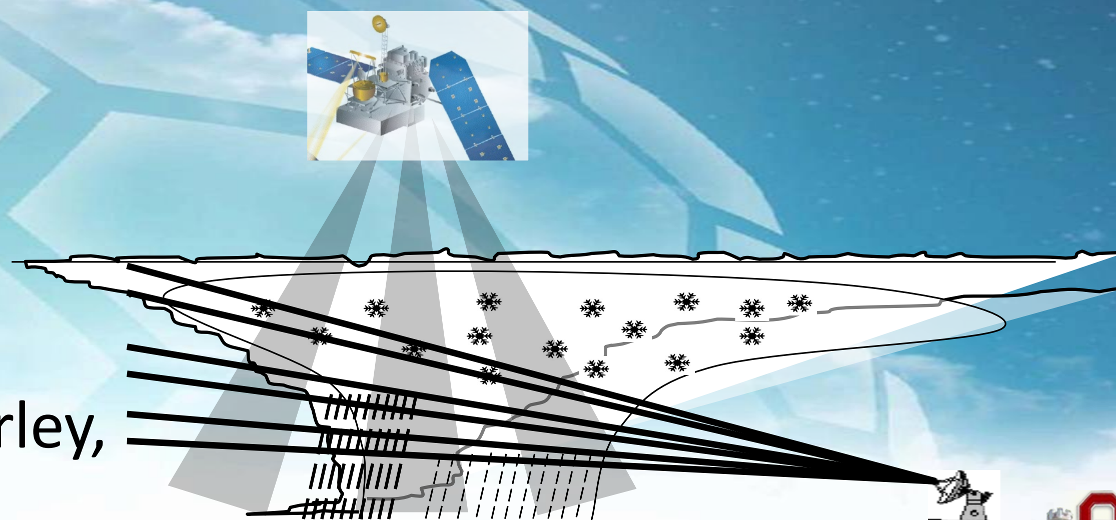
# Probabilistic precipitation estimation from satellites

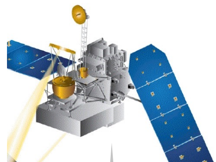
**Pierre Kirstetter**

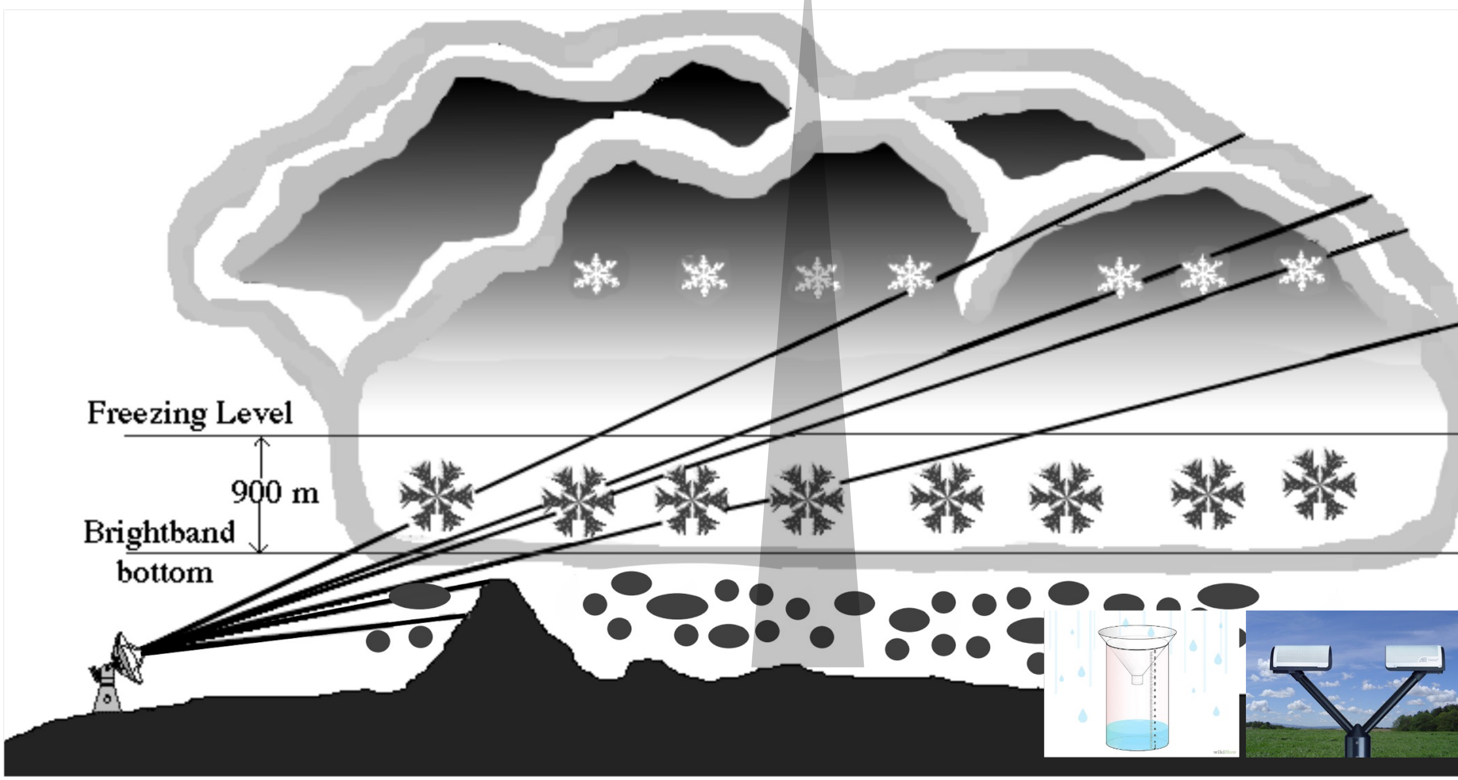


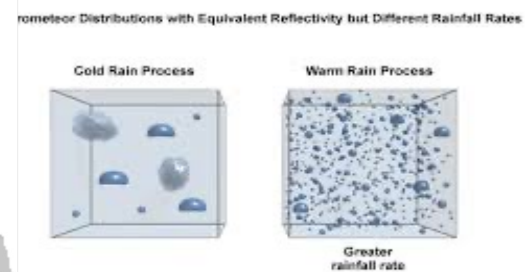
with contributions of:
S. Upadhyaya, M. Simpson,
J. Zhang, S. Martinaitis, J. Gourley,

# Challenges in remote sensing hydrometeorology

Example: **deterministic** QPE… but **indirect and often underdetermined relationship** between observations and precipitation





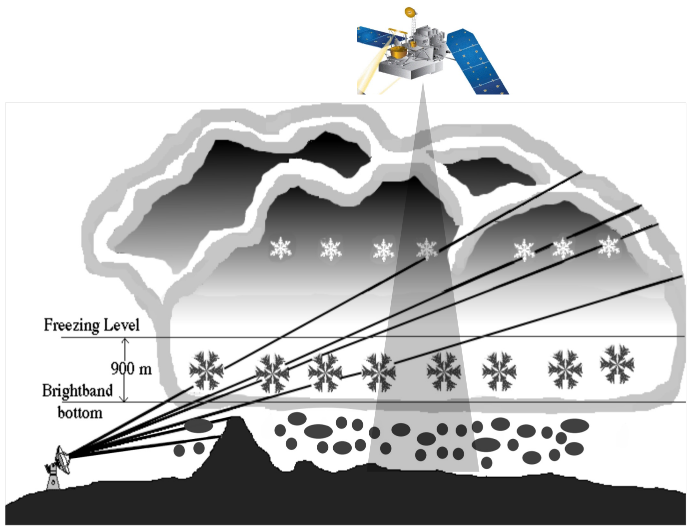
# Challenges in remote sensing hydrometeorology

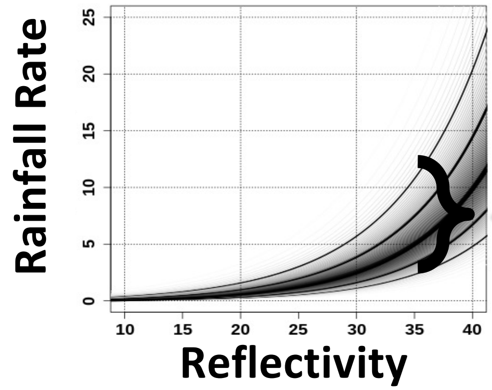
- **Remote sensing, atmospheric sciences, and hydrology:**
  - precipitation variability is ignored;
  - partially resolved / mixtures of precipitation processes;
  - limited characterization of extremes;
  - impacts hazard applications.
- **Classical parameterization approach is insufficient: deterministic, based on / depicting averaged properties.**

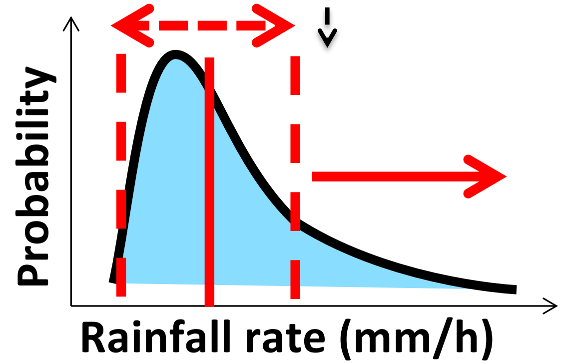
# Moving forward: increase the information content

- **Use uncertainty as an integral part of precipitation estimation**
  - data fusion
  - data assimilation
  - water budget
- **Quantify the likelihood of weather and water extremes**
  - hazard information
  - risk analysis

# Way forward: Probabilistic QPE



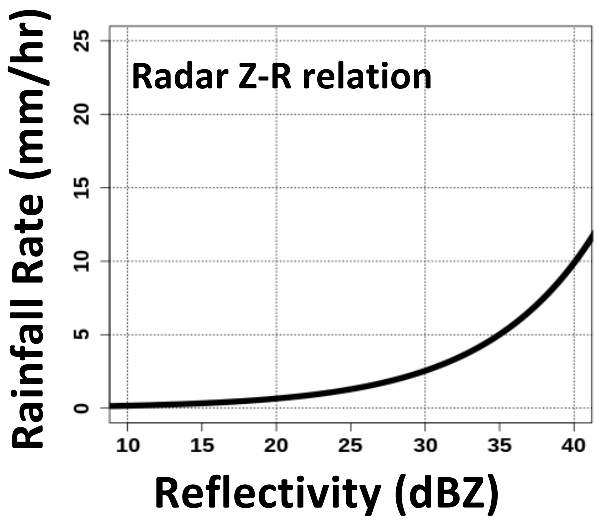



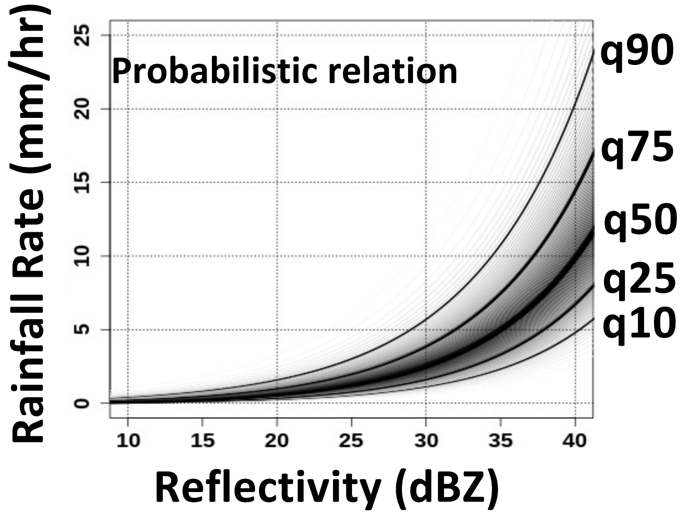

- **Uses uncertainty as an integral part of QPE**
- **Depicts the most likely value (➔ bias reduction)**
- **Quantifies certainty bounds (➔ data fusion & assimilation)**
- **Quantifies the likelihood of extreme cases (➔ risk analysis)**

Kirstetter, P.E., et al. , 2015: Probabilistic Precipitation Rate Estimates with Ground-based Radar Networks. *Water Resources Research*, 51, 1422–1442. doi:10.1002/2014WR015672

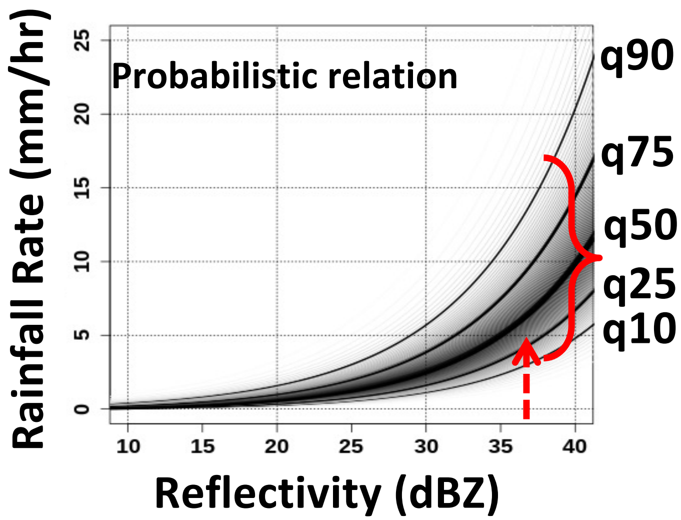
# Space outside the deterministic relation = space of error

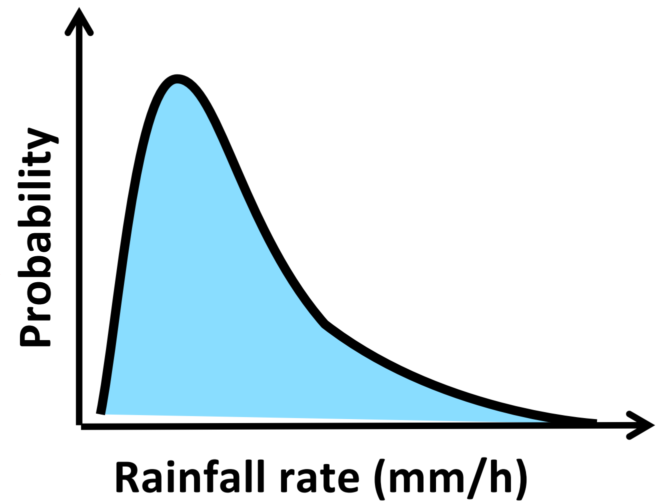


# Probabilistic relation = possible precipitation rates



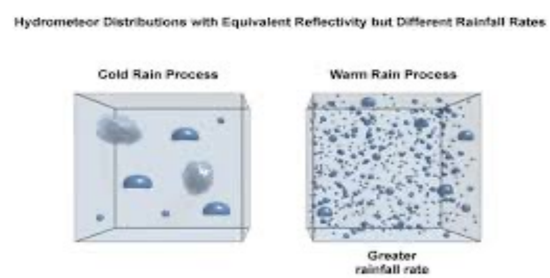
# Estimating distributions of possible precipitation rates



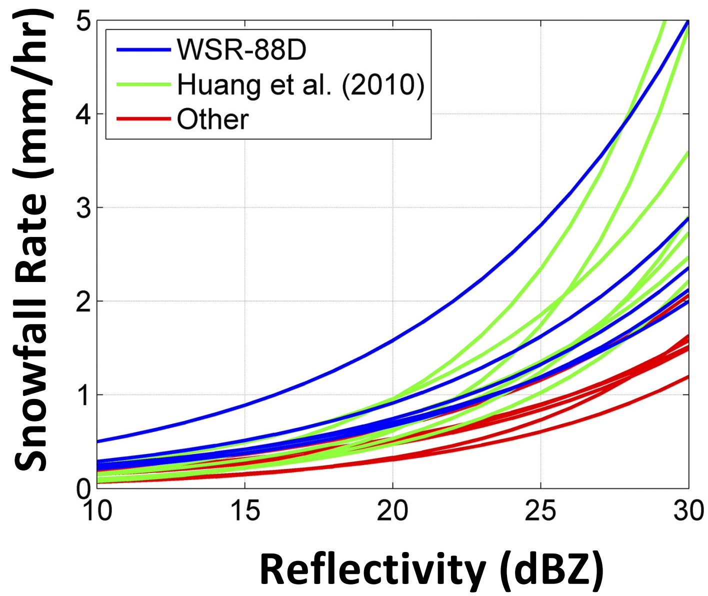

**Same reflectivity** $$Z_\infty = \int_0^\infty D^6 N(D)\,dD$$

**2 different rain rates** $$R_\infty = \frac{\pi}{6}\int_0^\infty w_t D^3 N(D)\,dD$$



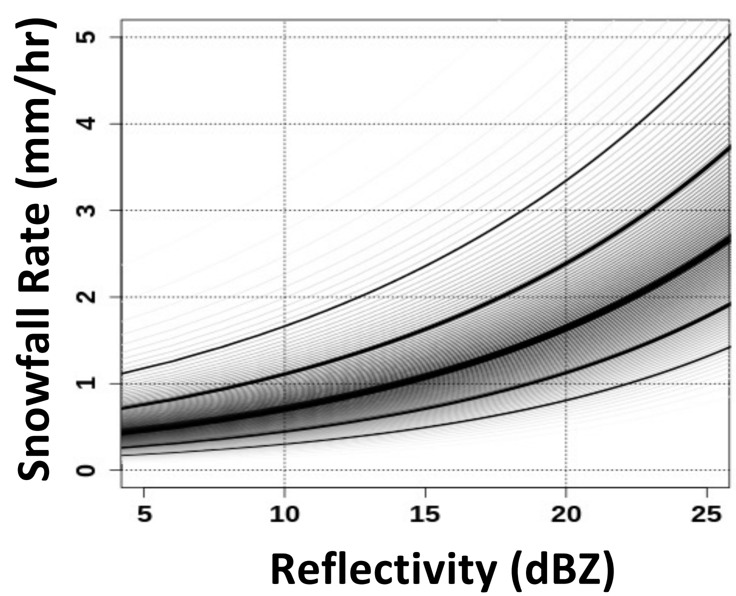
# Distribution of precipitation rates: Snow

