A Physical Approach for a Simultaneous Retrieval of Sounding, Surface, Hydrometeor and Cryospheric Parameters from SNPP/JPSS ATMS

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1 Overview and Description of the Physical Algorithm

2 Products, Performance and Validation

3 Algorithm Future Enhancements

1 **Overview and Description of the Physical Algorithm**

2 Products, Performance and Validation

3 Algorithm Future Enhancements

MiRS Overview

Microwave Integrated Retrieval System

S-NPP ATMS

Megha-Tropiques
SAPHIR/MADRAS

MetOp-A AMSU/MHS
MetOp-B AMSU/MHS

NOAA-18 AMSU/MHS
NOAA-19 AMSU/MHS

Inversion Process

- Consistent algorithm across all sensors
- Uses CRTM for forward and jacobian operators
- Use forecast, fast regression or climatology as first guess/background

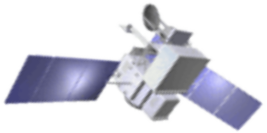
MiRS

Assimilation/Retrieval

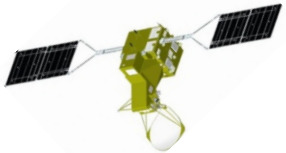
- All parameters retrieved simultaneously
- Valid globally over all surface types
- Valid in all weather conditions
- Retrieved parameters depend on information content from sensor frequencies

DMSP F16 SSMI/S
DMSP F18 SSMI/S
DMSP F17 SSMI/S

TRMM TMI

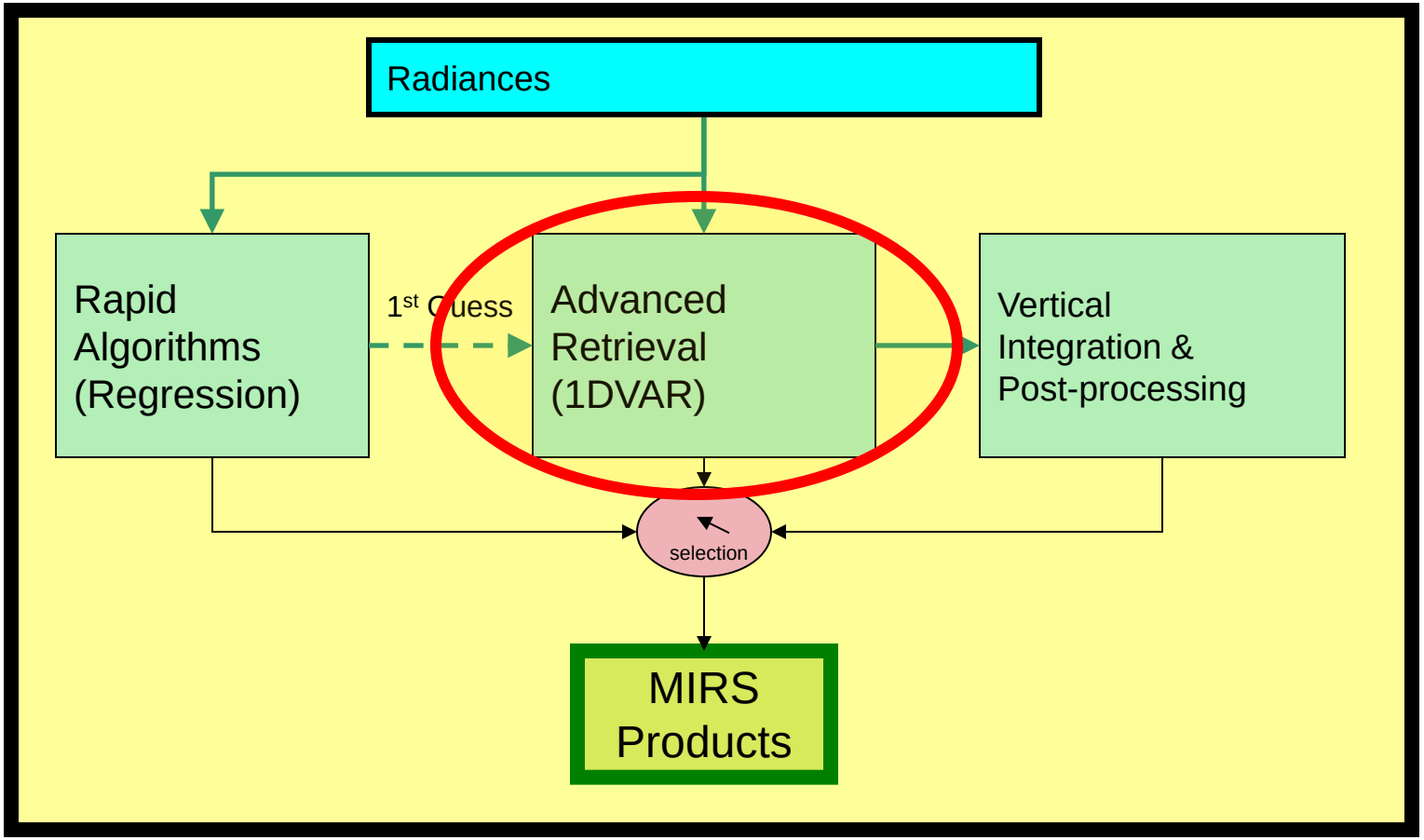


GPM GMI

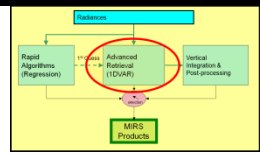


GCOM-W1 AMSR2

MiRS General Overview



1D-Variational Retrieval/Assimilation



Measured Radiances

MiRS Algorithm

T<p>
Q<p>
CLW<p>
RWP<p>
GWP<p>
Tskin
Emiss

Initial State Vector

Simulated Radiances

Comparison: Fit Within Noise Level ?

Yes

Solution Reached

No

Jacobians

Update State Vector

Forward Operator (CRTM)

New State Vector

Measurement & RTM Uncertainty Matrix E

Geophysical Mean Background

Geophysical Covariance Matrix B

Climatology (Retrieval Mode)

Forecast Field (1D-Assimilation Mode)

1 Overview and Description of the Physical Algorithm

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3 Algorithm Future Enhancements

MiRS Products Overview

Official Products

1. **Temperature profile**
2. **Moisture profile**
3. **TPW (global coverage)**
4. **Surface Temperature**
5. **Emissivity Spectrum**
6. **Surface Type**
7. **Snow Water Equivalent (SWE)**
8. **Snow Cover Extent (SCE)**
9. **Sea Ice Concentration (SIC)**
10. **Cloud Liquid Water (CLW)**
11. **Ice Water Path (IWP)**
12. **Rain Water Path (RWP)**
13. **Rainfall rate**

