



# GPM Observations of Microwave Land Surface Emissivity and Radar Backscatter

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# Background/Motivation

- GPM precipitation algorithms require knowledge of surface emissivity and/or backscatter cross-section
  - DPR algorithms rely on Surface Reference Technique to estimate path-integrated attenuation (PIA)
  - Combined DPR+GMI algorithm uses PIA and performs radiative transfer simulations in optimization procedure
  - Generation of GPROF database for partner constellation members require transfer from GMI freq/angle to other imagers/sounders
- Existing atlases (TELSEM) used in at-launch algorithms, but missing:
  - Frequencies > 90 GHz
  - Relationship between emissivity and radar backscatter cross-section ( $\sigma_0$ )
- Unique capabilities of GPM instruments provide new opportunity for land surface studies

# Outline

- Overview of GMI and DPR instruments and precipitation algorithms
- Description of GMI surface emissivity retrieval & challenges
- One-year preliminary database of GMI emissivity matched to DPR  $\sigma_0$ :
  - Gridded means
  - Impact of seasonal cycle, snow cover, recent rainfall
  - EOF analysis
- GPM Combined Algorithm Implementation



# GMI Characteristics

- 13 channels from 10-183 GHz
- 1.2m reflector provides resolution ranging from 25km at 10 GHz to 6km at 89+ GHz
- Four-point calibration at 10-36 GHz (calibration standard for constellation 1C products)
- 52.8° EIA at 10-89 GHz and 49.1° EIA at 166-183 GHz (scan lines do not match)



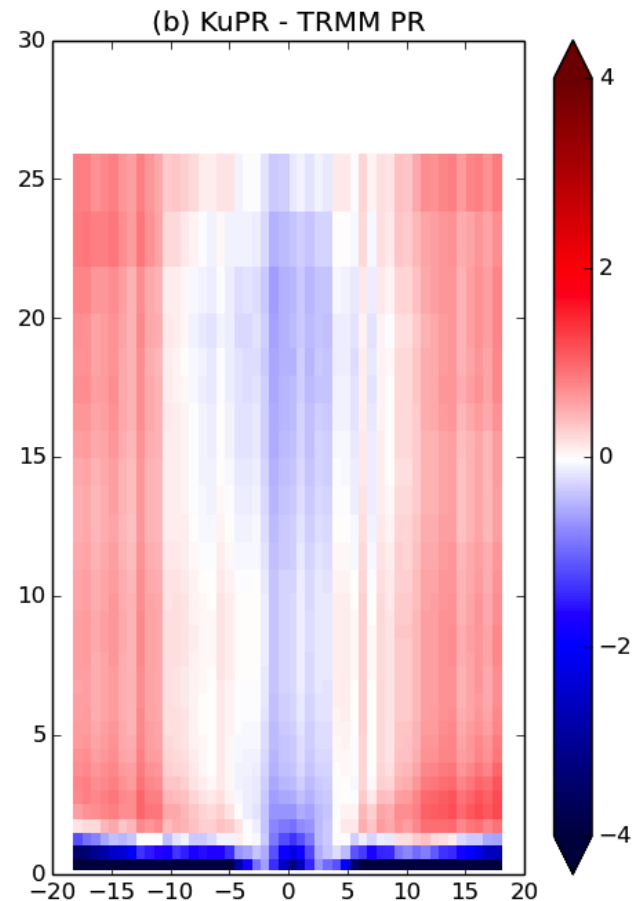
GMI precipitation algorithm (GPROF) is a Bayesian procedure that weights a database of profiles based upon closeness to observed TBs. **Explicit knowledge of surface emissivity not required**, but databases are separated based upon surface type classification (14 classes), T2m, and TPW.

Mean Simulated - GMI Tb (using buoy wind and SST + MERRA water vapor)

Emissivity Model	10 V	10 H	18 V	18 H	23 V	36 V	36 H	89 V	89 H	166 V	166 H	183 ± 3	183 ± 7
RSS	-1.1	-0.6	-0.3	0.9	0.0	0.5	1.3	0.6	1.7				
FASTEM6	0.2	-0.6	0.1	0.8	0.1	0.3	2.1	-0.2	2.2	-0.5	-0.5	-3.5	-1.0

# DPR Characteristics

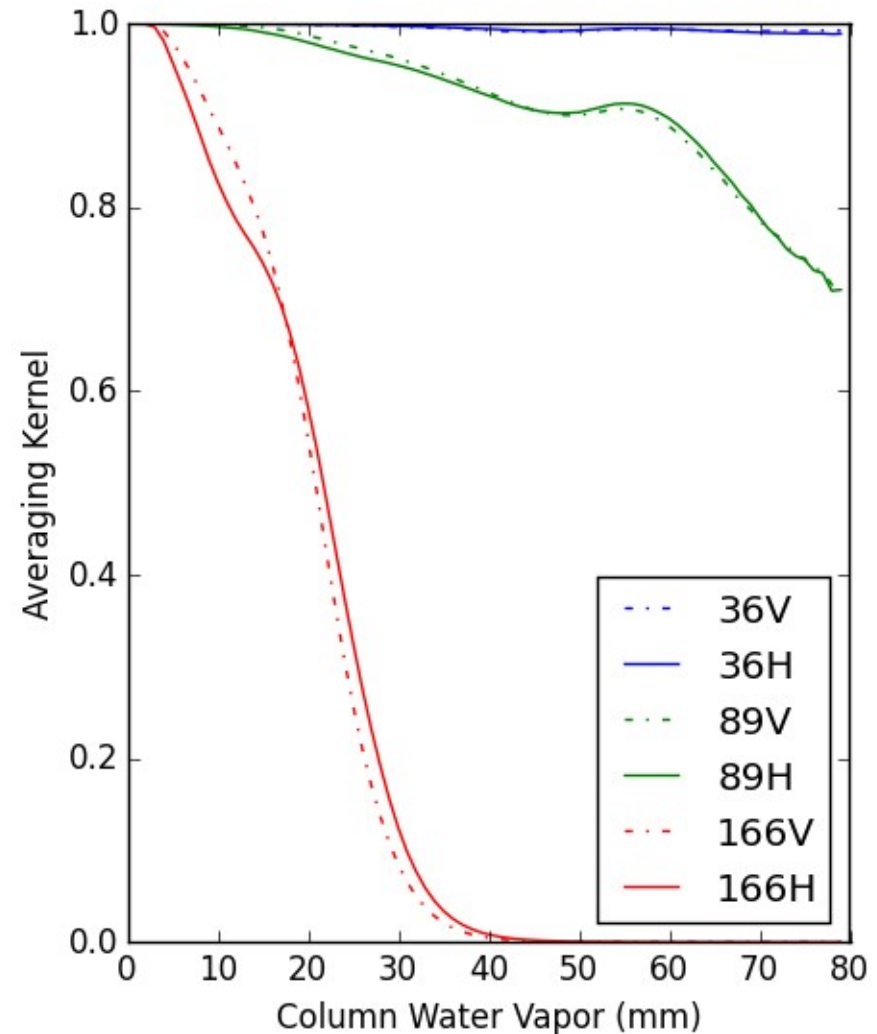
- Ku scans  $\pm 18^\circ$  at 49 positions and 250m range resolution, oversampled at 125m
- Ka scans  $\pm 9^\circ$  at 25 positions (matched to Ku) with an additional 24 interlaced positions in High-Sensitivity mode (500m range resolution oversampled to 250m)
- Ku receiver saturates at lower level than TRMM PR (22.5 dB)
- DPR algorithms use **Surface Reference Technique to infer PIA** (and its uncertainty) or differential PIA
- DPR+GMI algorithm uses **PIA and explicit surface emissivity estimates** (with uncertainty)