**Deterministic Z-S relations: compilation**



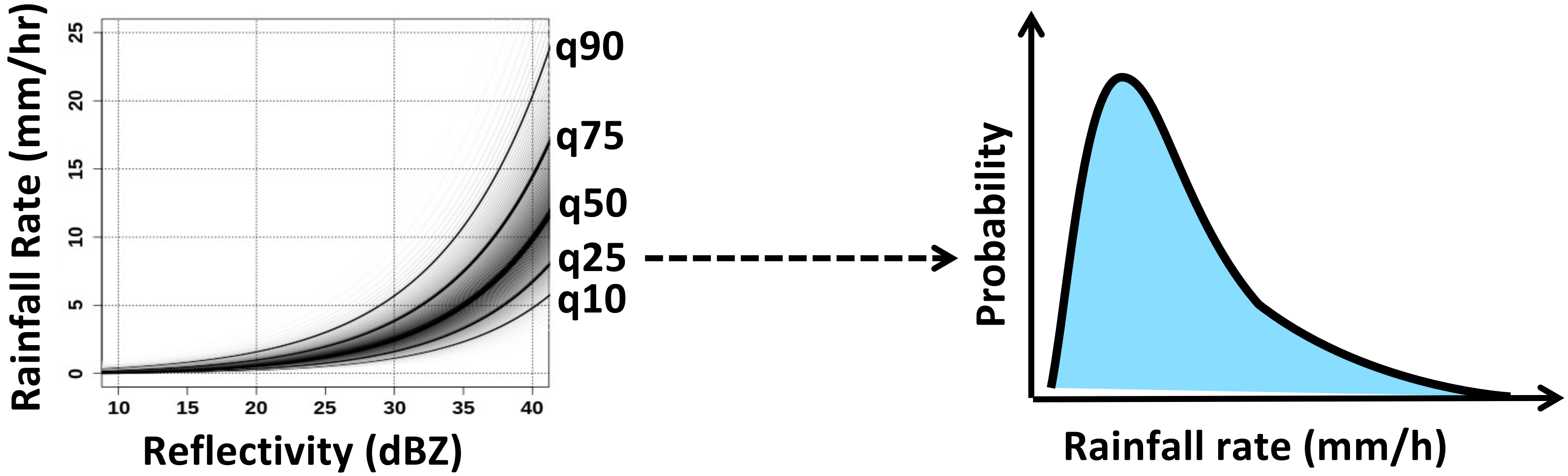

| Source | $Z(S)$ relation for dry snow |
|---|---|
| Gunn and Marshall (1958) | $Z = 448S^2$ |
| Sekhon and Srivastava (1970) | $Z = 399S^{2.21}$ |
| Ohtake and Henmi (1970) | $Z = 739S^{1.7}$ |
| Puhakka (1975) | $Z = 235S^2$ |
| Koistinen et al. (2003) | $Z = 400S^2$ |
| Huang et al. (2010) | $Z = (106\text{–}305)S^{(1.11\text{–}1.92)}$ |
| Szyrmer and Zawadzki (2010) | $Z = 494S^{1.44}$ |
| Wolfe and Snider (2012) | $Z = 110S^2$ |
| WSR-88D, Northeast | $Z = 120S^2$ |
| WSR-88D, north plains–upper Midwest | $Z = 180S^2$ |
| WSR-88D, high plains | $Z = 130S^2$ |
| WSR-88D, Intermountain West | $Z = 40S^2$ |
| WSR-88D, Sierra Nevada | $Z = 222S^2$ |

**Snow PQPE**



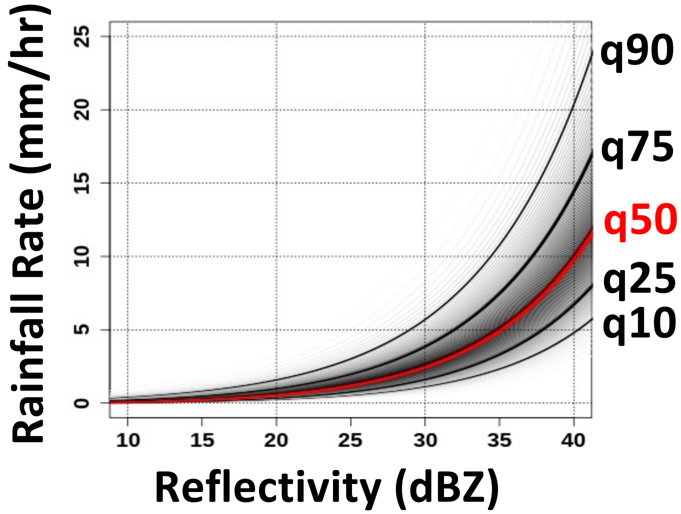

*Courtesy Bukovčić et al. (2018)*

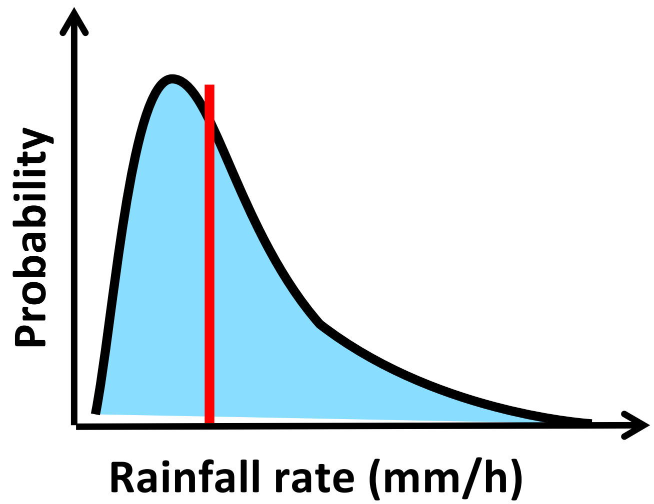
# Enhance QPE information content




- **Provide the PDF of precipitation rates at measurement scale**

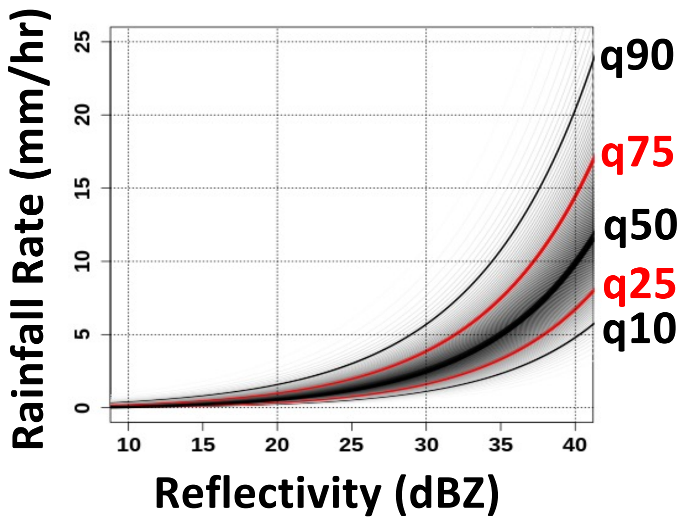
# Most likely value – mitigate bias

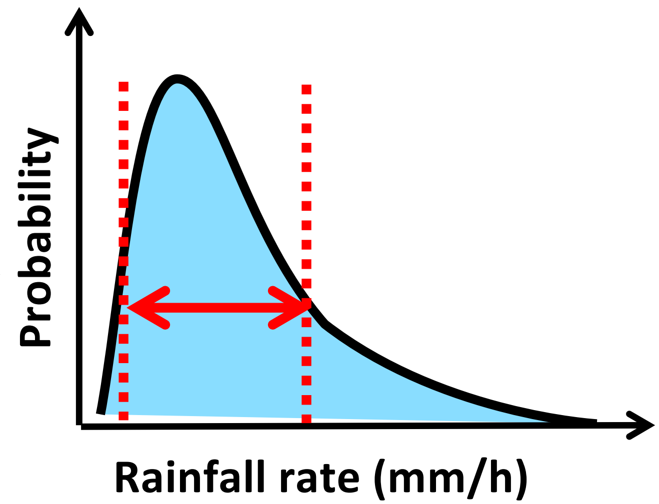



- **Provide the PDF of precipitation rates at measurement scale**
- **Depict the most likely value (deterministic users & applications)**

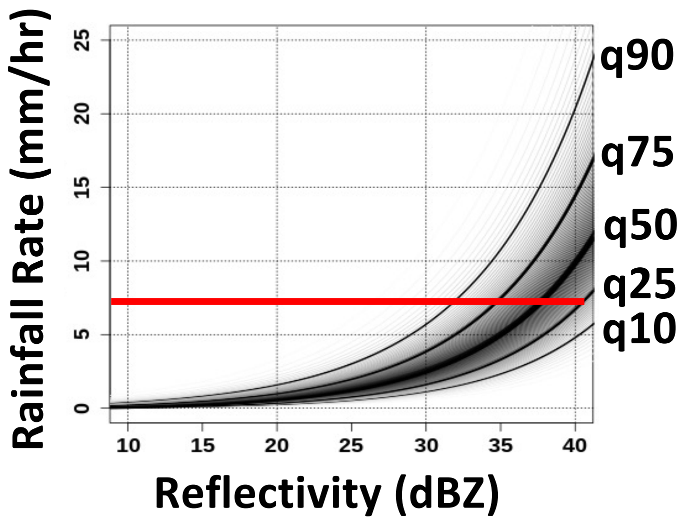
# Uncertainty

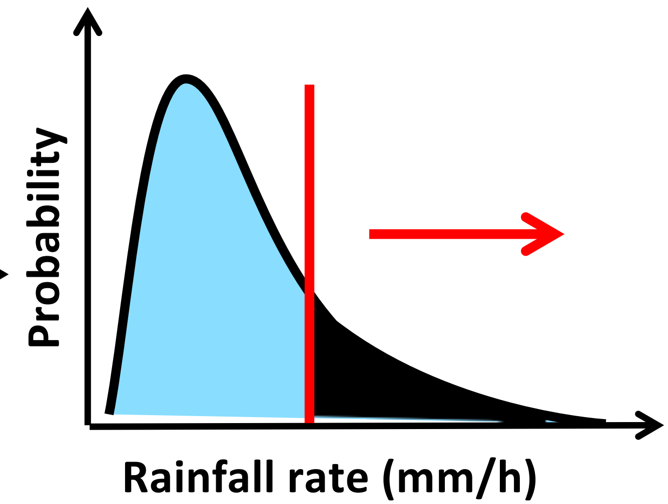



- **Provide the PDF of precipitation rates at measurement scale**
- **Depict the most likely value (deterministic users & applications)**
- **Quantify certainty bounds (data fusion & assimilation)**

# Monitoring the likelihood of extremes - hazards

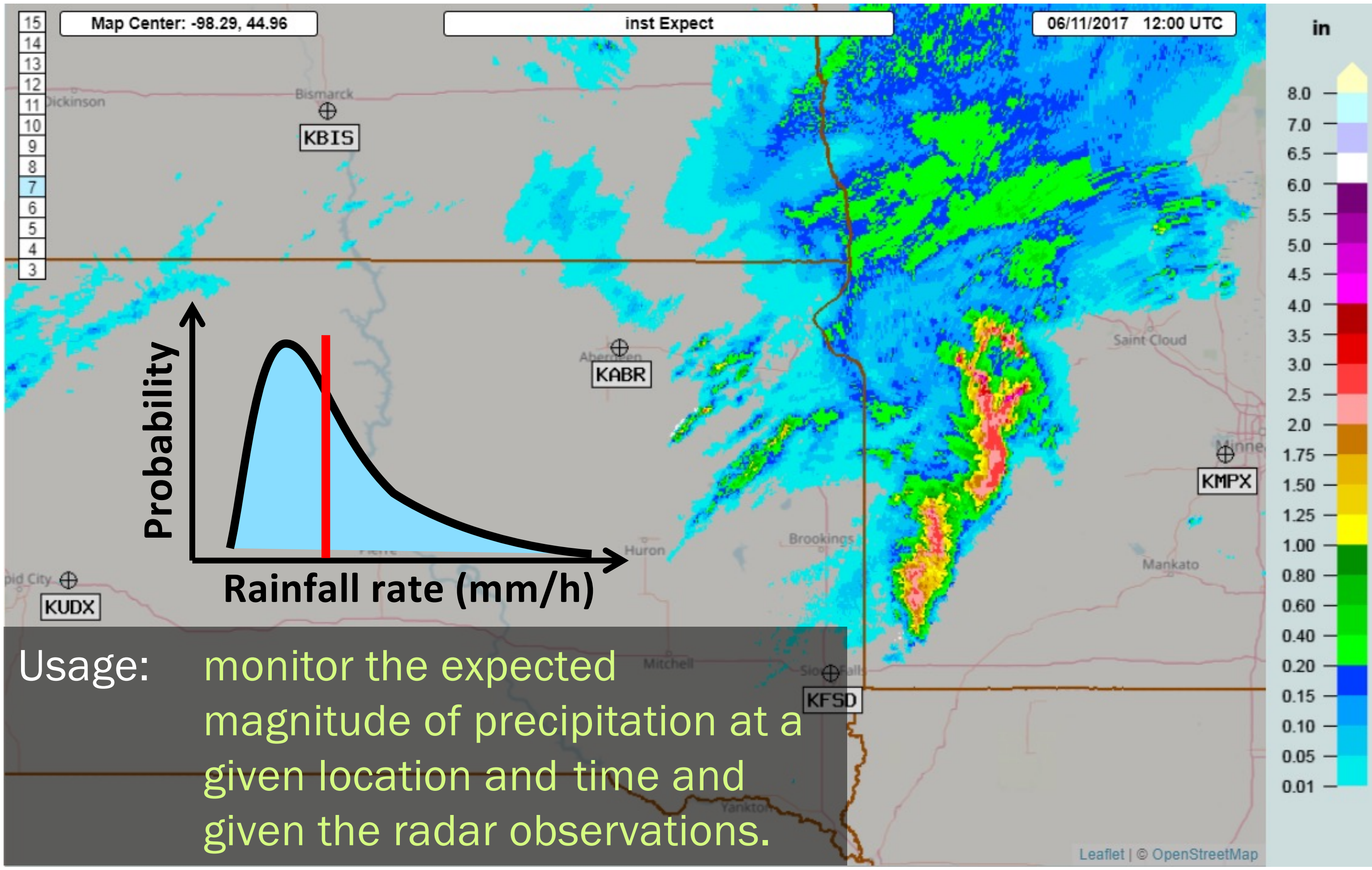



- **Provide the PDF of precipitation rates at measurement scale**
- **Depict the most likely value (deterministic users & applications)**
- **Quantify certainty bounds (data fusion & assimilation)**
- **Quantify the likelihood of extreme cases (risk analysis)**

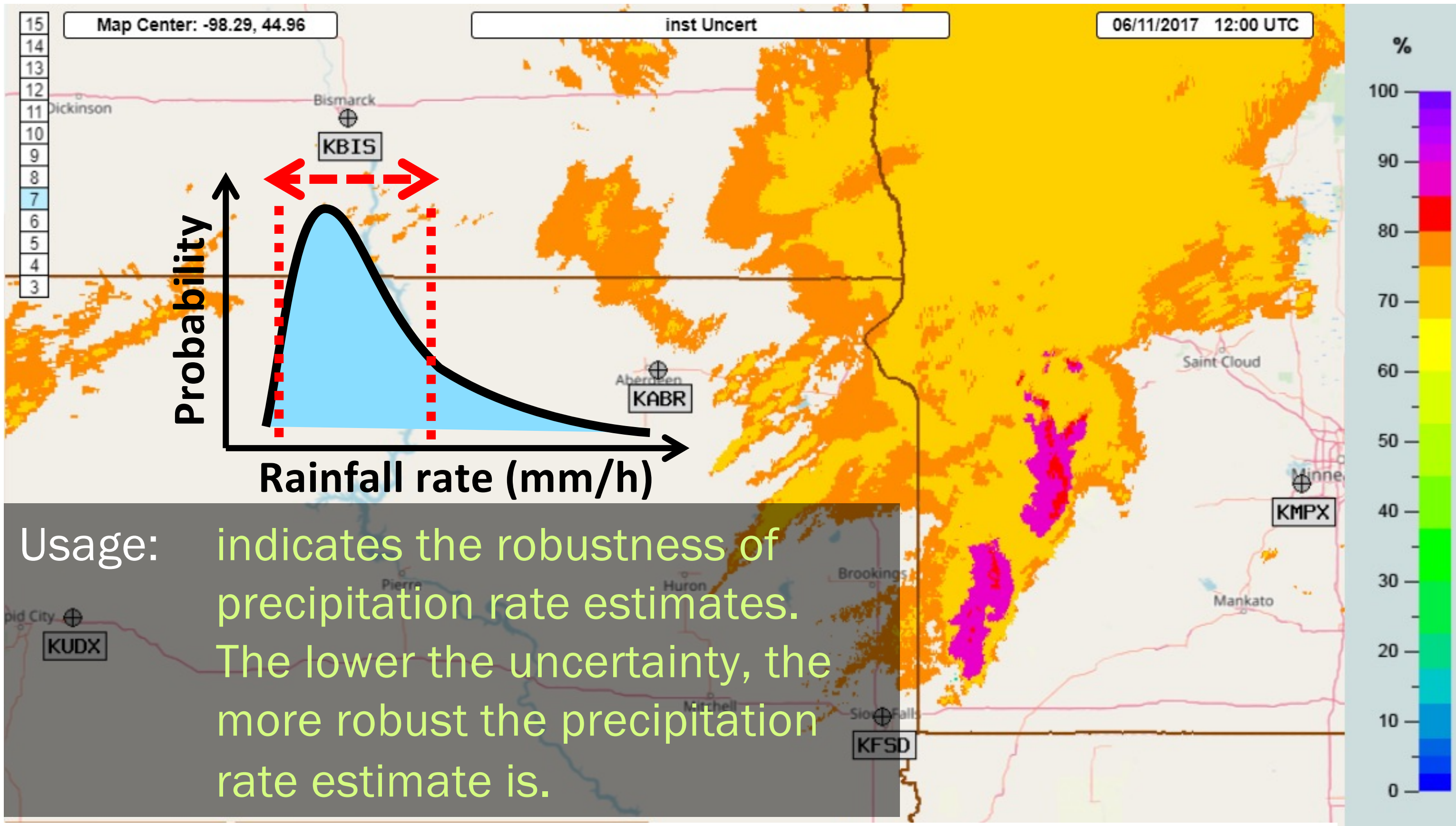

**Kirstetter, P.E., et al. , 2015: Probabilistic Precipitation Rate Estimates with Ground-based Radar Networks. *Water Resources Research*, 51, 1422–1442. doi:10.1002/2014WR015672**

# PQPE expectation




Usage: monitor the expected magnitude of precipitation at a given location and time and given the radar observations.