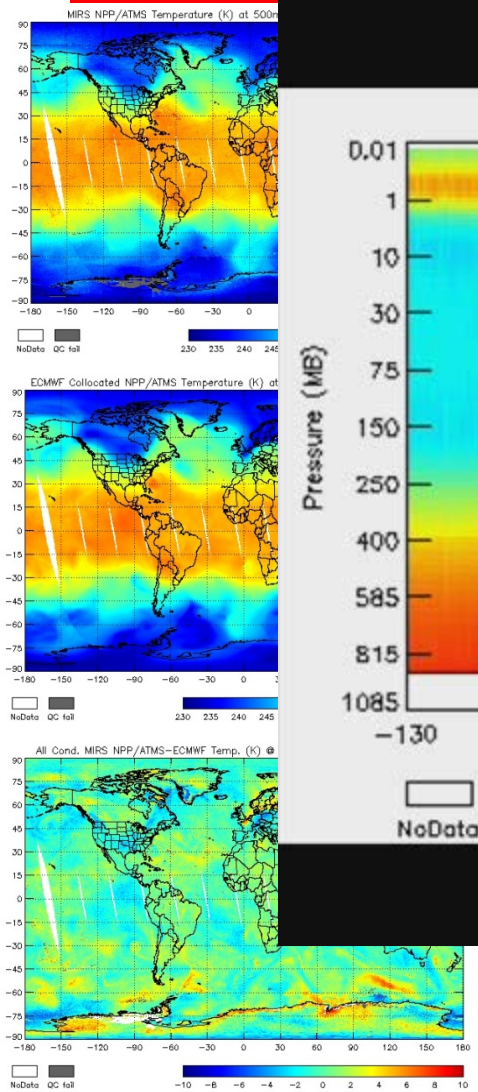
Products being investigated

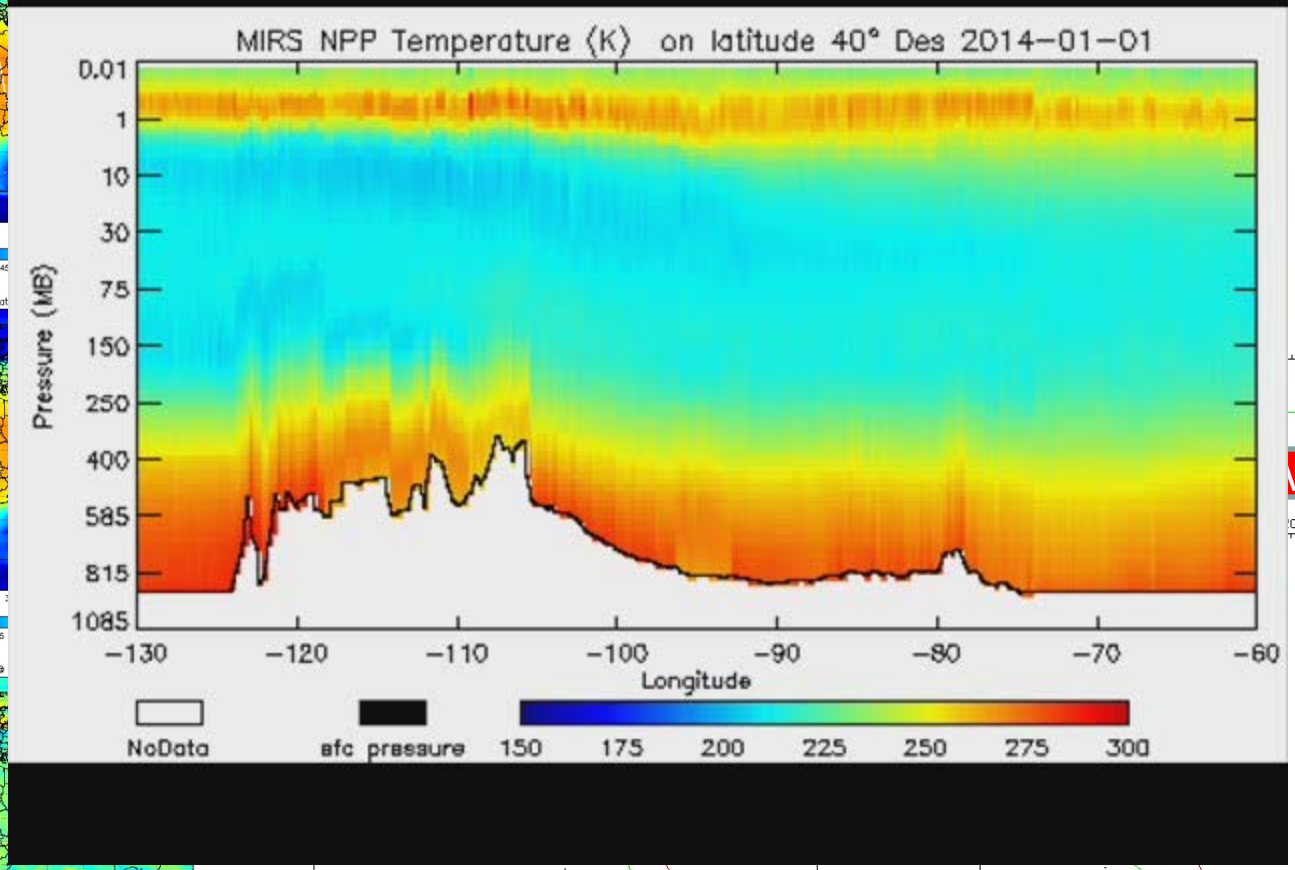
1. Cloud Profile
2. Rain Profile
3. Atmospheric Ice Profile
4. Snow Temperature (skin)
5. Sea Surface Temperature
6. Effective Snow grain size
7. Multi-Year (MY) Type SIC
8. First-Year (FY) Type SIC
9. Wind Speed
10. Soil Wetness Index

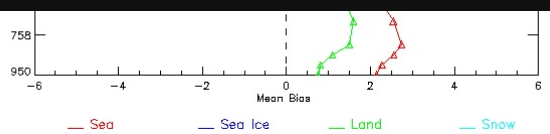
MiRS Temperature Sounding Assessment - NWP

