An Enterprise Environmental Data Fusion and Assimilation System for Nowcasting Applications

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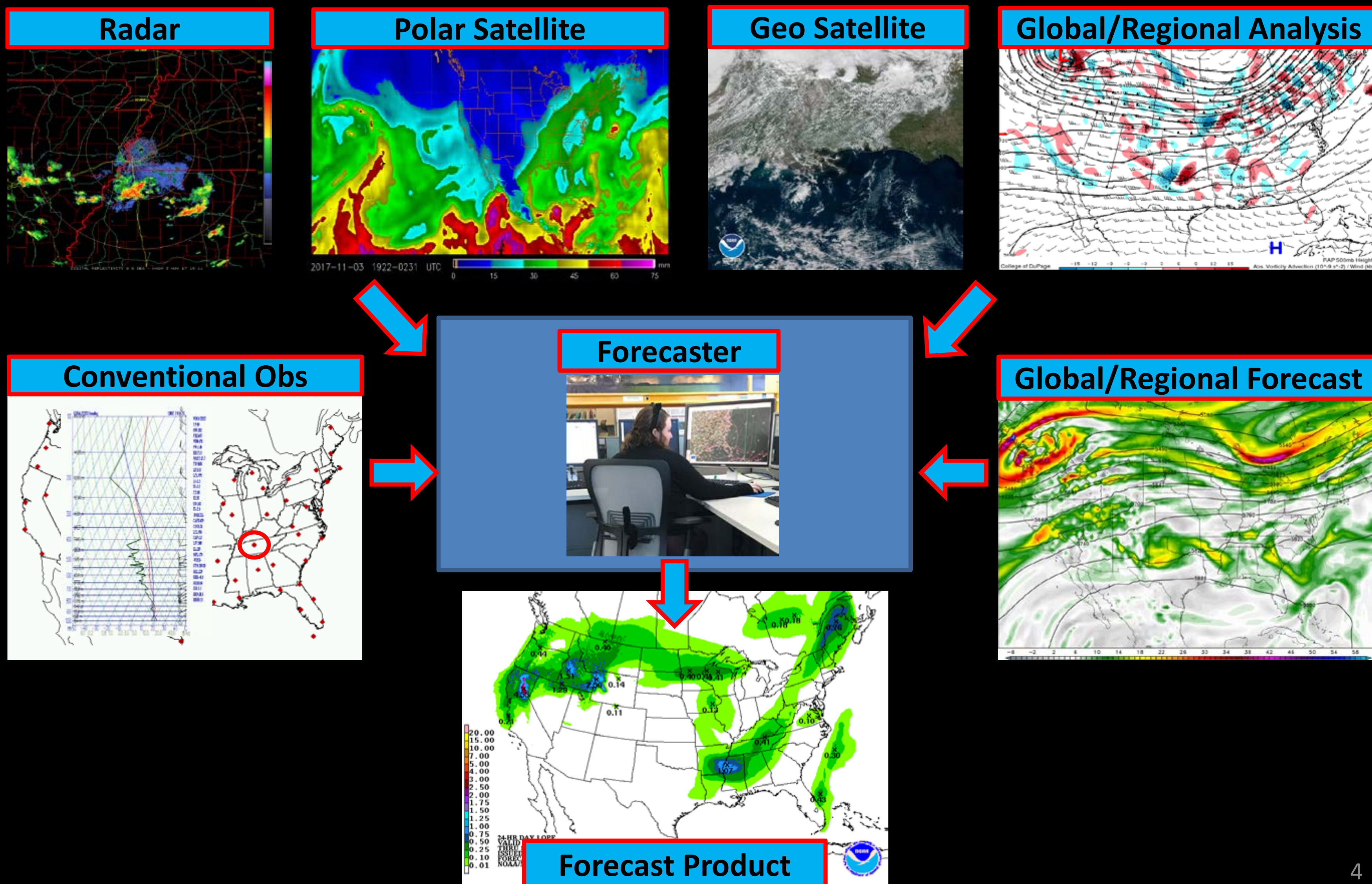
agenda

- environmental data fusion objectives and concept
- environmental data fusion preprocessing impact
- environmental data fusion analysis outputs
- future considerations

- ➢ **environmental data fusion objectives and concept**
- **environmental data fusion preprocessing impact**
- **environmental data fusion analysis outputs**
- **future considerations**

motivation for environmental data fusion

How do we streamline informing Situational Awareness for the forecast process?



motivation for environmental data fusion

Data Fusion synergizes Remote Sensing and Data Assimilation Techniques

Optimal | Moderate | Poor

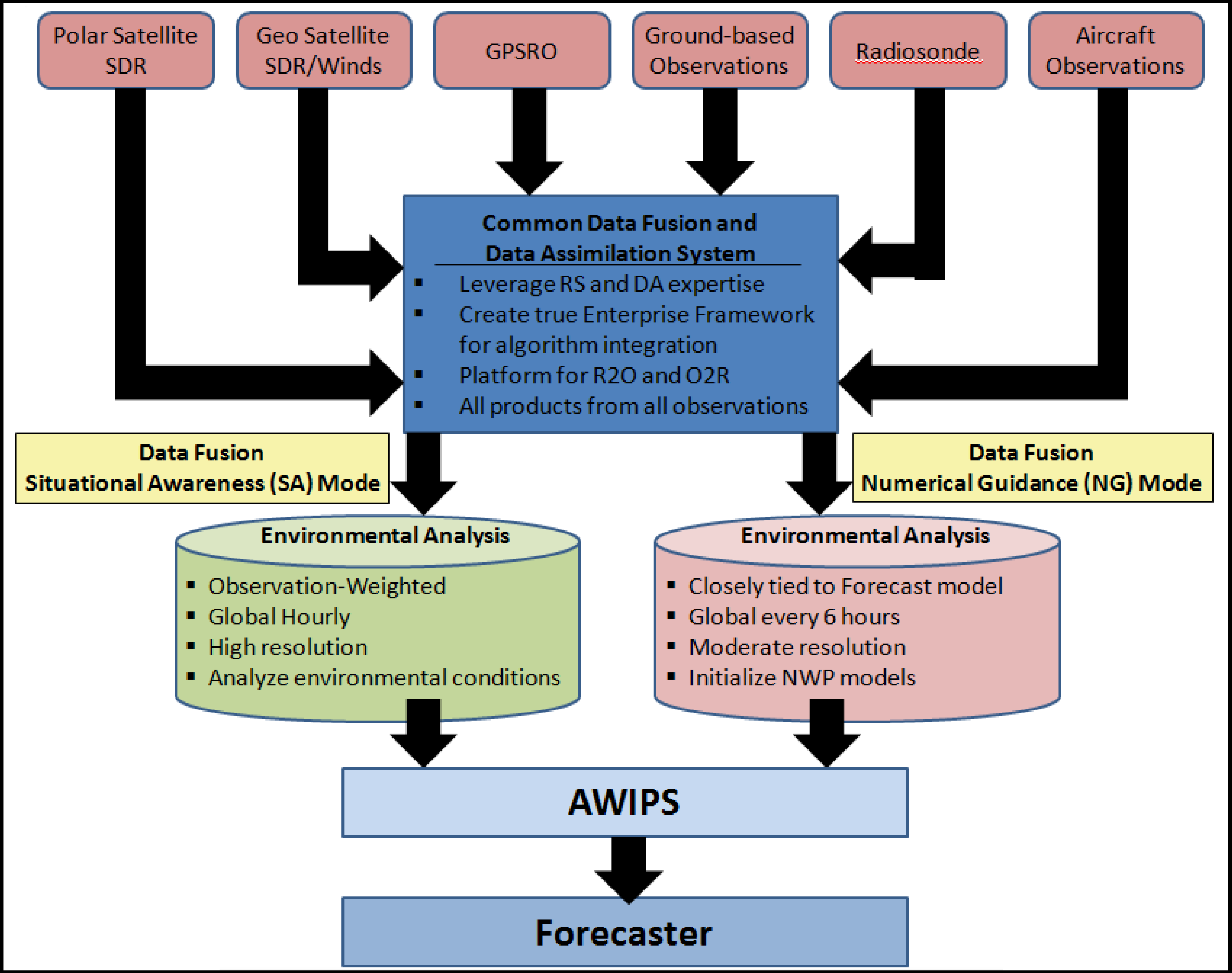
Algorithm/Product Attributes	Remote Sensing (sensor by sensor)	Traditional Blending or Merging (or morphing)	Data Assimilation	Data Fusion
User friendliness (data access) of multitude parameters		Only for single parameters		
Reliability (accuracy, spatial/vertical placement)			Good for single parameters	
Time Frequency			Usually every 6 hours, sometimes higher frequency	
Spatial & Vertical Resolutions	Depends on sensor			
Diversity of Geophysical Products	Depends on sensor		Only Parameters important for forecast	
Collocation of Observing Systems		Only for set of sensors		
Combination of Conventional Data and Satellites				
Accounting for Observation Sources Errors	Depends on sensor and algorithm	Depends on blending technique		
Application to Prediction				In theory yes, but not if observations and forecast inconsistent
Application to Situational Awareness				

