Satellite Rainfall Retrieval Over Coastal Zones

Deltas in Times of Climate Change II
Rotterdam. September 26, 2014

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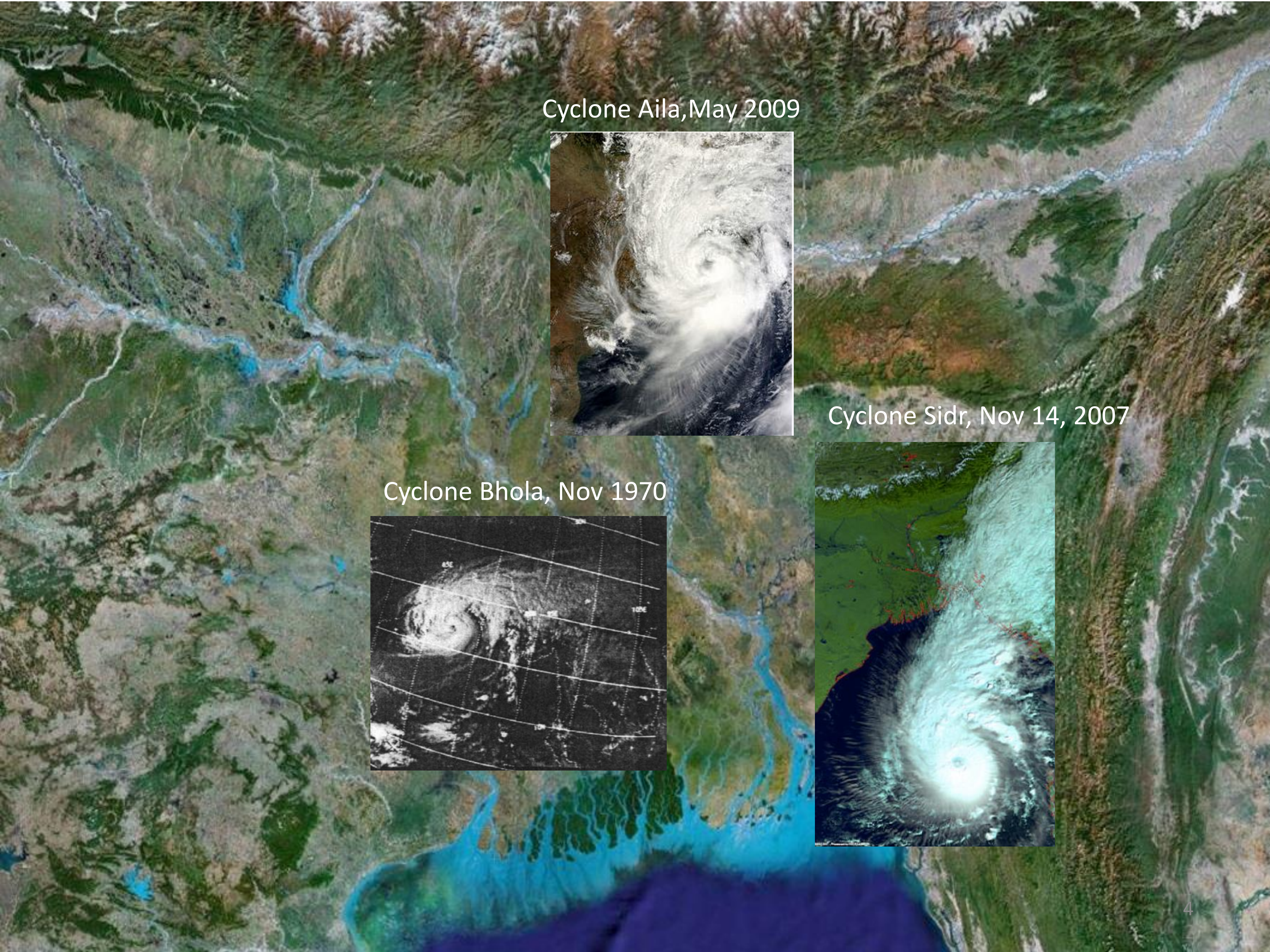
Discharge / Sediment
Local
activities
Ocean waves/tides

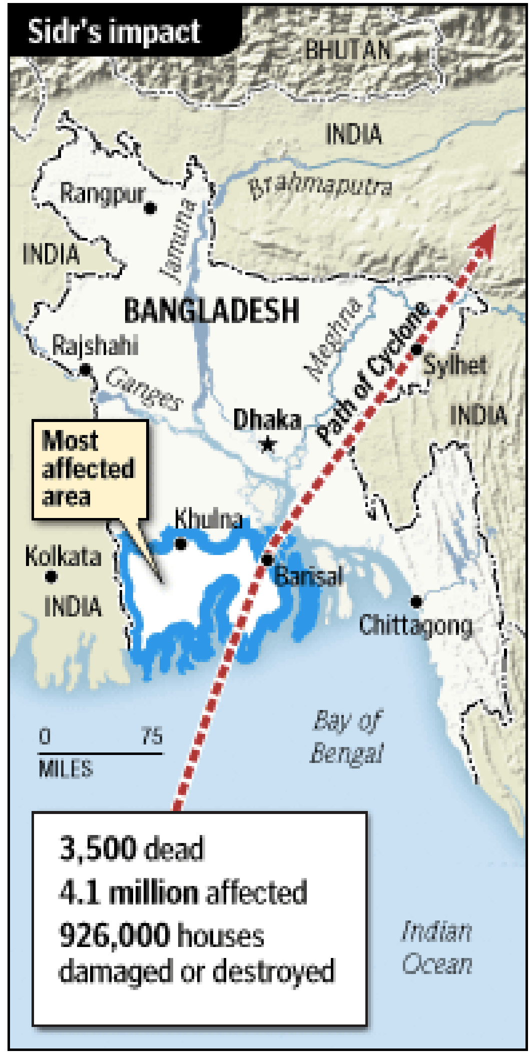

Discharge / Sediment
Local
activities
Sea level / Subsidence

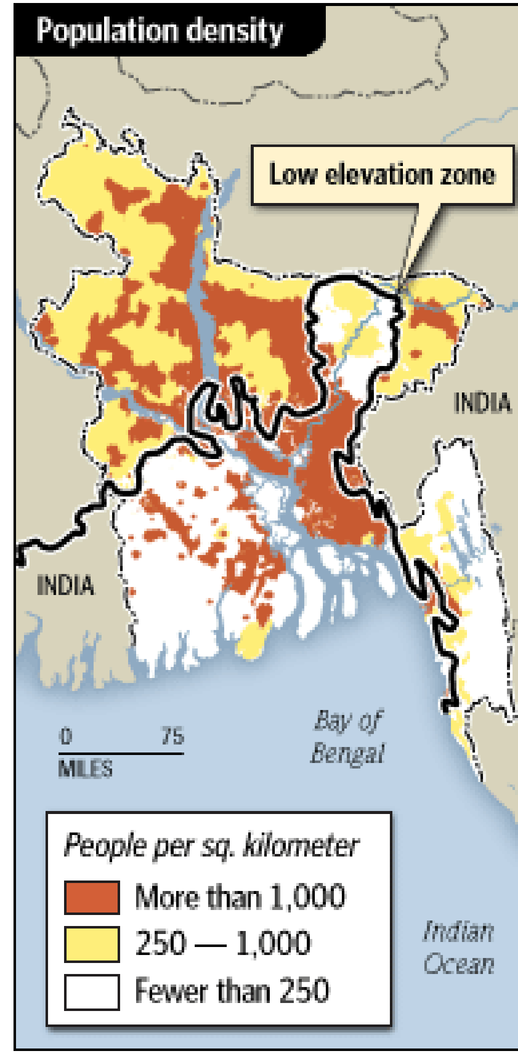

Cyclone Aila,May 2009
Cyclone Sidr, Nov 14, 2007
Cyclone Bhola, Nov 1970

Cyclone Sidr in November 2007

10/17

A snapshot of worst flood disasters in Bangladesh





Nation's Worst Disasters

1970 Cyclone kills 300,000 to 500,000.

1988 Monsoon floods kill 2,000 to 5,000.

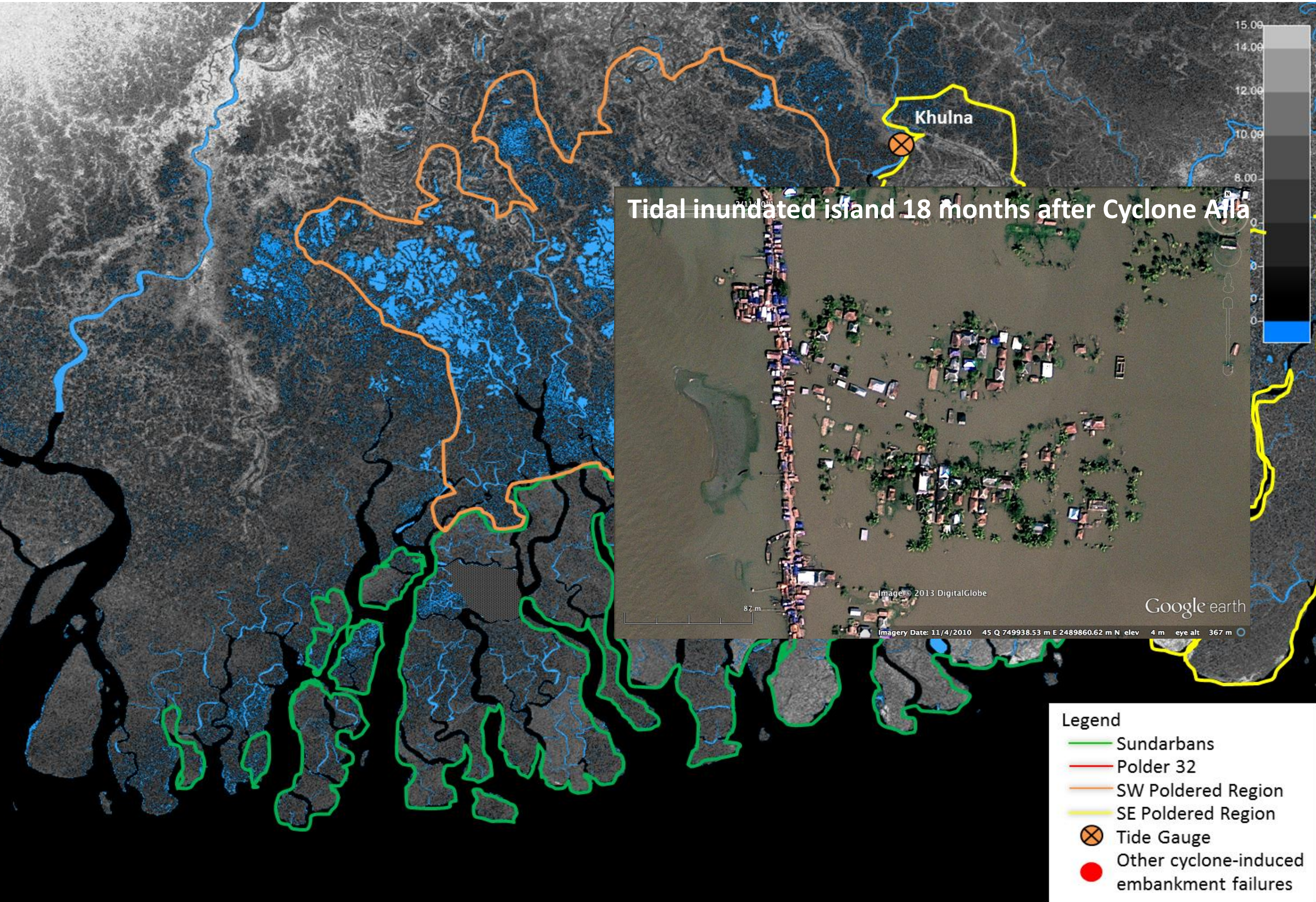
1991 Cyclone kills 143,000.

