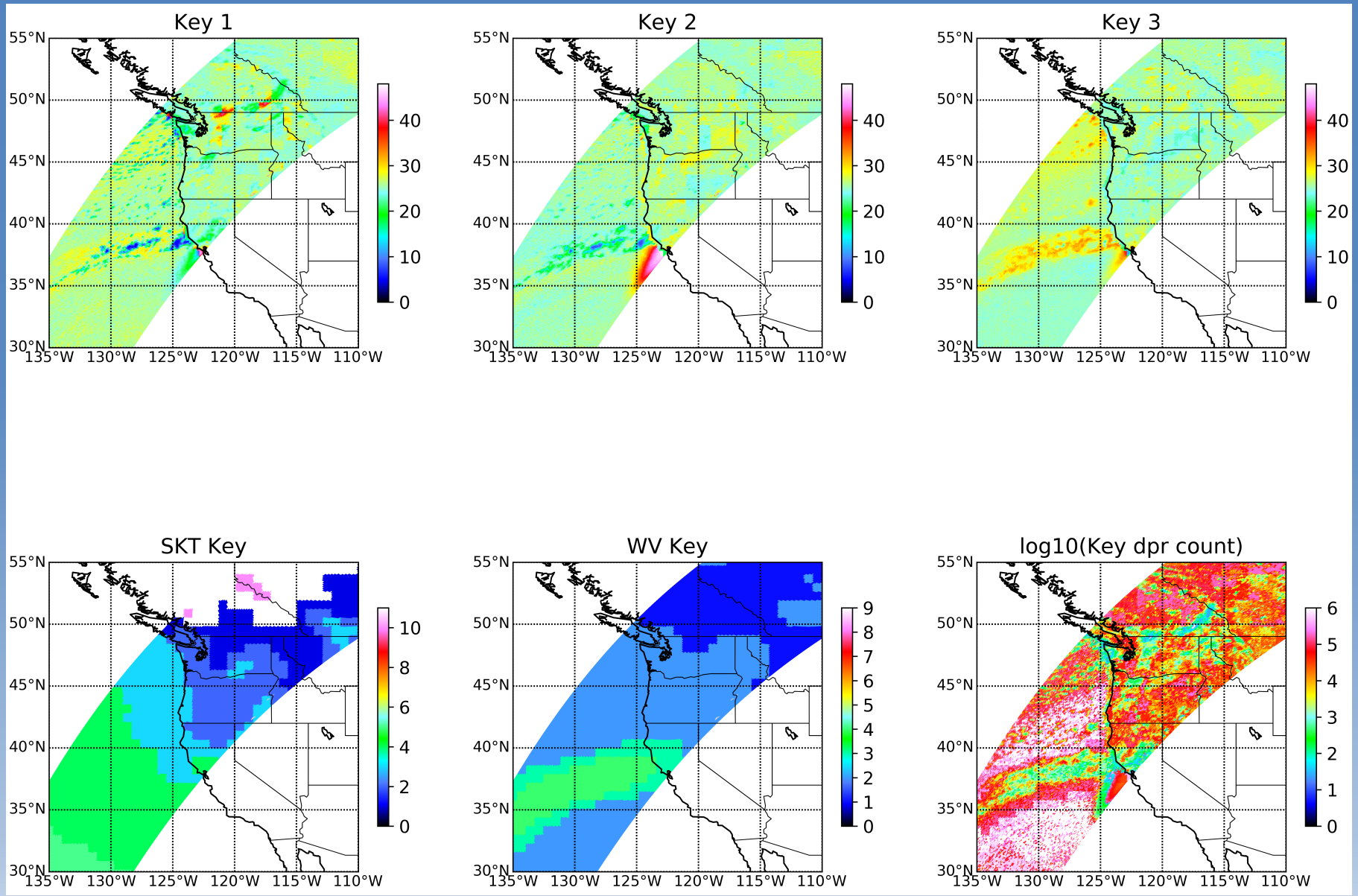