environmental data fusion objectives

- **Overarching Objective: Provide a complete 4D cube environmental analysis**
  - Enhance/simplify forecaster "Situational Awareness" experience
  - Global analysis with high spatial resolution (horizontal and vertical)
  - Hourly or sub-hourly updates
  - Fusion of all available satellite and conventional observations
  - Traditional remote sensing products
  - Unify products with model fields (physically balanced)
  - Straight-forward quality control metrics
- **How is this achieved?**
  - Develop framework to integrate remote sensing algorithms with data assimilation
    - Work with partners in STAR to integrate remote sensing algorithms
    - Work with partners in EMC to maintain data assimilation system
  - Enhance scientific aspects to improve satellite data assimilation and fusion
  - Work with operational (forecast) partners for evaluation and feedback

data fusion concept

Build a Data Fusion system which combines remote sensing and data assimilation for analyses tailored for "Situational Awareness" (Observation-weighted) or "Numerical Guidance" (Background-weighted)



data fusion "SA" mode

Concept of Data Fusion goes beyond traditional data assimilation

- Provides higher spatial resolutic analysis (13-25 km)
- Provides analyses at hourly or su hourly intervals
- Reduces thinning of satellite dat (more observations used)
- Observation-weighted analysis (weight to background)
  … *Needed to remove displacem in moisture fields*
- Leverages remote sensing algorithms to improve analysis
  … *Use to specify unanalyzed variables which help constrain DA solution*
  … *Increase number of observations assimilated (passing QC)*

Plays a Crucial Role for data fusion:

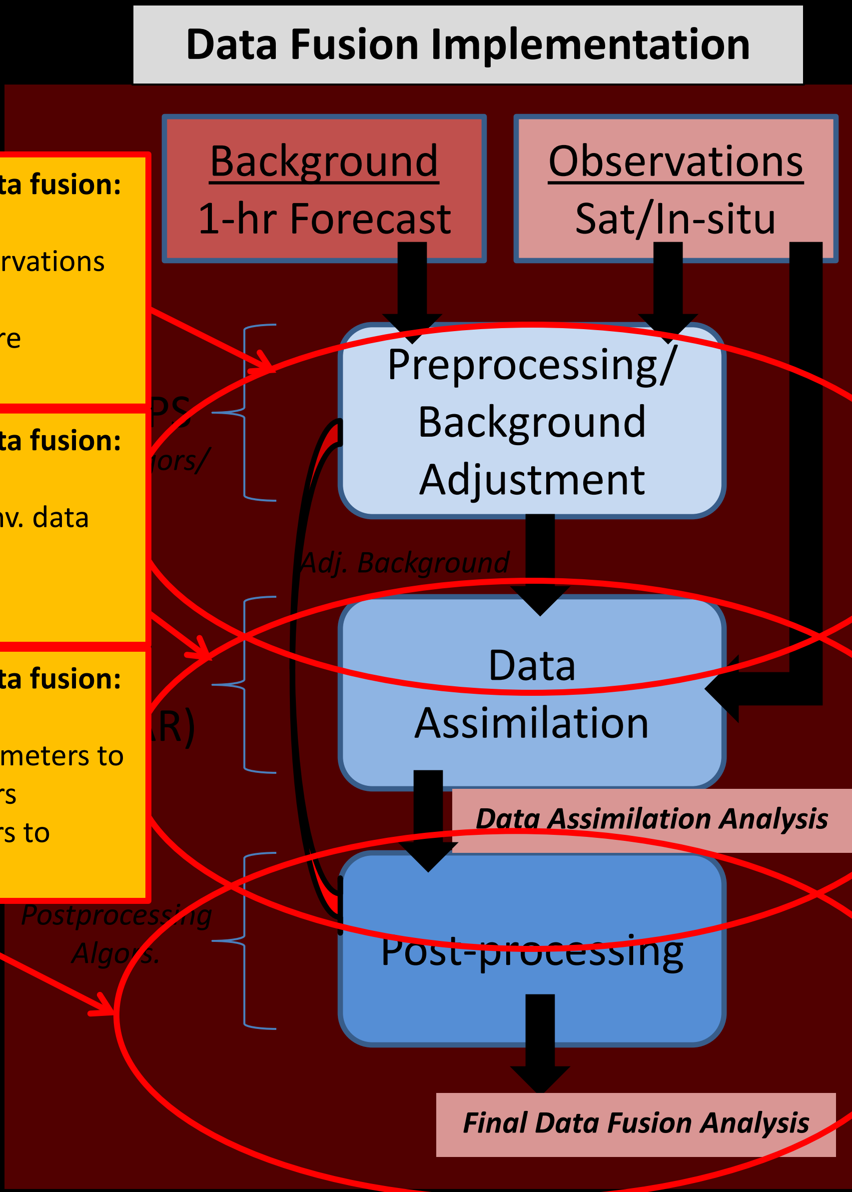
(1) fit background to Observations and
(2) extend analyses to more parameters

Plays a Crucial Role for data fusion:

(1) Fuses satellite with conv. data
(2) Smoothes the field
(3) Balances parameters

Plays a Crucial Role for data fusion:

(1) Links the inverted parameters to those expected by users
(2) Example: Hydrometeors to Rainfall Rate



what does data fusion analysis contain?