1996 Tornado kills 600 in the north.

1998 Floods kill 900.

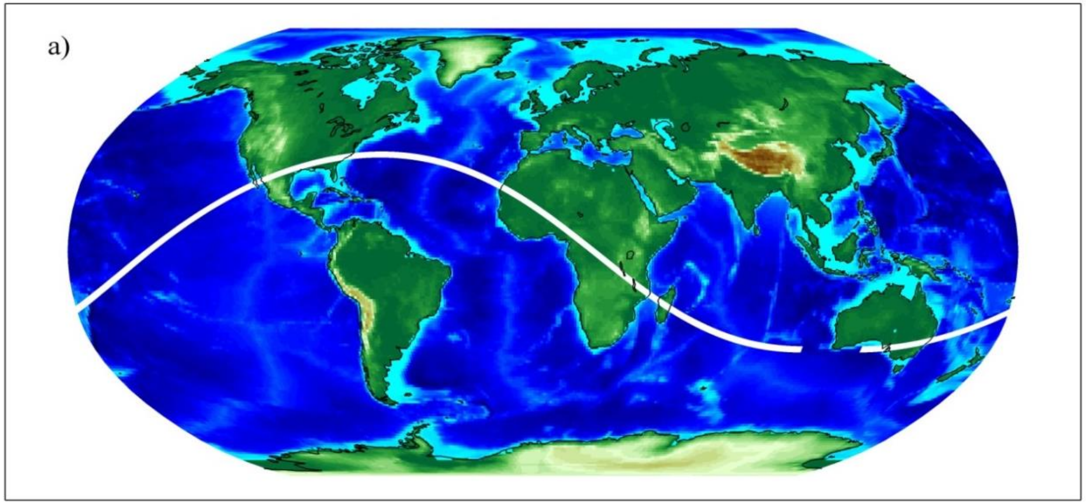
http://freshclick.wordpress.com/2009/03/27/causes-of-the-flooding-in-bangladesh/

Human amplified effects of tropical storms in low-lying delta settings



Estimating Precipitation from Space: from TRMM to GPM

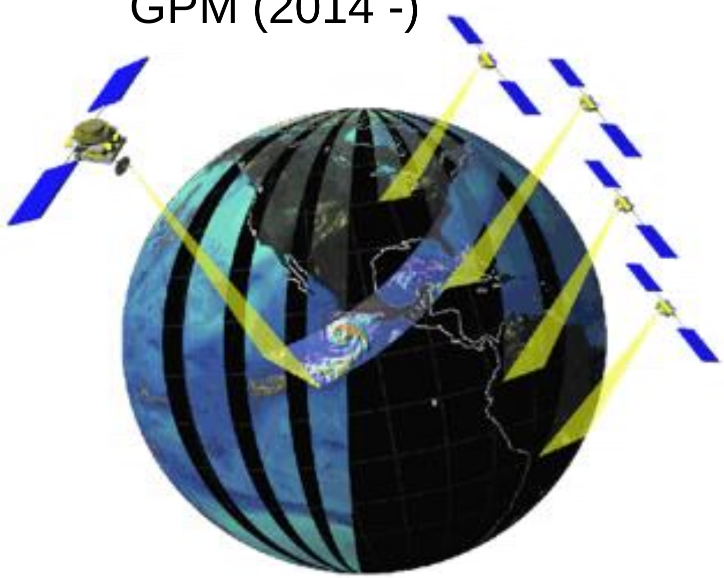
20080913-61698



TRMM
(1997 -)

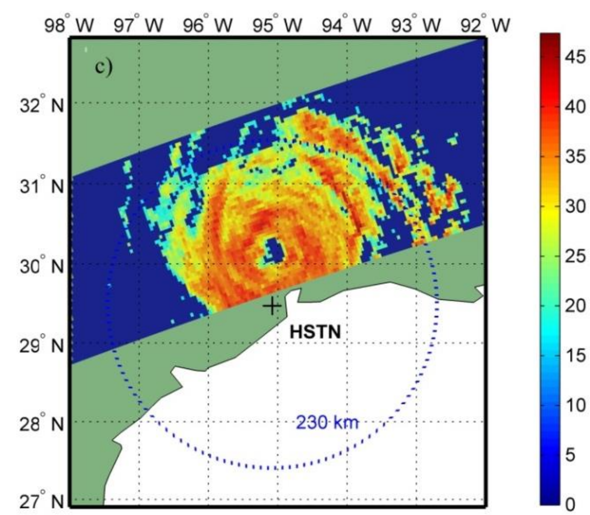
PR

GPM (2014 -)

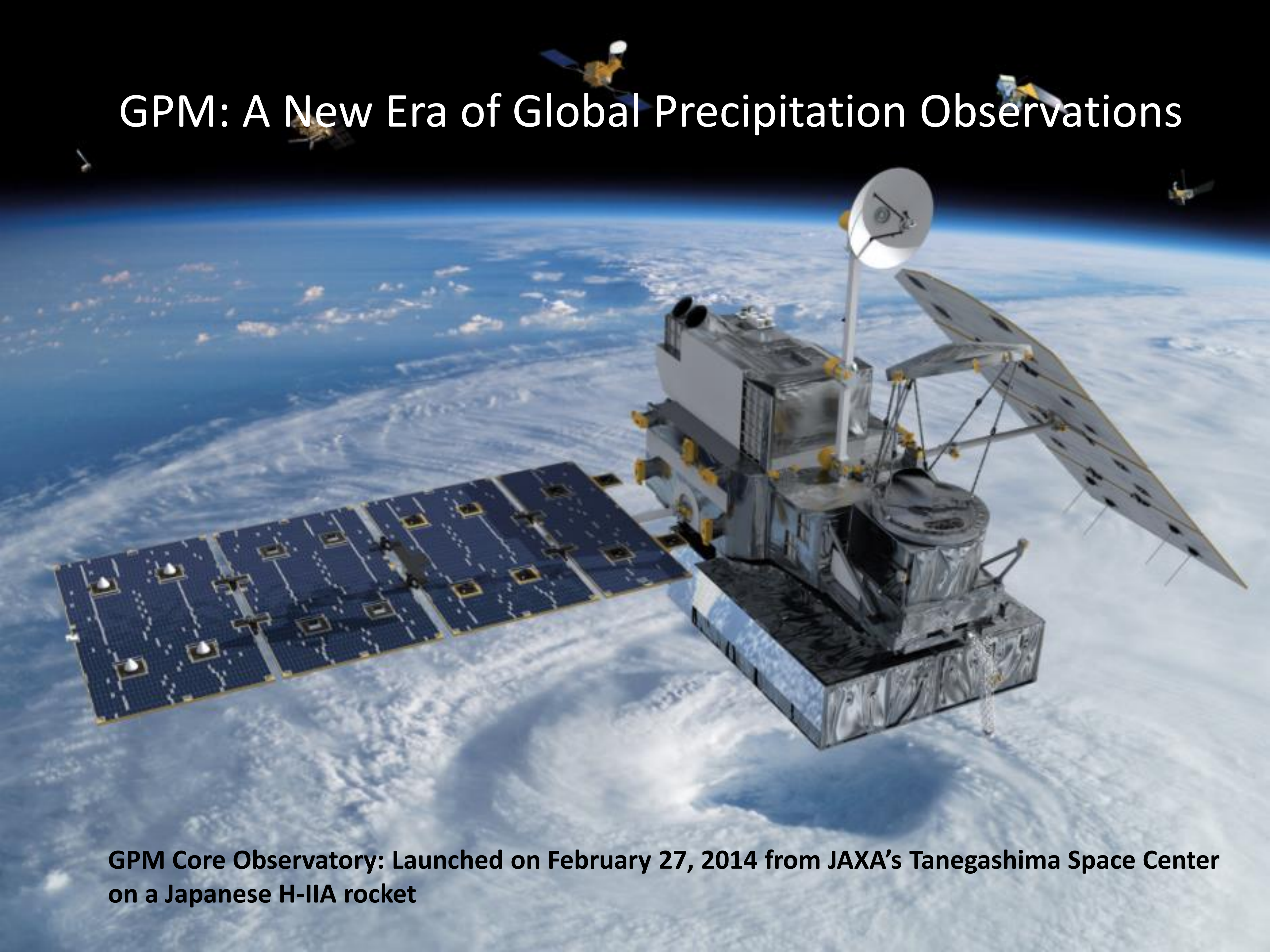


From TRMM to GPM:
New opportunities &
new challenges
in retrieval, fusion,
and downscaling
of precipitation

20080913-61698

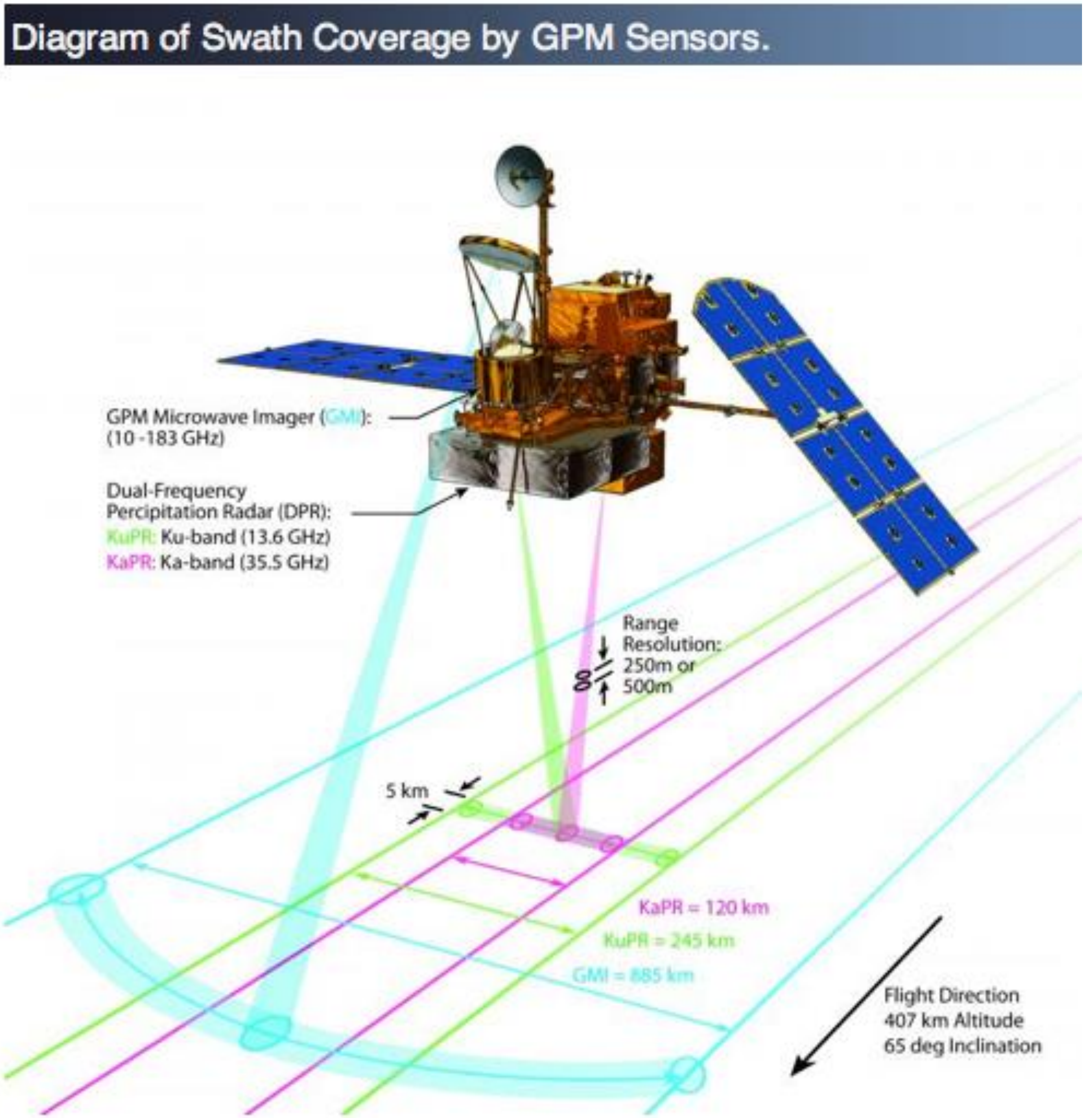


GPM: A New Era of Global Precipitation Observations



GPM Core Observatory: Launched on February 27, 2014 from JAXA's Tanegashima Space Center on a Japanese H-IIA rocket