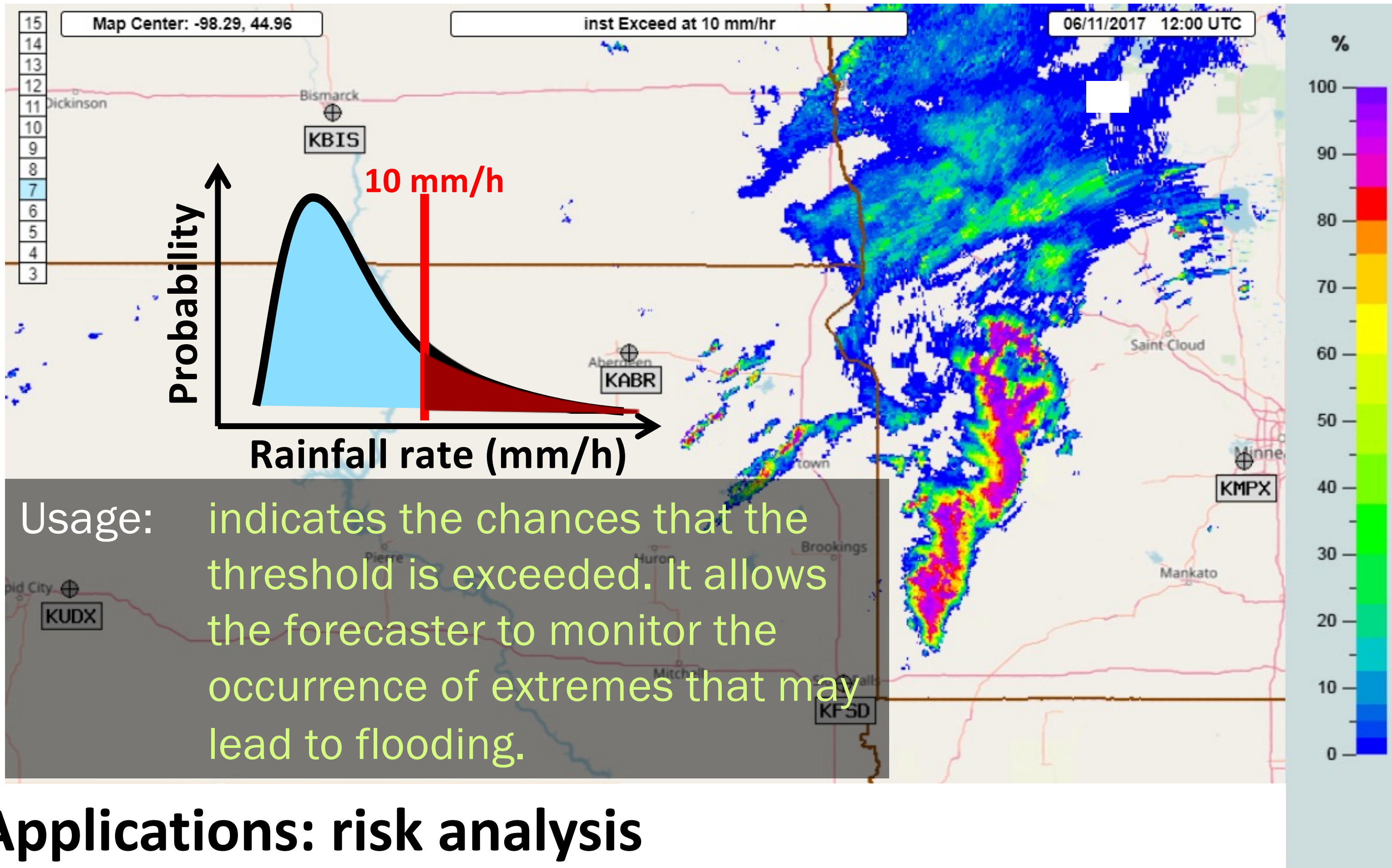
# Uncertainty estimates




Usage: indicates the robustness of precipitation rate estimates. The lower the uncertainty, the more robust the precipitation rate estimate is.

- **Applications: data fusion & assimilation**

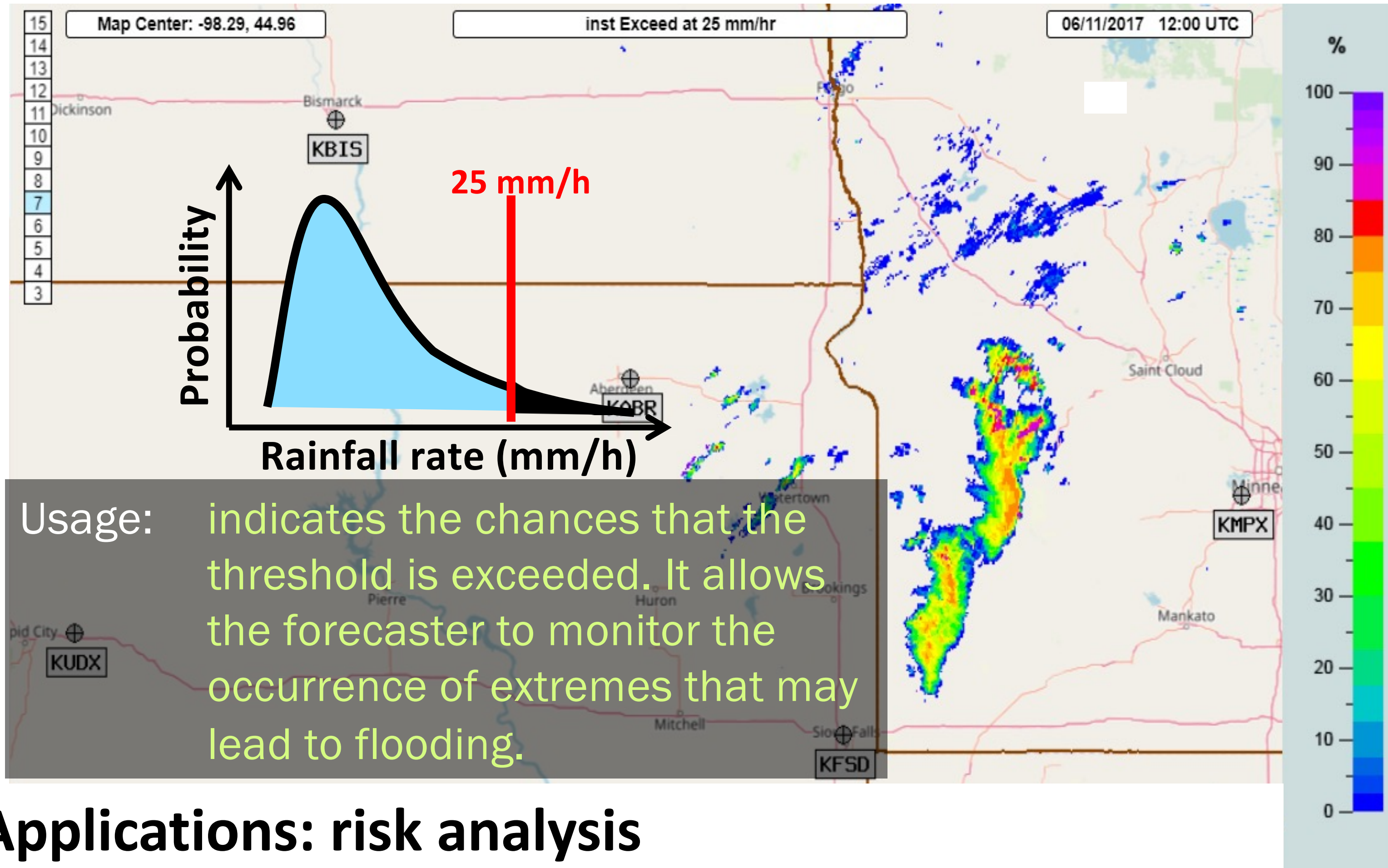
# Probability of exceeding threshold (10 mm/h)




Usage: indicates the chances that the threshold is exceeded. It allows the forecaster to monitor the occurrence of extremes that may lead to flooding.

- **Applications: risk analysis**

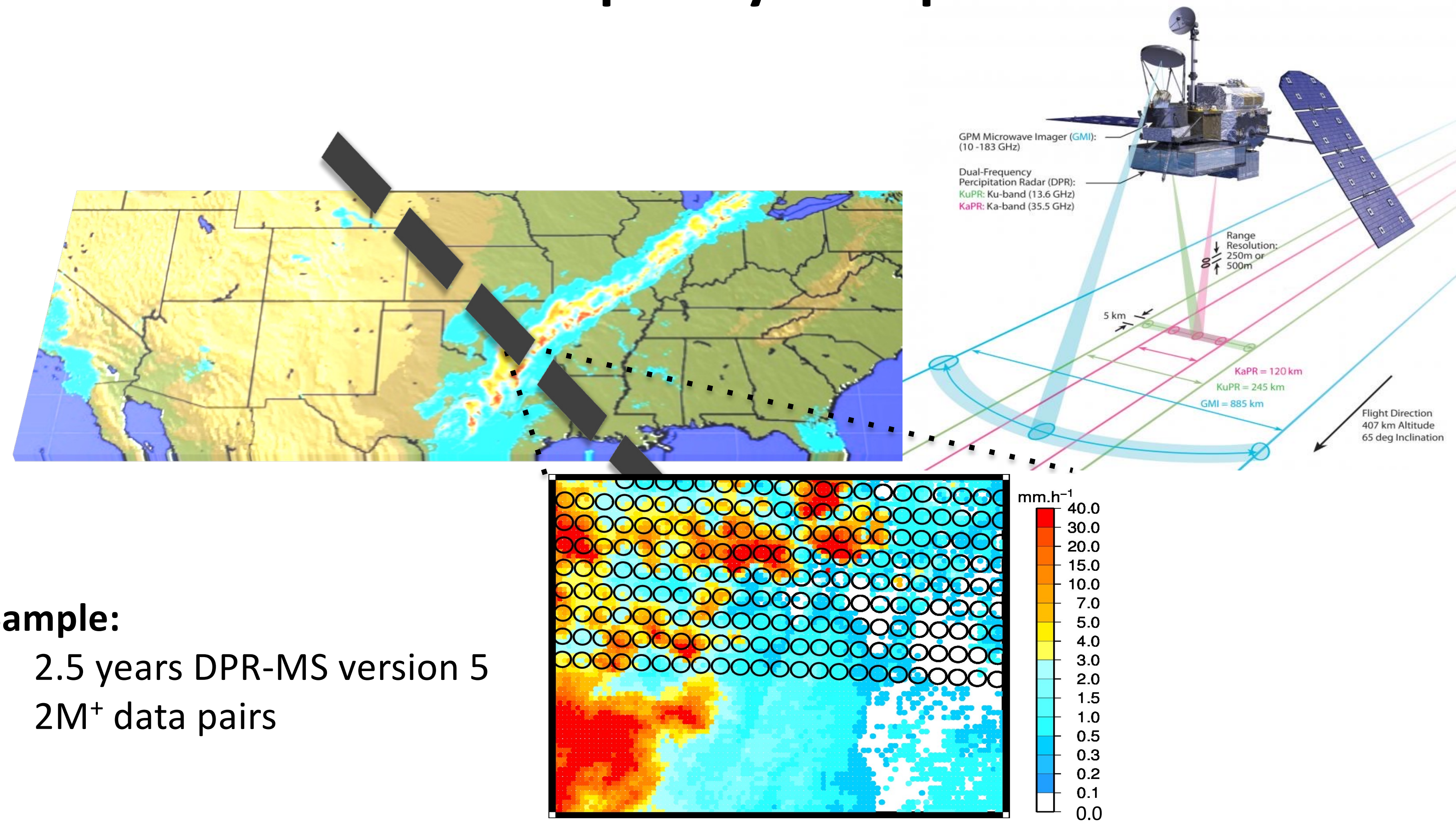
# Probability of exceeding threshold (25 mm/h)




Usage: indicates the chances that the threshold is exceeded. It allows the forecaster to monitor the occurrence of extremes that may lead to flooding.

- **Applications: risk analysis**

# GPM Dual-Frequency Precipitation Radar

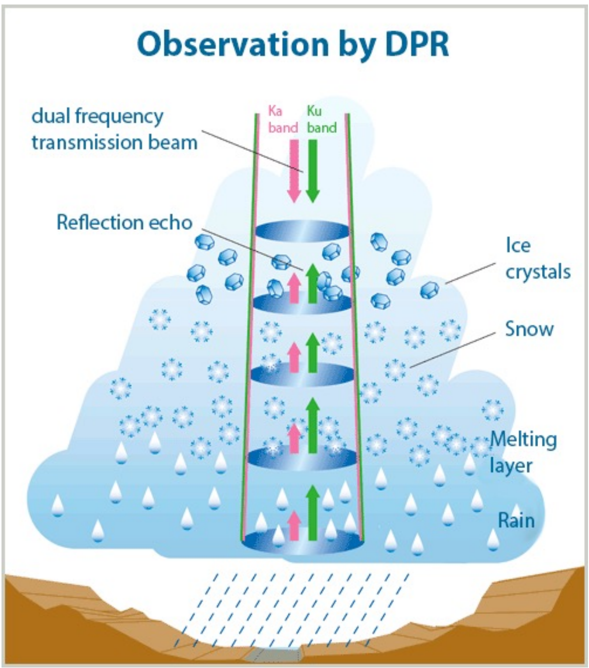



**Sample:**

- 2.5 years DPR-MS version 5
- 2M$^{+}$ data pairs

# Dual-Frequency Precipitation Radar algorithm

**Objective: estimate the profile of microphysics (PSD at each gate) and the surface precipitation rate R**




- Space radar algorithm fits 1D vertical model of precipitation microphysics to the observed profile of reflectivity

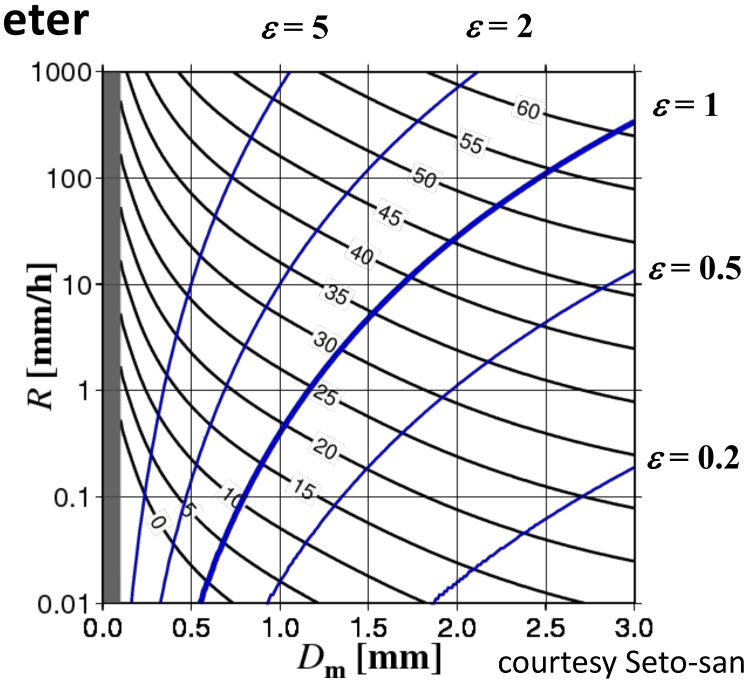
- Assumes microphysics: convective / stratiform
- Assumes primarily uniform precipitation in the field of view

- Challenge: get the microphysics right
- Challenge: deal with unresolved variability

# Dual-frequency Precipitation Radar QPE relations

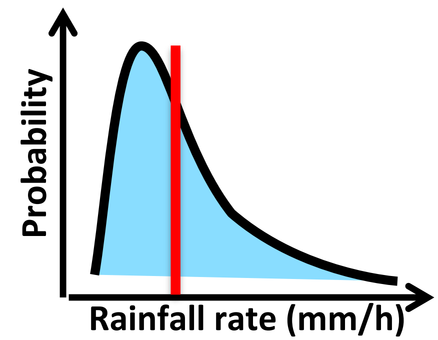
- **Rainfall – mass weighted mean diameter relation: R-Dm**
  - **stratiform: $R_{DPR} = 0.401\ \varepsilon^{4.649}\ D_m^{6.131}$** **ε : adjustment parameter**
  - **convective: $R_{DPR} = 1.370\ \varepsilon^{4.258}\ D_m^{5.420}$** **Dm: mean diameter**

- **PQPE approach**
  - **stratiform: $R_{ref} \Leftrightarrow 0.401\ \varepsilon^{4.649}\ D_m^{6.131}$**
  - **convective: $R_{ref} \Leftrightarrow 1.370\ \varepsilon^{4.258}\ D_m^{5.420}$**