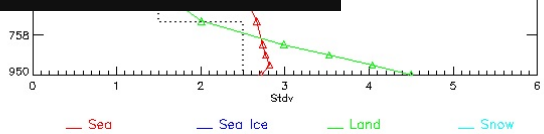
500 hPa Maps

Clear Sky Temperature Bias/Stdv



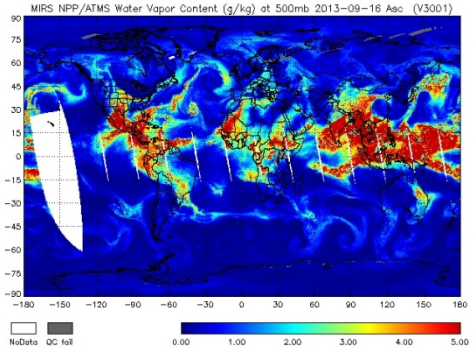


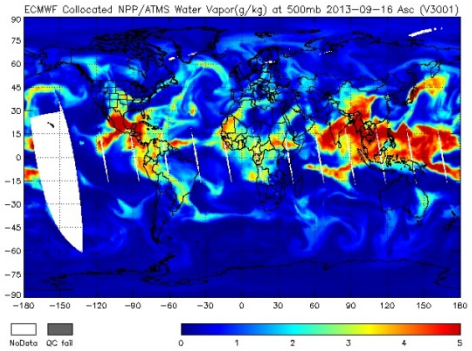


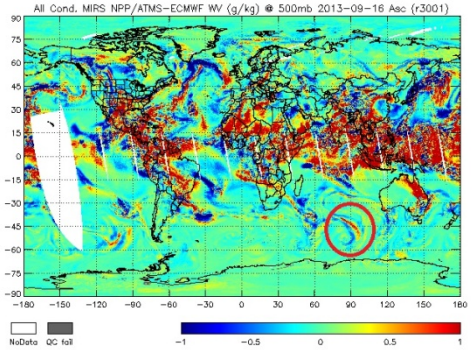


MiRS Water Vapor Sounding Assessment - NWP

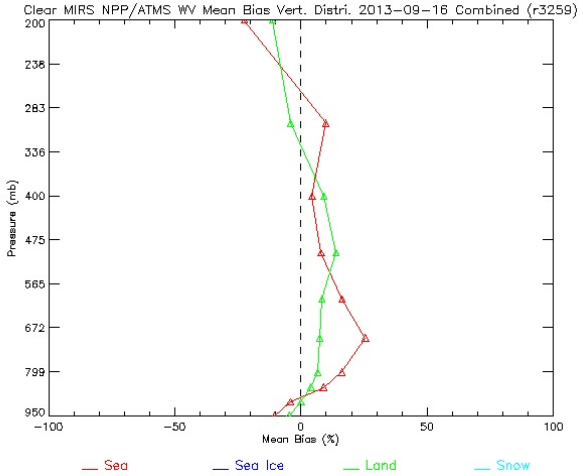
500 hPa Maps

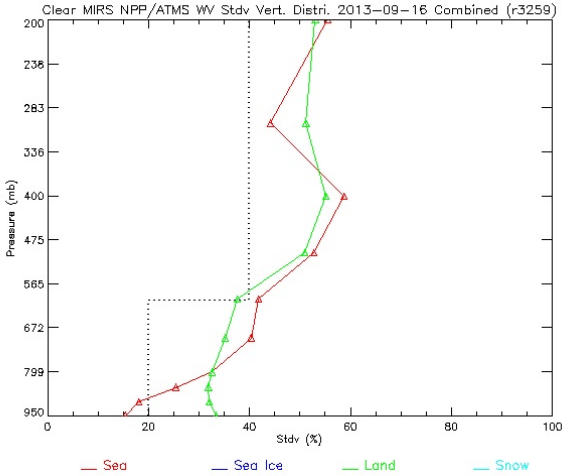




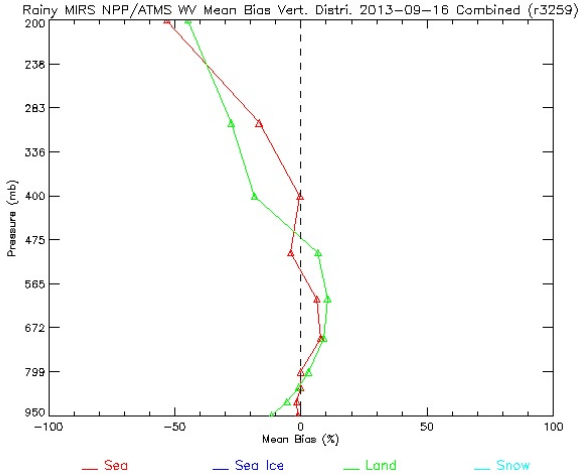


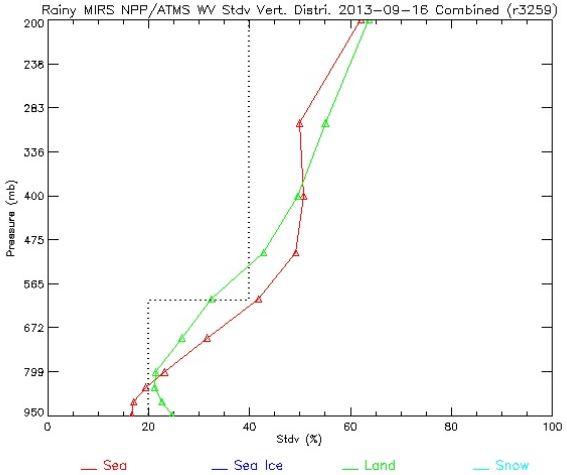
Clear Sky Water Vapor Bias/Stdv





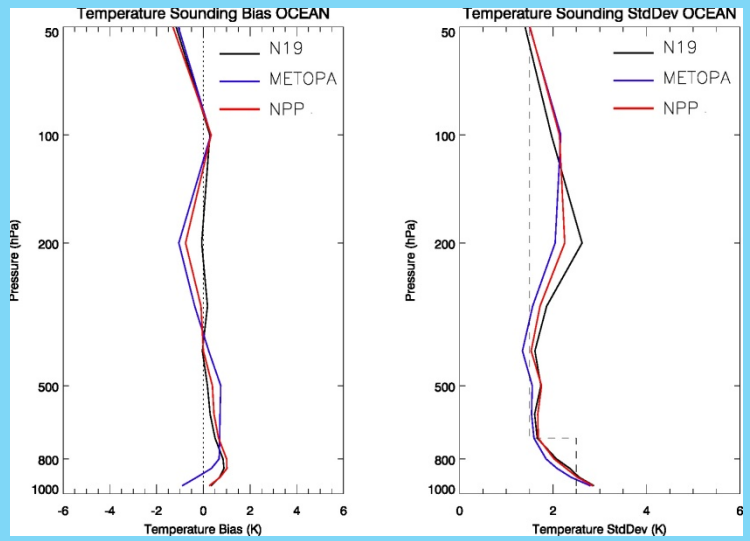
Precipitating Sky Water Vapor Bias/Stdv

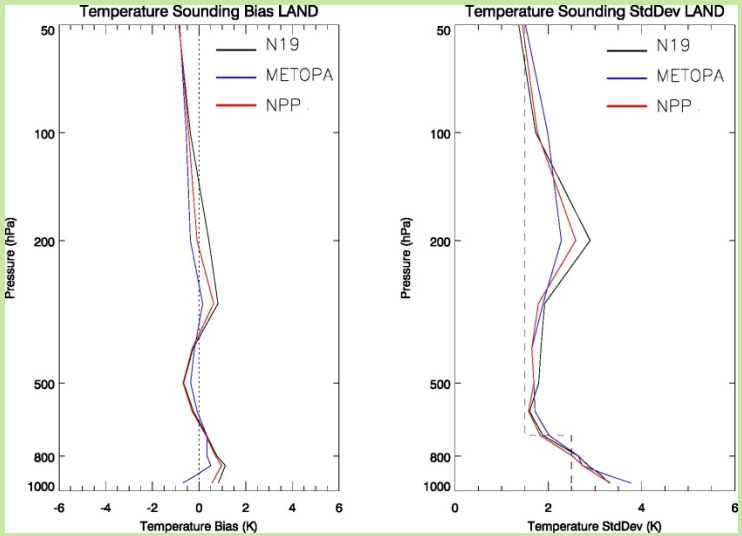


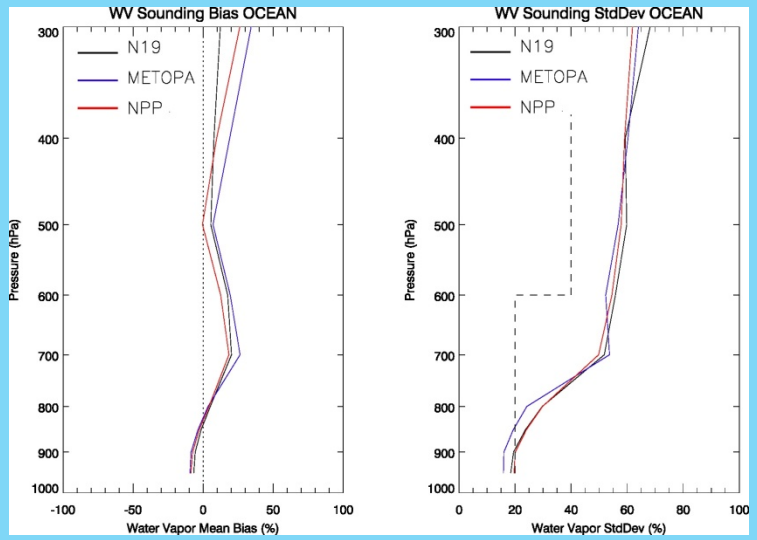


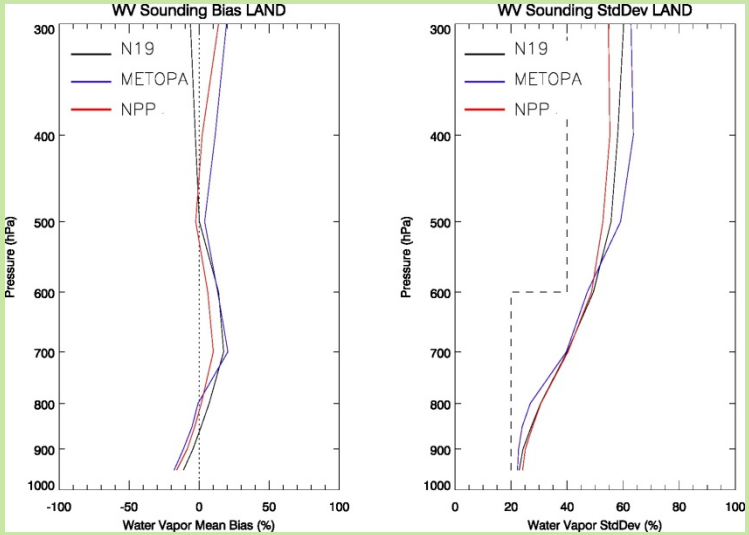
MiRS Sounding Intercomparisons - RAOB

Collocations July – September 2013 (~25,000 pts)









Application: Hurricane Rapid Intensification

MiRS/ATMS T,RH profiles used to compute ***(case of Hurricane Leslie, 2012)*****:**