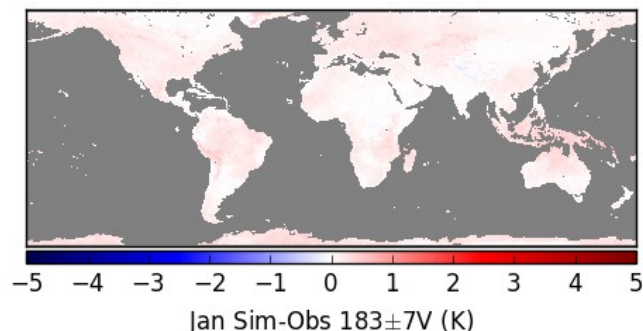
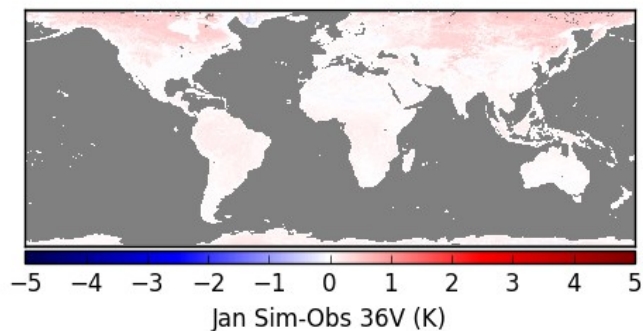
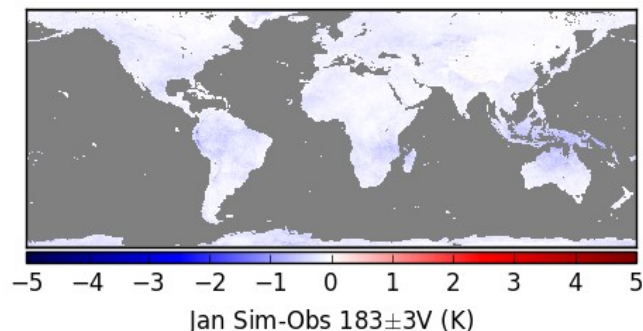
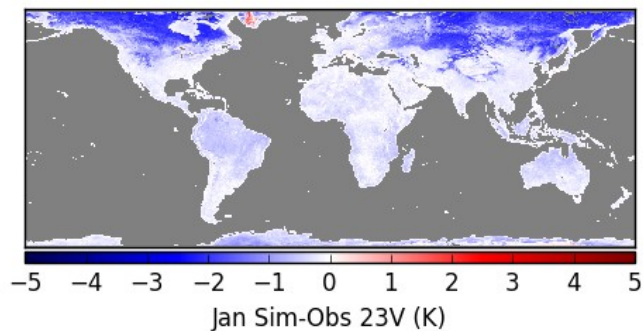
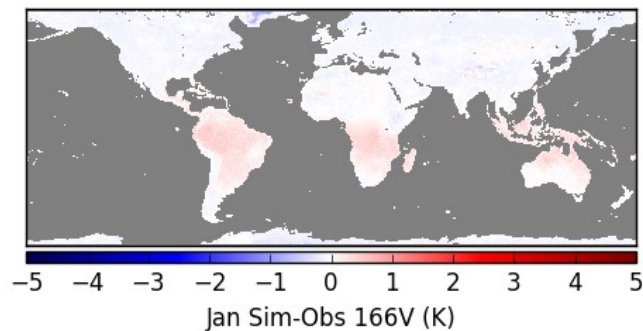
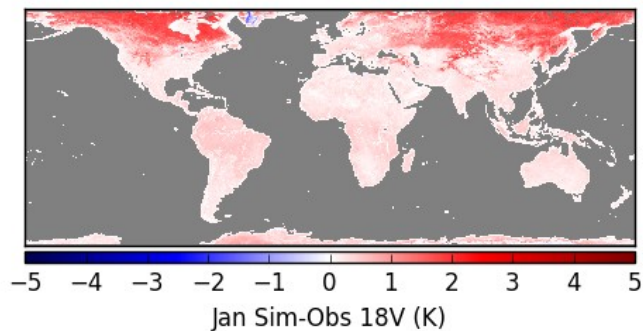
# Emissivity Retrieval from GMI

## Key assumptions:

- Skin temperature from ancillary data (MERRA/GANAL)
- All channels considered independent, except:
  - 23.8V (interpolated from 18.7V and 36.6V)
  - $183 \pm 3$  and  $183 \pm 7$ : Use same as 166V
- Adjust temperature/water vapor EOFs from analysis state
- No cloud liquid (IR Tb can be used to screen in post-processing)
- No post-1C RFI screening



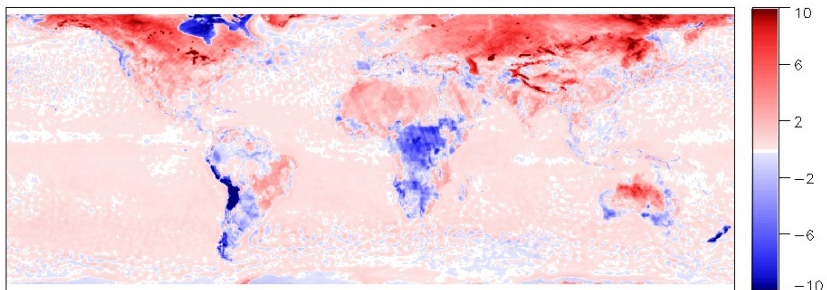
# Retrieval Issues: Simulated – Observed Tb Residuals