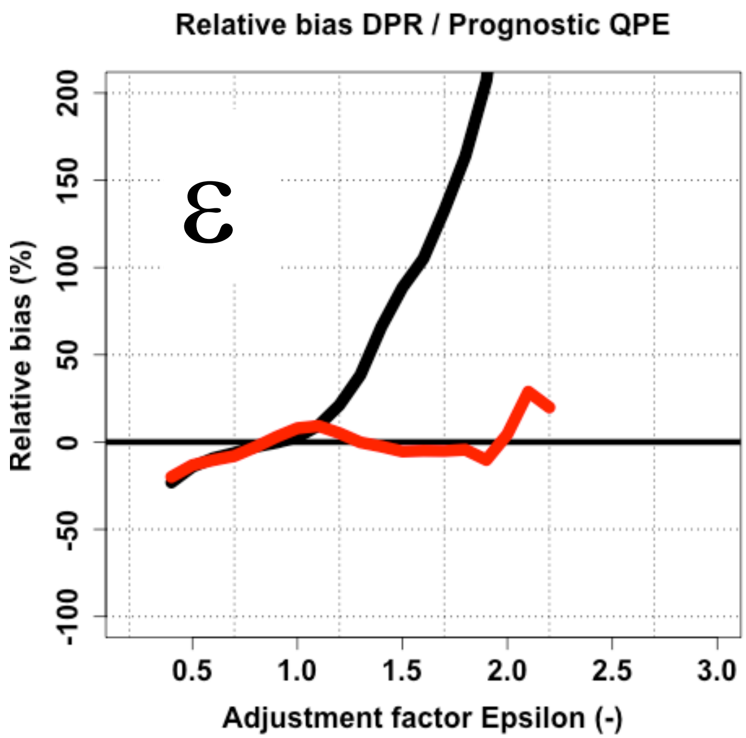

courtesy Seto-san

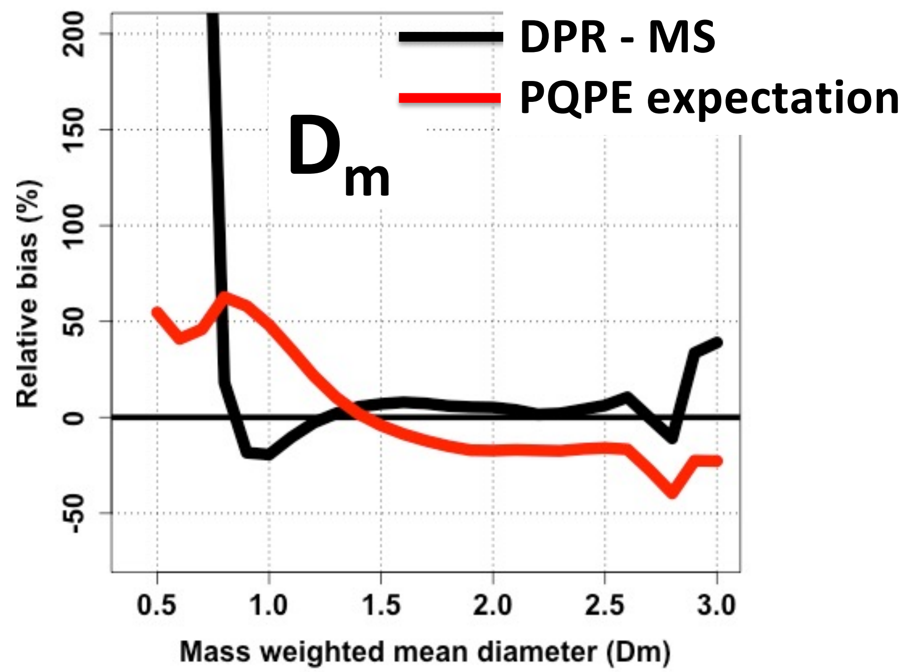
# Dual-frequency Precipitation Radar Conditional biases with ε and Dm




**DPR QPE = f (ε, $D_{m,}$ precipitation type, …)**

**PDF($R_{ref}$) = f (ε, $D_{m,}$ precipitation type, …)**



# Dual-frequency Precipitation Radar scores

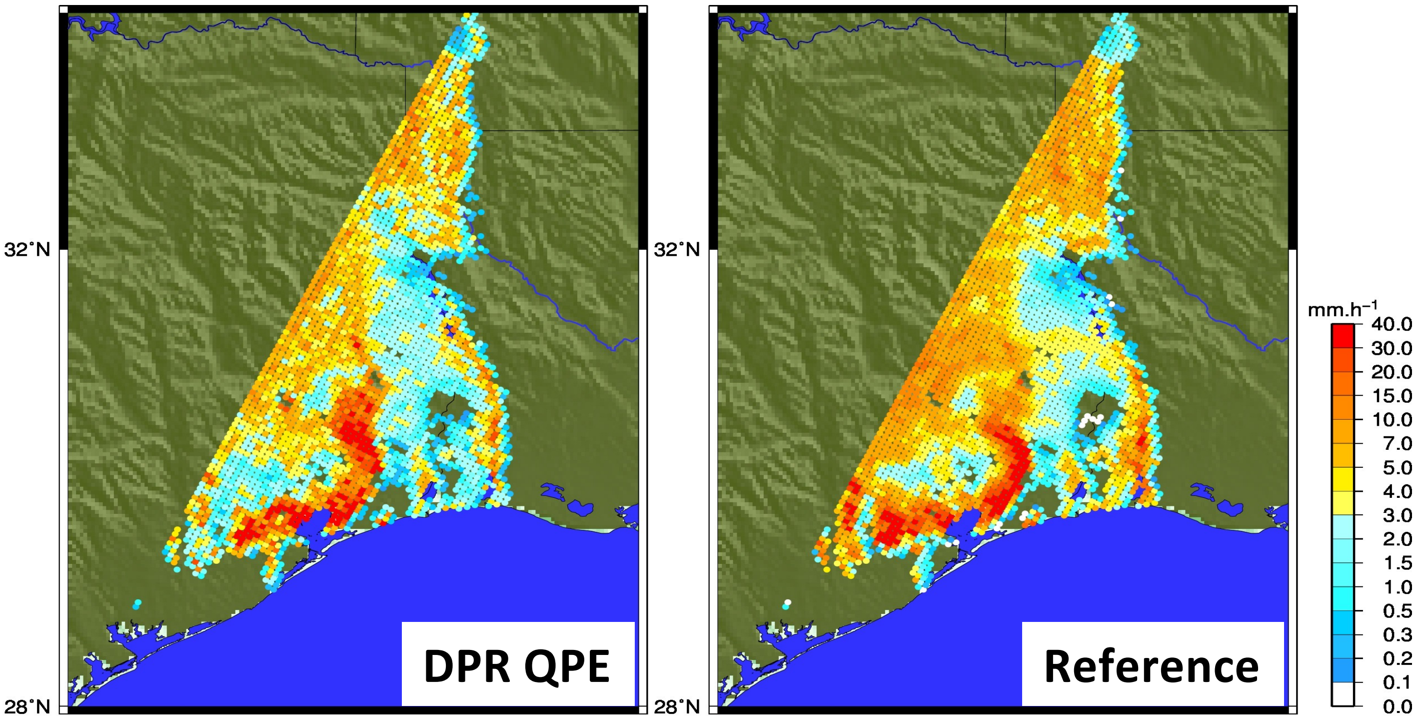
**DPR PQPE = f (reflectivity,**
**precipitation type,**
**incidence angle)**

| | brightband | | stratiform | | convective | |
|---|---|---|---|---|---|---|
| | Bias (%) | Correlation | Bias (%) | Correlation | Bias (%) | Correlation |
| DPR | +0.46 | 0.54 | -21.0% | 0.35 | -8.9% | 0.37 |
| PQPE | -0.32% | 0.61 | -3.3% | 0.43 | +2.9% | 0.52 |

➔ **Improving both bias and correlation cannot be achieved by post-processing**

# Space-based Precipitation Radar Probabilistic QPE

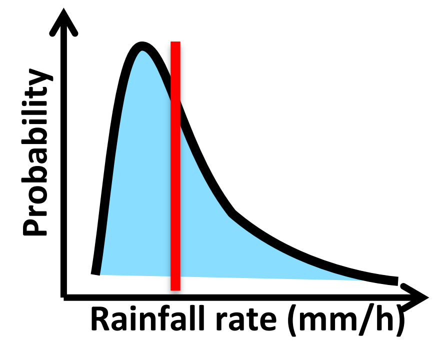
**DPR QPE = f (reflectivity,**
**precipitation type,**
**incidence angle,** Z-R relation, Non Uniform Beam Filling,...**)**

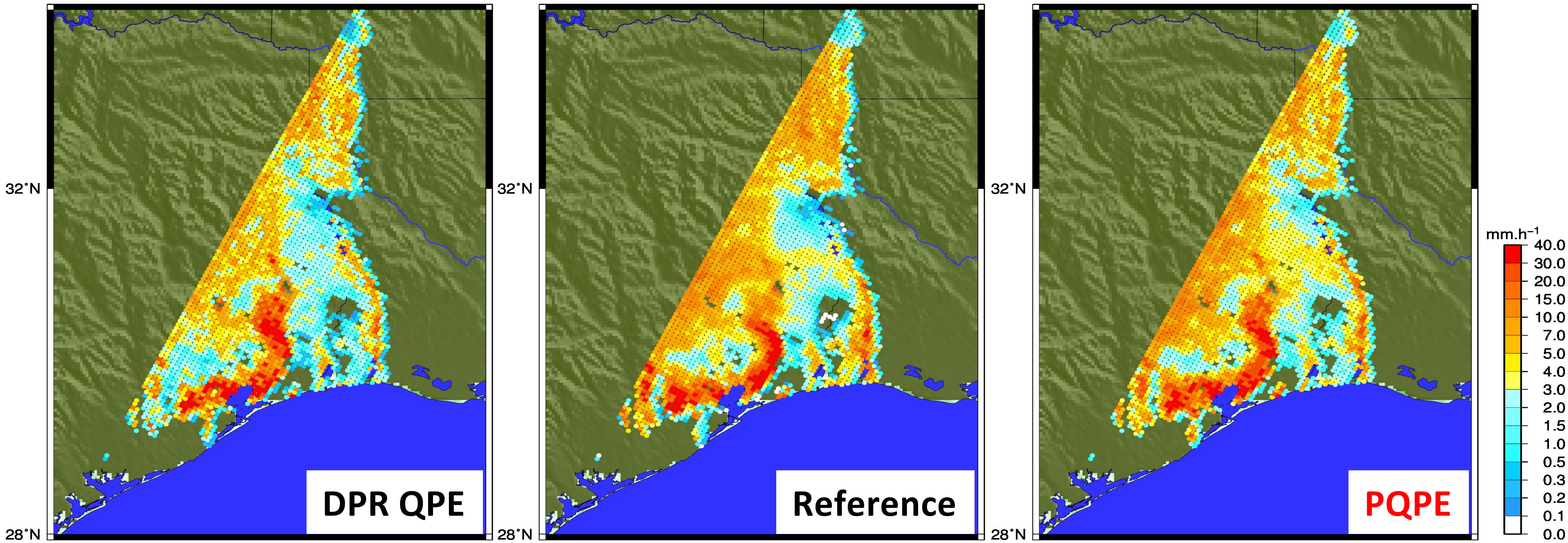



**Storm system at 12:30 UTC on 18 April 2016 near Houston**

# Space-based Precipitation Radar Probabilistic QPE

**DPR PQPE = f (reflectivity,**
**precipitation type,**
**incidence angle)**

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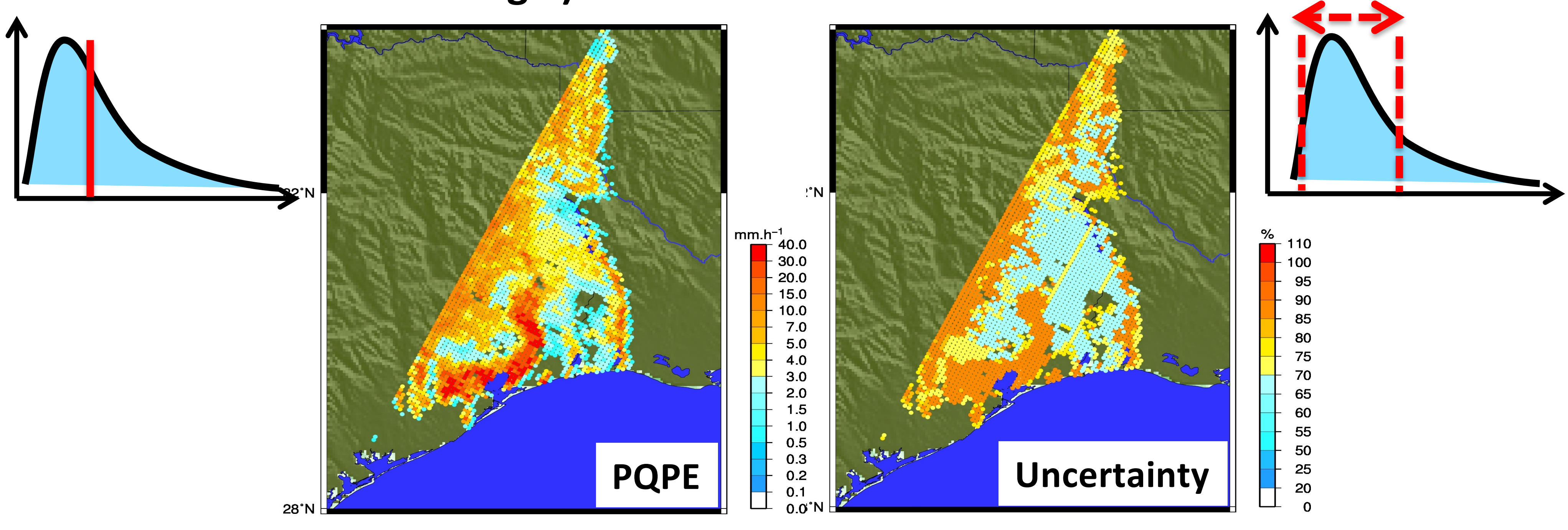



**Storm system at 12:30 UTC on 18 April 2016 near Houston**

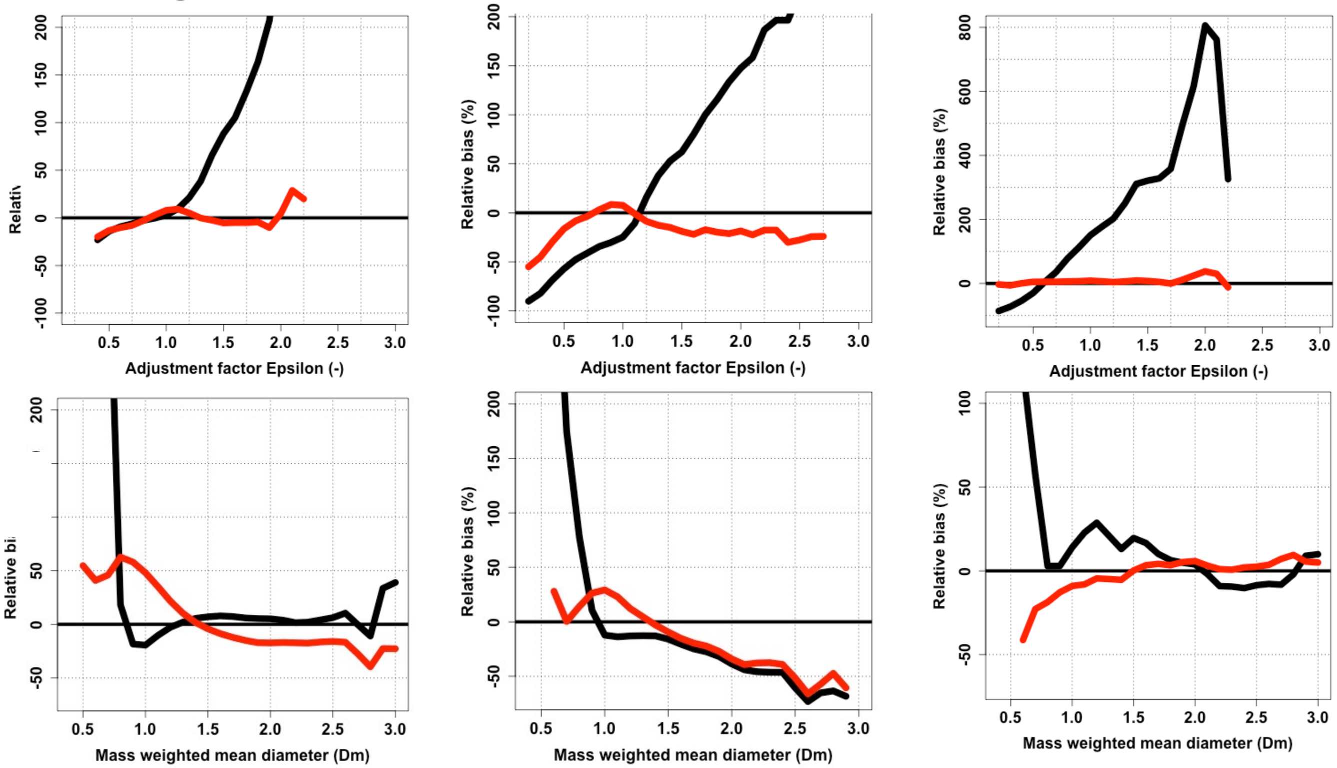
# Dual-frequency Precipitation Radar
# Conditional biases with ε and Dm

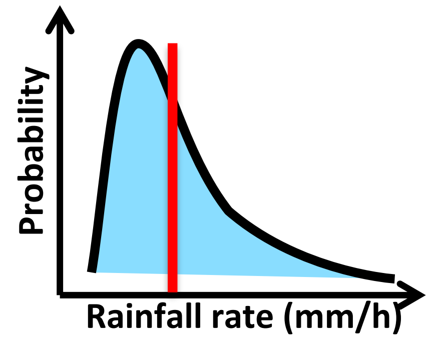
**DPR QPE = f (ε, $D_m$, precipitation type, …)** **PDF($R_{ref}$) = f (ε, $D_m$, precipitation type, …)**