Data Fusion includes integration of observations from multiple observing systems at each stage of processing for an observation-weighted analysis

Satellite & Conventional Data

Traditional Satellite Products	T	Q	SST/ LST	TPW	Cloud Amt	Cloud Top	QPE	Sfc Emiss	SIC/ SWE	Wind	Trace Gas	AOD	Soil Moisture	Lightning
POES	Optimal	Optimal	Optimal	Optimal	Optimal	Inadequate Signal	Optimal	Optimal	Optimal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal
Metop	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Inadequate Signal	Optimal	Optimal	Inadequate Signal	Inadequate Signal
SNPP	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Inadequate Signal	Inadequate Signal
DMSP	Optimal	Optimal	Optimal	Optimal	Optimal	Inadequate Signal	Optimal	Optimal	Optimal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal
Aqua	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Optimal	Inadequate Signal	Inadequate Signal
Megha-T	Inadequate Signal	Optimal	Inadequate Signal	Marginal	Marginal	Inadequate Signal	Optimal	Marginal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal
GPM	Inadequate Signal	Marginal	Optimal	Optimal	Optimal	Inadequate Signal	Optimal	Optimal	Optimal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal
GCOM-W1	Inadequate Signal	Marginal	Optimal	Optimal	Optimal	Inadequate Signal	Optimal	Optimal	Optimal	Optimal	Inadequate Signal	Inadequate Signal	Optimal	Inadequate Signal
GOES-15	Marginal	Marginal	Optimal	Optimal	Inadequate Signal	Optimal	Optimal	Optimal	Marginal	Optimal	Marginal	Inadequate Signal	Inadequate Signal	Inadequate Signal
Meteosat	Inadequate Signal	Marginal	Optimal	Optimal	Inadequate Signal	Optimal	Optimal	Optimal	Marginal	Optimal	Marginal	Inadequate Signal	Inadequate Signal	Inadequate Signal
Himawari-8	Inadequate Signal	Marginal	Optimal	Optimal	Inadequate Signal	Optimal	Optimal	Optimal	Marginal	Optimal	Marginal	Optimal	Inadequate Signal	Inadequate Signal
GOES-R	Inadequate Signal	Marginal	Optimal	Optimal	Inadequate Signal	Optimal	Optimal	Optimal	Marginal	Optimal	Marginal	Optimal	Inadequate Signal	Optimal
GPSRO	Optimal	Optimal	Inadequate Signal	Optimal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal
Radiosonde	Optimal	Optimal	Optimal	Optimal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Optimal	Inadequate Signal	Inadequate Signal	Inadequate Signal	Inadequate Signal

Added-Value Products (Derived)

Quality Control Products

Added Value Products		Quality Control Products
CAPE	Vertical Velocity (ω)	Observation Coverage
CIN	Divergence (D)	Observation Type
Lifted Index (LI)	Geopotential Height (Z)	Convergence (χ^2)
Surface Pressure	Freezing Level	Data Age
Stream Function (Ψ)	Parameter Trends	Summary QC Flags
Vorticity (ζ)		

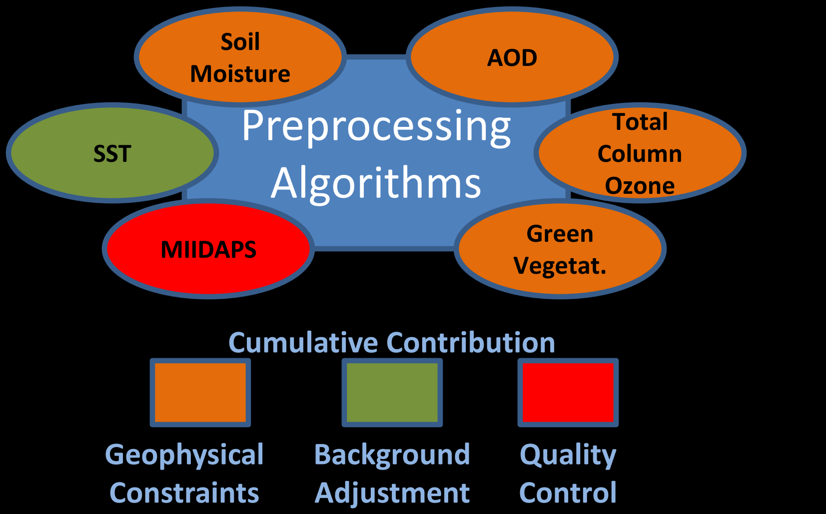
Satellite Capability	Optimal	Marginal	Inadequate Signal

- environmental data fusion objectives and concept
- **environmental data fusion preprocessing impact**
- environmental data fusion analysis outputs
- future considerations

integration of STAR algorithms

Preprocessing framework allows the integration of algorithms and products to enhance data assimilation by leveraging remote sensing for:

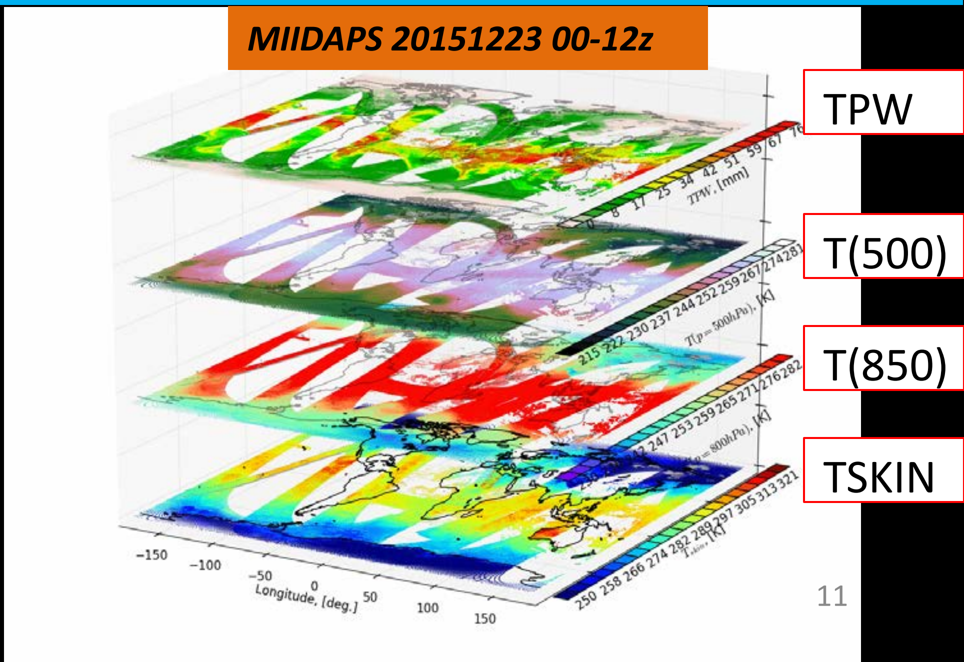
- Geophysical constraints
- Background adjustment
- Radiance Quality Control



The Multi-Instrument Inversion and Data Assimilation Preprocessing System (MIIDAPS)

MIIDAPS is based on the Microwave Integrated Retrieval System (MiRS).
Data Fusion effort focused on:

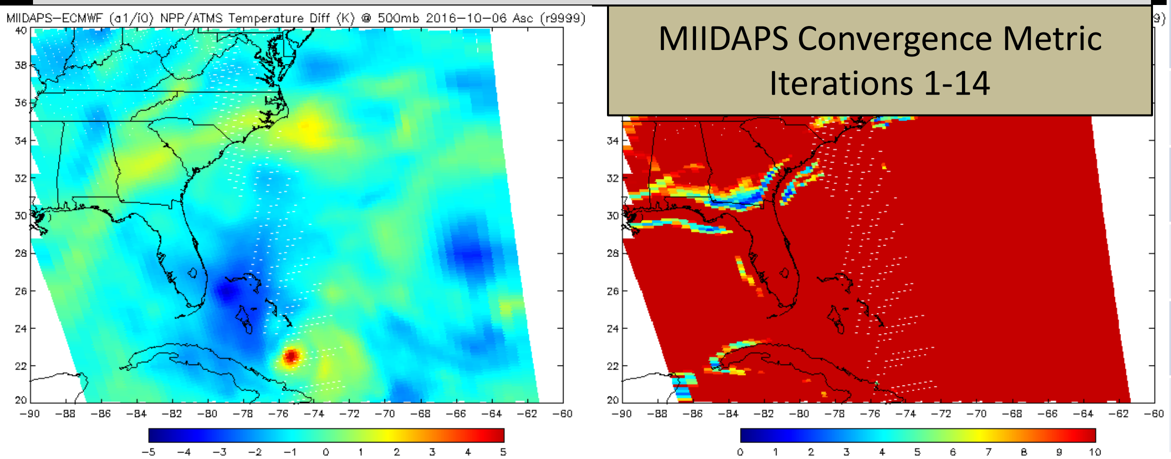
- Apply to multiple MW and IR sensors
- Use T, Q to perform background adjustment
- Use of emissivity, tskin and cloud as constraints in 3DVAR assimilation
- Use of algorithm outputs for 3DVAR assimilation QC (e.g. Chisq)



background adjustment

Remote sensing algorithms (e.g. MIIDAPS) used to remove displacement errors between background field and observations prior to data assimilation

MIIDAPS example: 1DVAR algorithm applied to SNPP-ATMS observations over Hurricane Matthew October 6, 2016 18Z



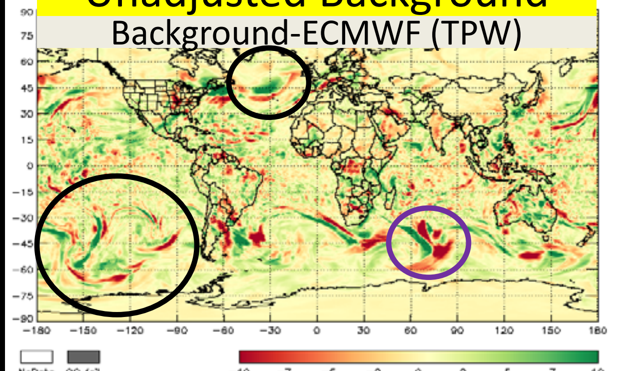
MIIDAPS Convergence Metric
Iterations 1-14

Used in Background Adjustment

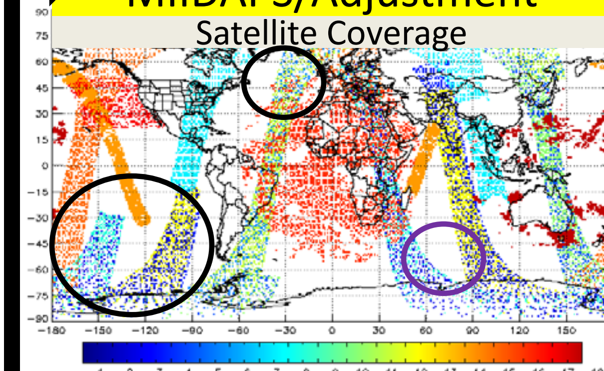
	T	Q	TPW	iCLW
POES	Yes	Yes	Yes	Yes
Metop	Yes	Yes	Yes	Yes
SNPP	Yes	Yes	Yes	Yes
DMSP	Yes	Yes	Yes	Yes
GPM			Yes	Yes
GOES-15			Yes	
Meteosat			Yes	
Himawari			Yes	