Spaceborne Rainfall: form TRMM to GPM



<u>DPR:</u>

125 and 245 Km swaths

Ka-band: 35.5 GHz

Ku-band: 13.6 GHz

<u>GMI:</u>

885 Km swath

13 channels 10 -183 GHz

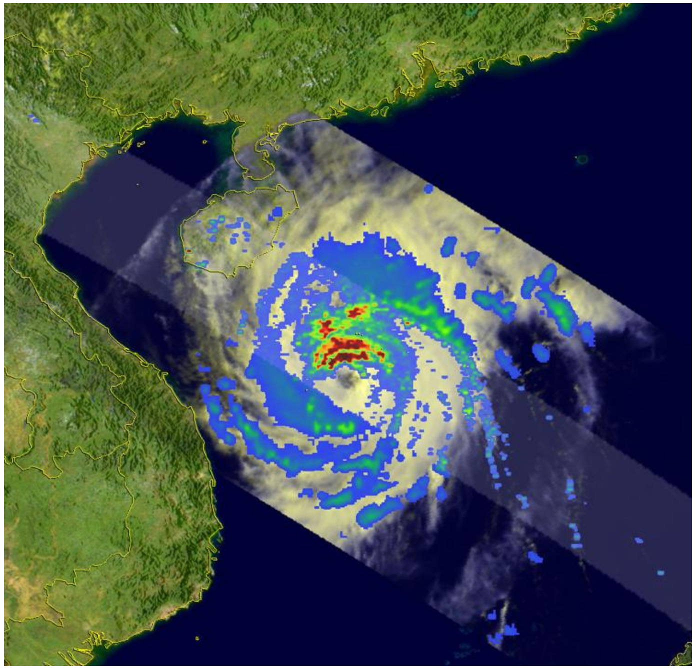
Rainfall Estimation Problems

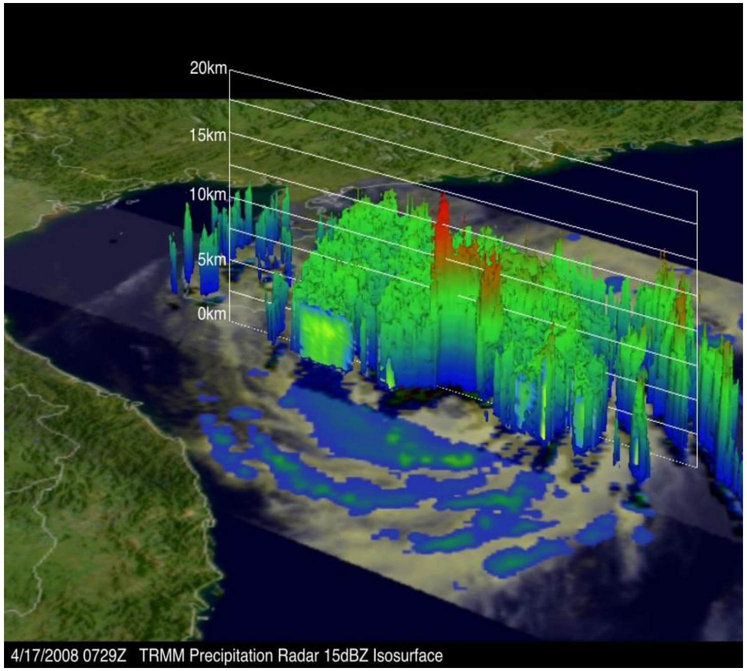
- **Downscaling**: Enhancing the resolution of a measured or modeled field
- **Data Fusion**: Produce an improved estimate of a field from a suite of noisy observations at different scales
- **Data Assimilation**: Estimate the initial conditions in a predictive model consistent with the available noisy observations and model dynamics
- **Retrieval**: Estimate rainfall from indirect noisy and lower resolution observations of brightness temperature

Increasing challenges over **heterogeneous surfaces and land-water interface**
Emphasis on preserving multi-scale features, sharp fronts, and **extremes**

Spatial Structure of Rainfall

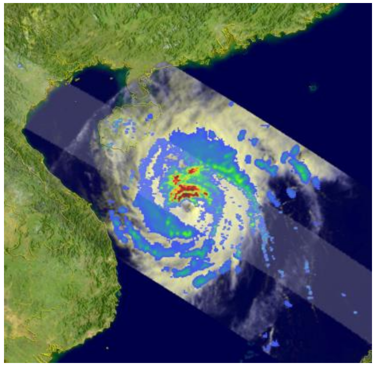
TRMM PR and TMI



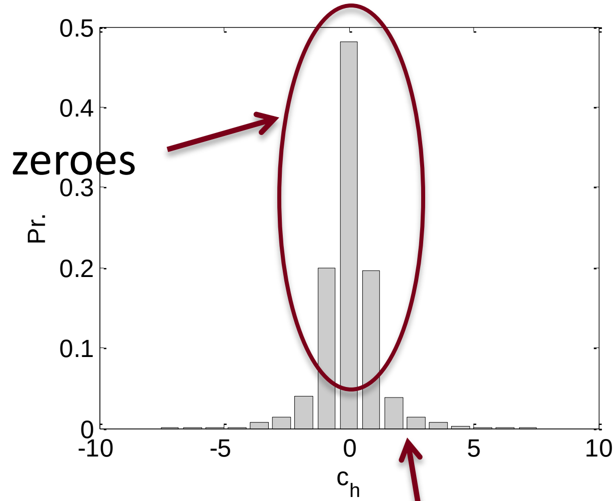


Typhoon Neoguri, Western Pacific, April, 2008, http://trmm.gsfc.nasa.gov

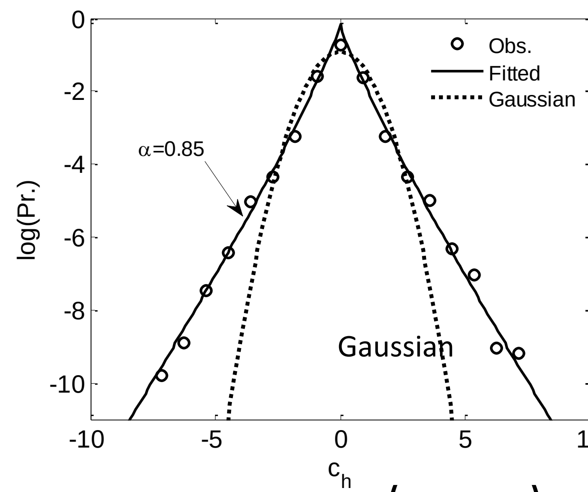
Non-Gaussian PDF in the Gradient Domain



PDF of gradients >>



Extreme gradients



$$p(x)\ \mu\ \exp\left(-\ /\ \left|x\right|^{a}\right)$$

Generalized Gaussian Density (GGD)
(**α=1 Laplace**)

"Sparsity"

Passive Microwave Retrieval: an Inverse Problem

Rain → **Physics** → Spectral Radiances

Physics
Radiation regime
- Absorption
- Emission
- Scattering
- Land-surf emissivity
- ….

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{n_r} \end{bmatrix} \qquad \mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{n_c} \end{bmatrix}$$

$$\mathbf{y} = \mathcal{F}\left(\mathbf{x}\right) + \mathbf{v}$$

Retrieval problem:

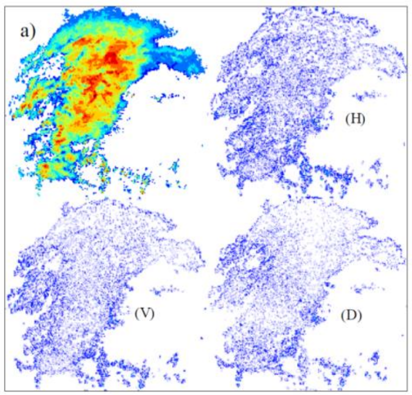
$$\text{Given } \mathbf{y} \Longrightarrow \quad \mathbf{x} = \mathcal{F}^{-1}\left(\mathbf{y}\right) + \epsilon$$

New ideas:
- Preserve sharp features in estimation by choosing the proper prior
- Learn patterns in a “smart way” from the data=> key to retrieval
- Explore Compressive sensing methodologies to retrieve from fewer observations

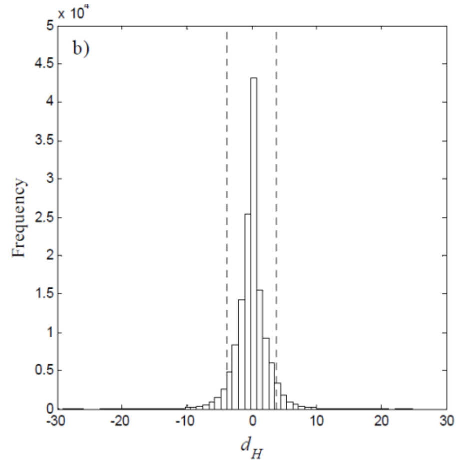
NEW IDEAS for GPM—1

1. Preserve unique features during estimation

-- Precipitation has an intermittent and multi-variable space-time structure ➔ when projected in a derivative domain it displays **“sparsity”**

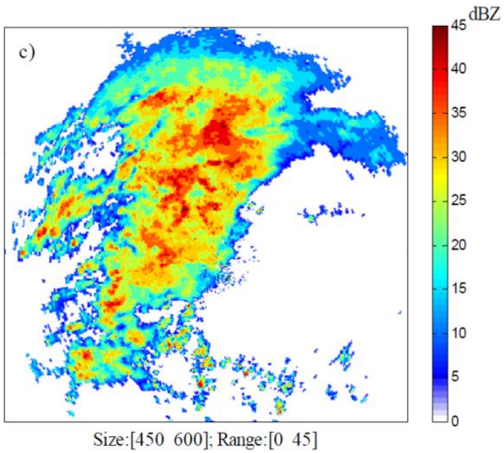


Wavelet Decomposition



PDF of Coefficients

Replace 80% by zeroes



Reconstructed image

-- Sparsity requires moving away from standard Least Squares (L2) estimation paradigms and working with L1 norms (preserve a non-Gaussian prior)