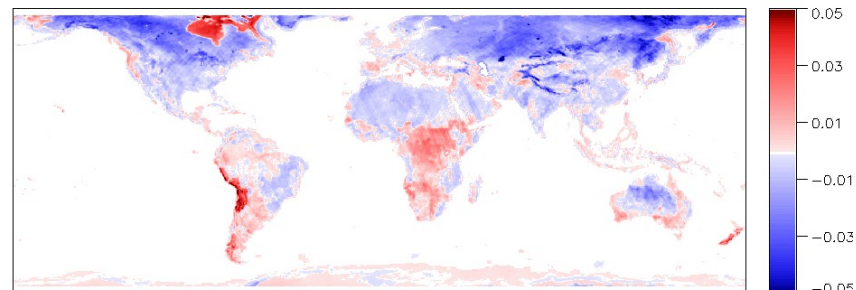


# Retrieval Issues: Dependence on Skin Temperature Source

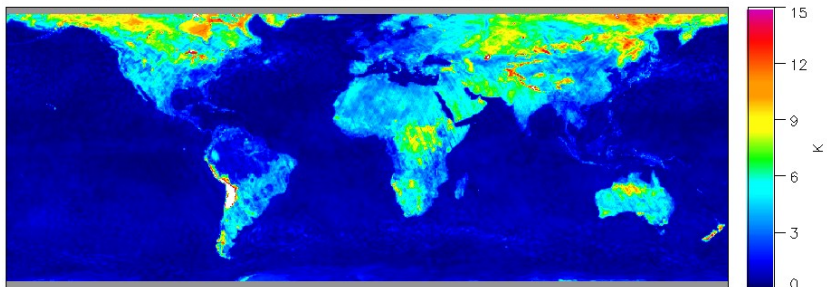
GANAL-MERRA initial Tskin Dec-Jan



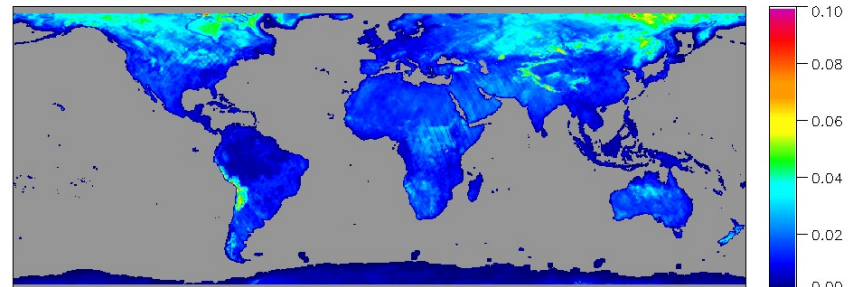
GANAL-MERRA emis Dec-Jan 10V



GANAL-MERRA initial Tskin rms difference Dec-Jan



GANAL-MERRA emis rms difference Dec-Jan 10V

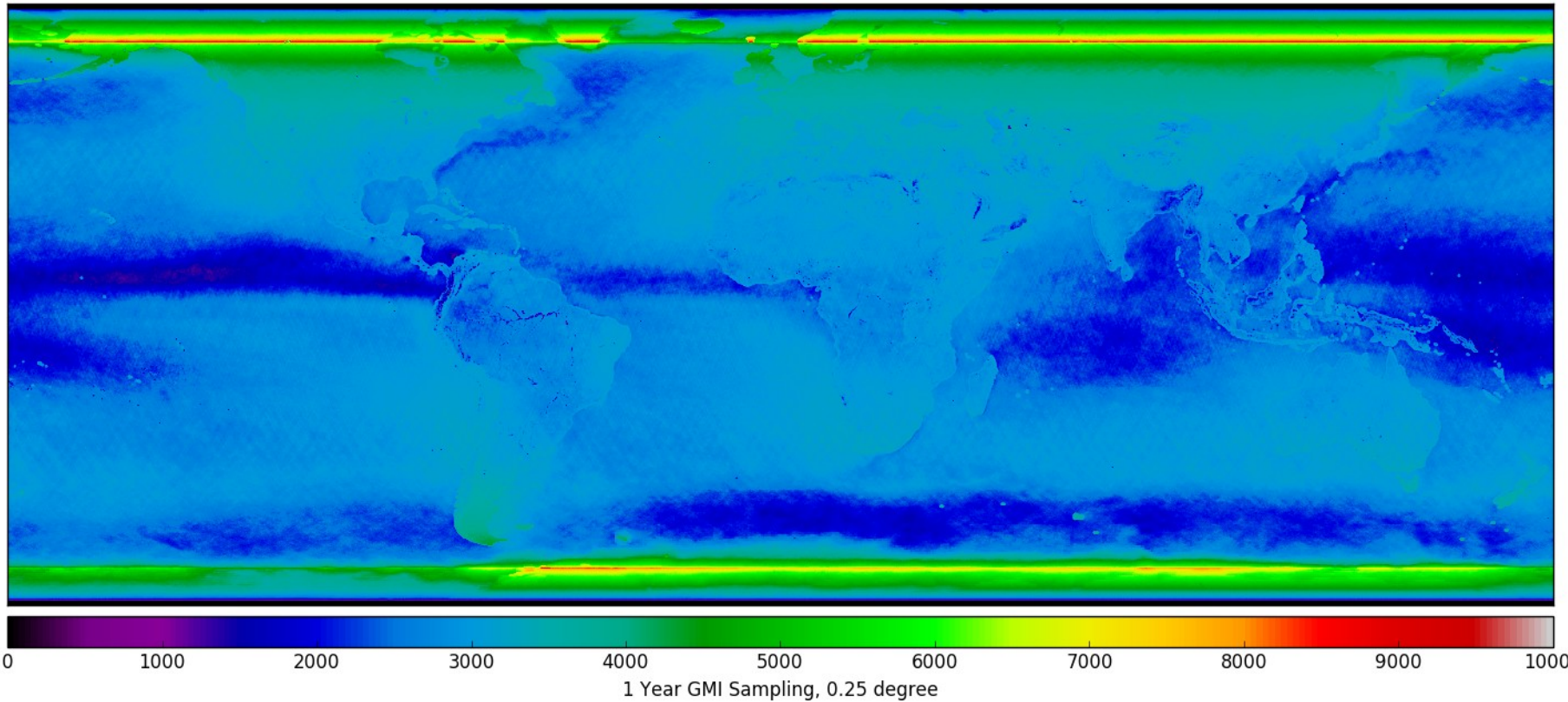




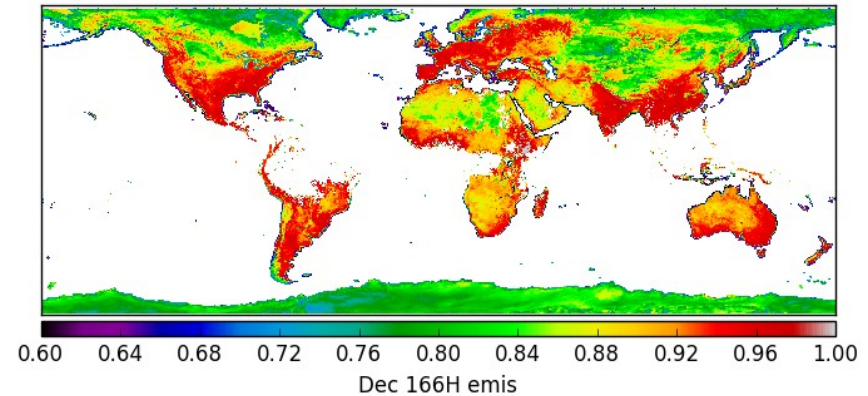
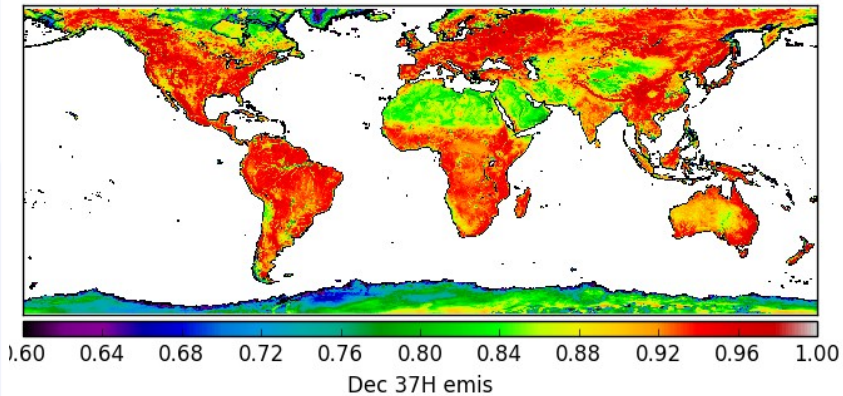
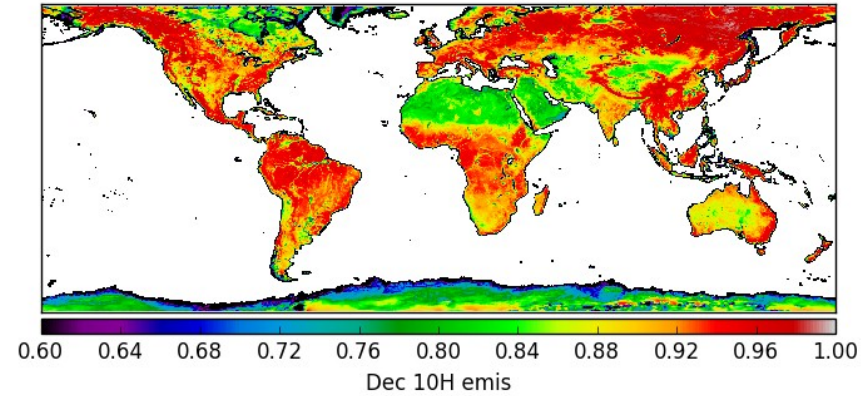
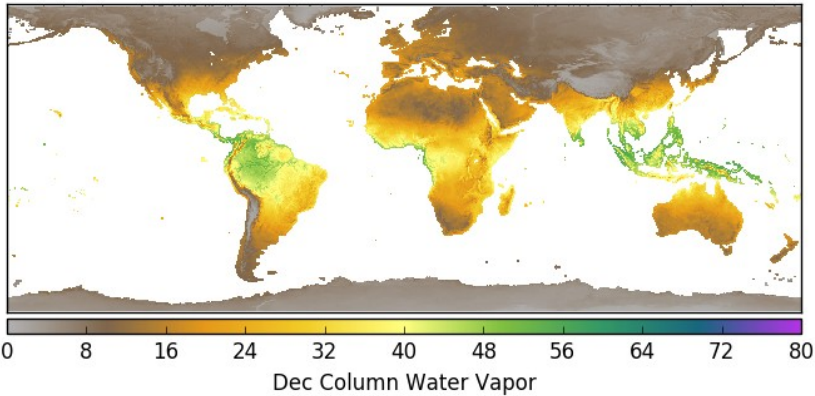
# Database Overview

- Database is designed to meet combined algorithm needs:
  - Gridded means of emissivity at each frequency and  $\sigma_0$  at each frequency and incidence angle
  - Covariance matrix between emissivity and  $\sigma_0$  at all incidence angles to derive EOFs
- Challenge 1: Poor sampling of DPR at a given incidence angle
- Challenge 2: How to effectively use ancillary data to condition the mean and covariance matrix?

# DPR sampling



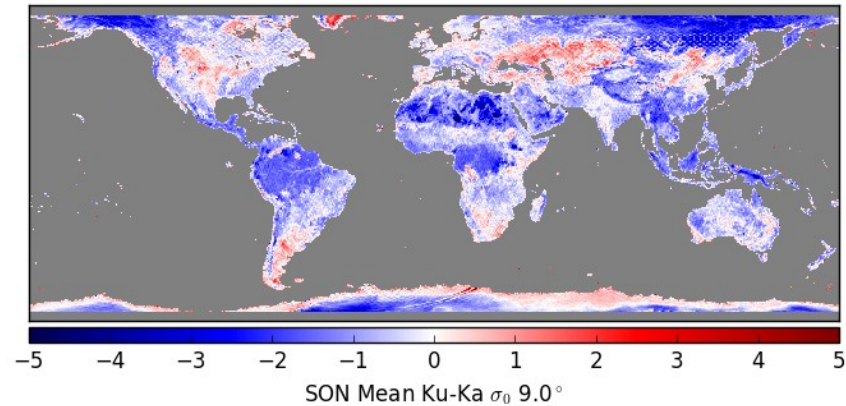
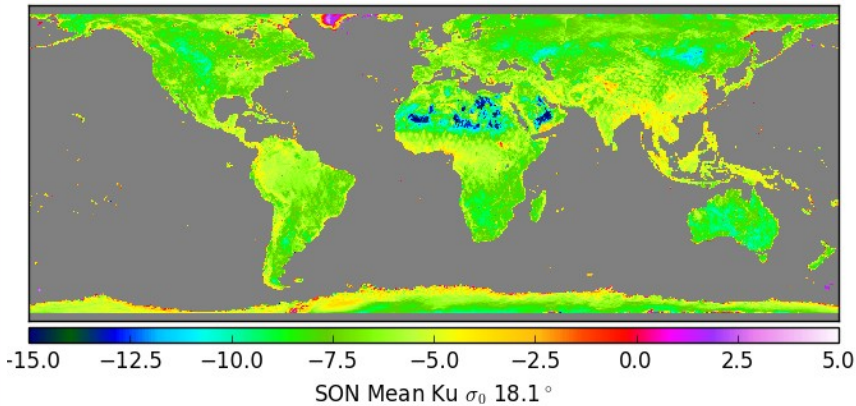
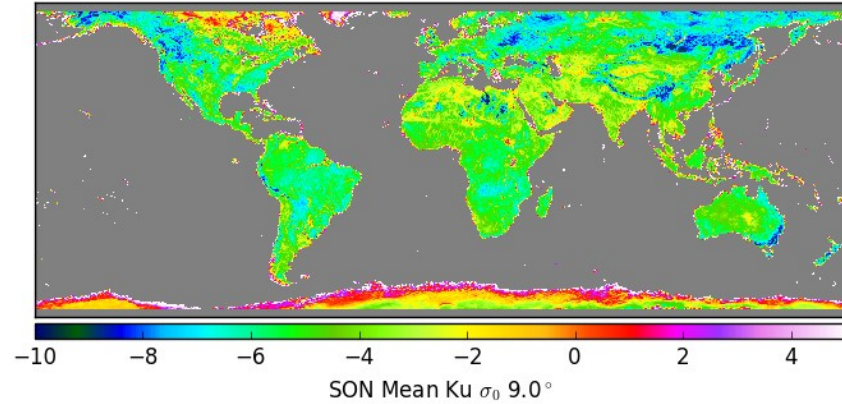
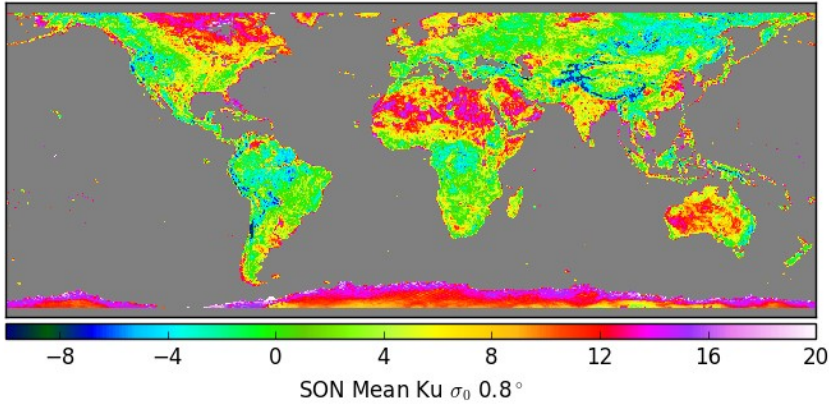
# Conditional Subsets – Impact of Seasonal Cycle on Emissivity