-Radial-height cross section

- Temperature Anomaly

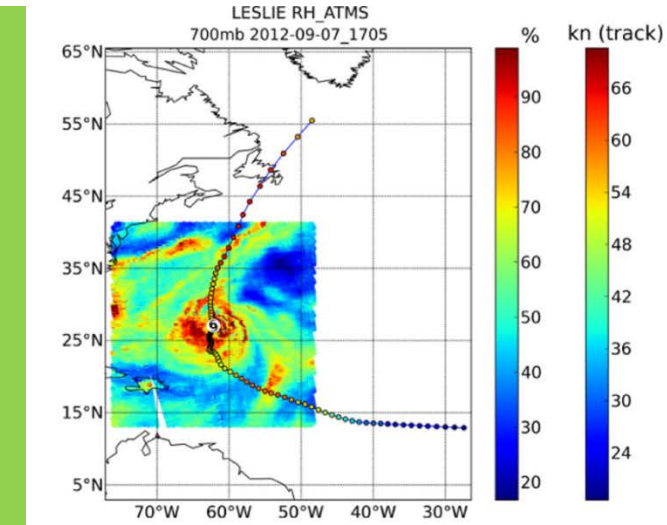
-500-800mb averaged values

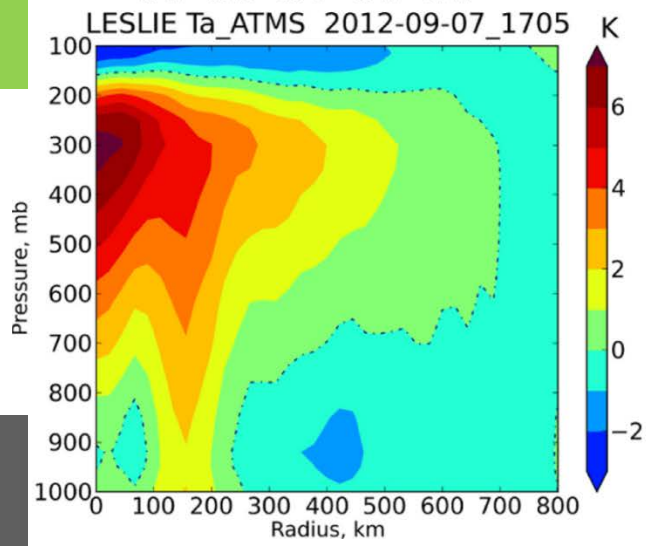
These are fed to :

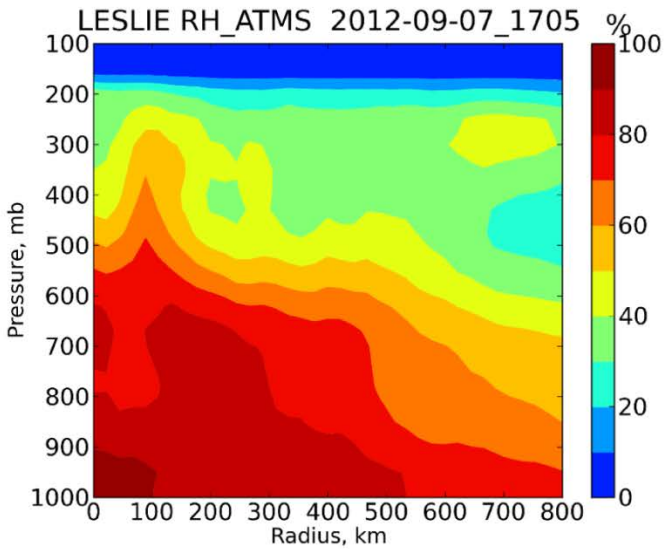
- Maximum Potential Intensity (**MPI**) algor.

MPI is then fed to :

- Rapid Intensification Index (**RII**) algor.



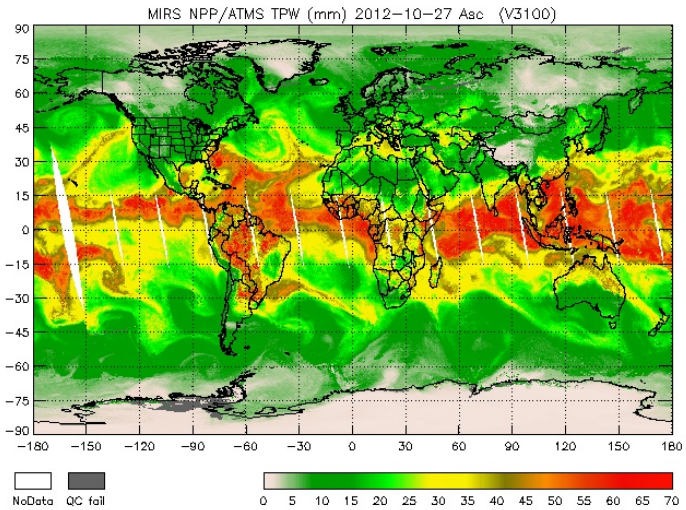


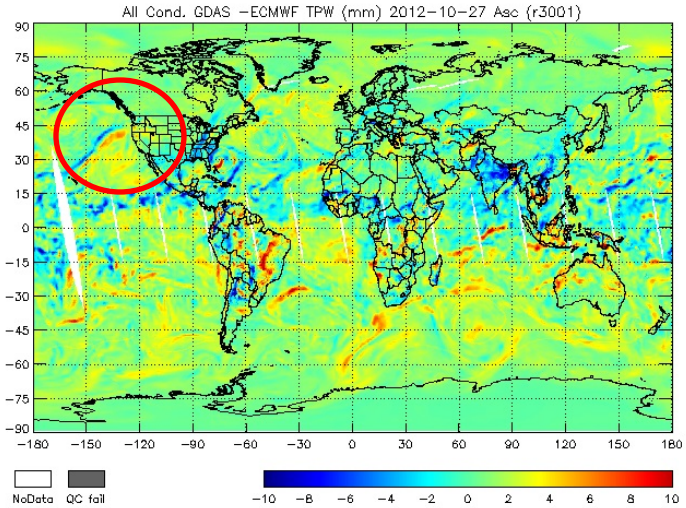


1. Average T, RH between r = 500 to 800 km to get $\overline{T}(p)$, $\overline{RH}(p)$
2. Input $\overline{T}(p)$, $\overline{RH}(p)$ environmental profiles to Emanuel (1988) MPI algorithm
3. Replace empirical MPI with ATMS MPI in RII and models

Slide courtesy of Galina Chirokova and Mark DeMaria

MiRS Total Precipitable Water Assessment – NWP





Summary of TPW Performance

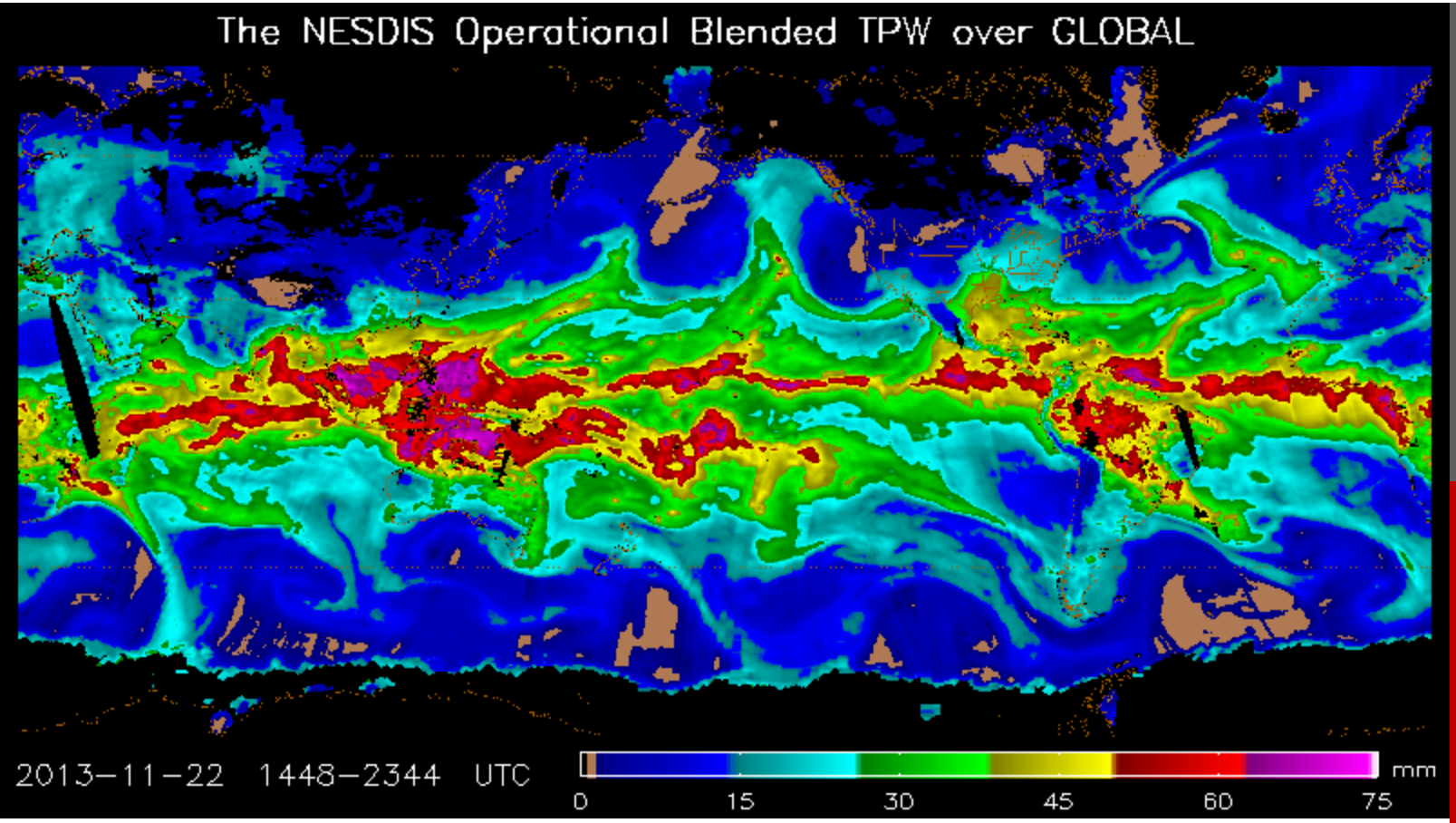
	Bias (mm)	*Stdv (mm)*	*Corr.*	*RMSE (mm)*
Ocean	0.46	2.55	0.98	2.59
Land	0.48	4.47	0.95	4.50
Sea-Ice	0.42	1.28	0.82	1.35
Snow	0.25	0.89	0.93	0.92