-- Downscaling, Fusion, Variational Data Assimilation

1. Ebtehaj A.M., G.Lerman, E Foufoula-Geogiou, ***JGR-A***, 2012
2. Ebtehaj, A.M. and E. Foufoula-Georgiou, ***WRR,*** 2013
3. Ebtehaj, A.M., M. Zupanski, G. Lerman, and E. Foufoula-Georgiou, ***Tellus A***, 2014
4. Foufoula-Georgiou, E., A.M Ebtehaj, S. Zhang, A. Hou, ***Surveys in Geophysics***, 2014

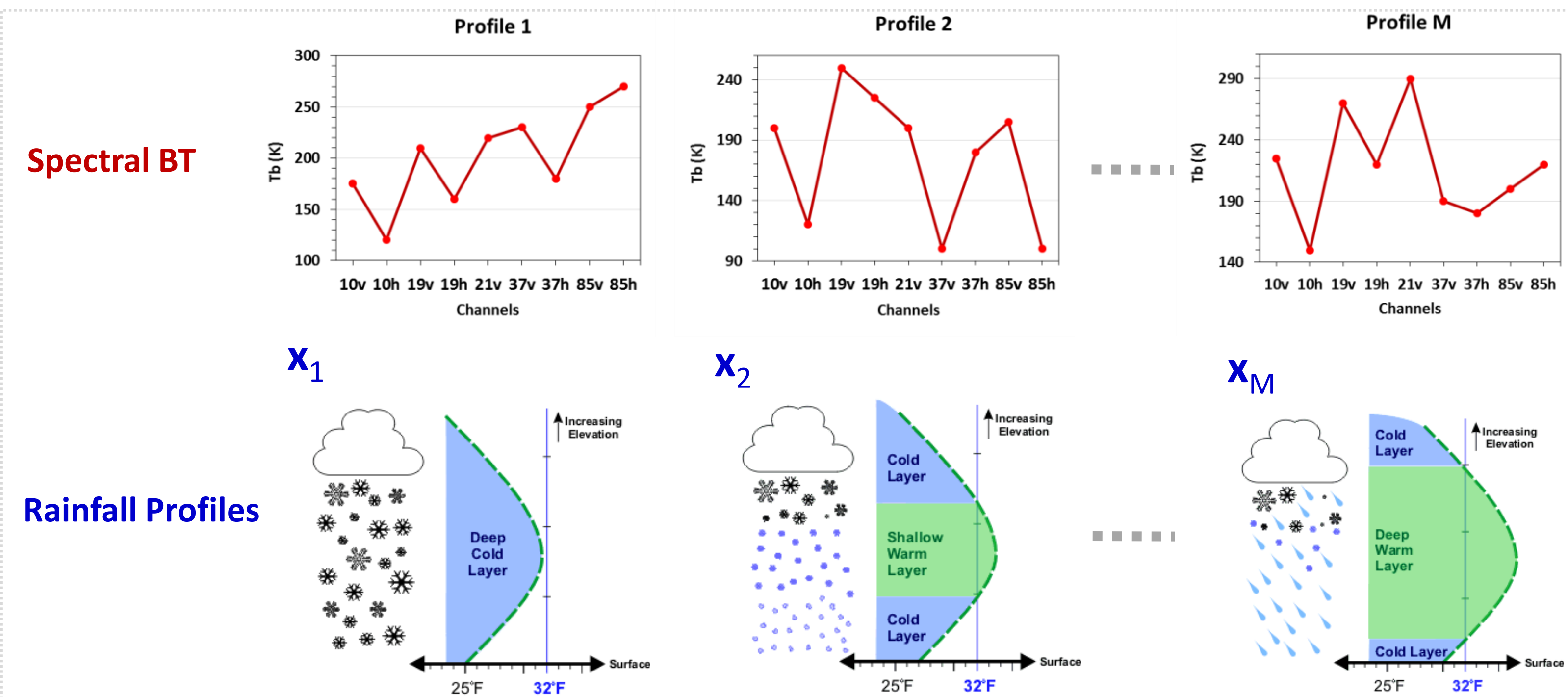
NEW IDEAS for GPM—2

2. Learn patterns from data for retrieval

Spectral BT		Rainfall Profiles
9-dim space (each point is a BT vector) ***Manifold of BT***	"Manifold learning" Advanced estimation	n-dim space (each point is a Z, surf R vector) ***Manifold of R***

ShARP: Shrunken Locally Linear Embedding for Passive Retrieval of Precipitation

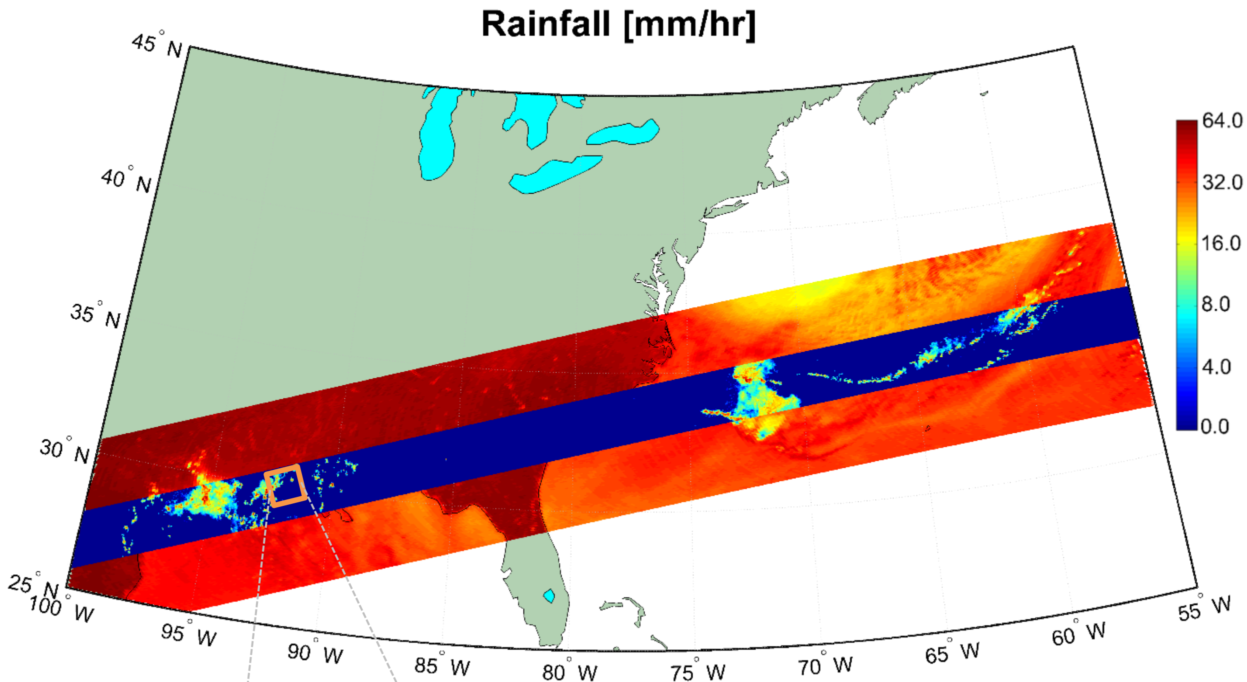
Database



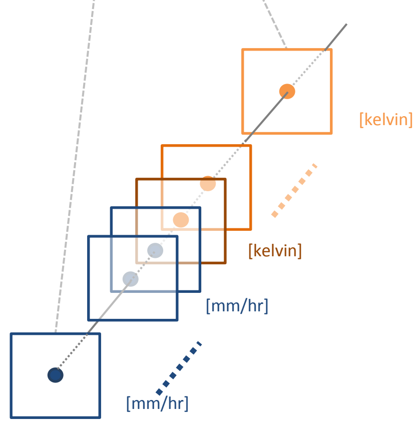
CONCEPTS AND RESULTS ON RETRIEVAL

Overlapping measurements of TMI and PR

- **Rainfall and Radiometric Observations:**



  - **Dictionaries**



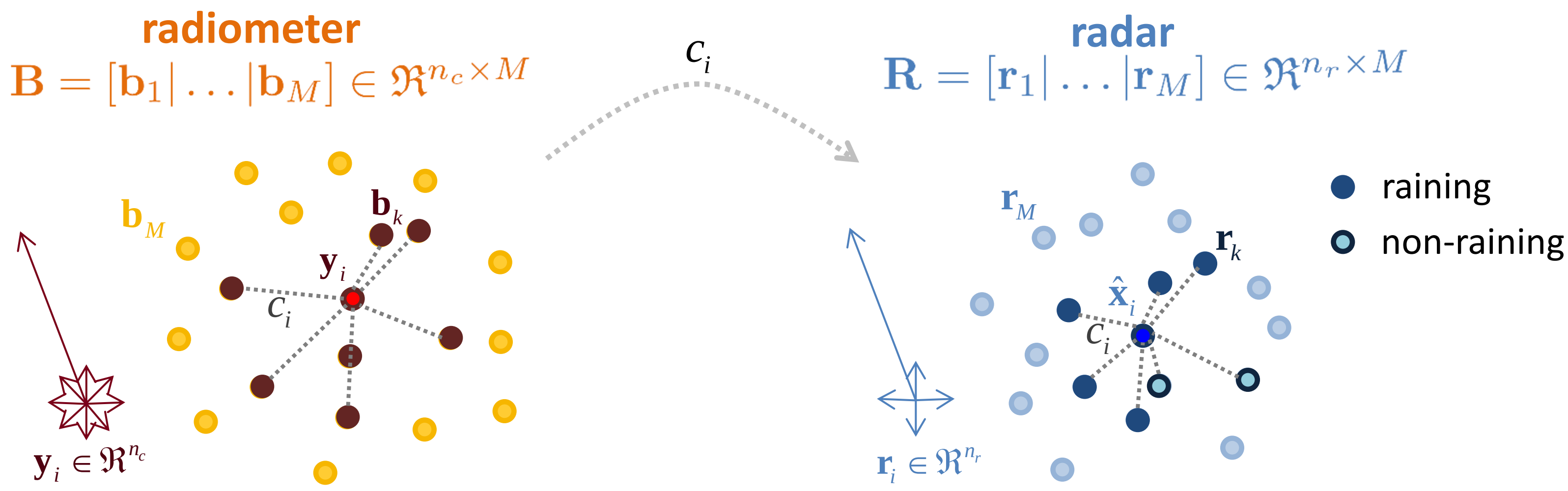
$$\mathbf{b}_i = \begin{bmatrix} b_{1i} \\ b_{2i} \\ \vdots \\ b_{n_c i} \end{bmatrix} \Longrightarrow \mathbf{B} = [\mathbf{b}_1 | \ldots | \mathbf{b}_M] \in \Re^{n_c \times M}$$

$$\mathbf{r}_i = \begin{bmatrix} r_{1i} \\ r_{2i} \\ \vdots \\ r_{n_r i} \end{bmatrix} \Longrightarrow \mathbf{R} = [\mathbf{r}_1 | \ldots | \mathbf{r}_M] \in \Re^{n_r \times M}$$

Built by $25\text{x}10^6$ randomly chosen pixels of spectral observations + rainfall

ShARP: Locally linear embedding for rainfall retrieval

- **A New Algorithm (concept):**
  - Concept of the locally linear embedding (supervised NL manifold learning):



  - Search for the **K-nearest neighbors** to detect raining signatures

$$\mathbf{B}_{\mathcal{S}} = [\mathbf{b}_1 | \ldots | \mathbf{b}_K] \in \Re^{n_c \times K} \qquad \mathbf{R}_{\mathcal{S}} = [\mathbf{r}_1 | \ldots | \mathbf{r}_K] \in \Re^{n_r \times K}$$