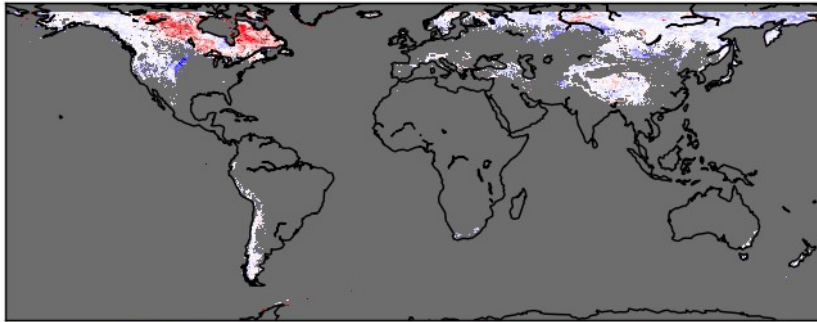


# Conditional Subsets – Impact of Seasonal Cycle on DPR Backscatter

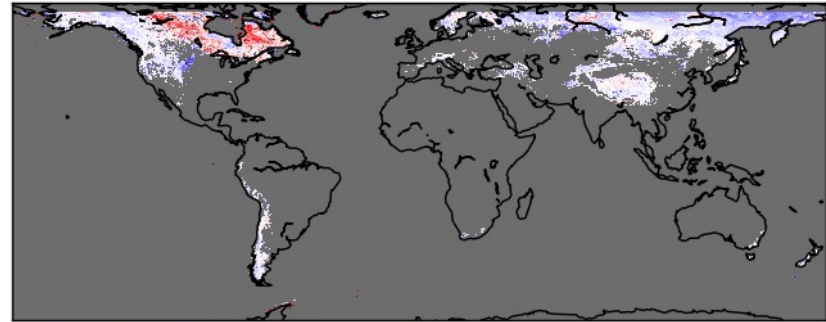
GLOBAL PRECIPITATION MEASUREMENT



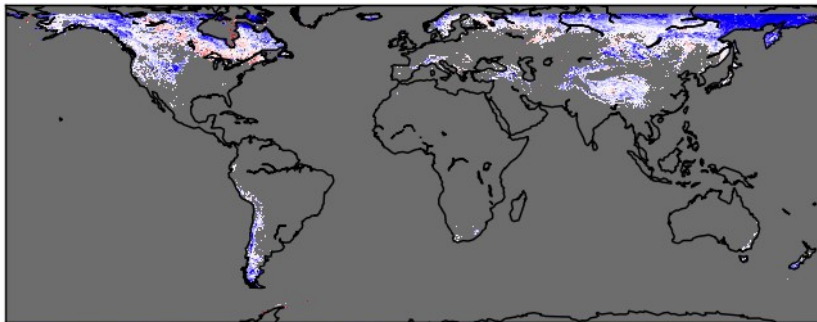
# Conditional Subsets – Impact of Snow Cover on Emissivity



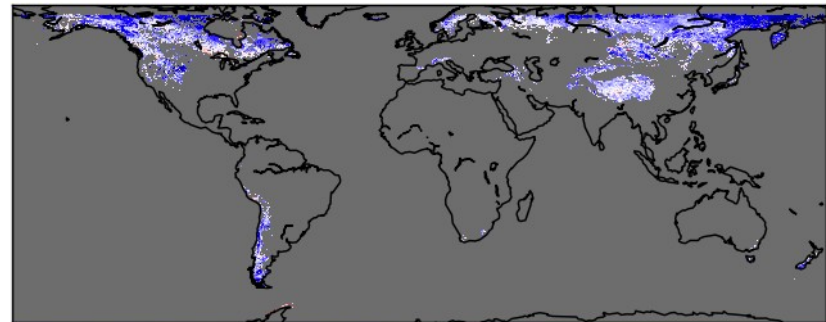
0.30 -0.24 -0.18 -0.12 -0.06 0.00 0.06 0.12 0.18 0.24 0.30  
DJF Snow-Bare Emissivity 10H



-0.30 -0.24 -0.18 -0.12 -0.06 0.00 0.06 0.12 0.18 0.24 0.30  
DJF Snow-Bare Emissivity 18H