**brightband** **stratiform** **convective**

ε

$D_m$




**DPR - MS**

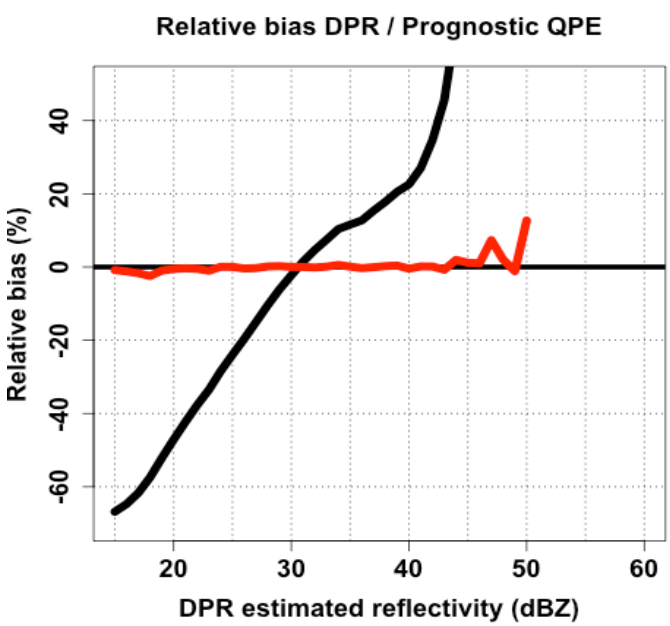
**PQPE expectation**

# Space-based radars
# A multi-parameter estimation

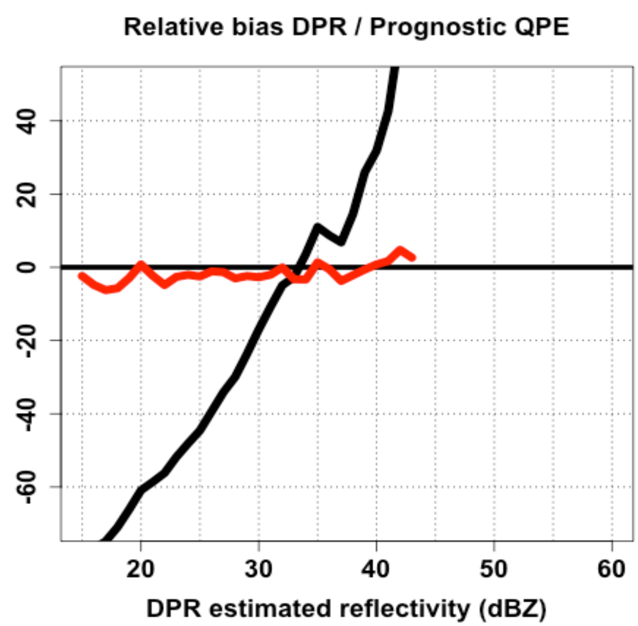
**DPR QPE = f (reflectivity,**
**precipitation type,**
**incidence angle)**

DPR
PQPE expectation

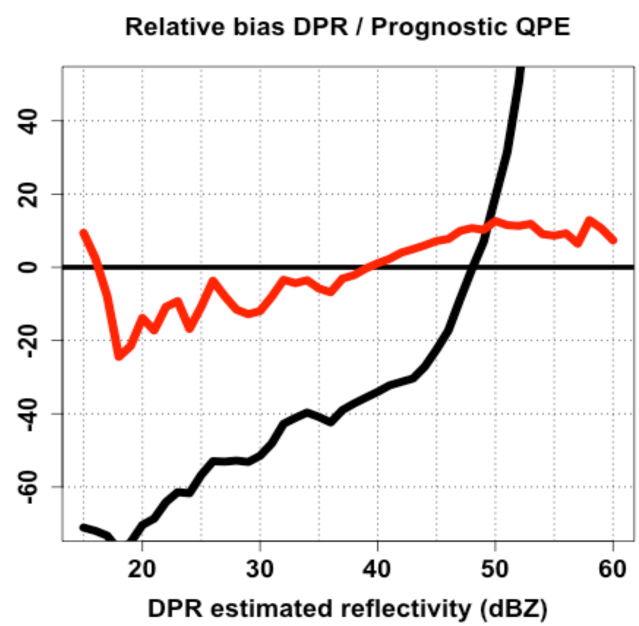
## brightband




## stratiform




## convective

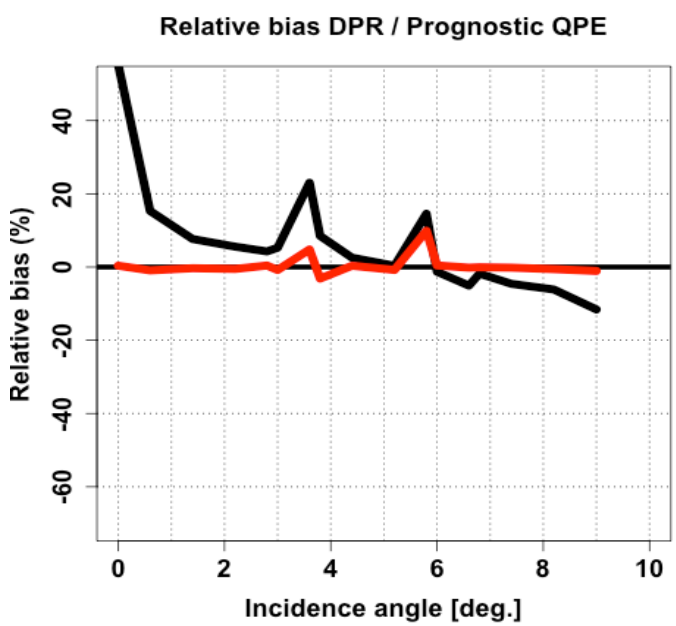


# Space-based radars
# A multi-parameter estimation

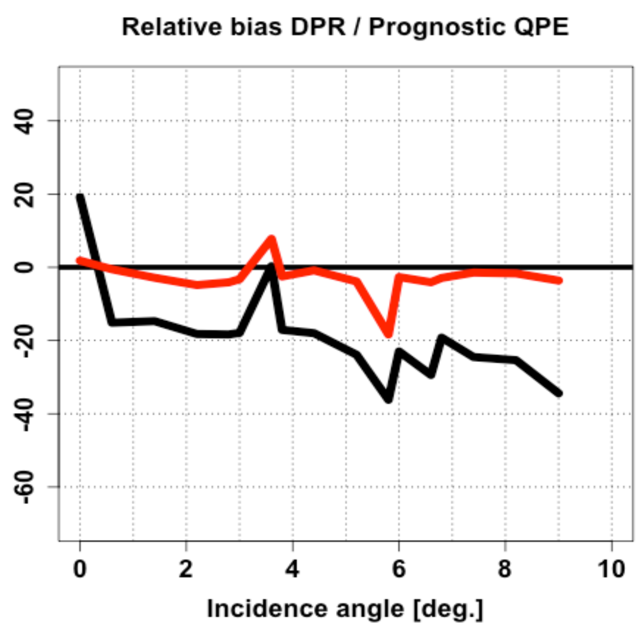
**DPR QPE = f (reflectivity,
precipitation type,
incidence angle)**

**Hamada et al. (2012)**
**DPR**
**PQPE expectation**

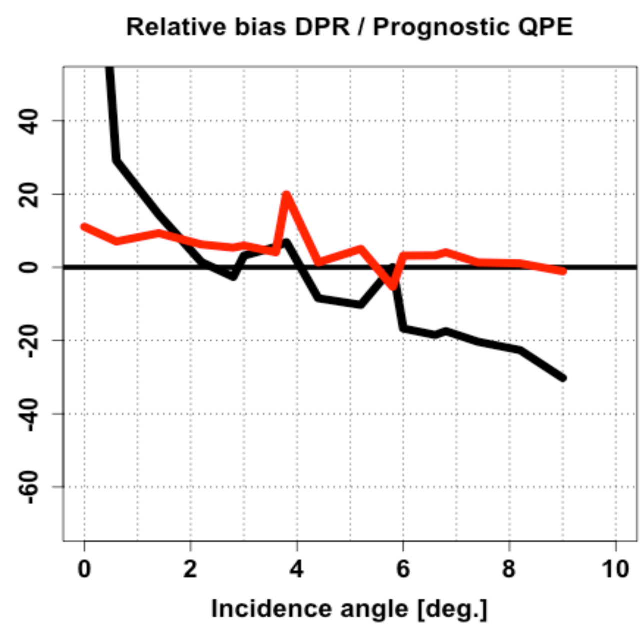
## brightband




## stratiform




## convective

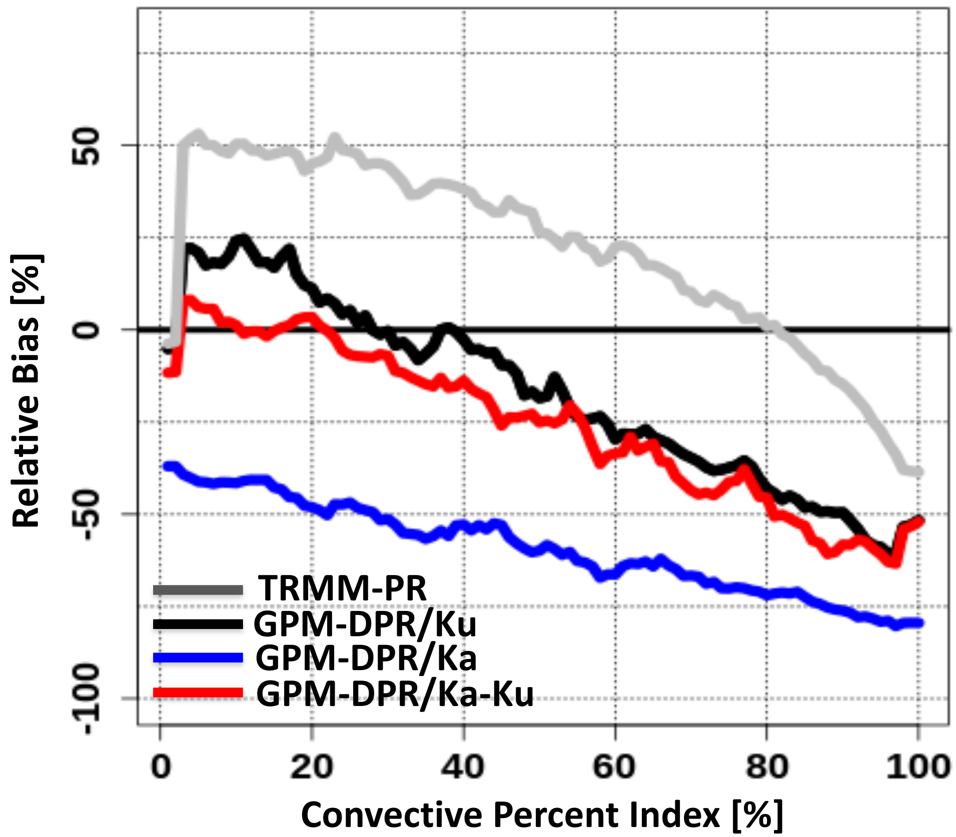


# Dual-frequency Precipitation Radar scores

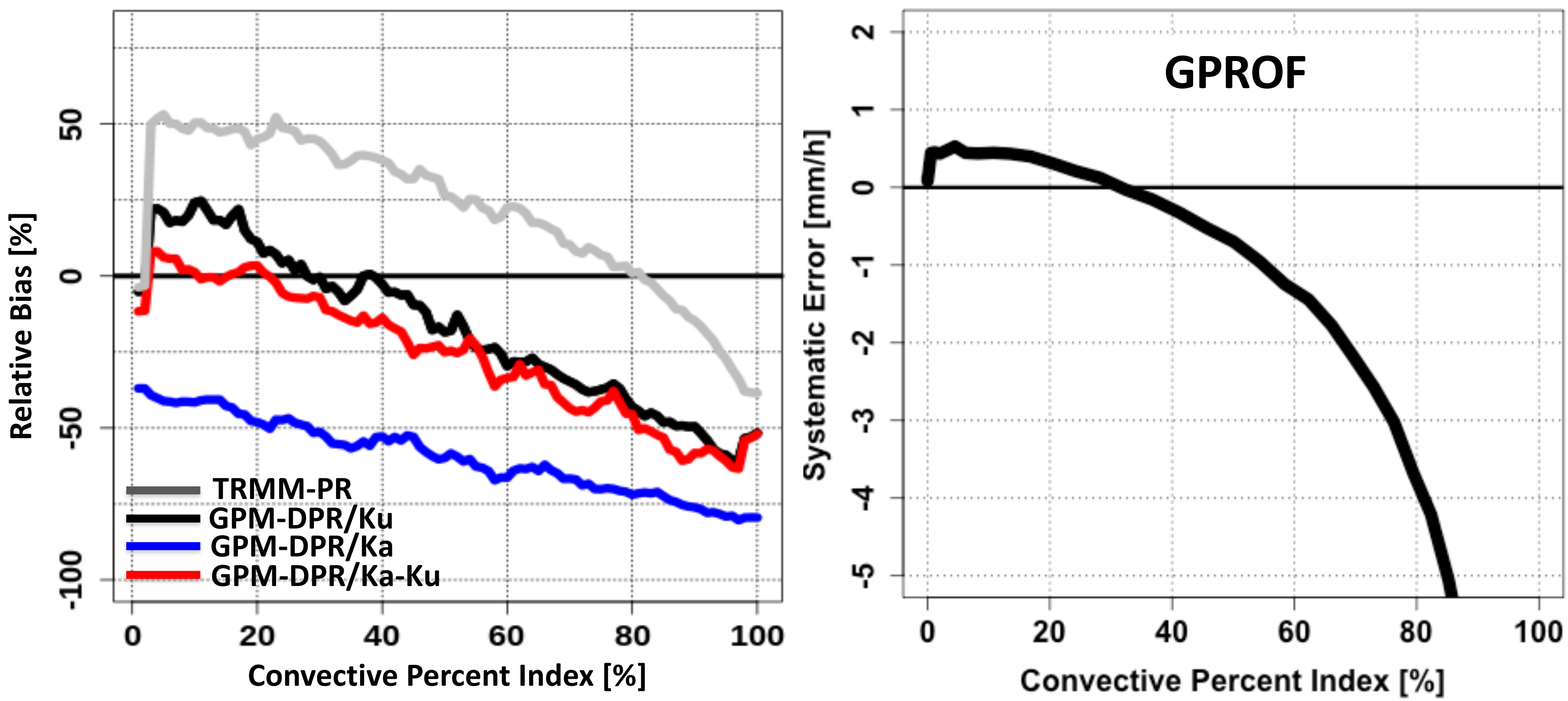
| | brightband | | stratiform | | convective | |
|---|---|---|---|---|---|---|
| | ε | $D_m$ | ε | $D_m$ | ε | $D_m$ |
| DPR | 4.649 | 6.131 | 4.649 | 6.131 | 4.258 | 5.420 |
| PQPE | 2.321 | 3.941 | 1.833 | 3.165 | 1.647 | 3.365 |

| | brightband | | stratiform | | convective | |
|---|---|---|---|---|---|---|
| | Bias | Correlation | Bias | Correlation | Bias | Correlation |
| DPR | +0.46 | 0.54 | -21.0% | 0.35 | -8.9% | 0.37 |
| PQPE | -0.32% | 0.61 | -3.3% | 0.43 | +2.89% | 0.52 |

# Spaceborne radars: convective contribution



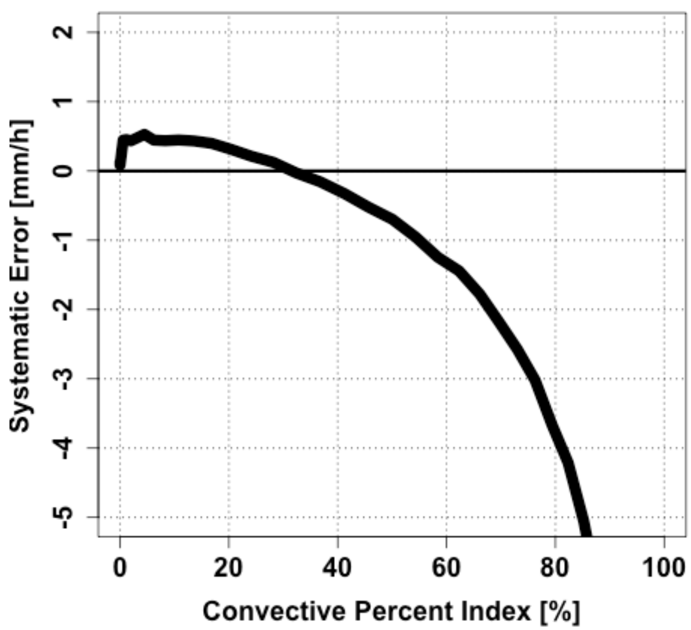
# Spaceborne radars and PMW: convective contribution