  - Estimate the **representation coefficients** and thus the rainfall profile

$$\mathbf{y}_i = \Sigma_{k=1}^{K} c_k \mathbf{b}_k + \mathbf{v}_k \longrightarrow \hat{\mathbf{x}}_i = \Sigma_{k=1}^{K} c_k \mathbf{r}_k$$

Saul and Roweis, Science, 2000

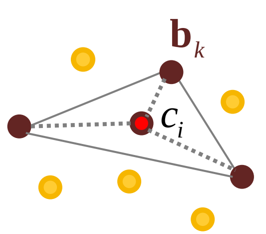
ShARP: Algorithmic sketch

- **Shrunken Locally Linear Embedding Algorithm for Precipitation Retrieval**
  - **Detection step:**
    - K-nearest neighborhood search + a probabilistic voting rule for rain/no-rain
  - **Estimation Step:**
    - Estimation of the representation coefficients

$$\begin{aligned} \underset{\mathbf{c}}{\text{minimize}} \quad & \left\| \mathbf{W}^{1/2}\left(\mathbf{y} - \mathbf{B}_{\mathcal{S}}\mathbf{c}\right)\right\|_2^2 + \lambda_1 \|\mathbf{c}\|_1 + \lambda_2 \|\mathbf{c}\|_2^2 \\ \text{subject to} \quad & \mathbf{c} \succeq 0, \;\; \mathbf{1}^{\mathrm{T}}\mathbf{c} = 1, \end{aligned}$$

ℓ_p -norm: $\|\mathbf{c}\|_p^p = \Sigma_i |c_i|^p$

$\lambda_1, \lambda_2 > 0$



$$\mathbf{B}_{\mathcal{S}} = [\mathbf{b}_1|\ldots\boxed{|\mathbf{b}_{i-1}|\mathbf{b}_i|}\ldots\boxed{|\mathbf{b}_{j-1}|\mathbf{b}_j|}\ldots|\mathbf{b}_K] \in \Re^{n_c \times K}$$

L1-L2 regularization for stability and reduced estimation error

- Rainfall estimates

$$\hat{\mathbf{x}} = \mathbf{R}_{\mathcal{S}}\hat{\mathbf{c}}$$

ShARP methodology

From: coincidental TMI, PR Obs. → $\mathbf{b} \in \mathbb{R}^9$ Spectral Radiance Dictionary: $\mathbf{B}$ & $\mathbf{r} \in \mathbb{R}^{n_r}$ Precipitation Dictionary: $\mathbf{R}$ → (1) Prob. of voting (2) Channel weights

$$w_i = \frac{CV_i}{\max_i (CV_i)}$$

Detection Step:

(1) Find K-nearest neighbors of $\mathbf{y}$ in $\mathbf{B} \rightarrow \mathbf{B}_{\mathcal{S}}$ (sub-dictionaries)

(2) Determine corresponding k-nn in $\mathbf{R} \rightarrow \mathbf{R}_{\mathcal{S}}$

(3) Determine if raining/non-raining on surface

Estimation Step:

(1) Estimate representation coefficients of $\mathbf{y}$ in $\mathbf{B}$ using a locally linear model : $\mathbf{y} = \mathbf{B}_{\mathcal{S}}\mathbf{c} + \mathbf{v}$

$$\hat{\mathbf{c}}_i = \underset{\mathbf{c}_i}{\text{minimize}} \quad \left\| \mathbf{W}^{1/2} \left(\mathbf{y} - \mathbf{B}_{\mathcal{S}}\mathbf{c}_i \right) \right\|_2^2 + \lambda_1 \left\| \mathbf{c}_i \right\|_1 + \lambda_2 \left\| \mathbf{c}_i \right\|_2^2$$

$$\text{subject to} \quad \mathbf{c}_i \succeq 0, \ \ \mathbf{1}^{\mathrm{T}}\mathbf{c}_i = 1,$$

(2) Estimate rainfall : $\hat{\mathbf{x}}_i = \mathbf{R}_{\mathcal{S}}\hat{\mathbf{c}}_i$

Important Note: →

Estimation of representation coefficients in ShARP

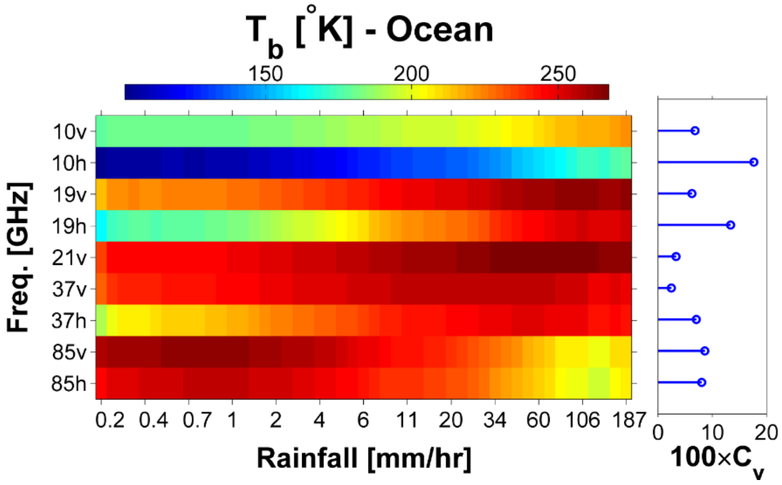
- **Combined L1-L2 estimation**

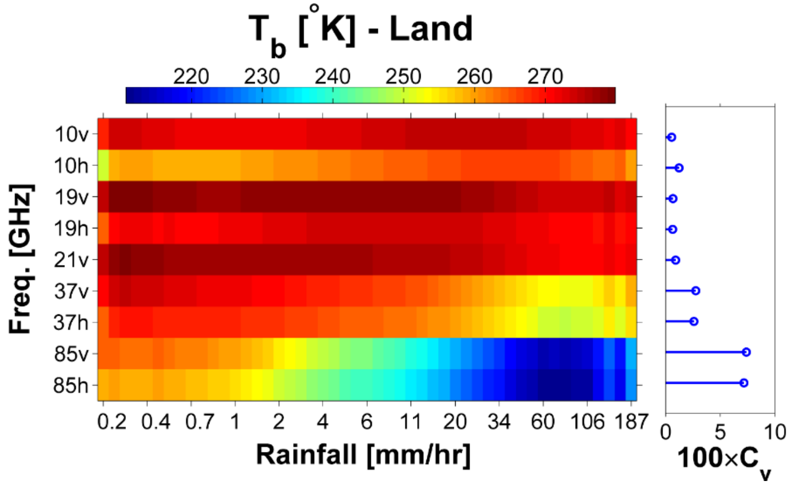
$$\begin{aligned}
&\underset{\mathbf{c}}{\text{minimize}} \quad && \left\| \mathbf{W}^{1/2} \left(\mathbf{y} - \mathbf{B}_{\mathcal{S}} \mathbf{c} \right) \right\|_2^2 + \lambda_1 \left\| \mathbf{c} \right\|_1 + \lambda_2 \left\| \mathbf{c} \right\|_2^2 \\
&\text{subject to} \quad && \mathbf{c} \succeq 0, \ \ \mathbf{1}^{\mathrm{T}} \mathbf{c} = 1,
\end{aligned}$$

1) Some representation coefficients are very large and some very small (shrinkage due to L1 regularization chooses the most important neighbors)
2) The L2 regularization stabilizes the inversion for efficient and stable solution

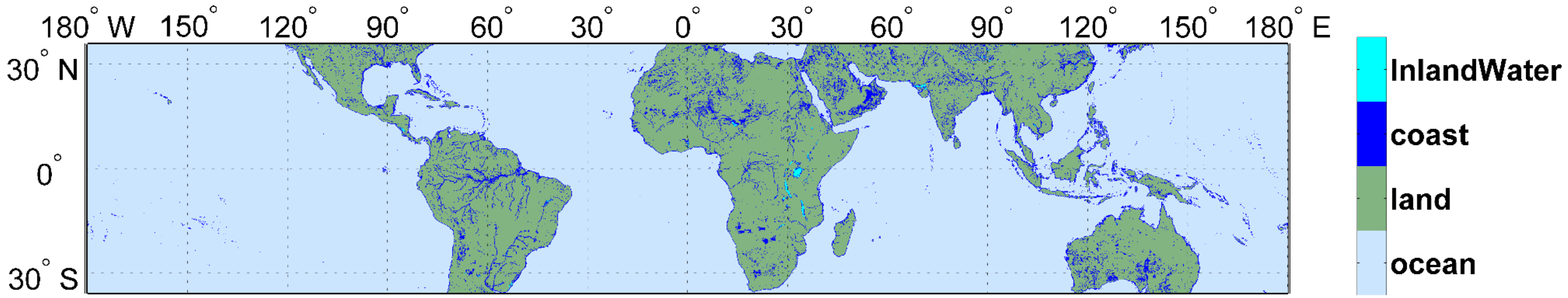
ShARP spectral weights (W) and land surfaces