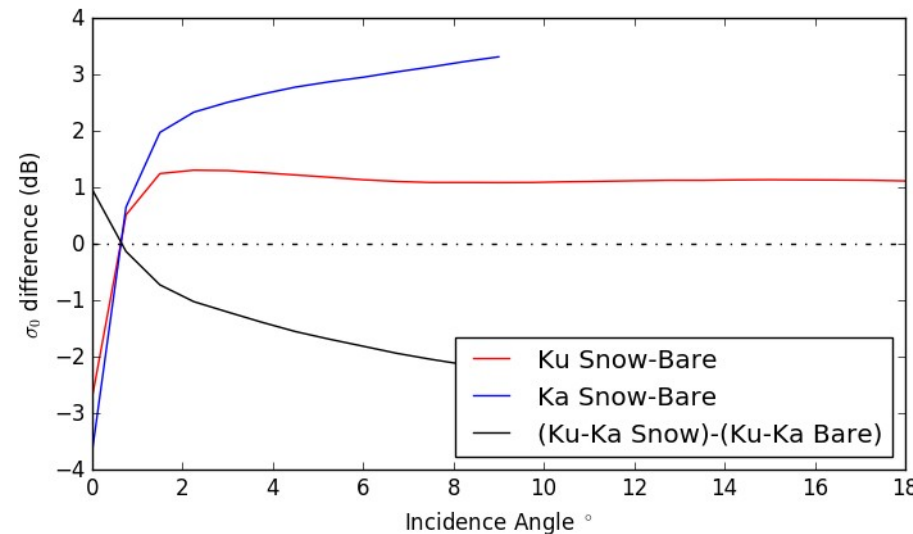
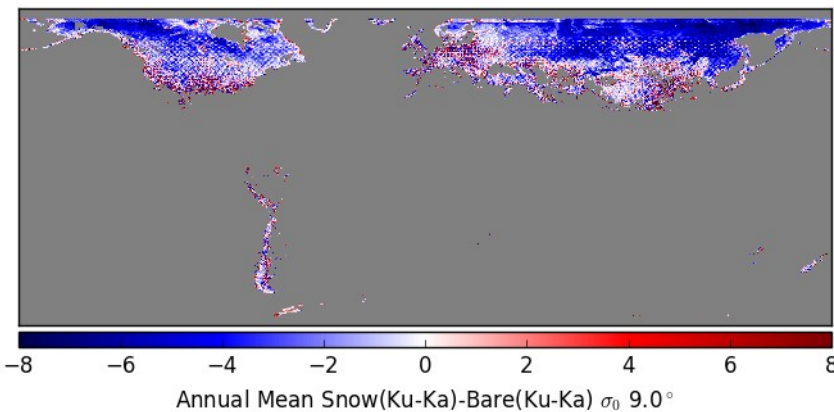
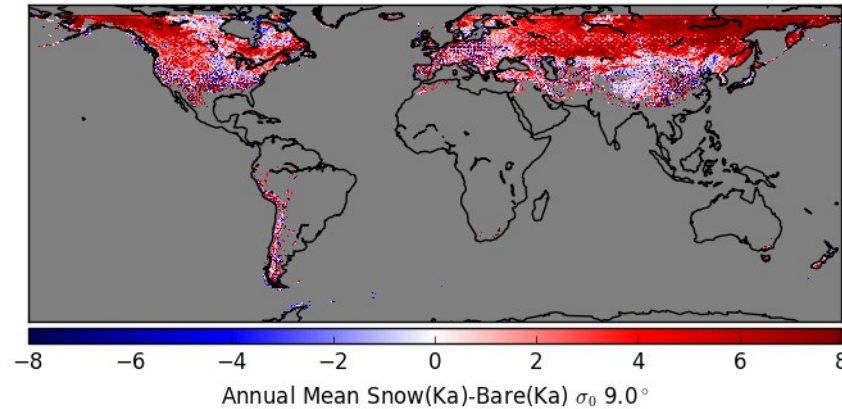
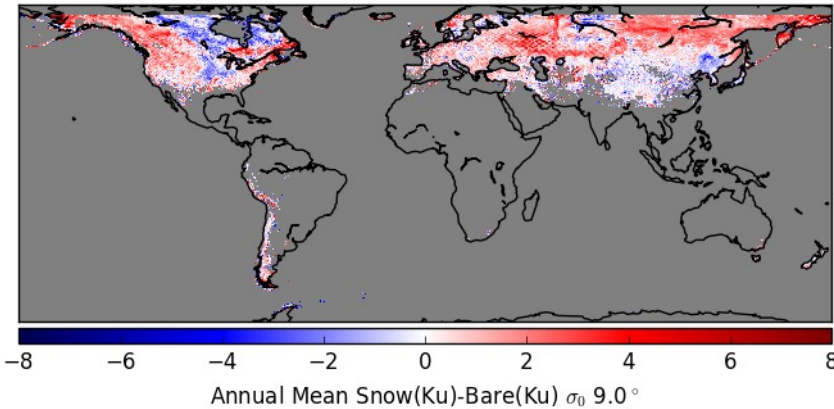


0.30 -0.24 -0.18 -0.12 -0.06 0.00 0.06 0.12 0.18 0.24 0.30  
DJF Snow-Bare Emissivity 89H



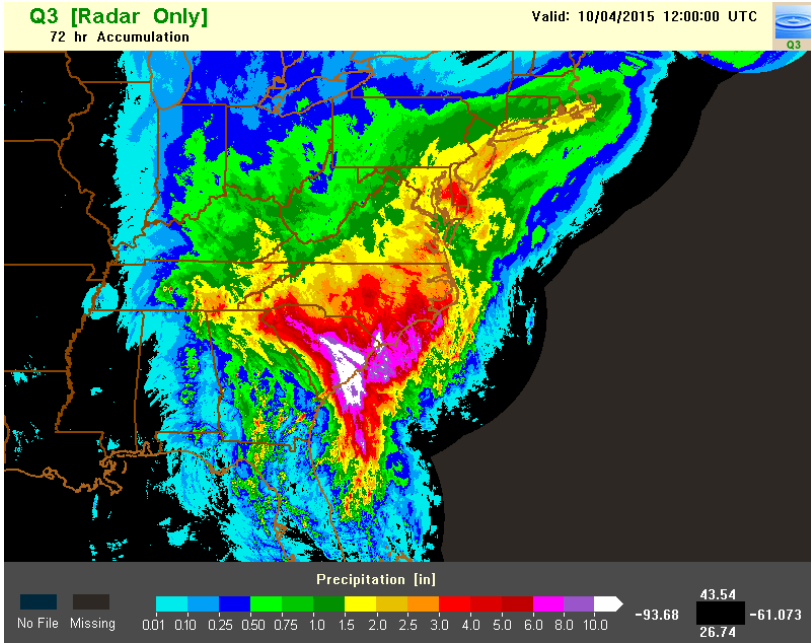
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DJF Snow-Bare Emissivity 166H

# Conditional Subsets – Impact of Snow Cover on DPR Backscatter

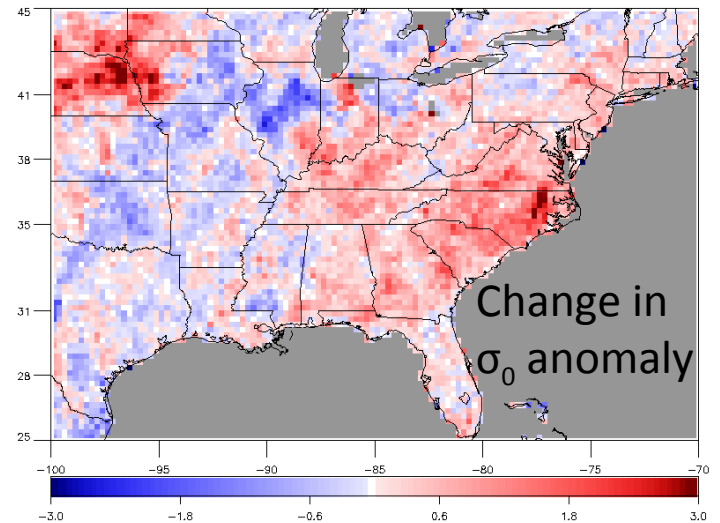
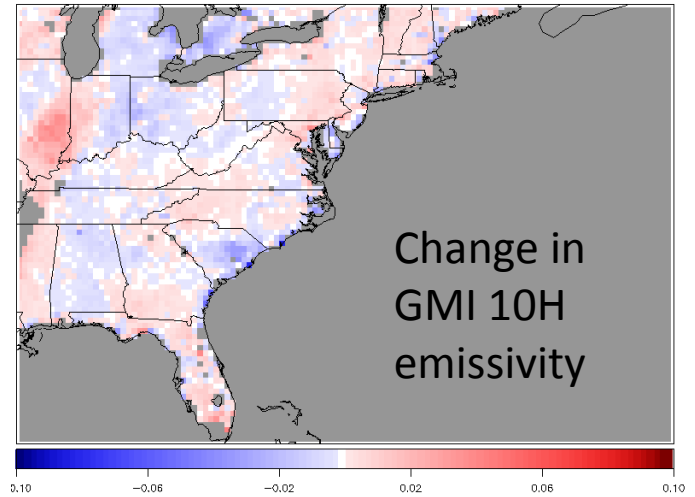