Background Adjustment Example, All Satellite Data: December 23, 2015 00Z

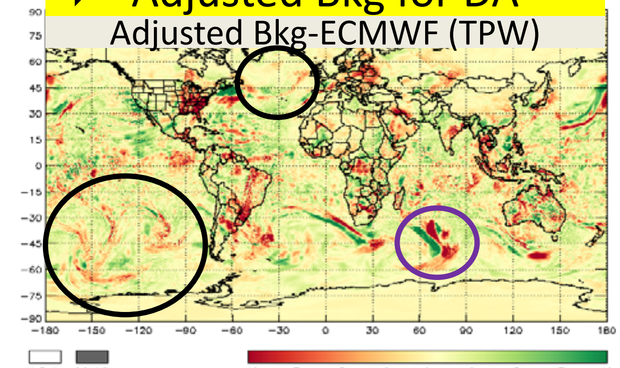
Unadjusted Background



MIIDAPS/Adjustment



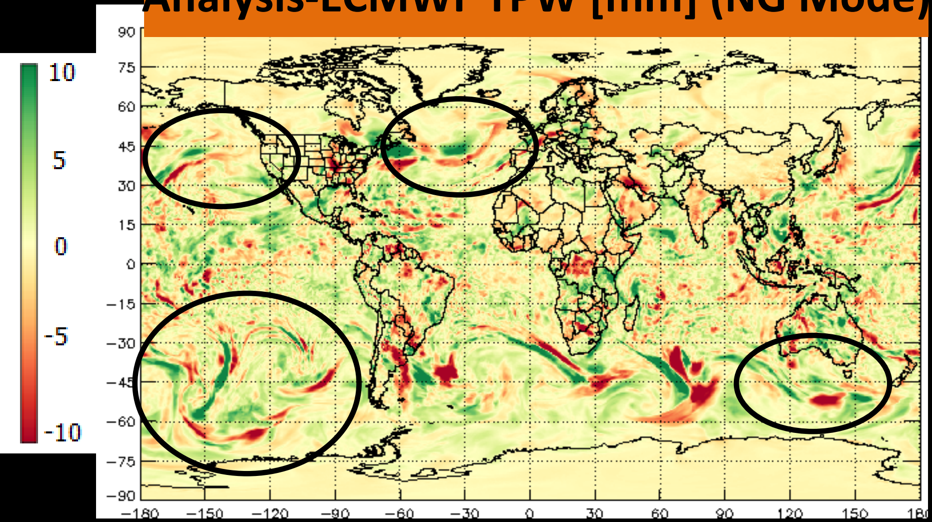
Adjusted Bkg for DA



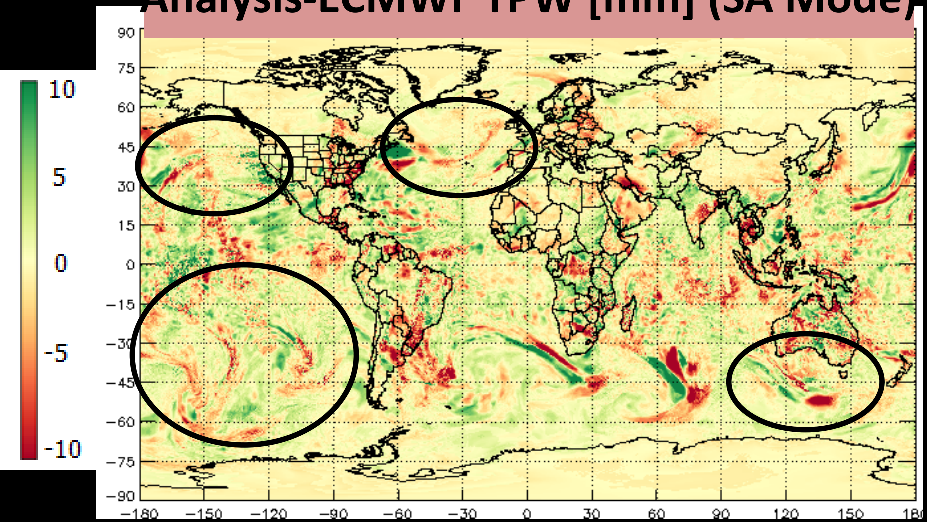
data assimilation analysis

Example of Data Fusion Analyses for 2015-12-23 12Z Cycle

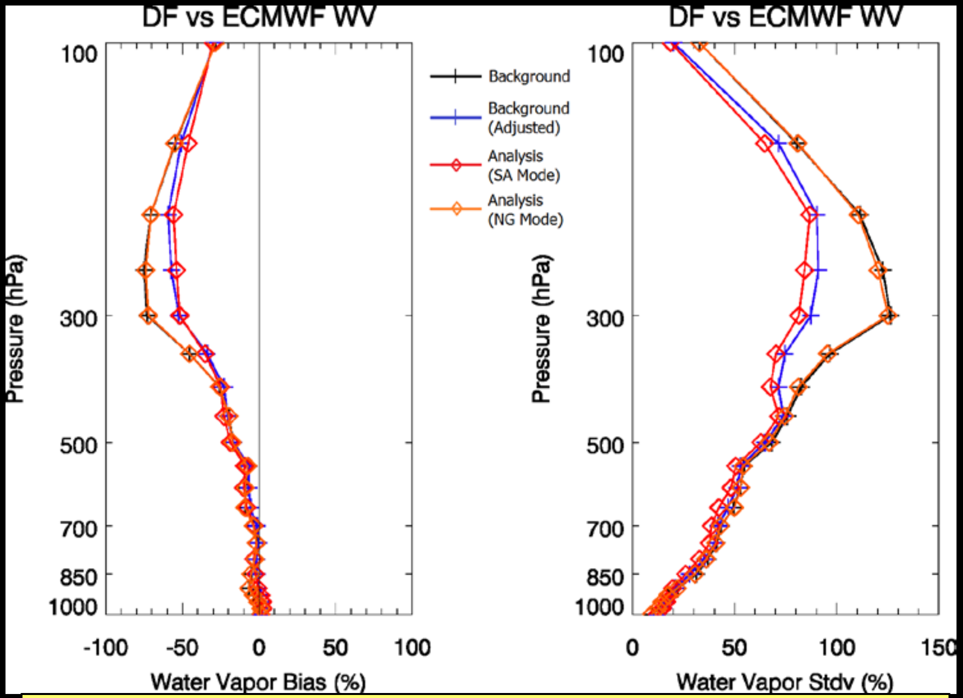
Analysis-ECMWF TPW [mm] (NG Mode)



Analysis-ECMWF TPW [mm] (SA Mode)



Performance at observation locations



- **Background Adjustment provides displacement correction not attained in NG Mode.**
- **DA using Adjusted Background refines analysis (smoothing, balance)**

preprocessing impact in radiance space

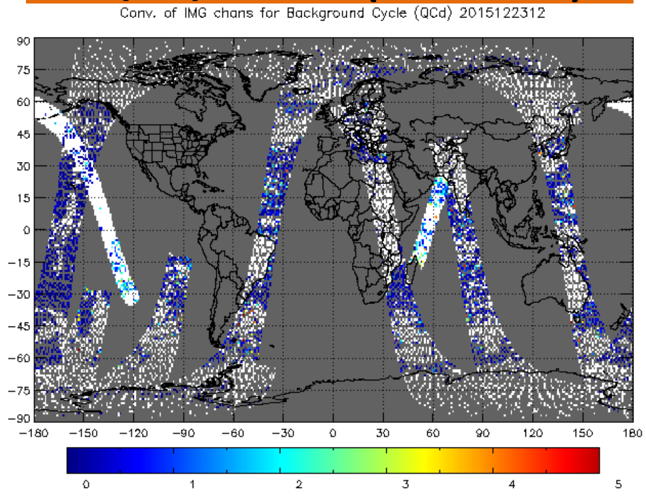
ChiSq/QC from Observation-Background (O-B)

“NG” Mode Data Assimilation

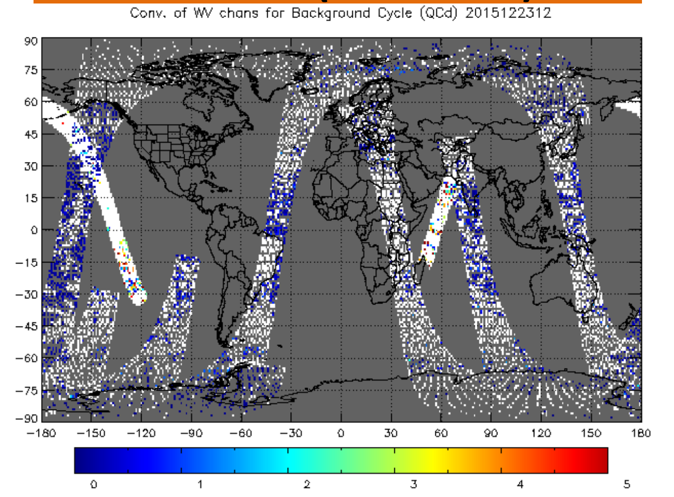
Failed QC (white) due to:

- ❖ Displacement in moisture fields (obs vs background)
- ❖ Poorly prescribed surface emissivity/CLW
- ❖ Strict quality control checks

23/31/89 GHz (NG Mode)



183 GHz (NG Mode)

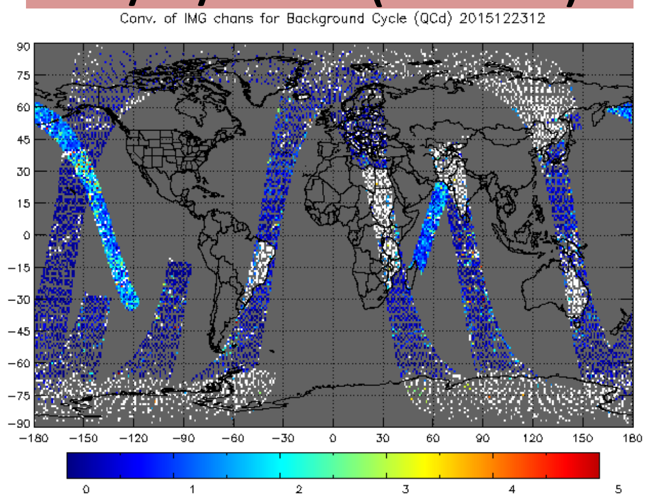


“SA” Mode Data Assimilation

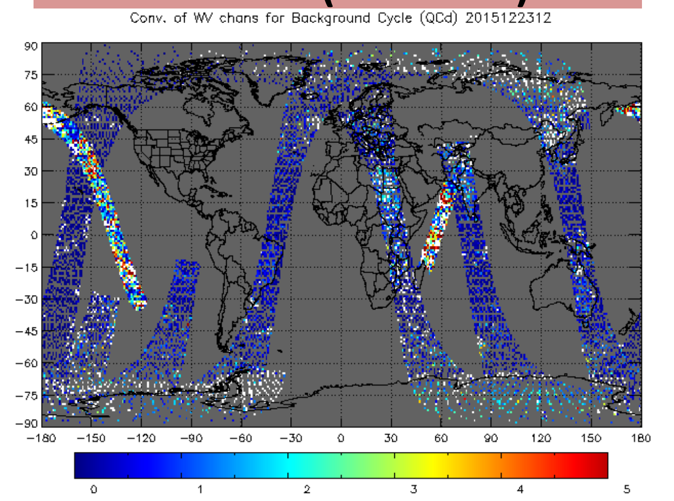
Use of background adjustment, boundary constraints, and MIIDAPS QC:

- ❖ Improved convergence
- ❖ More channels assimilated
- ❖ More observations assimilated

23/31/89 GHz (SA Mode)



183 GHz (SA Mode)



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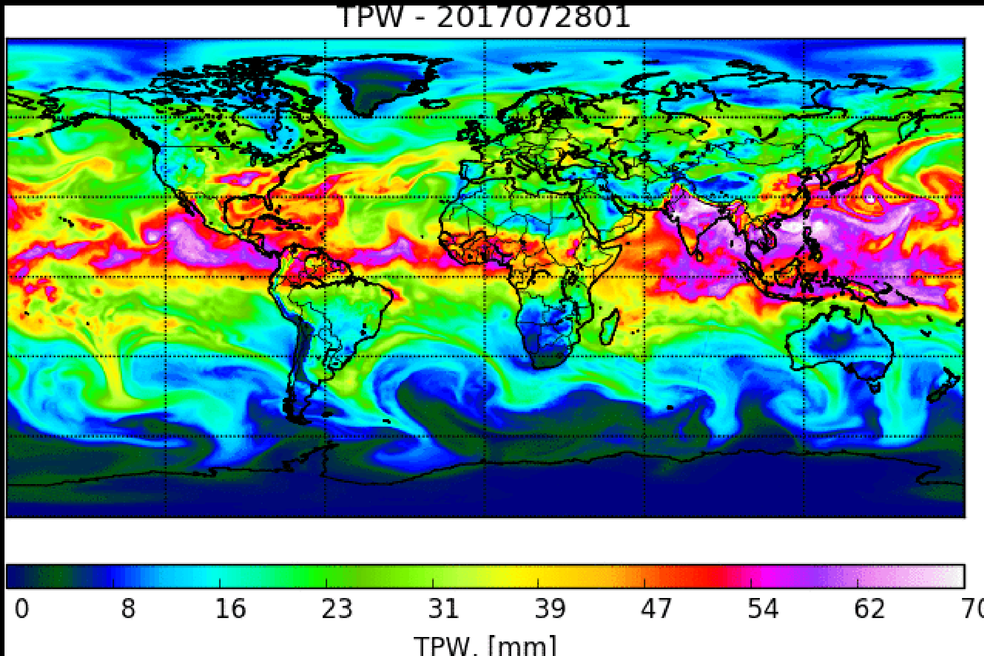
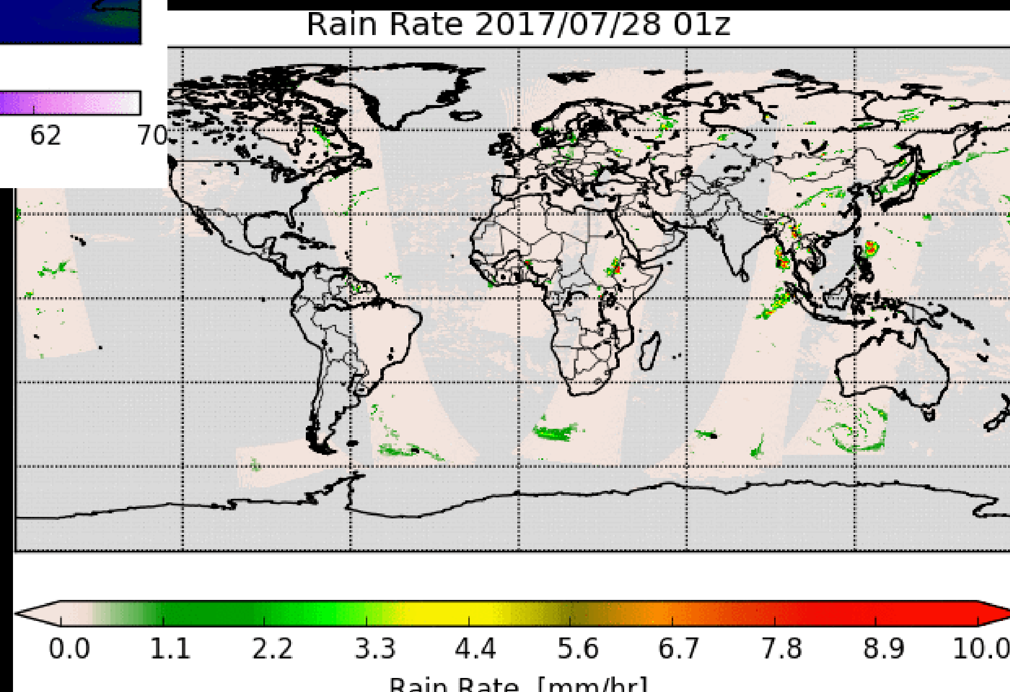
environmental data fusion analysis output

Global coverage with hourly cycling



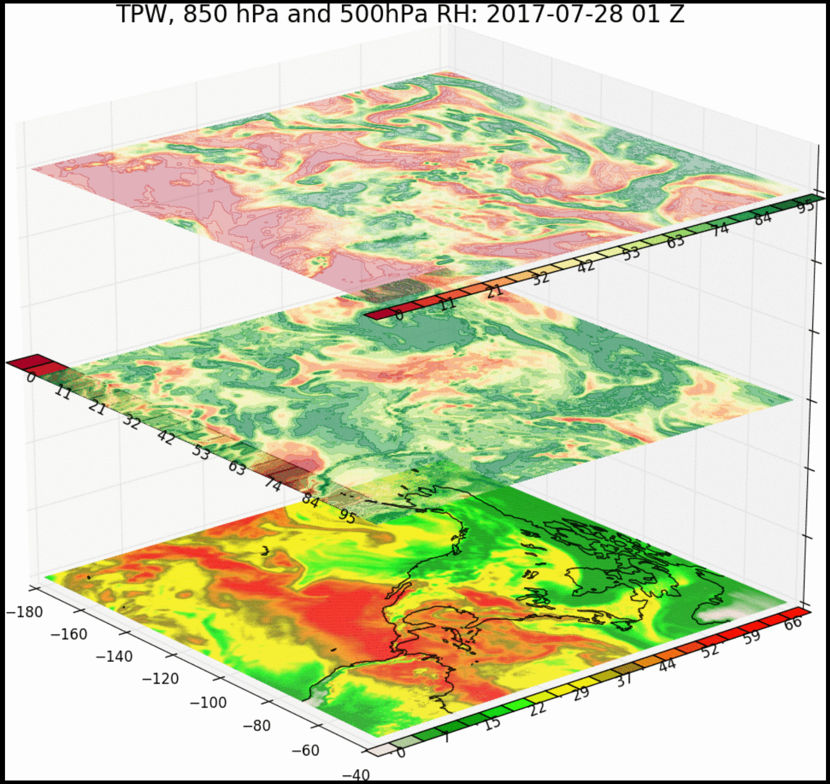
Total Precipitable Water
Derived from and physically consistent with all observations