- Spectral weights denote relative importance of each channel



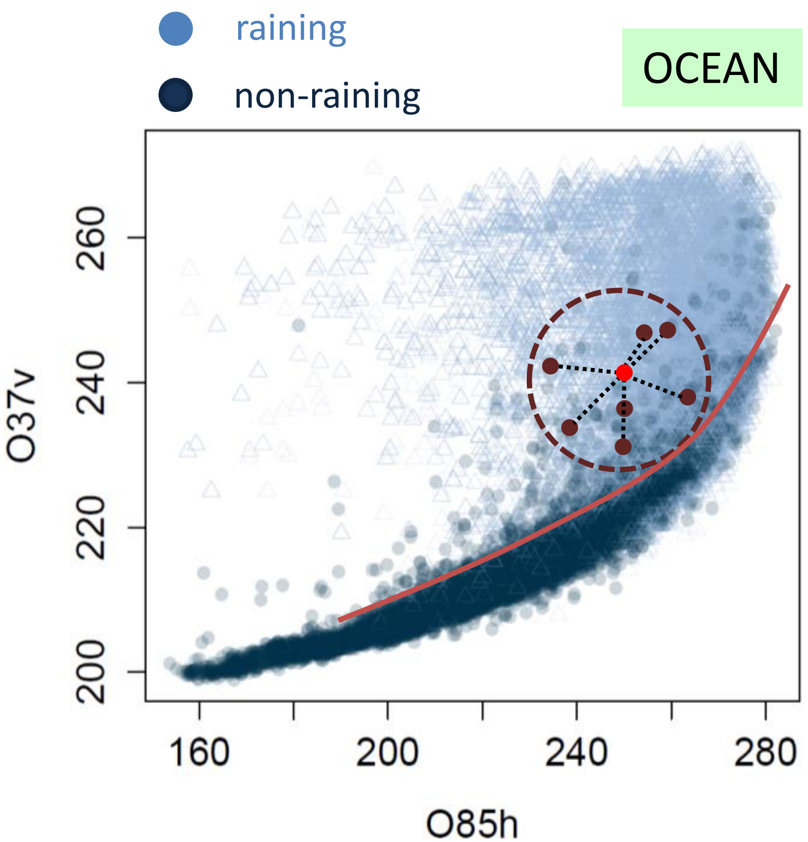


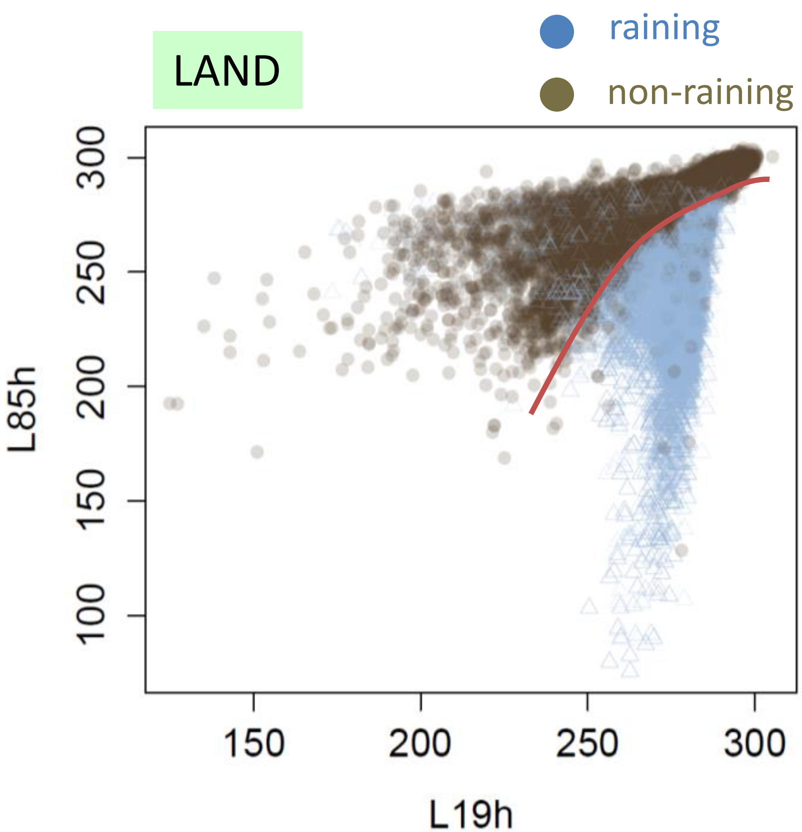
$$w_i = \frac{CV_i}{\max_i(CV_i)}$$



TMI rain/non-rain spectral signatures

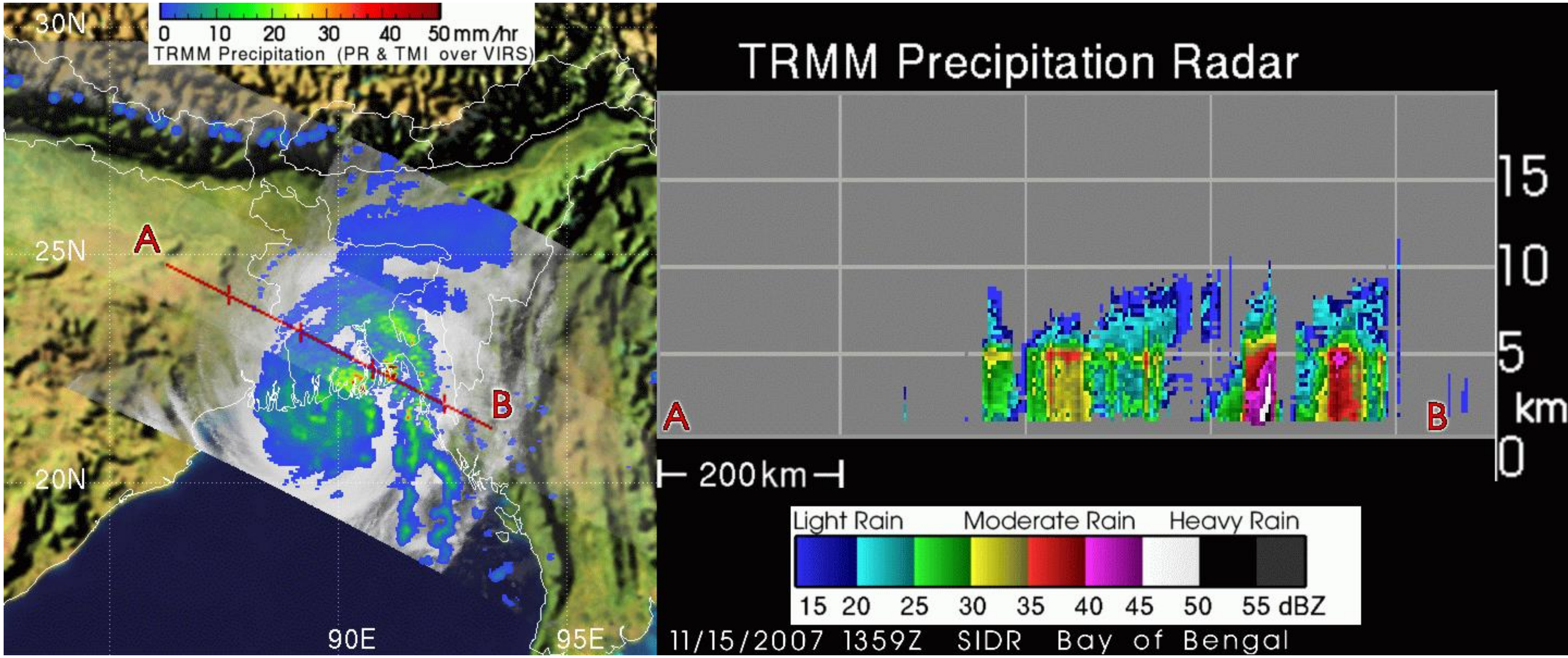
- **A local estimation-detection model**

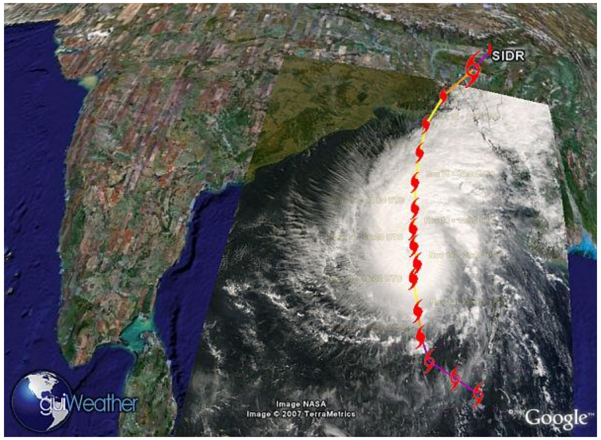




  – Neighborhood Euclidean distance in a multi-spectral sense

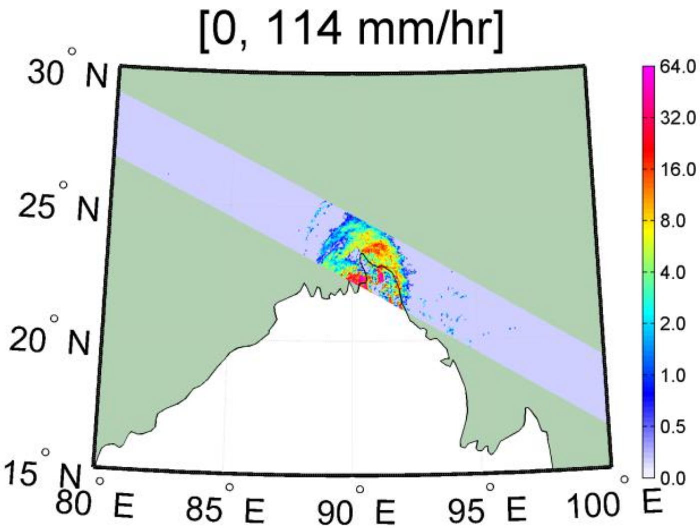
Cyclone Sidr, Nov. 2007



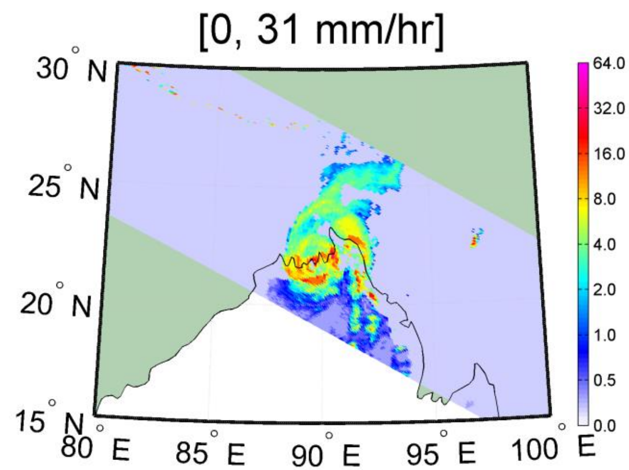


Date: Nov. 15 at 13:59 UTC (8:59 a.m. EST)