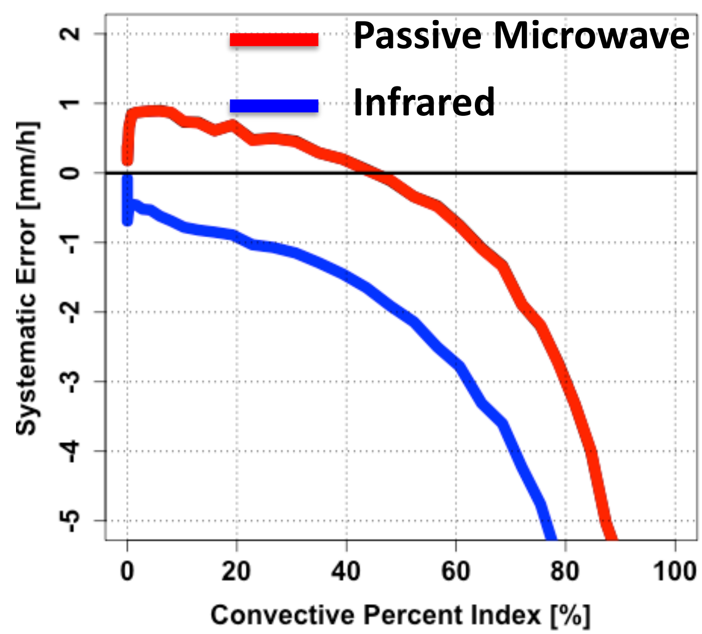
# GPROF and IMERG: convective contribution

- Currently GPROF does not condition the retrieval by precipitation types ➔ systematic error propagates to IMERG
- Demonstrated the interest of accounting for convective contribution in GPROF

**GPROF**

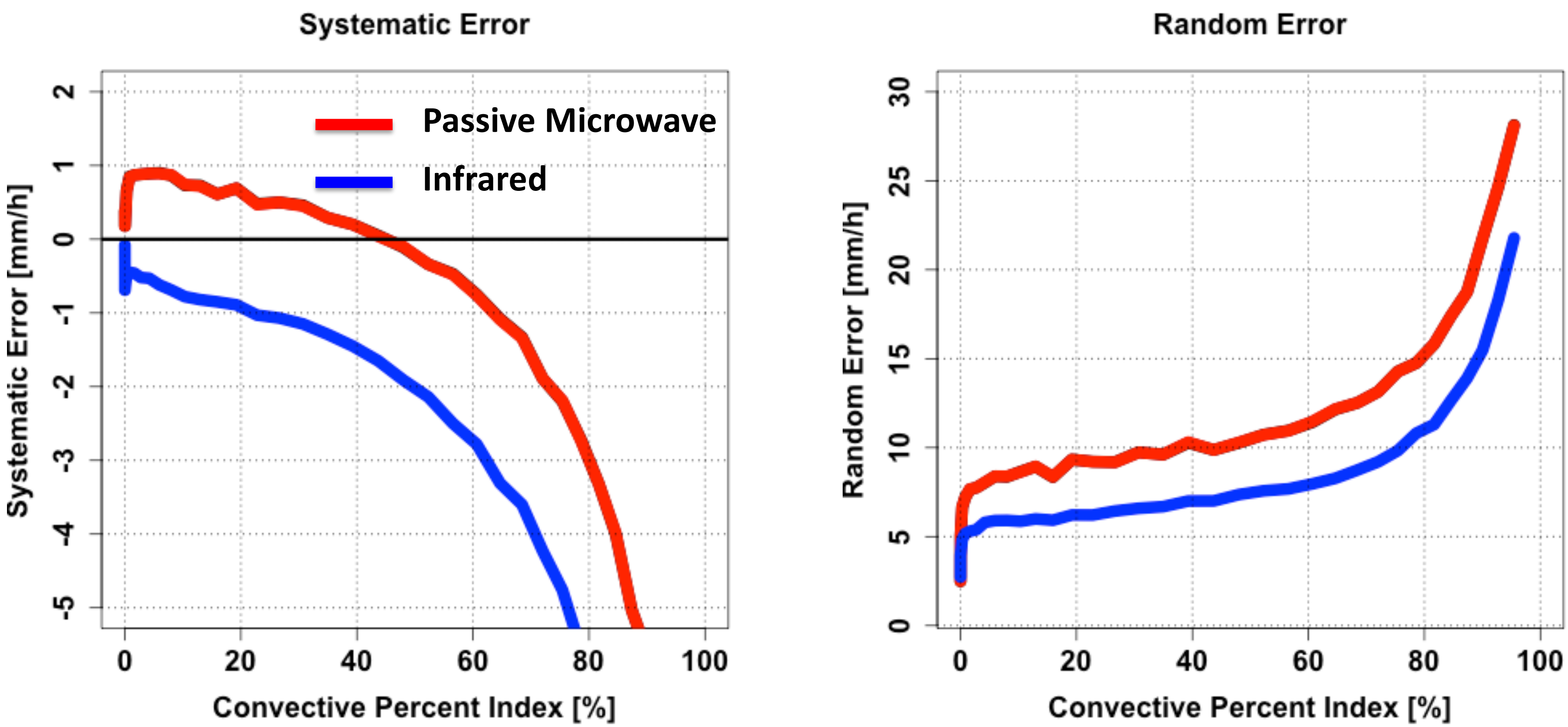



**IMERG**




➔ Kirstetter et al. (2020)

# IMERG diagnostic analysis: convective index



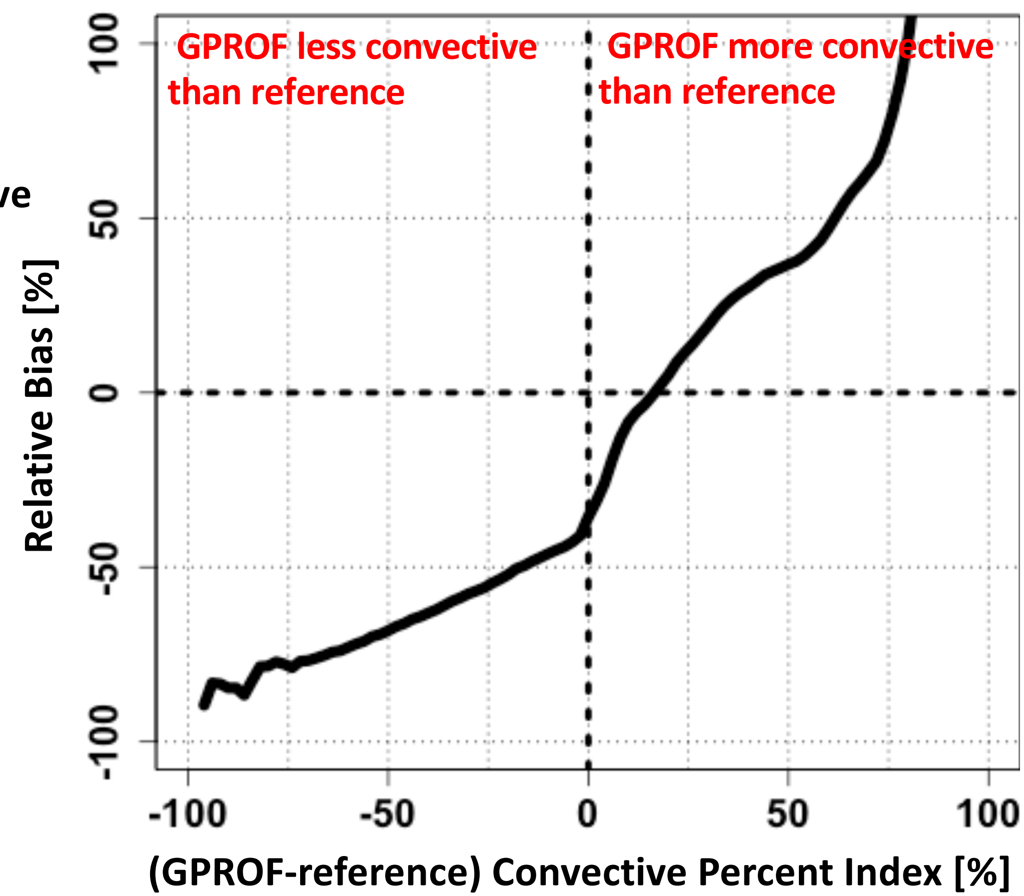
# PMW: convective contribution

- currently GPROF does not condition the retrieval by precipitation types (convective/stratiform)
- Can we see an improvement in precipitation rate estimates if GPROF correctly estimates the convective contribution?

➔ **Develop a convective index for GPROF**

| | Gopalan (2010) | Model in progress |
|---|---|---|
| Correlation | 0.31 | 0.55 |

➔ Petkovic et al. (2019)



# PMW: convective contribution

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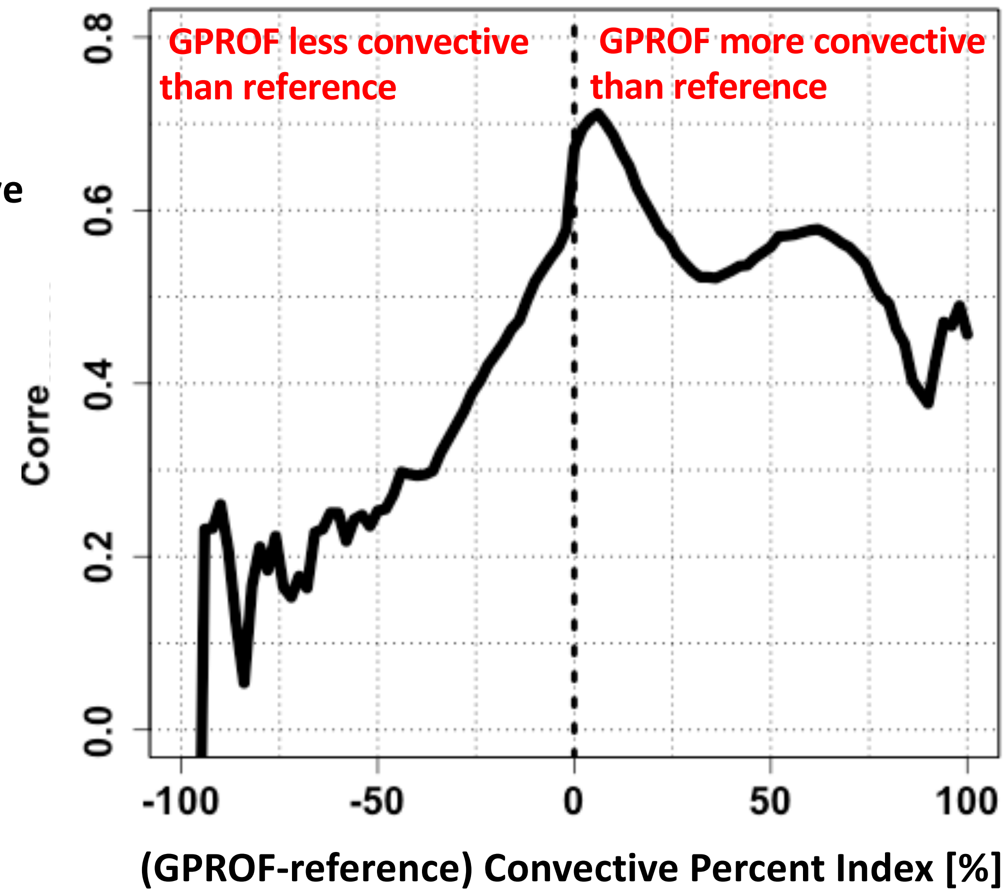
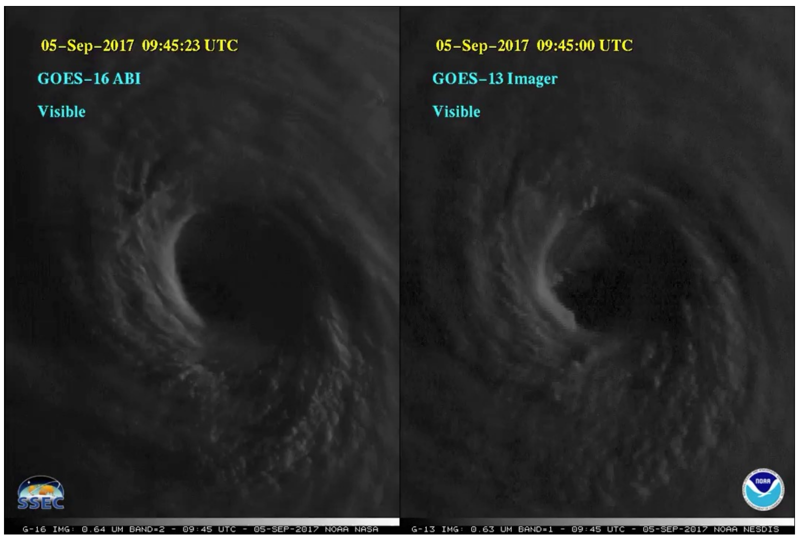



➔ Kirstetter et al. (2020)

# Exponential growth of observations

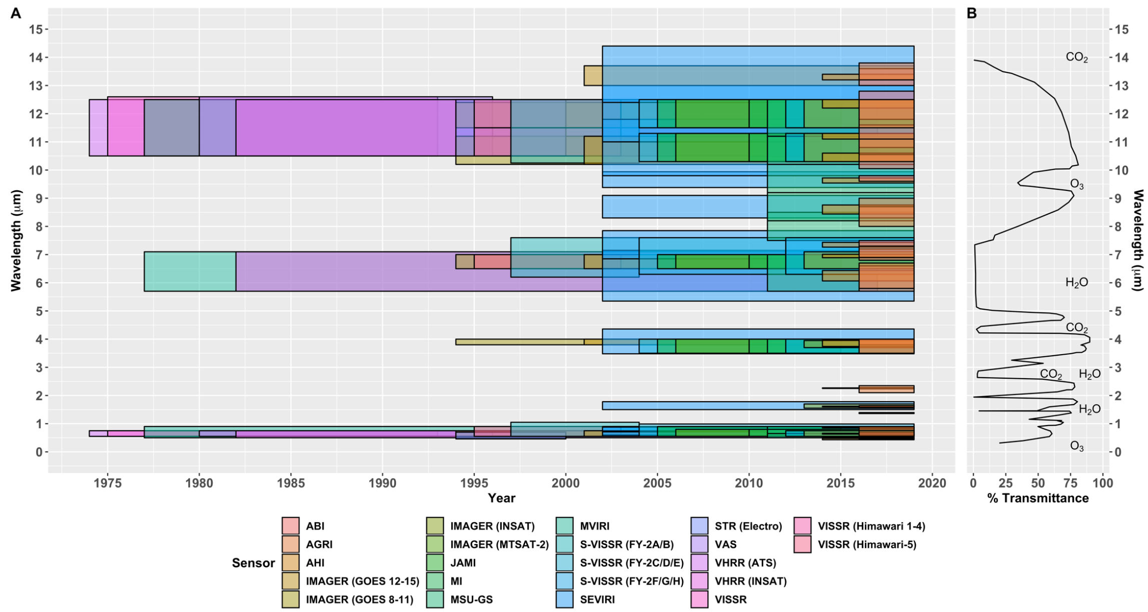
## Temporal Resolution

GOES-16: 1-min GOES13: 15-min




Animation Source: [http://www.nhc.noaa.gov/](http://www.nhc.noaa.gov/)

## Spectral Resolution




➔ **efficiently utilizing this wealth of information to target precipitation**

# Current operational precipitation retrievals

Arkin and Meisner (1987)
Upadhyaya and Ramsankaran (2014)
So and Shin (2018)

**SCaMPR – 5 channels**

**PERSIANN-CCS – 1 channel**

Meyer et al. (2017)
Min et al. (2018)
Lazri and Ameur et al. (2018)
Thebbi and Haddad (2016)
Hong et al. (2004)

| | |
|---|---|
| Thresholding | Regression |
| Machine Learning/ Deep Learning | Probabilistic |

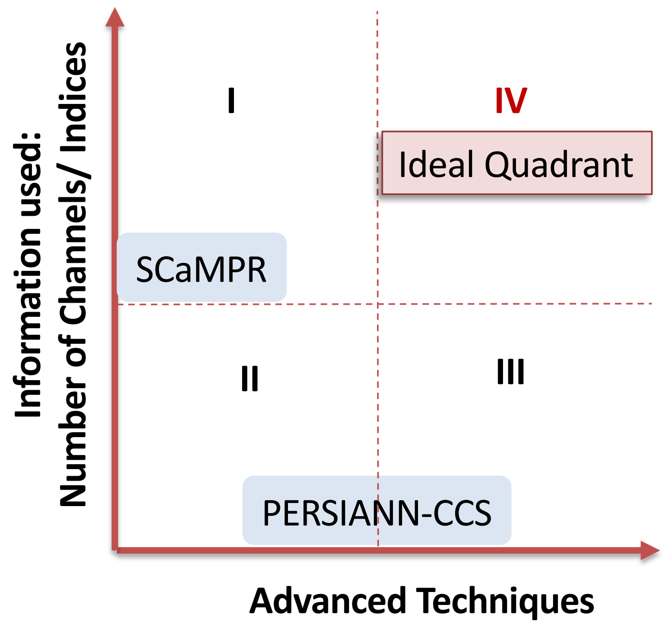
**Techniques**

Vincente et al. (1998)
Kuligowski (2010)
Upadhyaya and Ramsankaran (2016)

Grams et al. (2016)
Kirstetter et al. (2018)

- ➔ Satellite precipitation has been deterministically computed despite the under-constrained relation between satellite measurements and surface precipitation rate.
- ➔ Probabilistic QPE