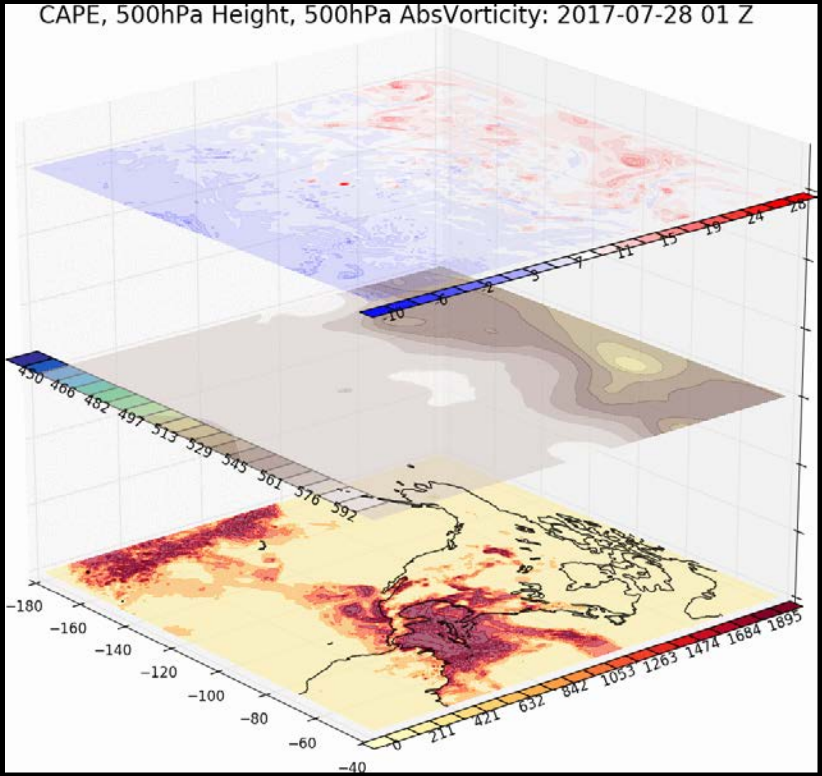
Rainfall Rate
Parameter added to EDF products by remote sensing algorithms



environmental data fusion analysis output

Consistency between traditional remote sensing and model physics

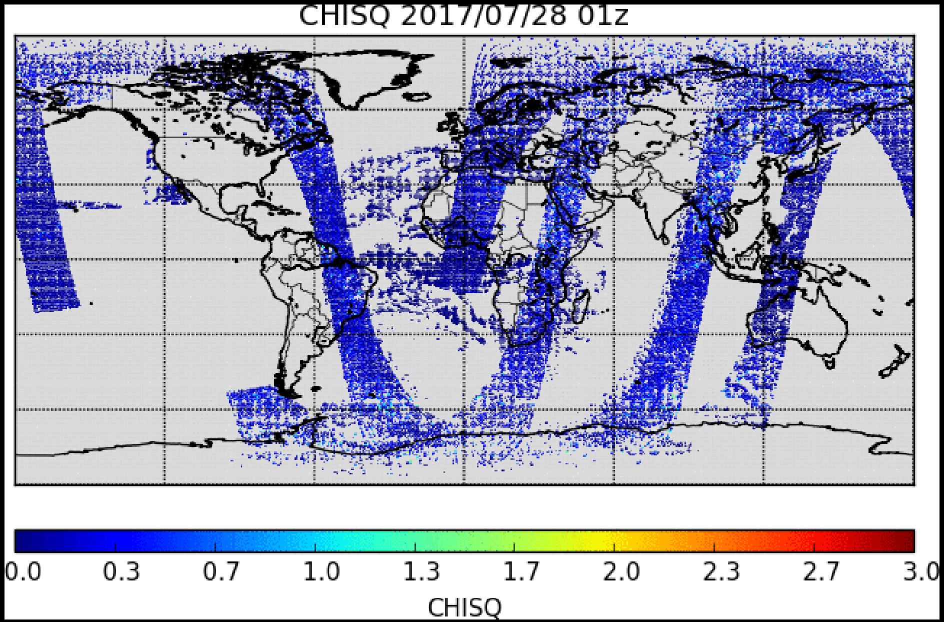




Parameters tied together by covariance and mass/wind balance constraints

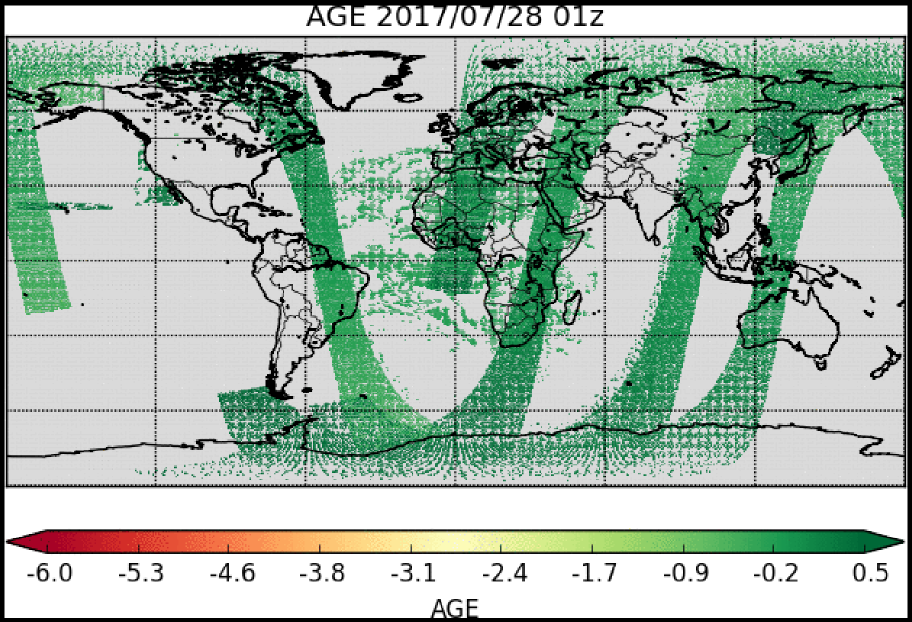
environmental data fusion analysis output

Quality Control of Analysis



Fit to Observations

- Analysis fields physically consistent with all observations
- Convergence/non-convergence gives level of trust to analysis fields