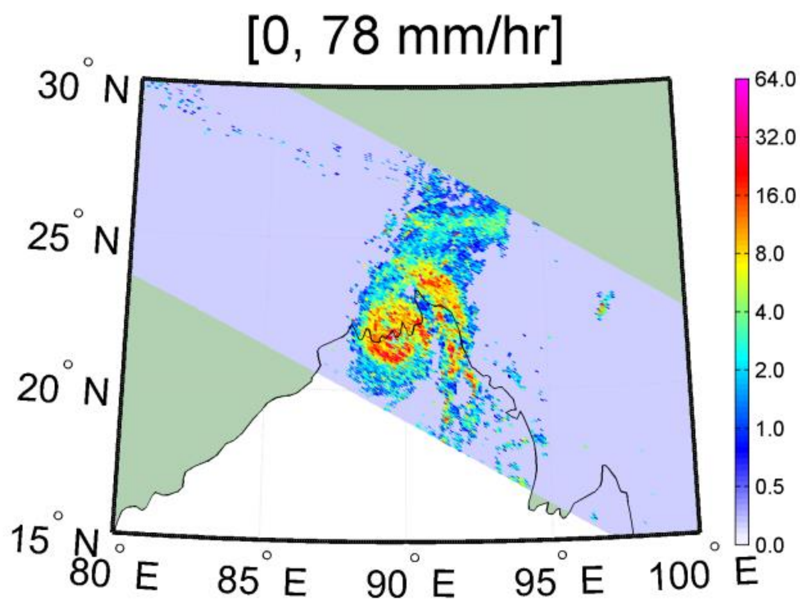
Retrieval of Tropical Cyclone Sidr



Radar -- 2A25-V7

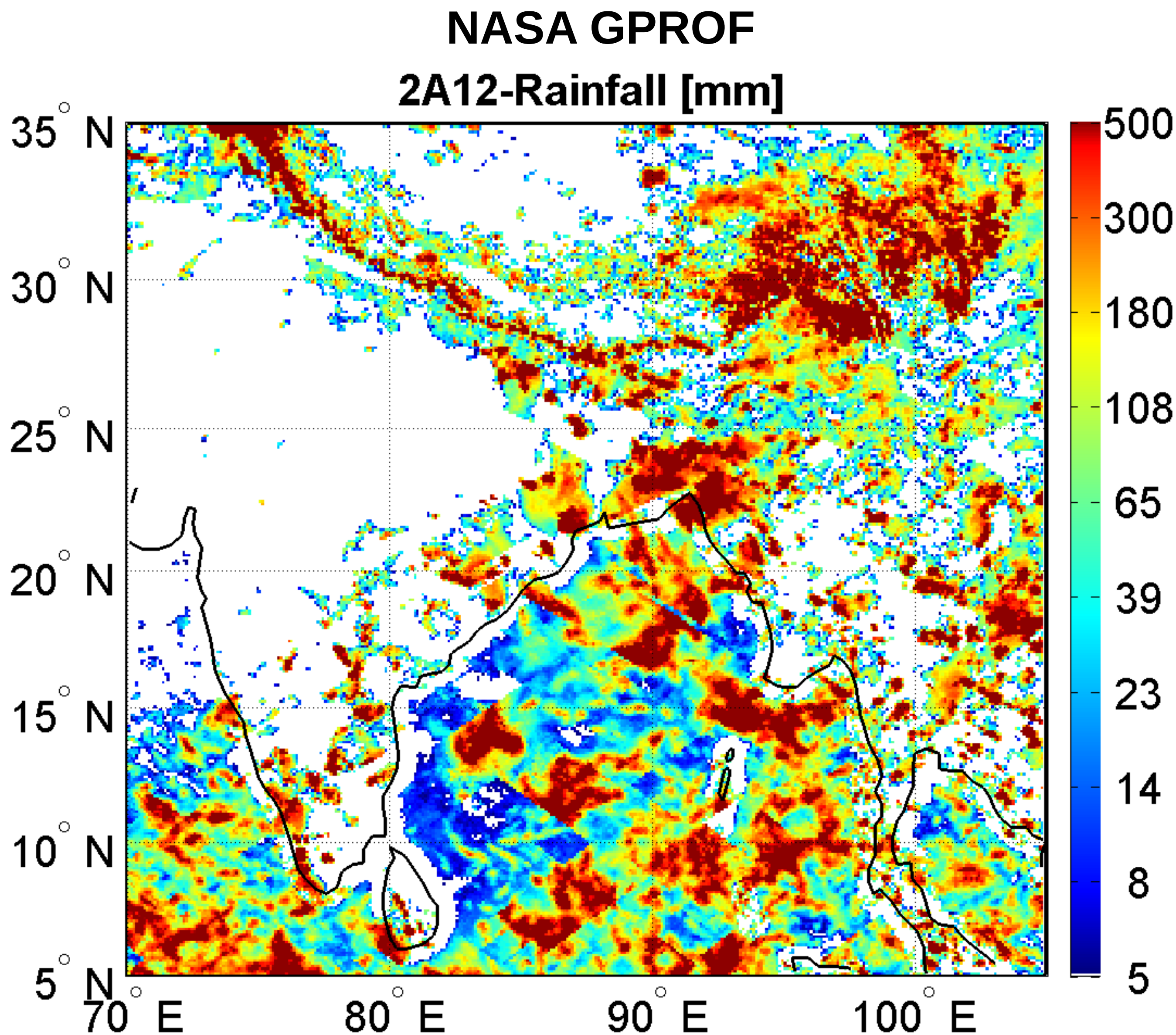


NASA GPROF -- 2A12-V7

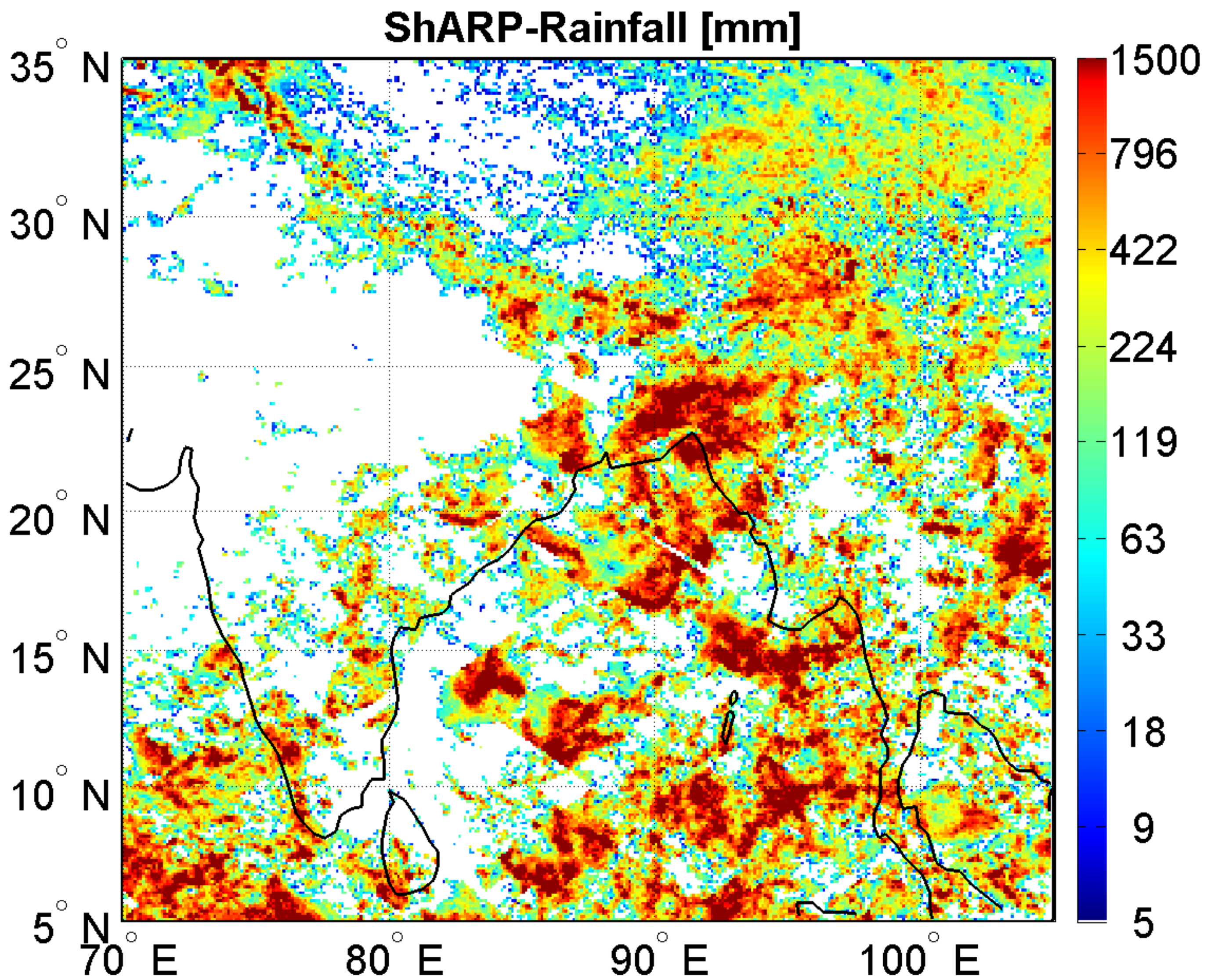


ShARP-V1

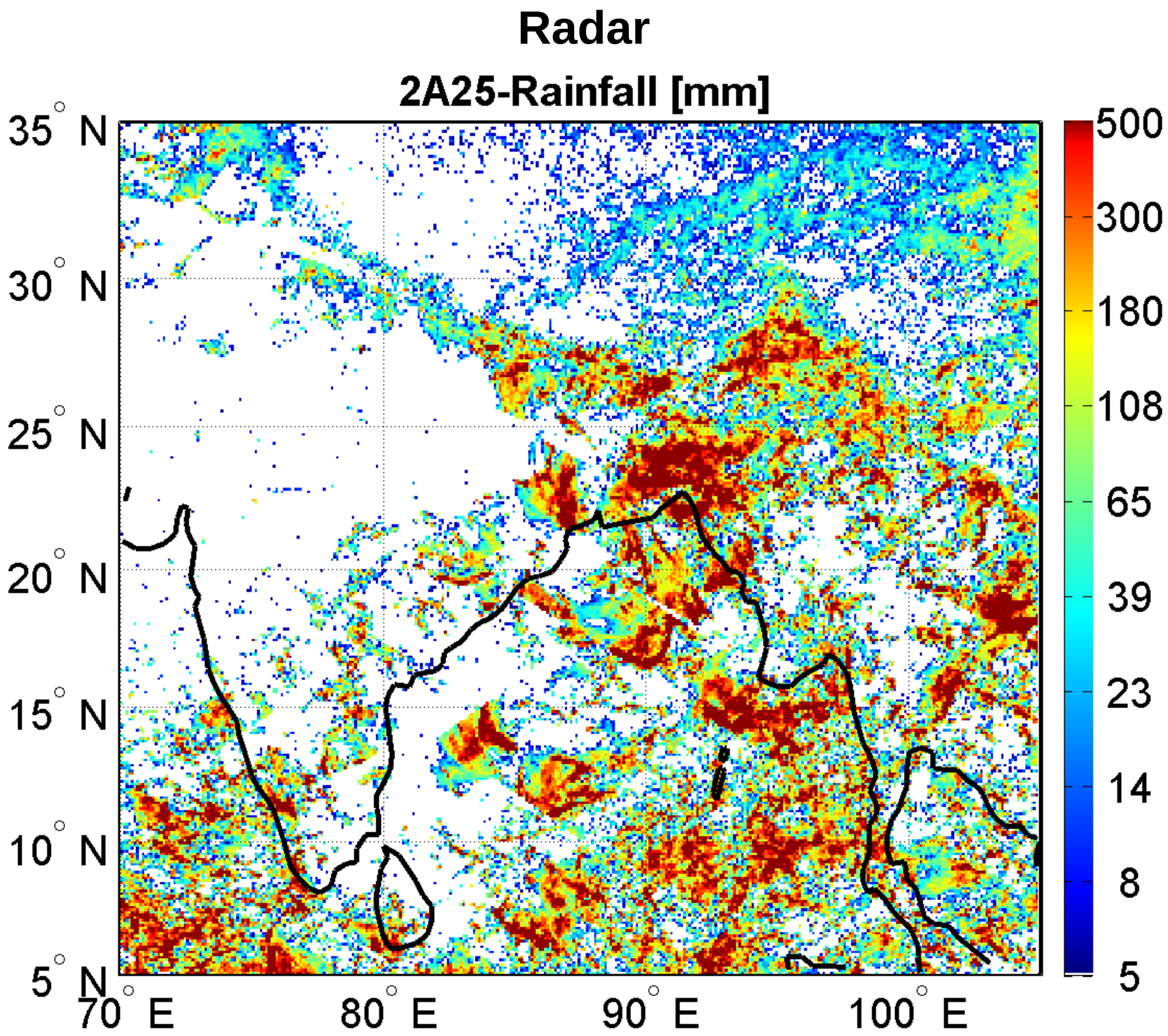
Retrieval of Monthly Rain, May 2013



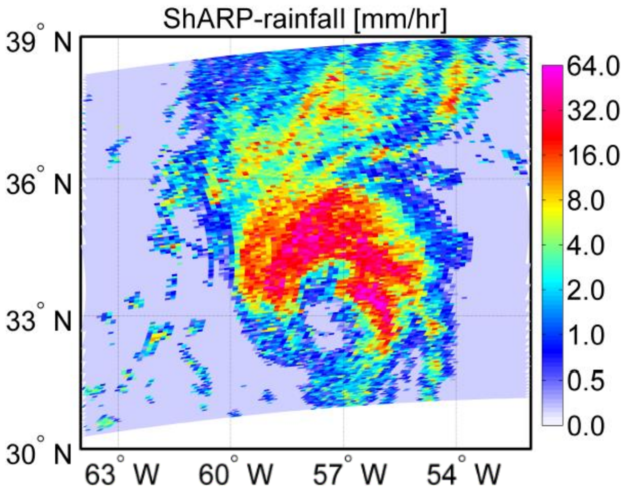
Retrieval of Monthly Rain, May 2013



Retrieval of Monthly Rain, May 2013

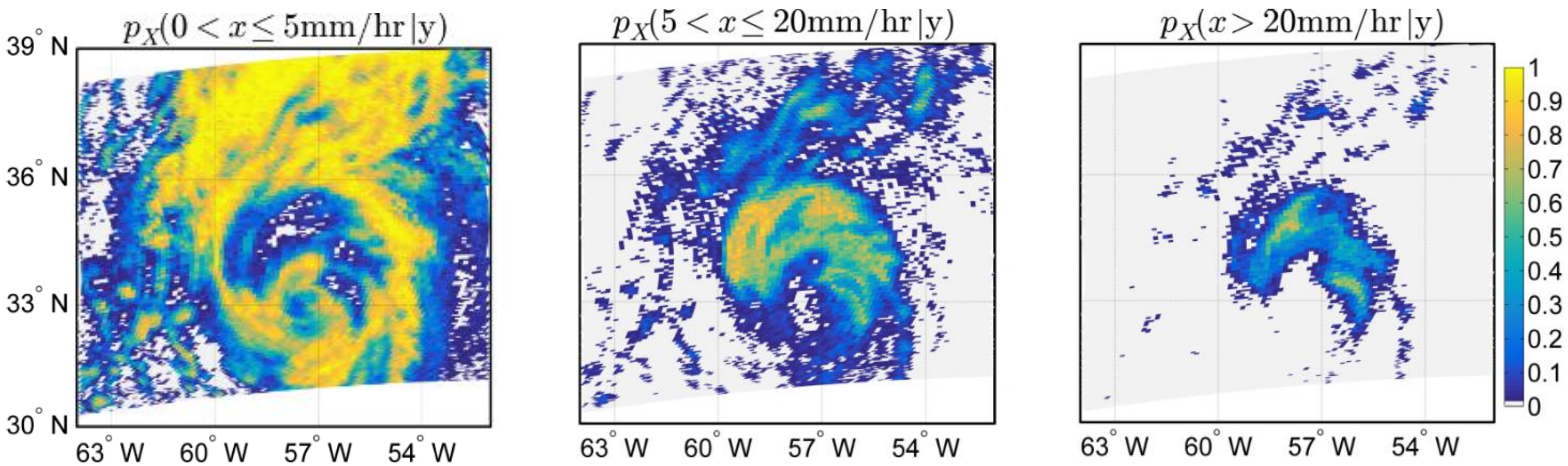


ShARP retrieval uncertainty



- **Hurricane Danielle (2010)**

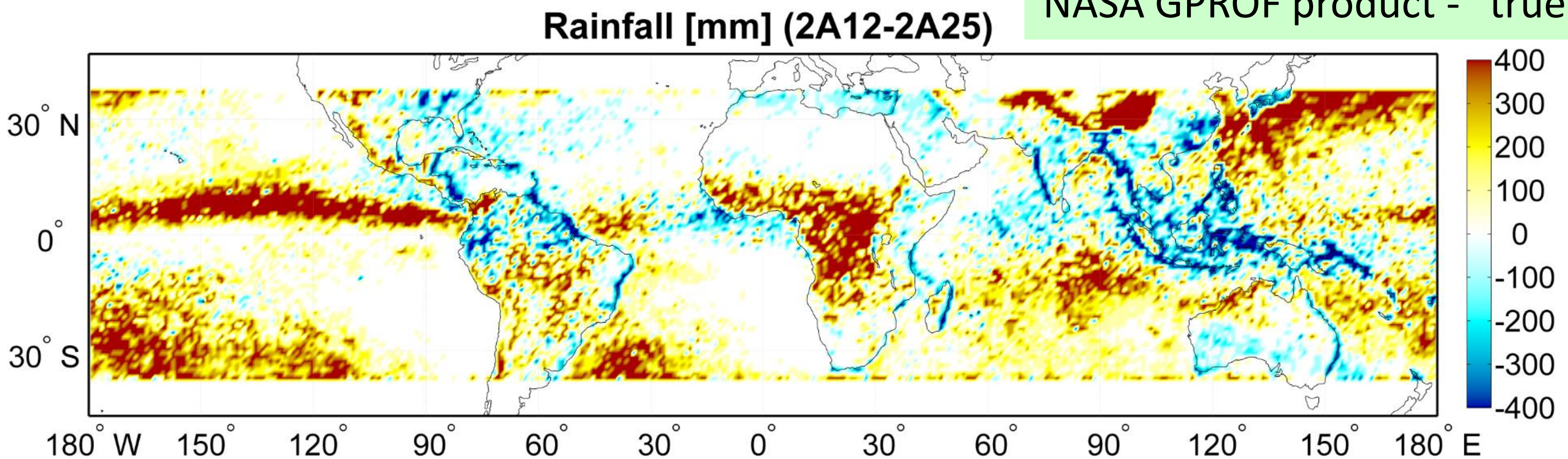
- Approximate the entire posterior PDF of the ShARP retrievals
- Probability of exceedance for the extreme rainfall for risk analysis



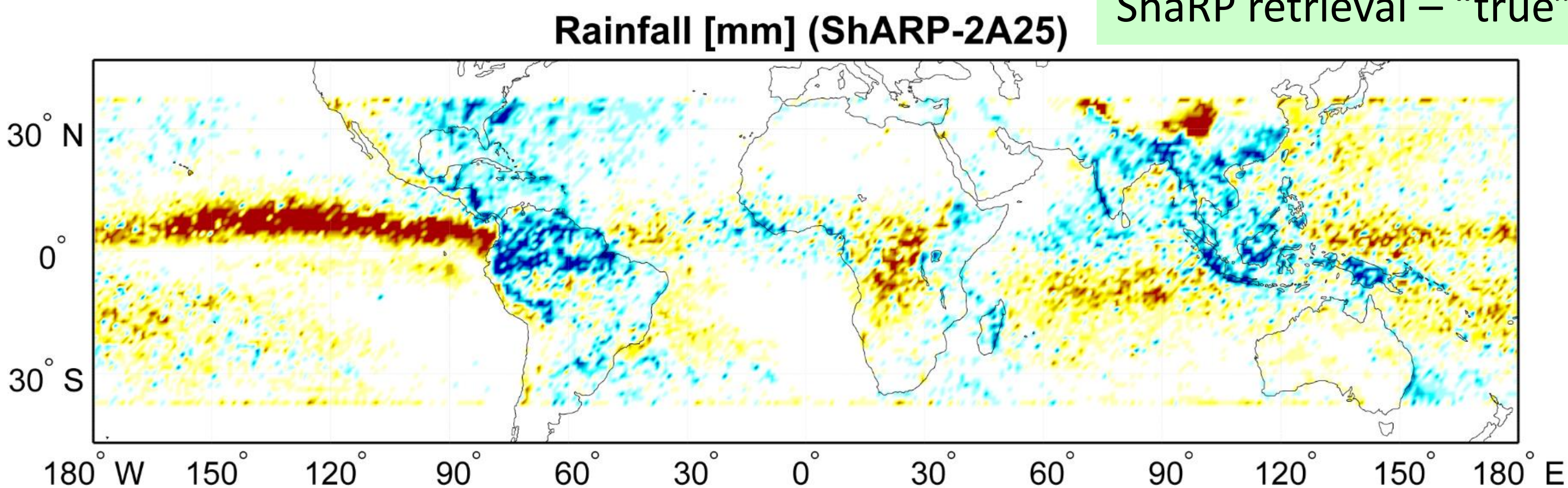
ShARP cumulative results

- Difference of the total rainfall in calendar year 2013 (1^{o}-degree)

NASA GPROF product - “true”



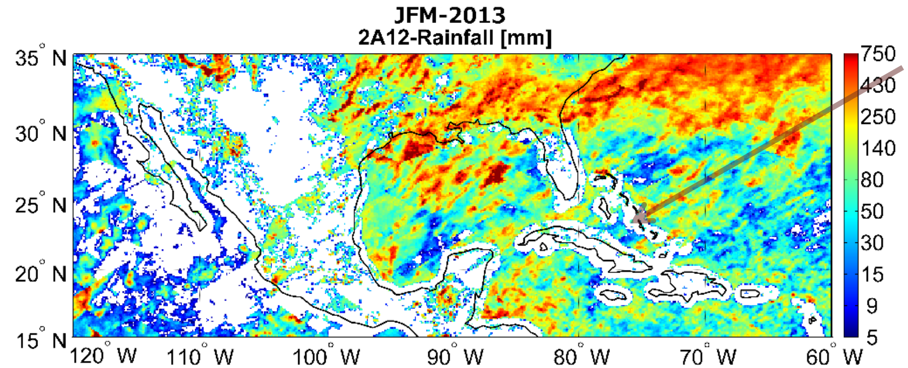
ShaRP retrieval – “true”



ShARP cumulative results

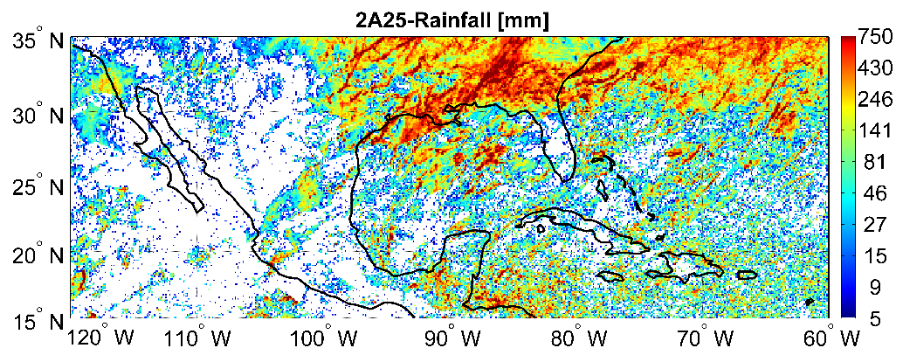
- Rainfall accumulation thought **January, February and March** in calendar year 2013 (0.5º-degree)