Comparison vs. ECMWF

	SNPP bias/stdv (mm)	*NOAA-19 bias/stdv (mm)*	*Metop-A bias/stdv (mm)*
Ocean	7.25/15.40 (%)	8.26/15.69 (%)	8.89/13.7 (%)
Land	2.39/23.65 (%)	5.68/23.76 (%)	2.57/22.11 (%)

Comparison vs. Radiosonde

Application: Blended TPW



The blended TPW is available through AWIPS sectors that NWS forecasters use

MiRS NPP ATMS data to be implemented once it becomes available from NESDIS OSPO

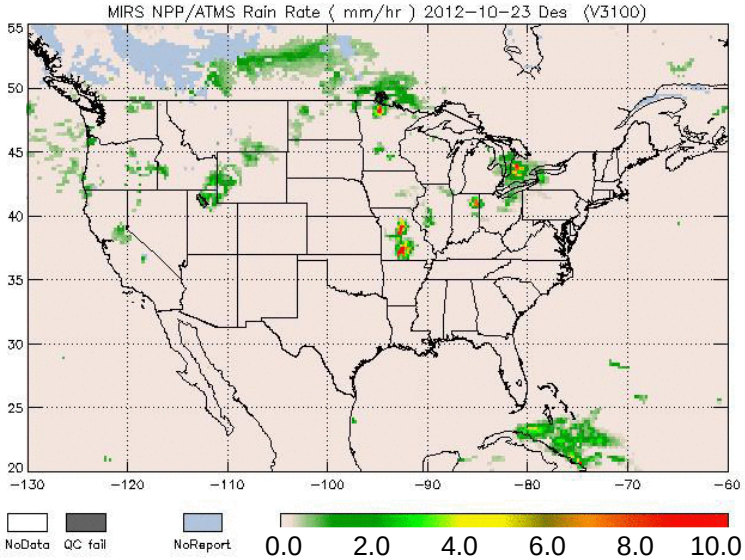
MiRS from NOAA-18, -19, Metop-A are included in the blended TPW. Extension in progress (for more sensors, over sea-ice, snow, etc)

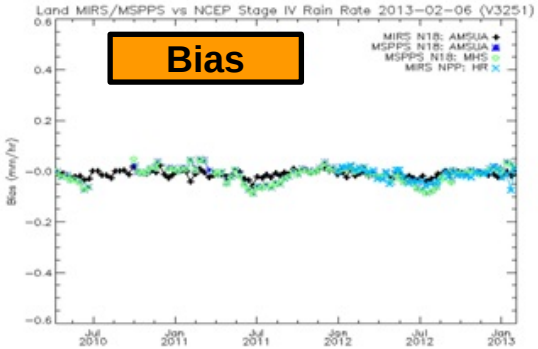
Slide courtesy of the OSPO website: Effort led by CIRA: S. Kidder, J. Forsyth, L. Zhao and R. Ferraro

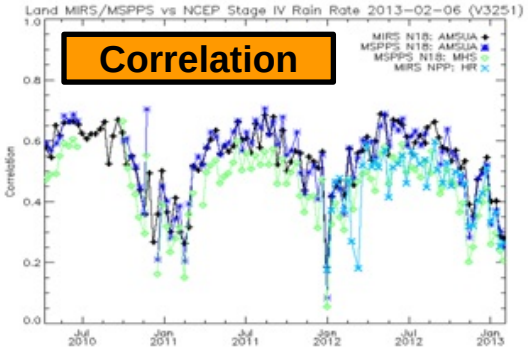
MiRS Rainfall Rate Assessment – NCEP Stage IV Hourly

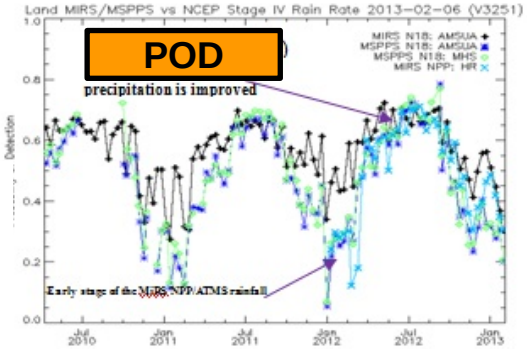
Right: Rainfall rate skill scores between MiRS sensors (including ATMS) between December 2009 and January 2013 using NCEP Stage IV as reference.

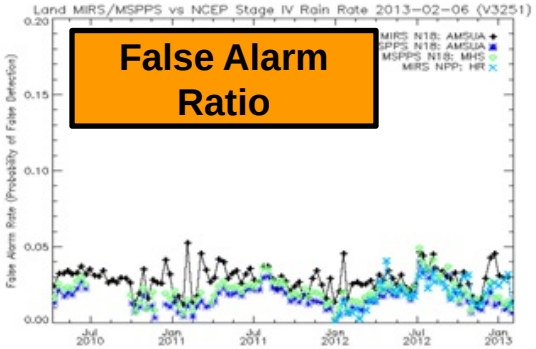
Bottom: Timeseries of MiRS ATMS Rainfall Rate over Hurricane Sandy.