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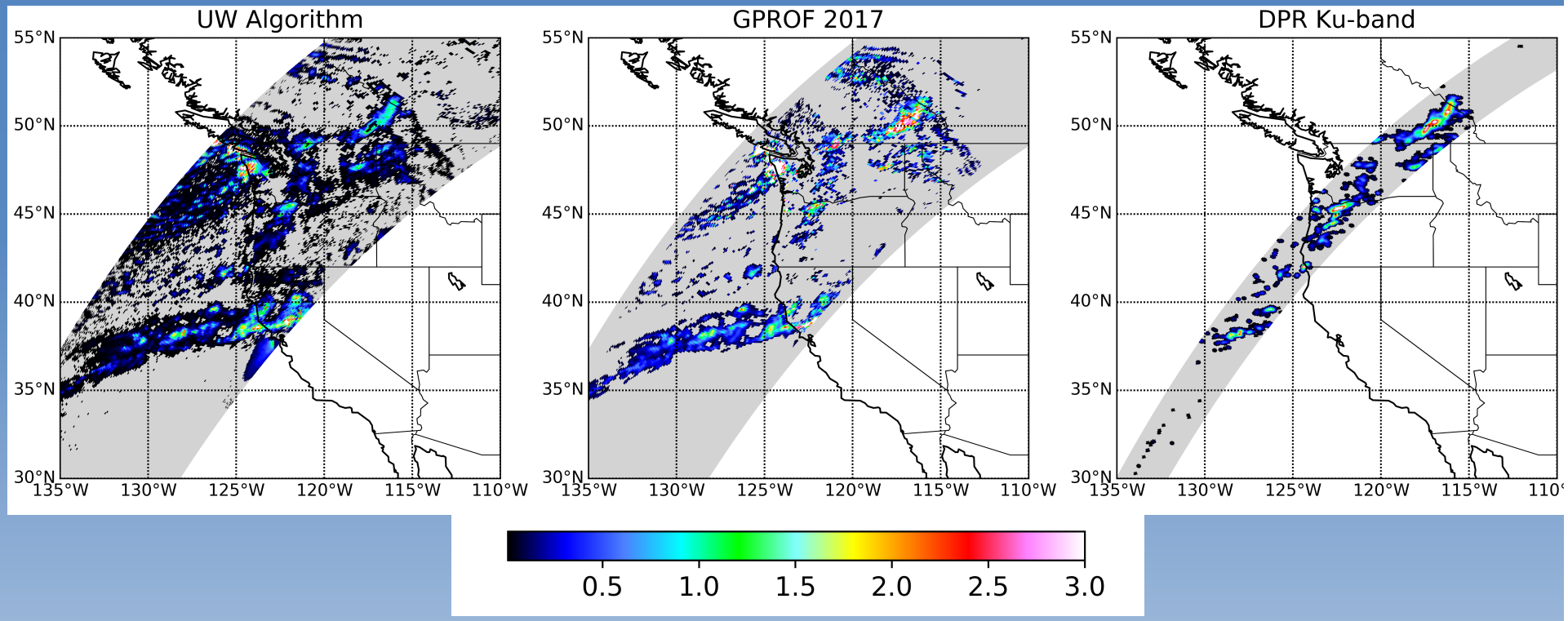