NASA
Passive retrieval

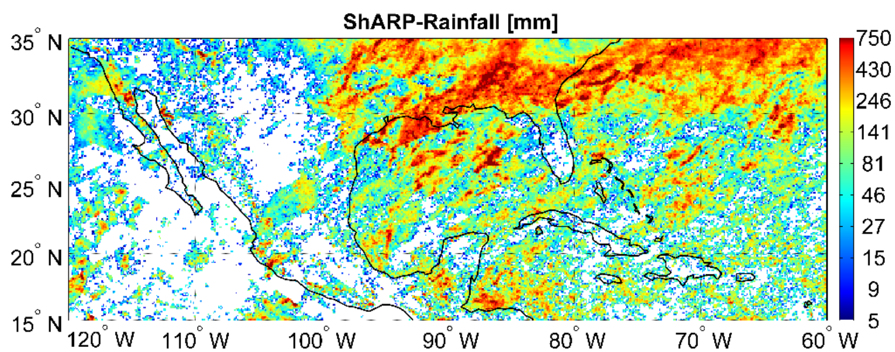


Coastal zones

NASA
Active retrieval
(reference)



ShARP
Passive retrieval



Take home message and future research

- GPM offers opportunities for accurate estimation of rainfall over coastal zones
- The proposed ShARP algorithm introduces two innovations: (1) smart selection of estimation neighborhod and (2) advanced estimation within it (screens out irrelevant spectral candidates and reduces the effects of land surface heterogeneity in emissivity)
- The superiority of the proposed algorithm, compared to the standard NASA retrieval algorithm especially over coastal areas, was demonstrated
- Perform extensive testing over delta regions and examine improvement in retrieval, early warning systems, and modeling of inundation and floods

Co-authors: Mohammad Ebtehaj & Rafael Bras (Georgia Tech); Zach Tessler (CUNY)

Ebtehaj A.M., R. L. Bras, E. Foufoula-Georgiou (2014), Shrunken Locally Linear Embedding Algorithm for Retrieval of Precipitation http://arxiv.org/abs/1405.0454