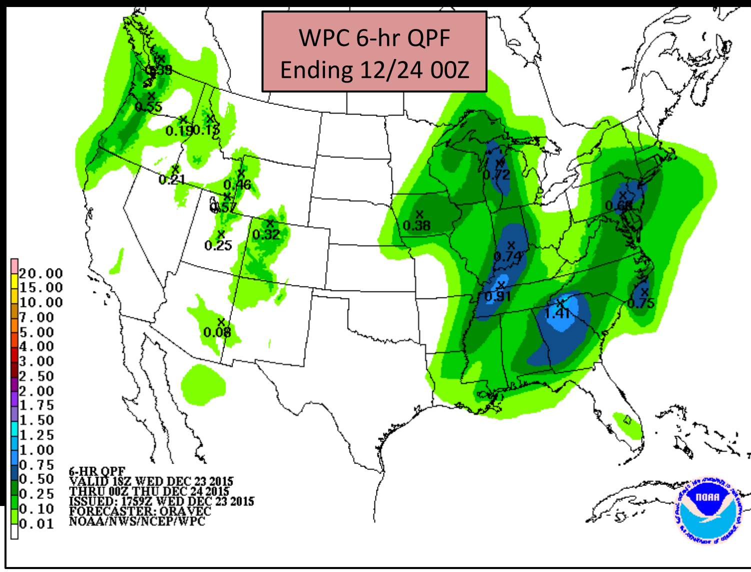


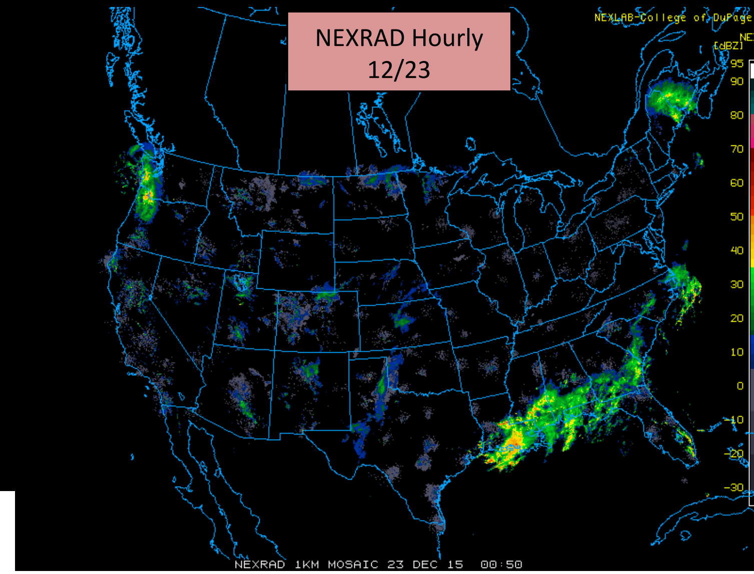
Observation Age

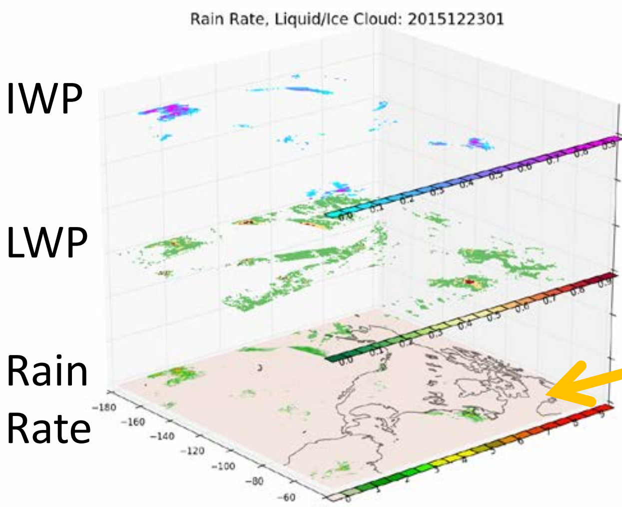
- Regions without recent observations
- Convergence/non-convergence gives level of trust to analysis fields

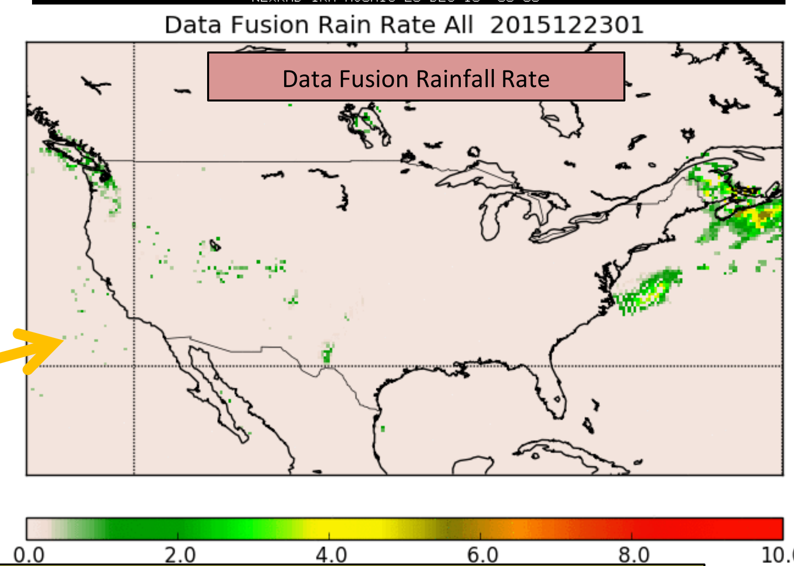
illustration of case study

Severe Weather Case December 23, 2015









Data Fusion system captures severe weather outbreak precipitation

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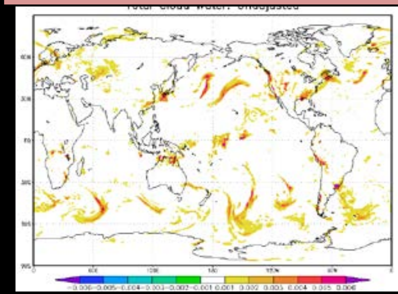
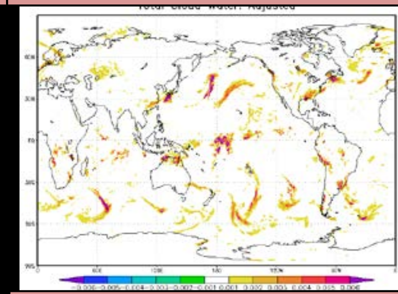
future considerations

- Extend use of constraints from preprocessing to surface emissivity, LST, cloud/hydrometeors
  - Establish consistency between MIIDAPS and GSI hydrometeors (qi/ql, CRTM microphysical/optical properties)
  - Turn on all-sky assimilation for other PMW sensors beyond AMSU-A?
  - Monitor bias correction, QC, O-B, O-A, etc.
  - Ensure physical consistency between parameters (change correlations length scales, background error covariance, etc.)
- Implement universal QC from MIIDAPS
- Extend the preprocessing to hyperspectral IR instruments
- Continue evaluation and feedback in an operational-type environment (AWIPS2)

CLW Background

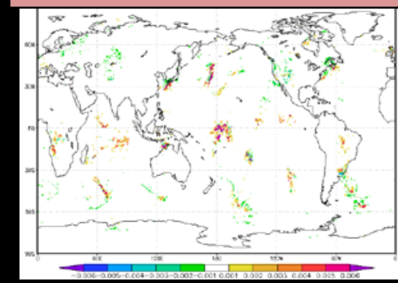


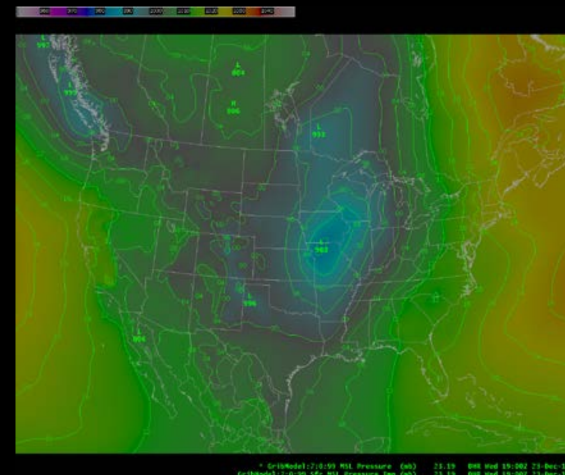
CLW Adjusted



Comparison of unadjusted and adjusted Cloud Water background for 1 cycle (900 hPa)

CLW Adjusted-Background





EDF Analysis in AWIPS2