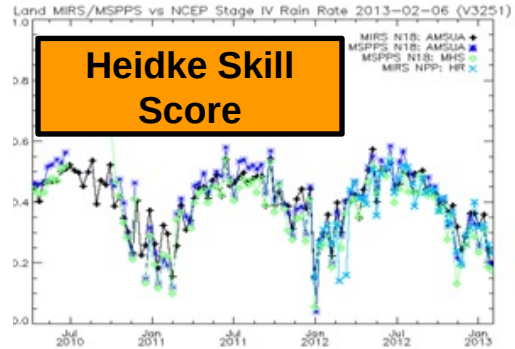


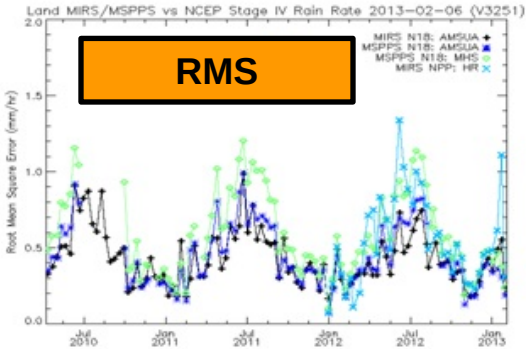








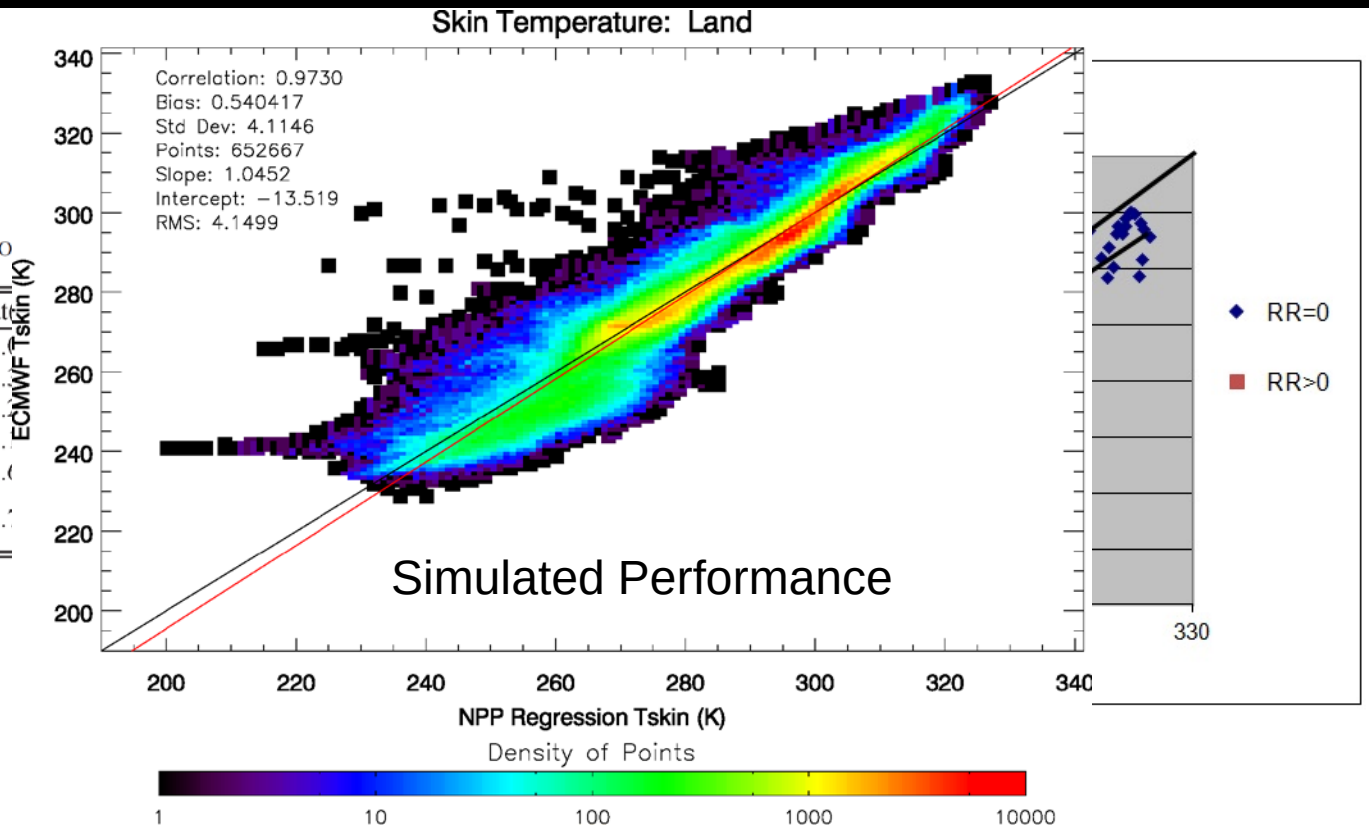




MiRS Land Surface Temperature Assessment – Surfrad

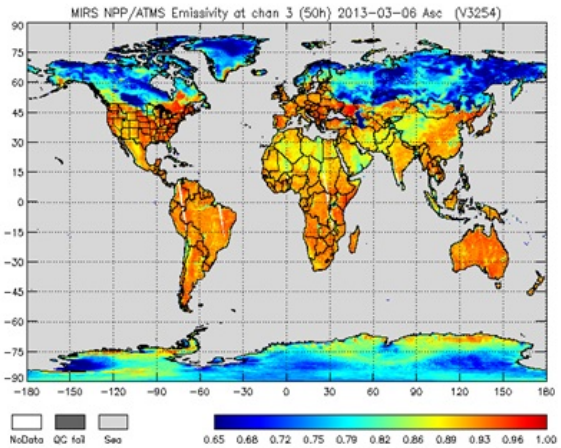
GEOLOCATION AND SURFACE TYPE O

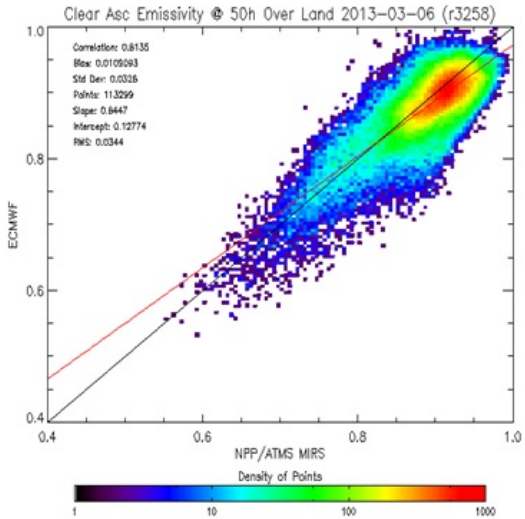
No.	Site Location	Lat
1	Bondville, IL	40.
2	Fort Peck, MT	48.
3	Goodwin Creek, MS	34.
4	Table Mountain, CO	40.
5	Desert Rock, NV	36.
6	Pennsylvania State University, PA	40.

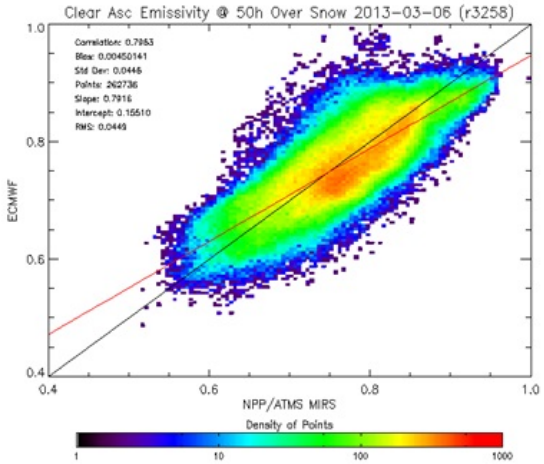


	Correlation Factor	Bias (K)	Standard Deviation (K)
Bondville IL (Cropland)	0.9	-4.7	3.8
Fort Peck, MT (Grass land)	0.6	-1.2	7.0
Goodwin Creek,MS (deciduous forest)	0.8	-4.6	4.7
Table Mountain, CO	0.9	-3.9	5.1
Desert Rock, NV	0.9	-1.9	4.6
Penn State Univ. (mixed forest)	0.8	-4.0	4.0
All sites (all weather-conditions)	0.8	-3.5	5.0

MiRS Surface Emissivity Assessment – Analytic



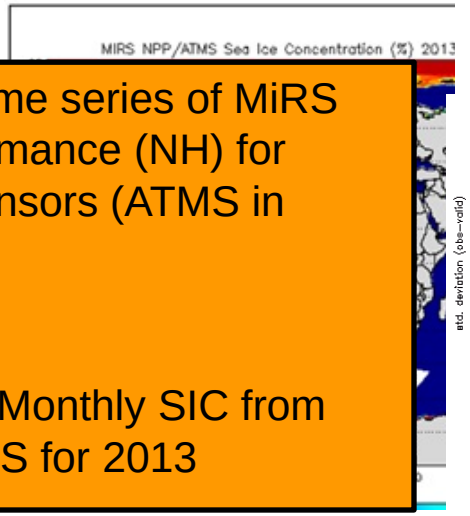




Summary of Emissivity Performance

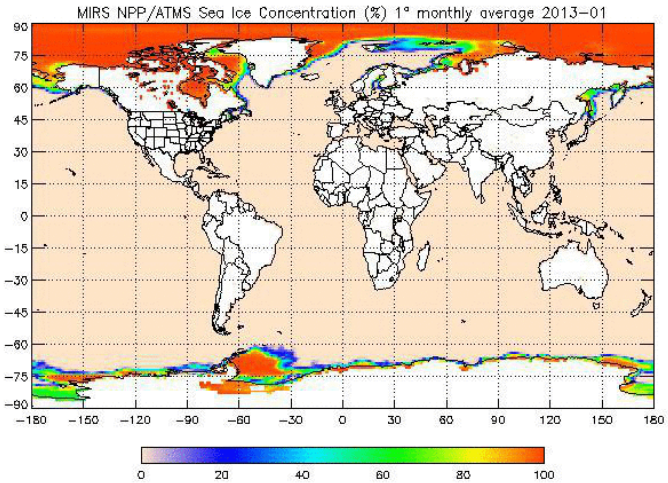
	23.GHz	31GHz	50.3 GHz	88 GHz
Land	Bias:0.01 Stand Dev.:0.02 Correlation:0.91	Bias:0.01 Stand Dev.:0.02 Correlation: 0.91	Bias: 0.01 Stand Dev.: 0.03 Correlation: 0.80	Bias:0.01 Stand Dev.:0.02 Correlation:0.86
Snow	Bias:0.02 Stand Dev.:0.03 Correlation:0.92	Bias:0.02 Stand Dev.:0.03 Correlation: 0.91	Bias: 0.01 Stand Dev.: 0.04 Correlation: 0.81	Bias:0.02 Stand Dev.: 0.03 Correlation: 0.86