# Current operational precipitation retrievals

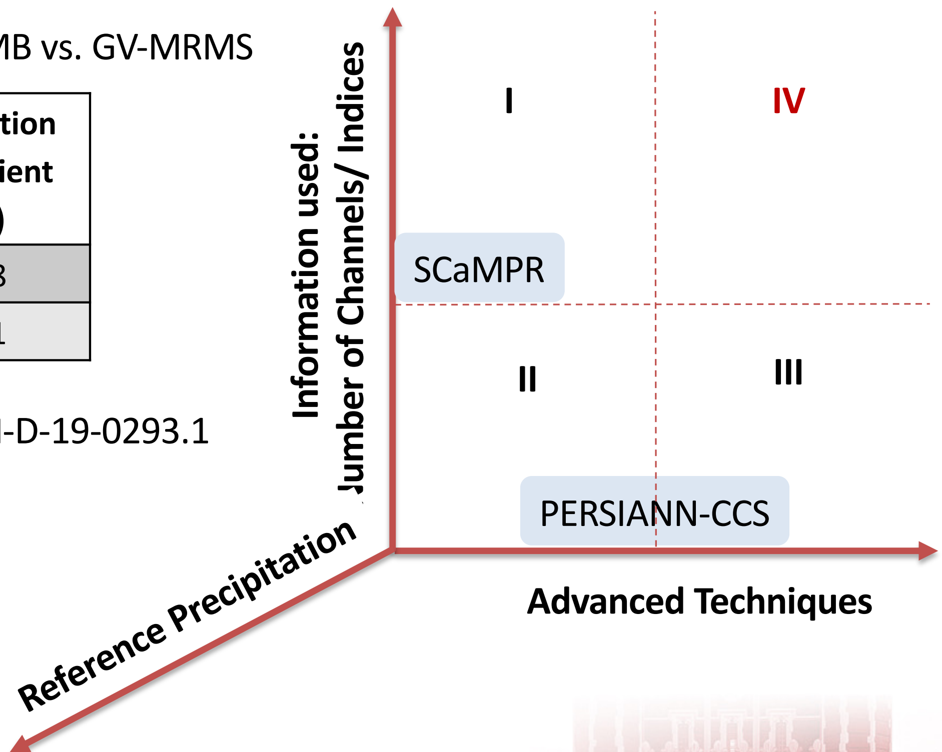


# Is uncertainty in SCaMPR propagating from its reference MWCOMB?

**Error Budget:** SCaMPR and MWCOMB vs. GV-MRMS

| | Probability of Detection (POD) | Correlation Coefficient (CC) |
|---|---|---|
| **MWCOMB** | 0.37 | 0.38 |
| **SCaMPR** | 0.35 | 0.31 |

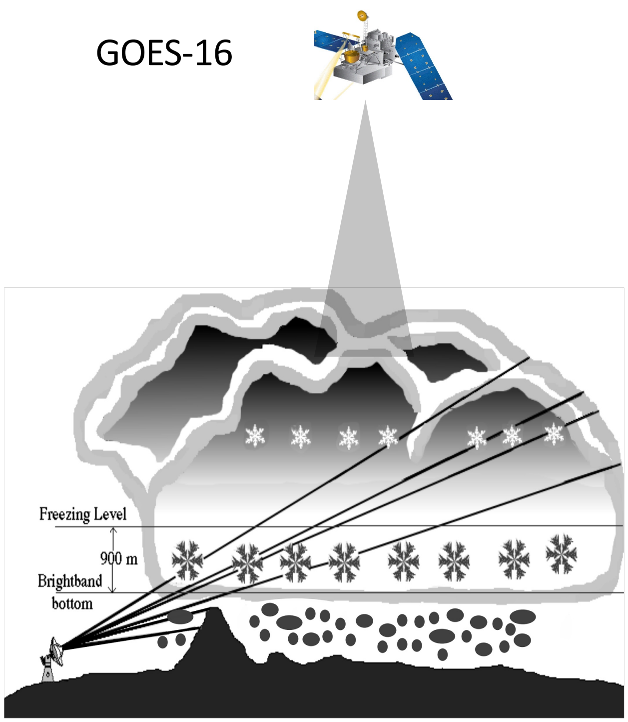
Upadhyaya al., 2020 - 10.1175/JHM-D-19-0293.1



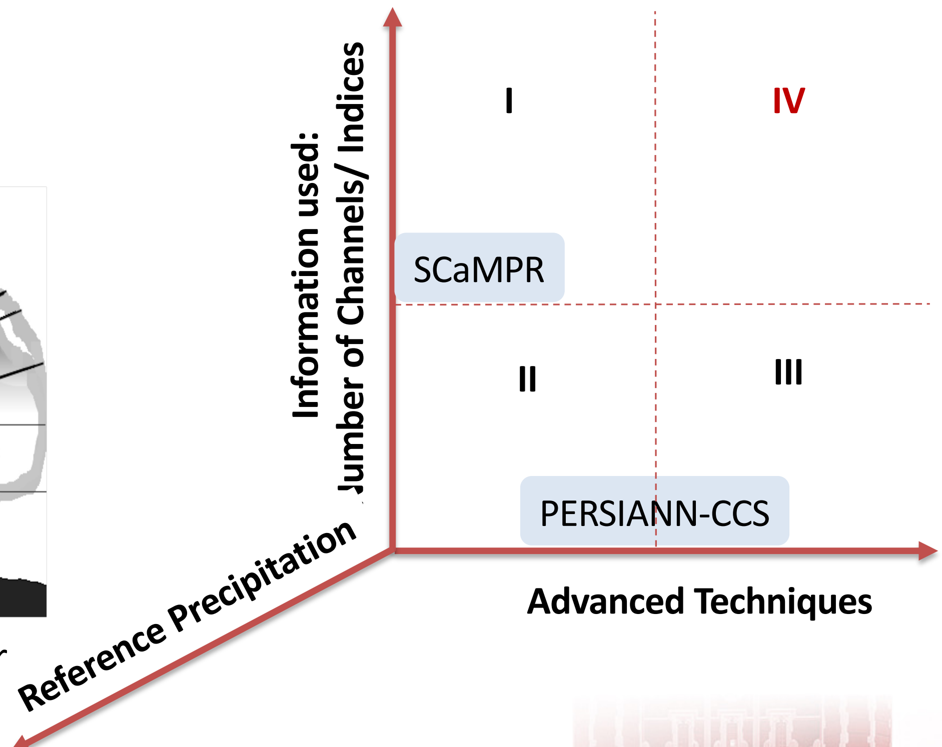

➔ Accuracy of reference bounds the accuracy/interpretation of GEO retrievals

# Current operational precipitation retrievals

GOES-16




Ground Validation Multi-Radar Multi-Sensor




➔ **Derive predictors for Probabilistic QPE**

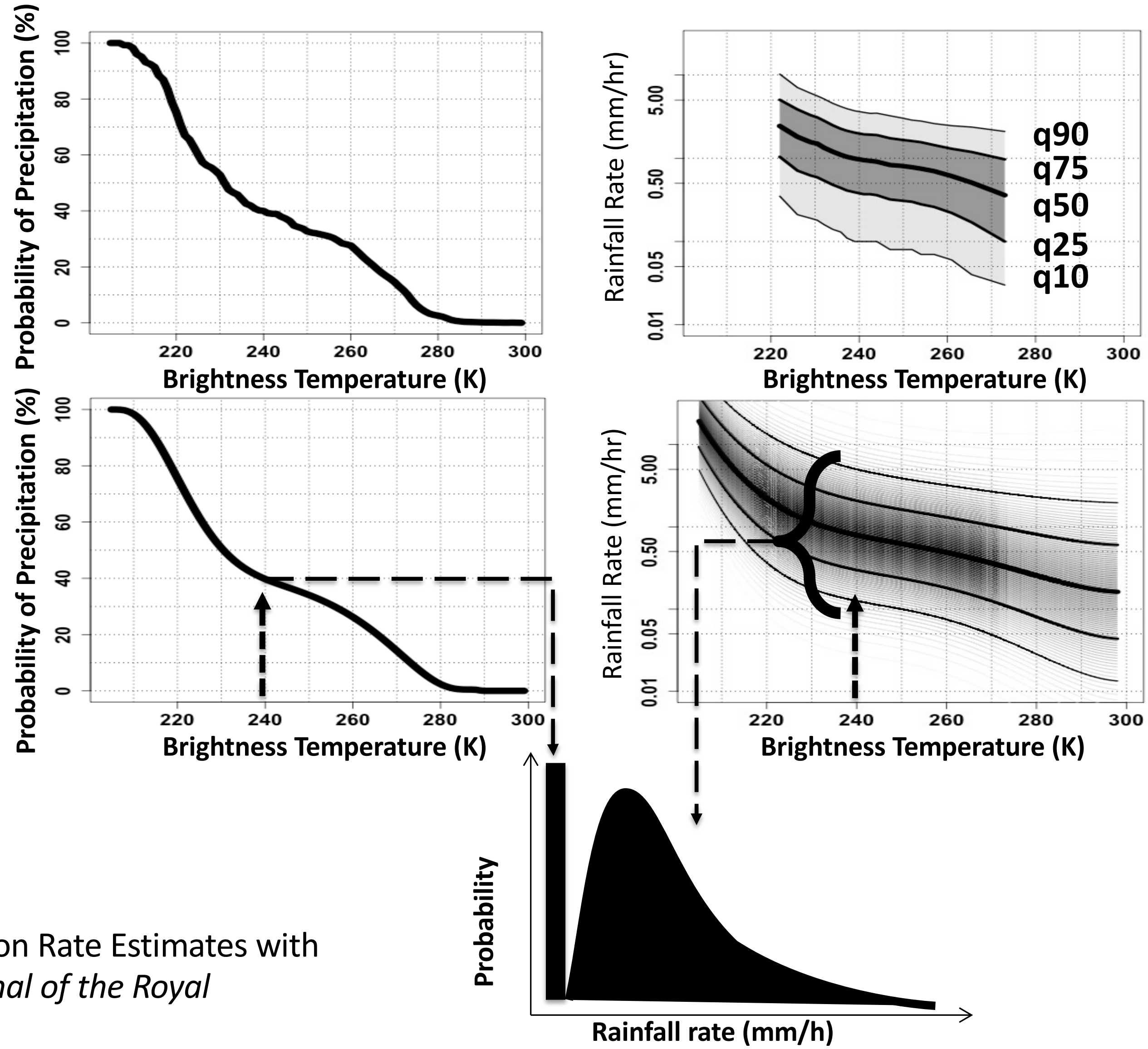
Associate brightness temperature and reference rain rate per cluster

↓

Model distribution of rain rates conditioned on brightness temperature per cluster

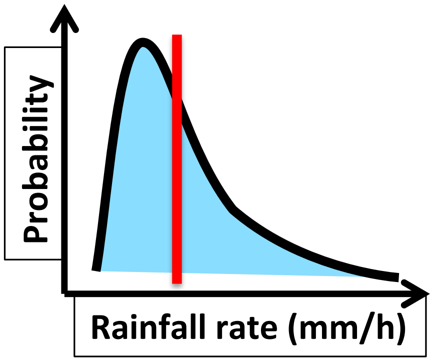
↓

Given cluster and brightness temperature, yields probability of precipitation and distribution of precipitation rates

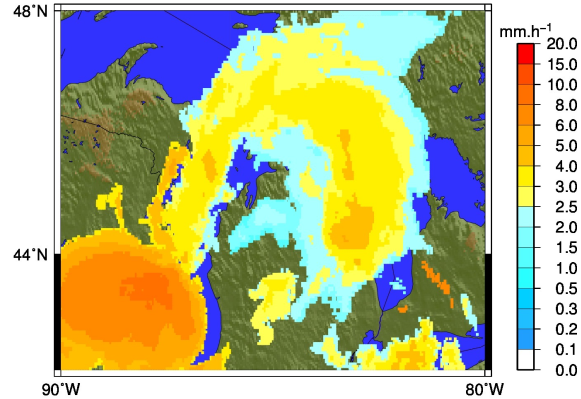



Kirstetter et al., 2018: Probabilistic Precipitation Rate Estimates with Space-based Infrared Sensors. *Quarterly Journal of the Royal Meteorological Society*.doi: 10.1002/qj.3243

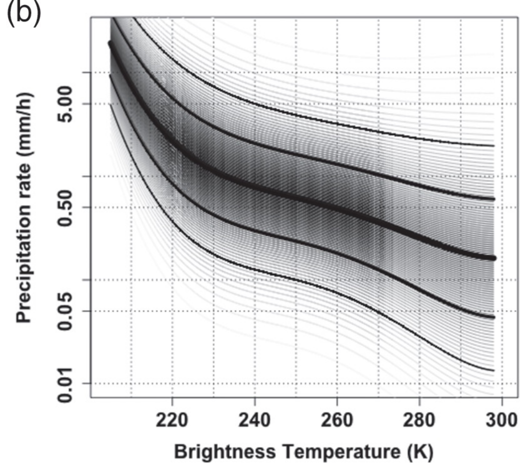
# Probabilistic QPE - expectation



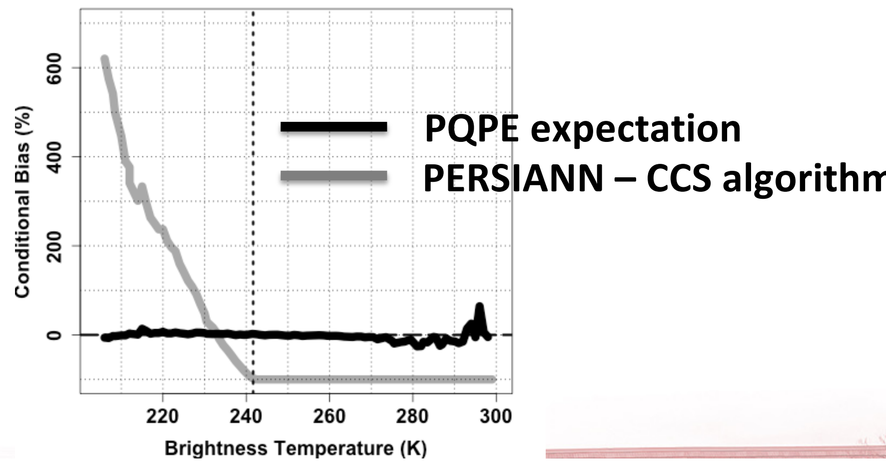

**Expected value**




**Probabilistic relation**

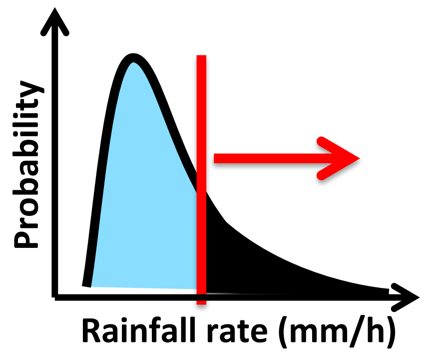



**Bias reduction**

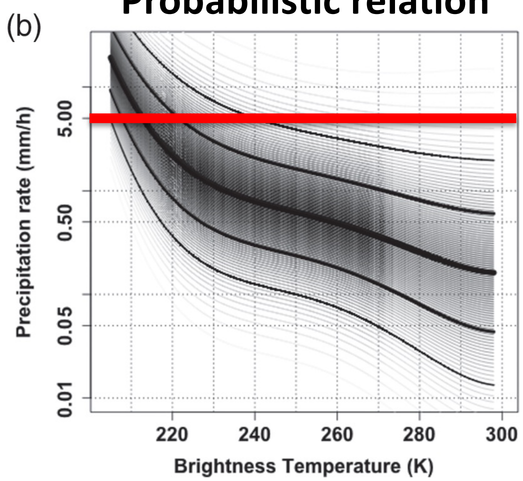



Kirstetter et al., 2018: Probabilistic Precipitation Rate Estimates with Space-based Infrared Sensors. *Quarterly Journal of the Royal Meteorological Society*.doi: 10.1002/qj.3243

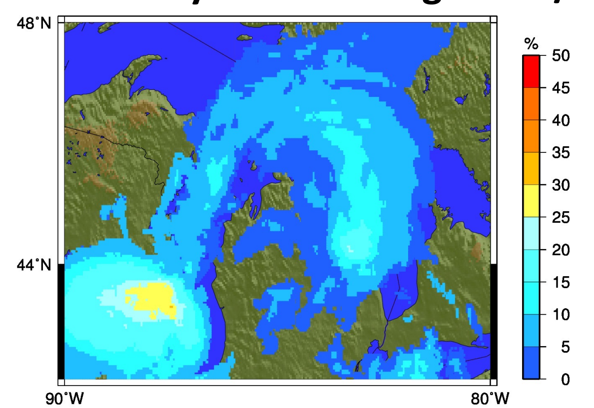
# Probabilistic QPE - risk




Probabilistic relation

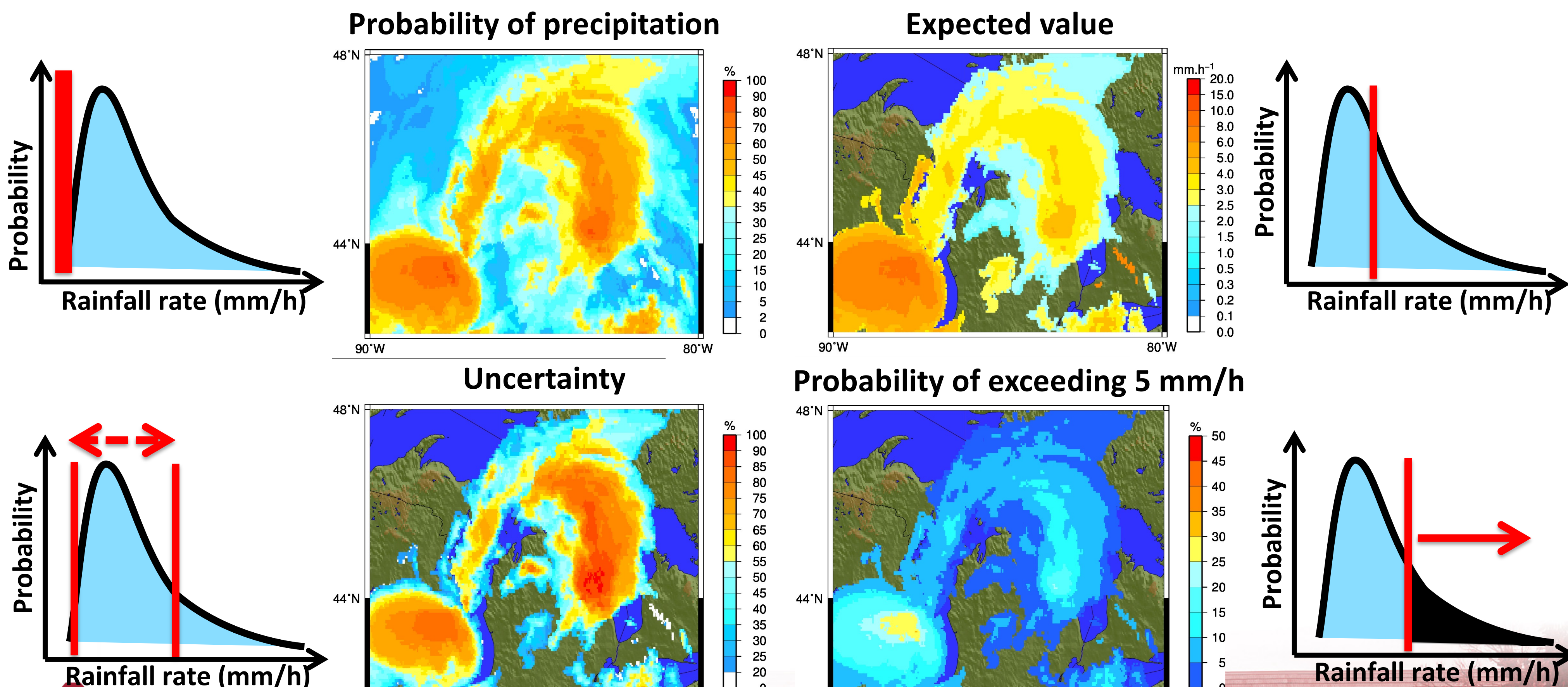



Probability of exceeding 5 mm/h




Kirstetter et al., 2018: Probabilistic Precipitation Rate Estimates with Space-based Infrared Sensors. *Quarterly Journal of the Royal Meteorological Society*.doi: 10.1002/qj.3243