# Impact of Recent Rainfall



Extreme flooding event in early October 2015

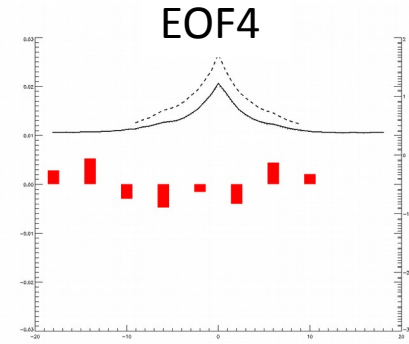
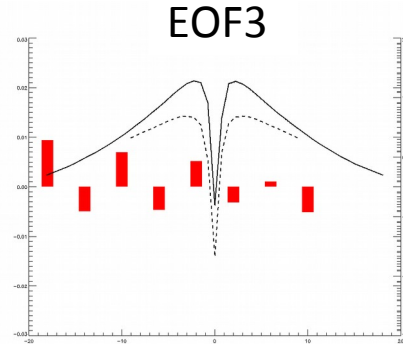
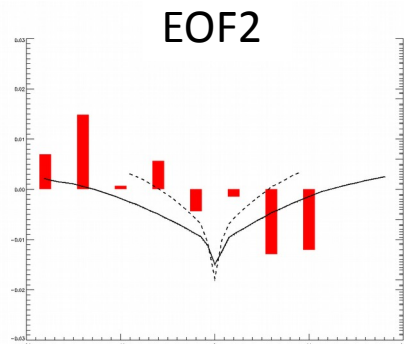
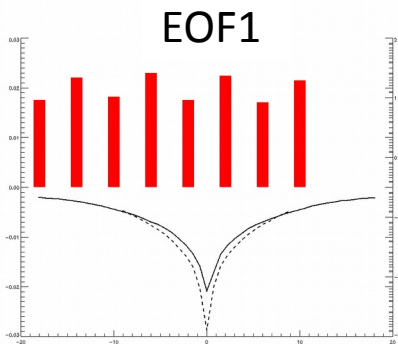
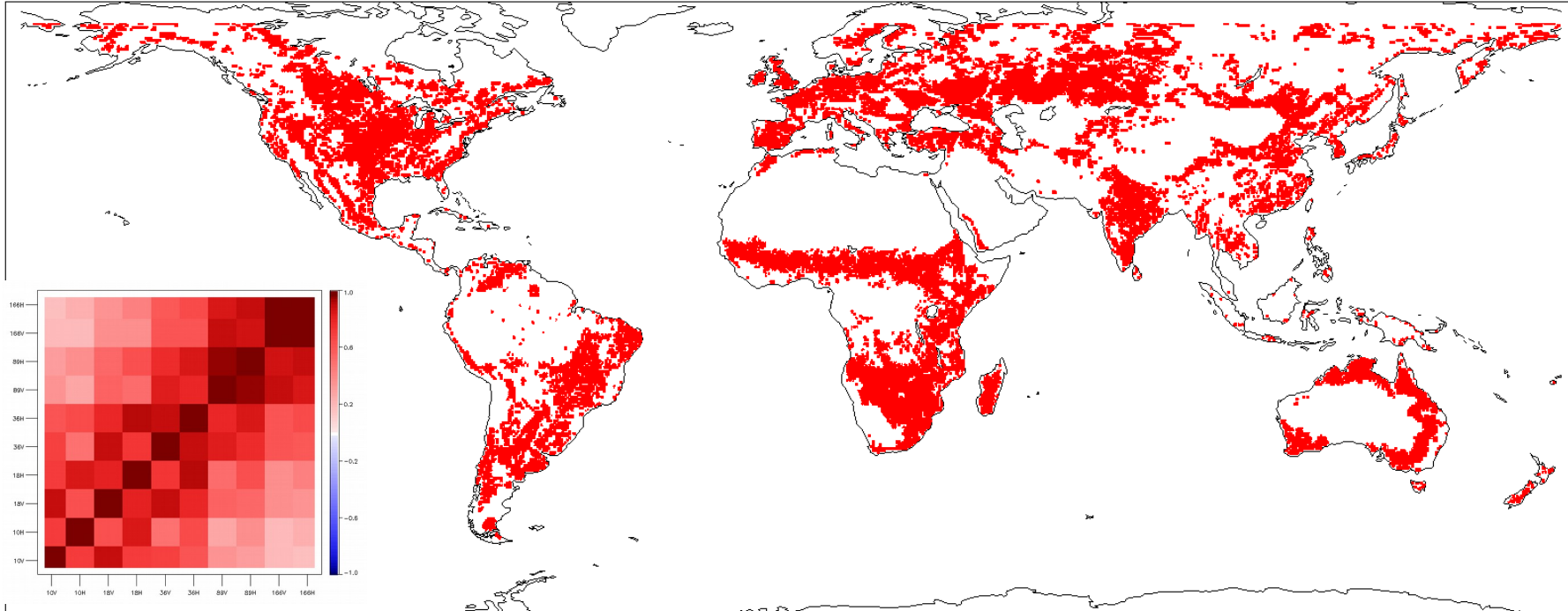


# GPM Combined Algorithm Implementation (Proposed for V5)

- Generate ensemble of solutions (modify precipitation profile and surface properties)
  - Use gridded mean (by month) as base state emissivity,  $\sigma_0$
  - Use class-based covariance-derived EOFs to guide perturbations to base state
- Ensemble filter uses sample covariance to determine sensitivity of measurements to precipitation/surface parameters and adjusts each ensemble member accordingly
- Final solution is mean of filtered ensemble