MiRS Sea-ice Concentation Assessment – NASA Team

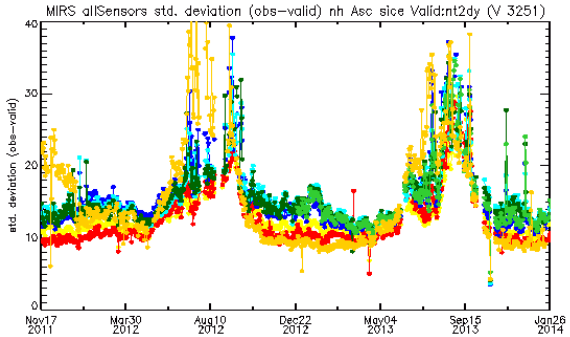


Right – Time series of MiRS SIC performance (NH) for various sensors (ATMS in Orange)

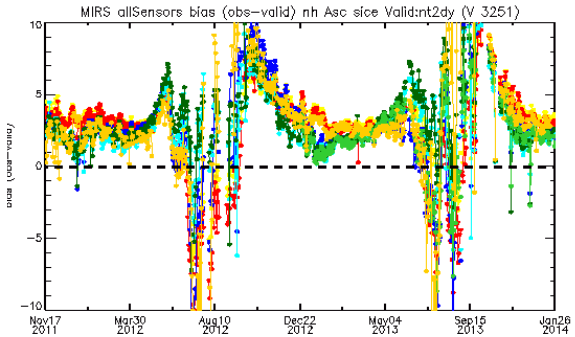
Bottom – Monthly SIC from MiRS ATMS for 2013



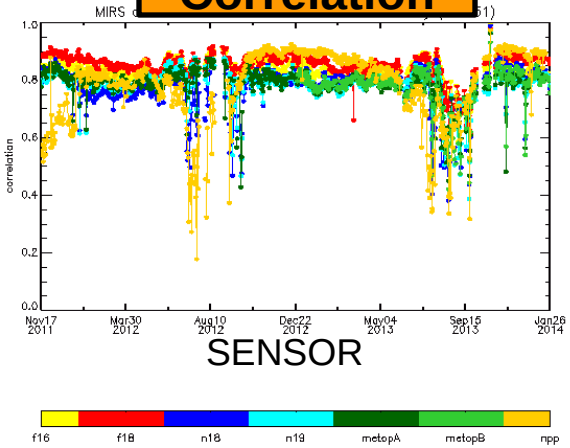
Stdv



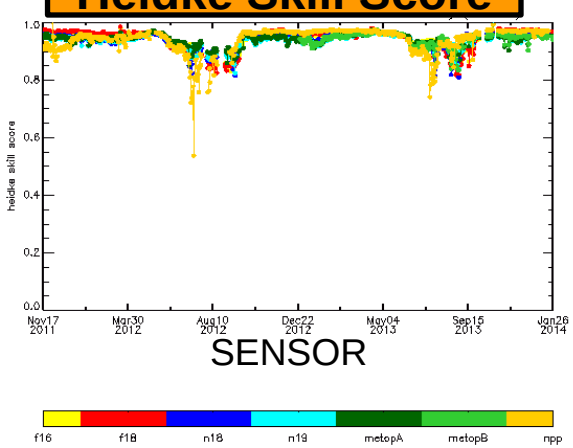
Bias



Correlation



Heidke Skill Score



1 Overview and Description of the Physical Algorithm

2 Products, Performance and Validation

3 **Algorithm Future Enhancements**

Algorithm Future Enhancements

- *Stratification of background and covariances*
  - *Geographic*
  - *Seasonal*
  - *Diurnal*

- *Upgrade to CRTM 2.1.3*
  - *Improvements to hydrometeor retrievals*

- *Extension to other sensors*
  - *AMSR2, GMI (research)*
  - *SAPHIR (operational)*
  - *Infrared (IASI, CrIS)*

- *Implementation within the NCEP Global Forecast System (GFS)*
  - *1DVAR Preprocessor to the GSI for PMW and Infrared radiances*
  - *Focus on increasing assimilation of surface sensitivity and all-sky observations*

http://mirs.nesdis.noaa.gov

BACKUP

Microwave Retrieval
Historical Background & Context

- **Background:**
  - **NOAA/NESDIS/STAR has developed a flexible physical algorithm: the Microwave Integrated Retrieval System (MiRS)**
  - **Cost to extend to new sensors greatly reduced (avoids stove-piping)**
  - **MiRS can be applied to sounders, imagers and combinations**
  - **MiRS uses the CRTM as forward operator (leverage)**
  - **Applicable on all surfaces and in all-weather conditions**
  - **1D-variational methodology (similar to NWP data assimilation)**
  - **Operational for N18,19,Metop-A,B, F16/F18 SSMI/S and SNPP/ATMS**
  - **Products from MiRS depend on Sensor: *Atmospheric Sounding, Hydrological, Cryospheric, Oceanic and Land parameters***
- **On-going:**
  - Extension operations to Megha-Tropiques (SAPHIR)
  - Research extension to TRMM, GPM and GCOM-W AMSR-2.
- **Future:**
  - **Extend to FY-3 MWTS, MWHS and MWRI imager**
  - **Extend applications of MiRS (hydrometeors profiling): Active sensors.**
  - **Extend MiRS to Infrared Remote Sensing**

Mathematical Basis: Cost Function Minimization

- Cost Function to Minimize:

$$J(X) = \left[\frac{1}{2}(X - X_0)^T \times B^{-1} \times (X - X_0)\right] + \left[\right.$$

Jacobians & Radiance Simulation from Forward Operator: CRTM

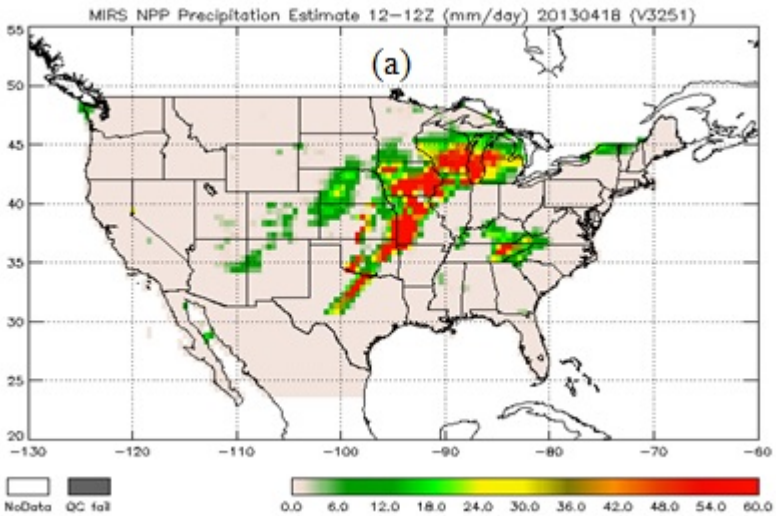
- To find the optimal solution, solve for:

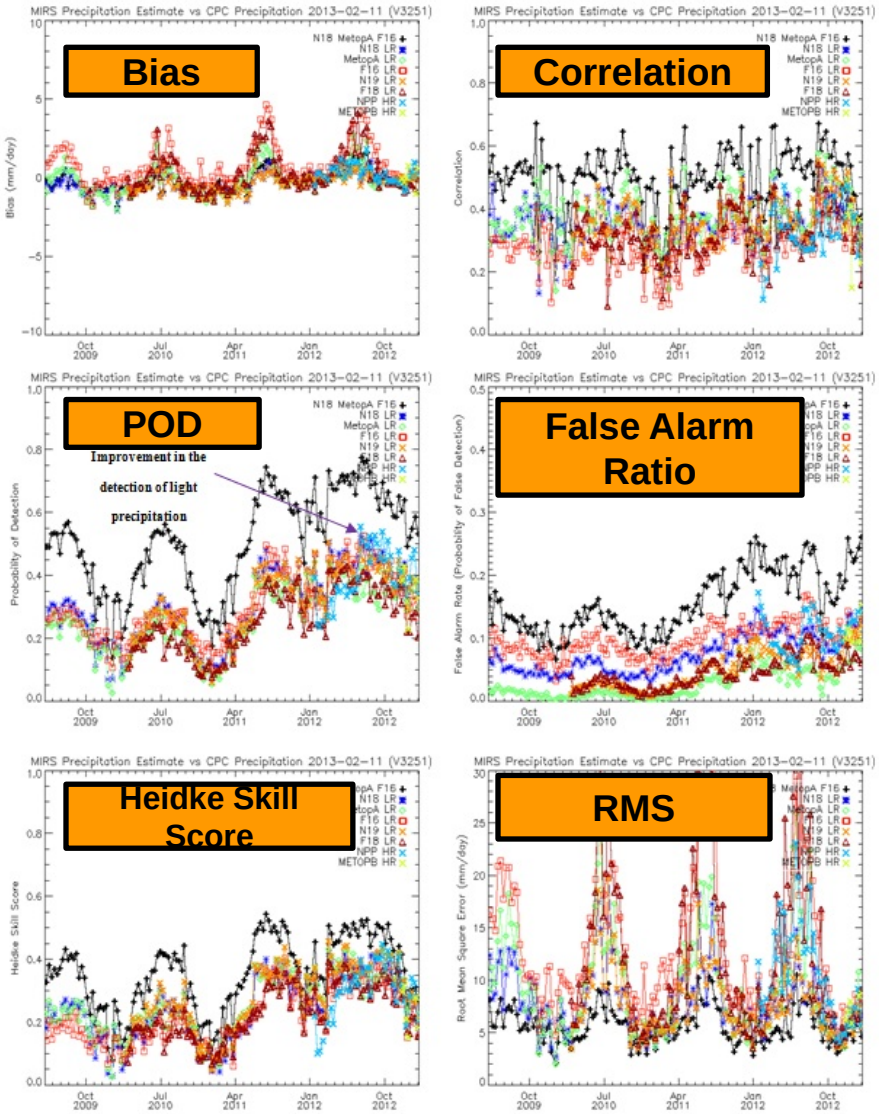
$$\frac{\partial J(X)}{\partial X} = J'(X) = 0$$

- Assuming Linearity $y(x) = y(x_0) + K[x - x_0]$
- This leads to iterative solution:

$$\hat{X}_{n+1} = \left\{ B K_n^T \left(K_n B K_n^T + E \right)^{-1} \right\} \left[\left(Y^m - Y(X_n) \right) + K_n \hat{X}_n \right]$$

MiRS Rainfall Rate Assessment – CPC Daily





Daily precipitation skill scores between MiRS sensors (including ATMS) between July 2009 and December 2012 using CPC as reference (right)

Note: All Parameters are Retrieved Simultaneously in MiRS

If X is the set of parameters that impact the radiances Ym, and F the Fwd Operator

If F(X) Does not Fit Y^m within Noise

X is not the solution

Necessary Condition (but not sufficient)

F(X) Fits Y^m within Noise levels

X is a solution

X is the solution

All parameters are retrieved simultaneously to fit all radiances together

Suggests it is not recommended to use independent algorithms for different parameters, since they don't guarantee the fit to the radiances

All-Weather and All-Surfaces

Sounding Retrieval:

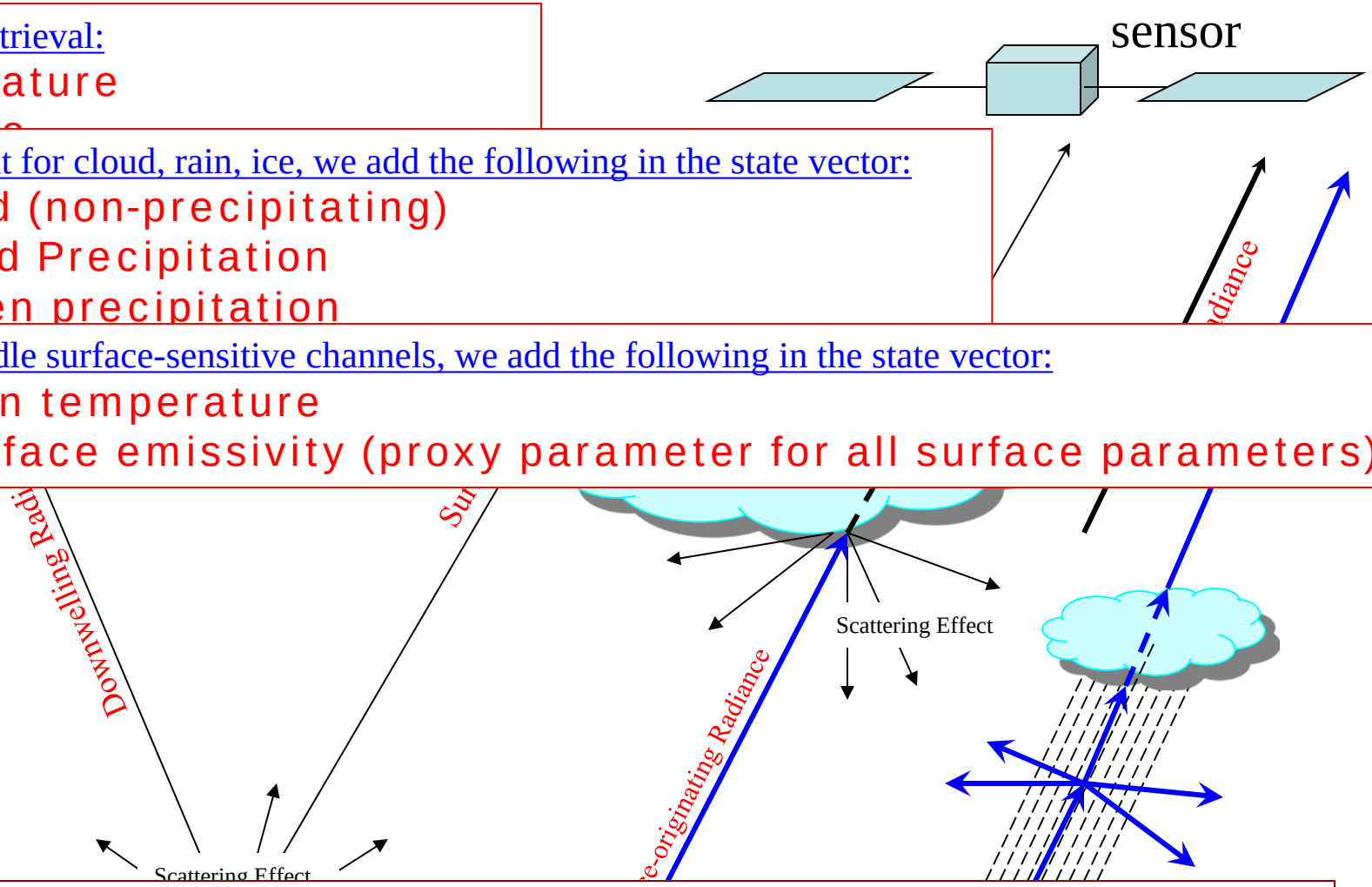
- Temperature
- Moisture

To account for cloud, rain, ice, we add the following in the state vector:

- Cloud (non-precipitating)
- Liquid Precipitation
- Frozen precipitation

To handle surface-sensitive channels, we add the following in the state vector:

- Skin temperature
- Surface emissivity (proxy parameter for all surface parameters)



- **Instead of guessing and then removing the impact of cloud and rain and ice on TBs (very hard), MiRS approach is to account for cloud, rain and ice within its state vector.**
- **It is highly non-linear way of using cloud/rain/ice-impacted radiances.**