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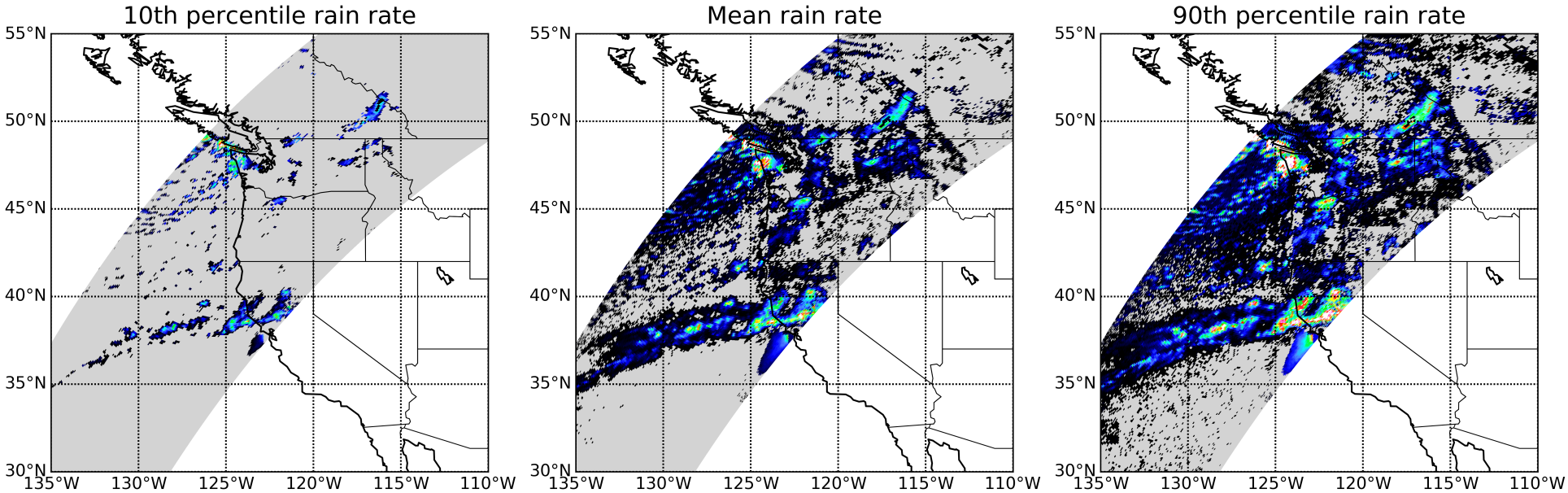
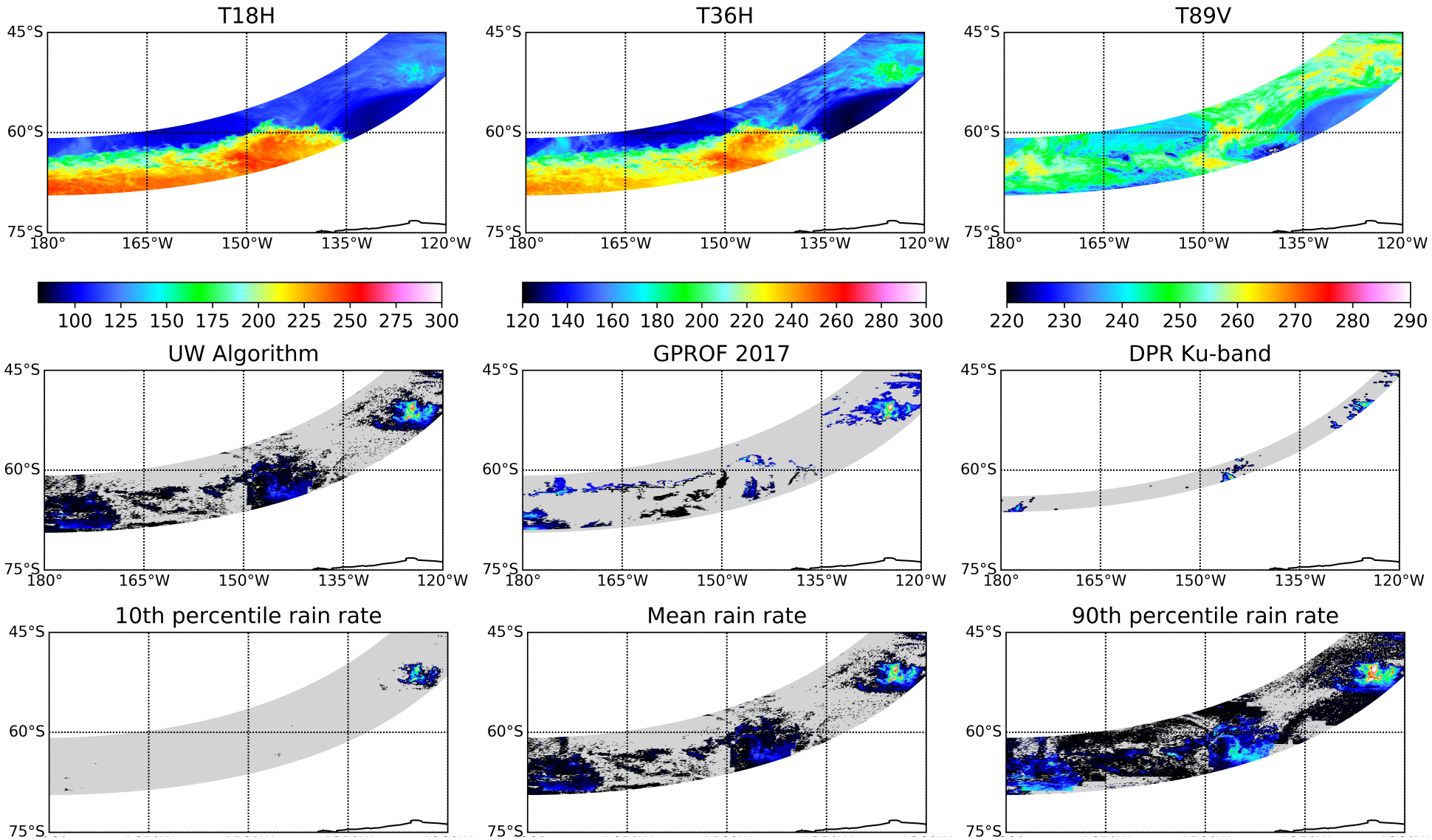