# Vegetation Class Example

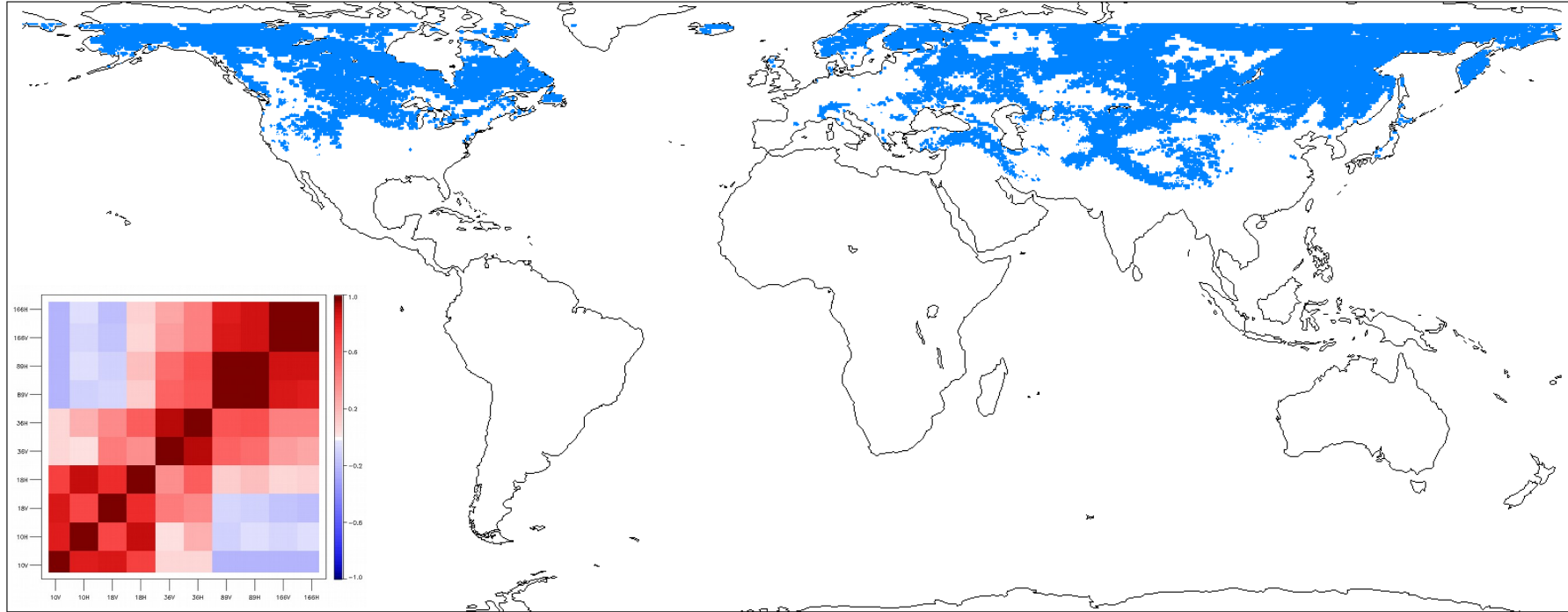
Surface Type 4



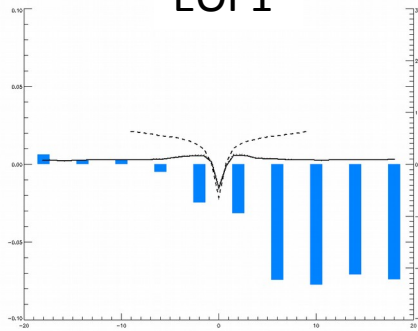


# Snow Class Example

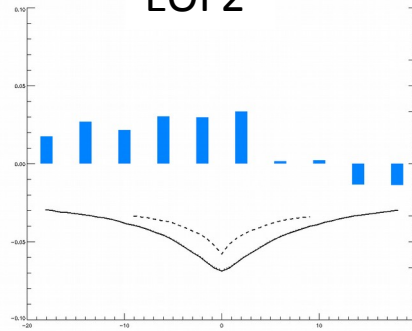
Surface Type 10



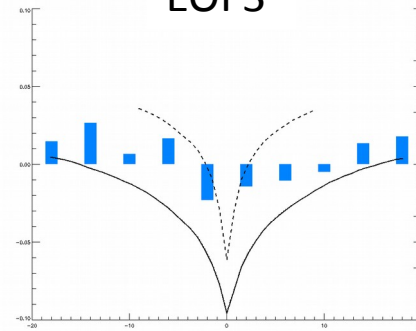
EOF1



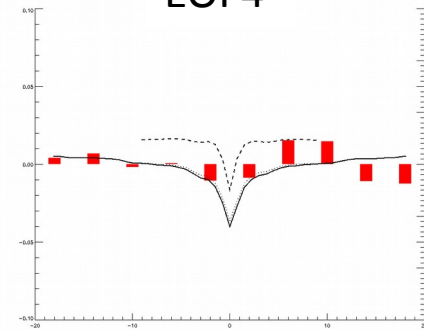
EOF2



EOF3

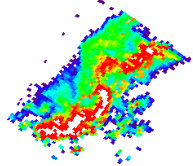


EOF4

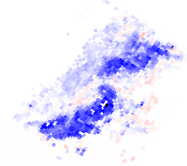


# Algorithm mechanics – generate ensemble and covariances, then filter ensemble

Initial Ensemble  
(Mean and Obs. Error)



Mean Rain



Ku  $\sigma_0$  error

+ Ensemble  
covariances

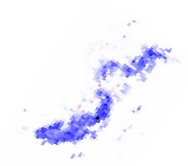


Rain-Ku

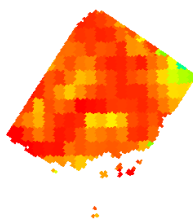


Rain-18H

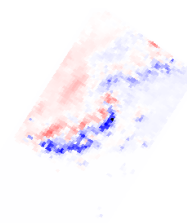
Rain adjustment (mean and  $\sigma$ )



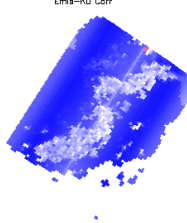
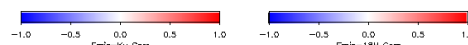
Emis adjustment (mean and  $\sigma$ )



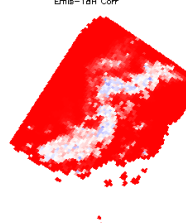
Mean 18H  
Emis



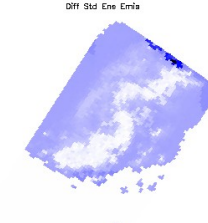
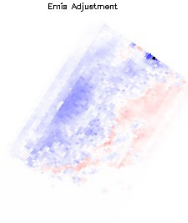
18H error



Emis-Ku



Emis-18H



# Summary

- GMI is well-calibrated; emissivity can be retrieved up to 166 GHz under some conditions
- A 1-year database (Sept 2014-Aug 2015) of co-located DPR backscatter and GMI emissivity has been created
- Snow cover is the most dominant variable affecting backscatter and emissivity at a given location, but soil moisture/surface water and vegetation changes also have an effect
- Plan to produce all-sky emissivity estimates and use database-derived covariances in next version (5) of GPM products
- Research Topics:
  - How to use ancillary data (snow cover/depth/SWE, soil moisture, vegetation data, ...) to optimize EOF selection
  - Move towards physically-based instead of statistical emissivity/backscatter models
  - Understand impact of recent or ongoing precipitation (rain or snow) on surface properties