# Probabilistic QPE




HYDROLOGY & W
The UNIVERSITY of OKLAHOMA

precipitation system at 1200 UTC on June 17, 2014

# Probabilistic QPE: perspectives

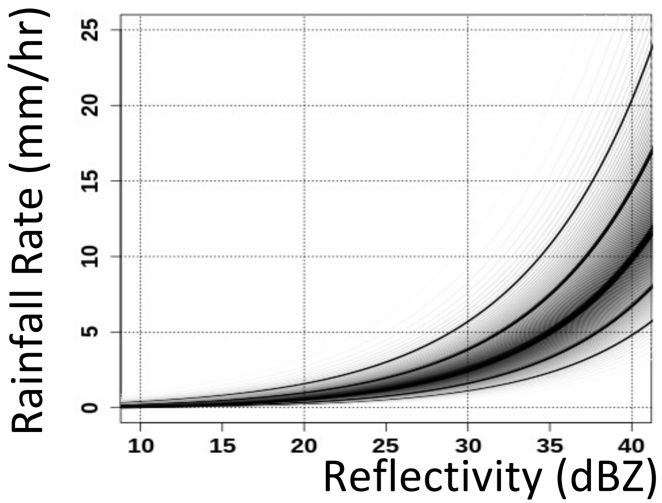
**Probabilistic Quantitative Precipitation Estimates:**

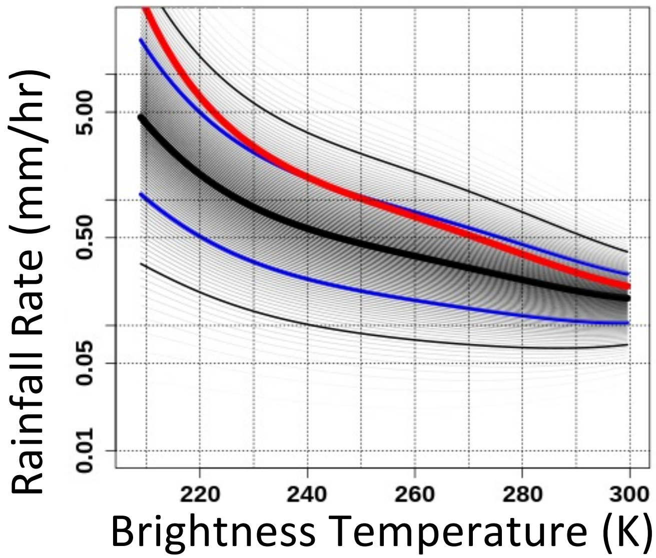
- ➔ **Ground-based radars**
- ➔ **Space-based radars**
- ➔ **IR-based (satellite) component of GPM**

**Other applications/developments in:**

- ➔ **GOES16**
- ➔ **snow water equivalent**
- ➔ **flash flood risk monitoring**

**Communicating probabilistic information is still an outstanding challenge.**



# 14th International Precipitation Conference

**Where, when: National Weather Center, Norman, Oklahoma – June 5-9, 2023**

**Theme: Emerging directions in precipitation observations, estimation, applications, forecasting, and climate projections.**

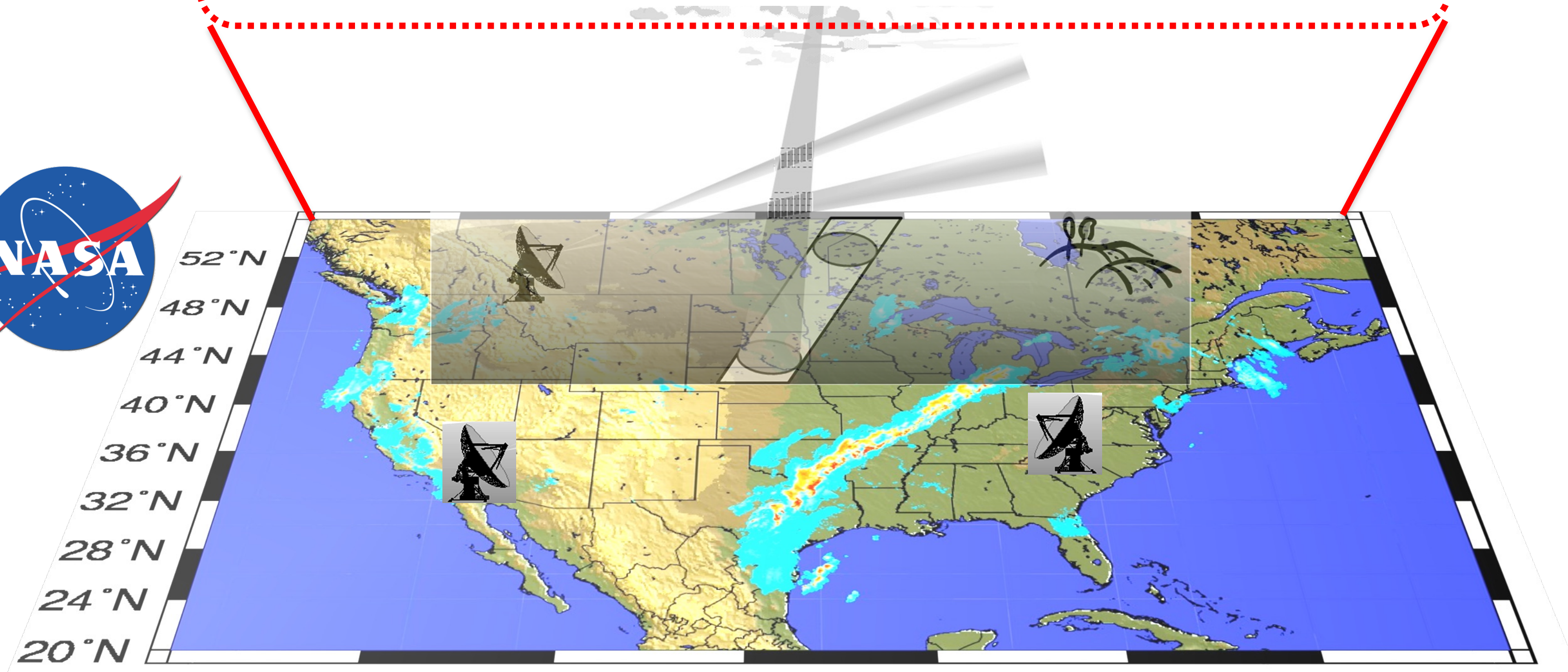
**Website: IPC14.org**

**Pre-conference online workshops:**

- **Early Career and Students**
- **India / South Asia**
- **possibly: Atmosphere Observing System**

**Short courses**

# THANK YOU




This work is made possible through support by NOAA and NASA Ground Validation program and Precipitation Measurement Mission program.

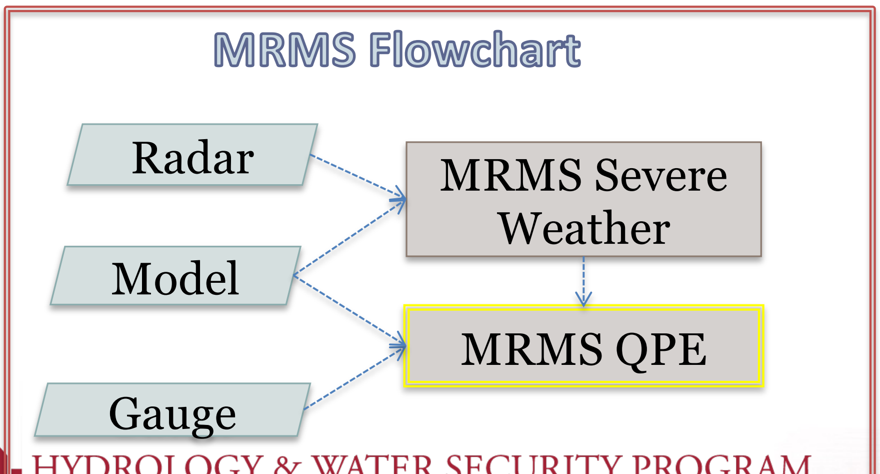
# Overview of the Multi-Radar Multi-Sensor System (MRMS)

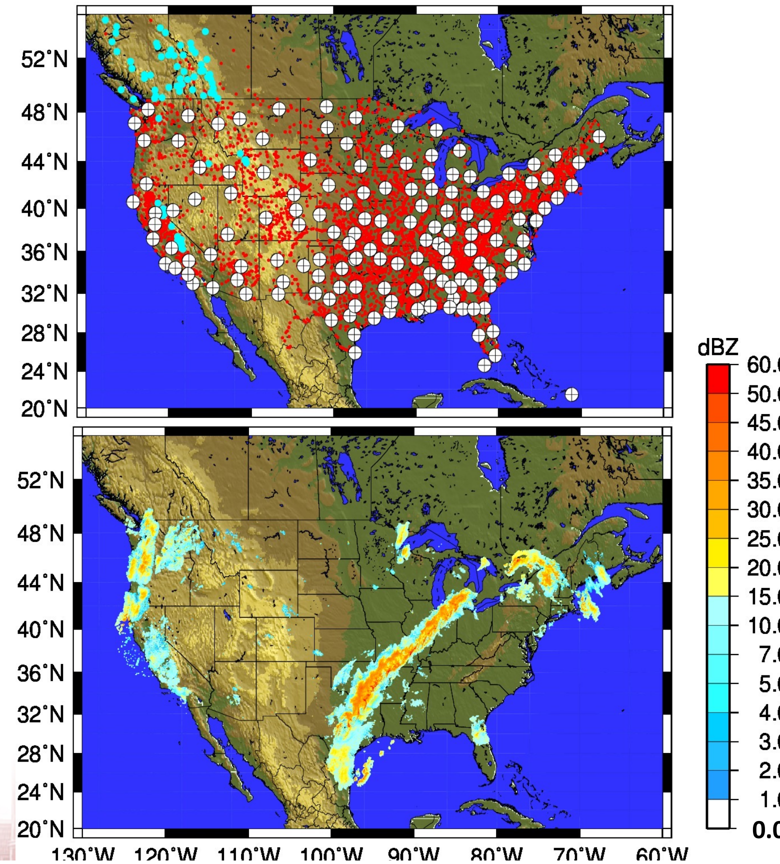
**Domain:** 20-55° N, 130-60° W

**Resolution:** 0.01°, 2 min update cycle

**Data Sources:**

- ~180 polarimetric radars every 4-5min
- ~9000 gauges every hour
- - RAP model hourly 3D analyses




frontal system at 0800 UTC on 11 April 2011

# GPM & GV-MRMS:
# bridging orbital Level-2 and gridded Level-3 precipitation

**Objective: improve precipitation across Level 2 and Level 3 products**

**Satellite L2**
- **orbital**
- **instantaneous**

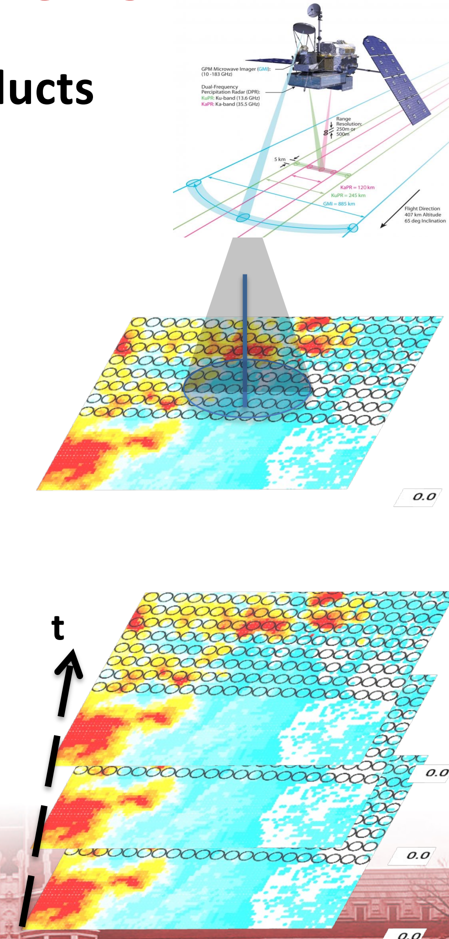
**Reference L2**
- **footprint**
- **2min**

**Precipitation features:**
- intermittency
- type
- rate variability
- …

**scale impact**

**Satellite L3**
- **gridded**
- **30-min**

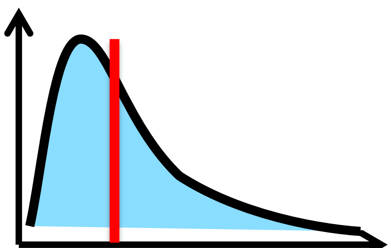
**Reference L3**
- **0.1°**
- **30min**

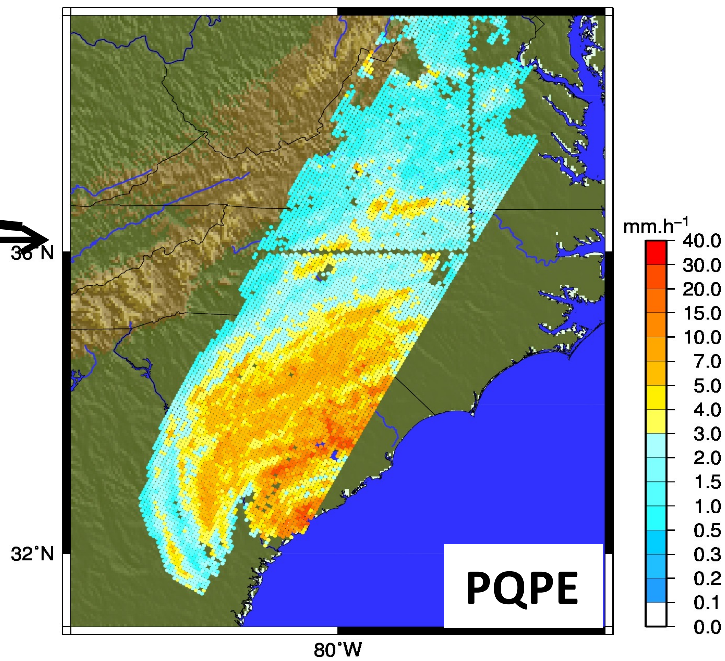


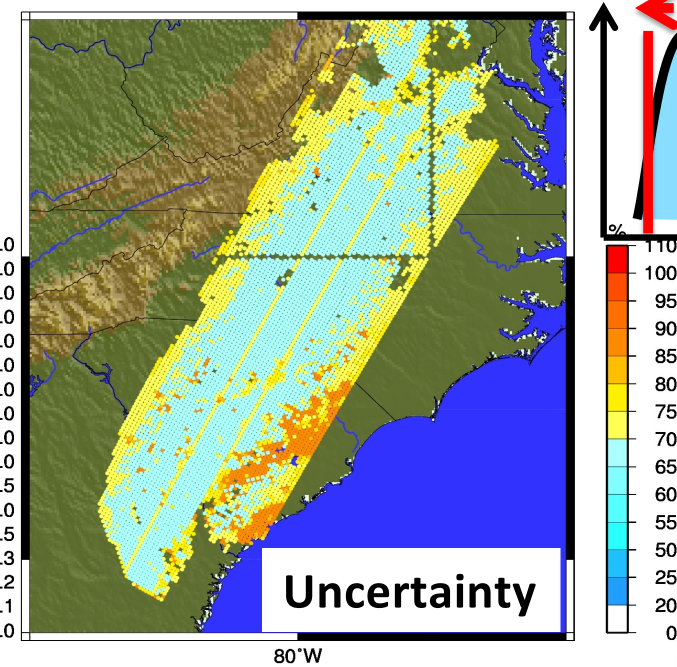

- **Identify conditions of agreement / disagreement**
- **Provide guidance to improve the retrievals**

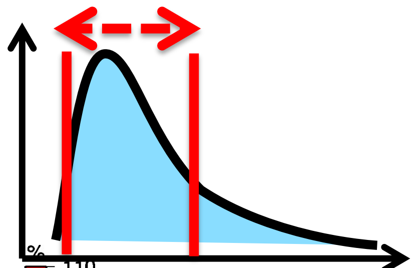
# Spaceborne radars

**DPR PQPE = f (reflectivity, microphysics,
precipitation type,
incidence angle)**





**Hurricane Matthew at 09:15 UTC on 08 October 2016 in North Carolina**