Antarctic Marginal Ice Zone

October 8, 2016



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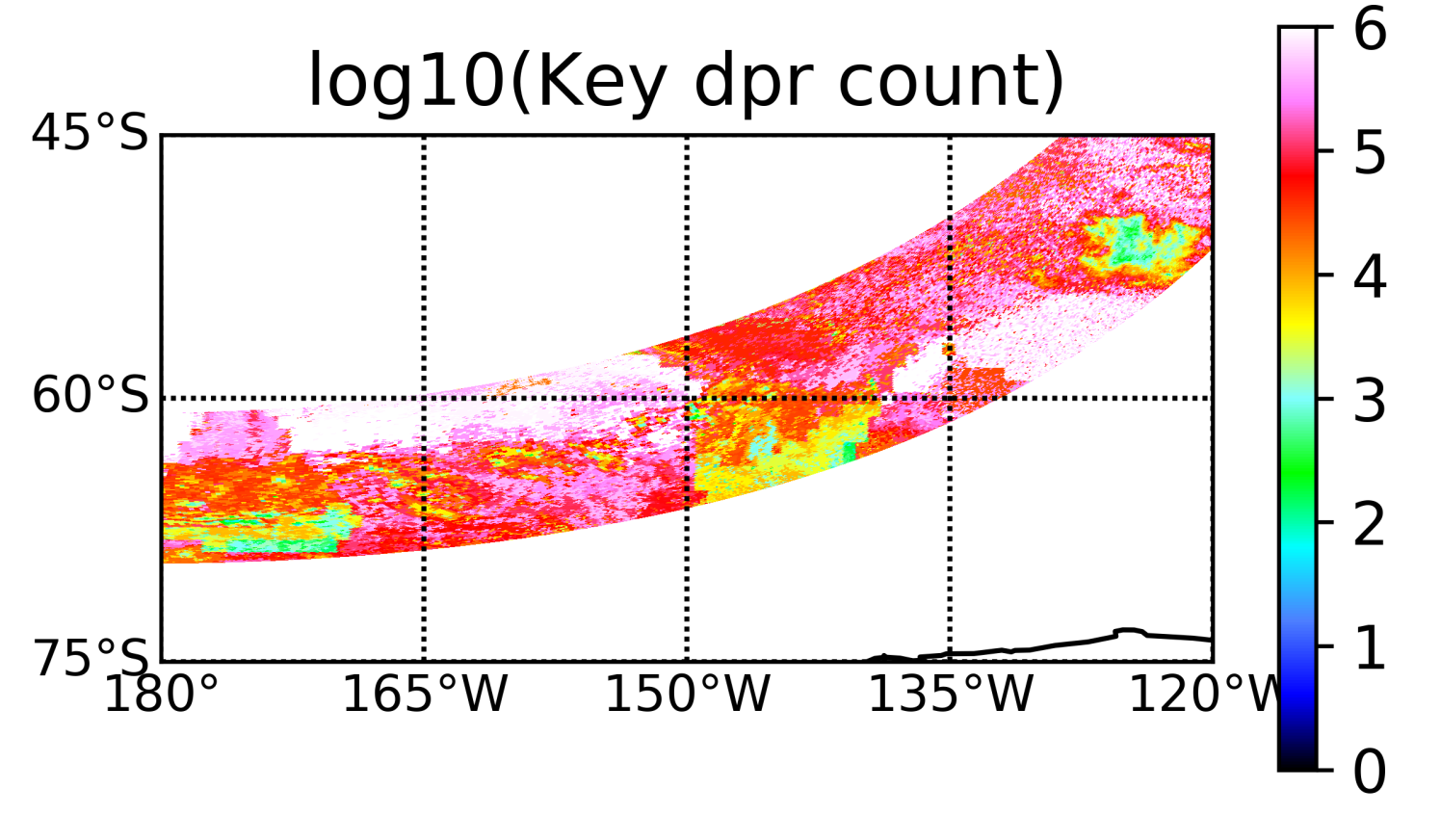

Summary

- The UW-Madison algorithm has been successfully adapted to GMI and has been “trained” on over 340 million matchups between near-nadir DPR and resolution-matched GMI.
- Raw validation statistics are not necessarily meaningful without context – question is whether they *improve* on alternative methods when applied to identical scenes.
  - Intercomparisons needed.
  - Metrics should including examination of the “noise floor”, not just traditional RMS error, bias, etc.
- The UW-algorithm is unique in providing not only estimates of the expected rain rate but also **posterior PDFs/CDfs/quantiles of rain rate** associated with a given scene, as determined by the typically large set of qualifiying matches.

Acknowledgments

- NASA PMM Grant #NNX16AF70G