

# Using AI to Better Exploit Polar and Geo Sensors - MW and IR Sounders and Imagers

*Status of the Multi-Instrument Inversion and Data Assimilation Preprocessing  
System MIIDAPS-AI*

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# Agenda

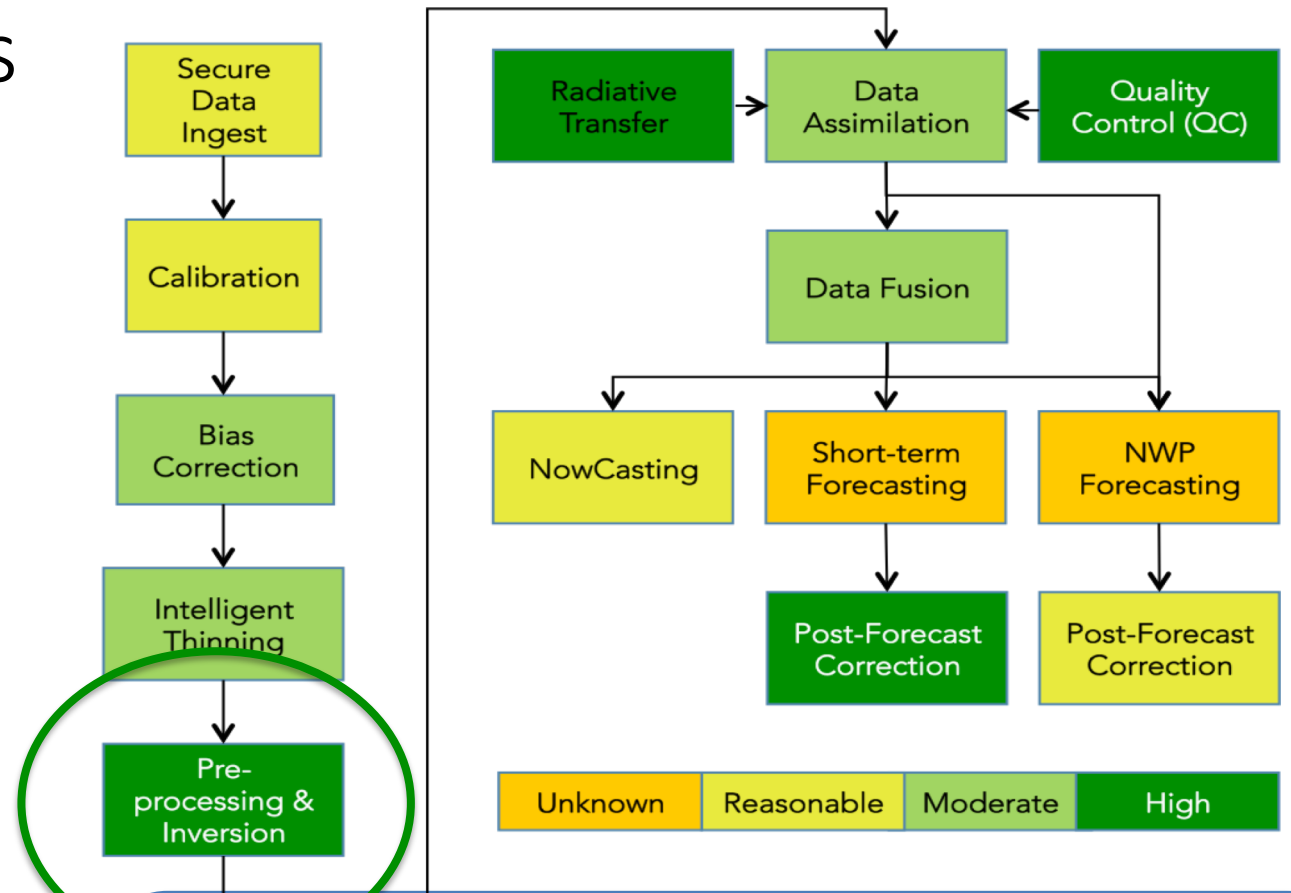
- Background and objectives
- Description of MIIDAPS-AI remote sounding algorithm and valid Sensors
- Description of algorithm tuning / training – Pre-processing and Neural Network hyper-parameters (layers, activations, nodes, ...)
- Description of MIIDAPS-AI product generation system
- System and product examples, validation, assessment and monitoring

# Background and Objectives

Explosion of GOS to new types of sensors with higher spatial and temporal resolutions, IoT, ... and budget constraints on HPC warrants development of new methodologies to better exploit satellite data.

Investigate the use Artificial Intelligence and Deep Learning techniques for

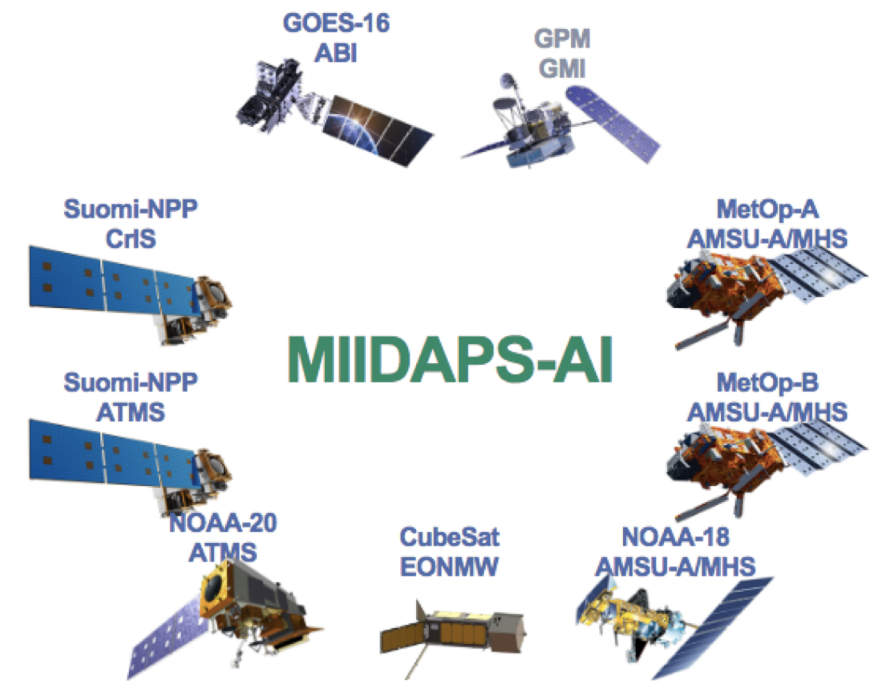
- Data fusion of satellite, surface and in situ datasets with NWP forecast.
- Prediction of hurricane track/intensity and severe weather from satellite and in situ datasets.
- Fast radiative transfer algorithms
- Remote sensing from MW/IR sounders and imagers – The *focus of this talk*.



*The status of the applicability of AI to the STAR processing chain for remote sensing, NWP, and situational awareness. The level of confidence that AI and in particular neural networks adds value to the processes is indicated by the colors in the bar at the lower right of the figure. All items labeled "High" level of confidence have been tested, as well as most labeled "Moderate".*

# What is MIIDAPS-AI?

- The Multi-Instrument Inversion and Data Assimilation Preprocessing System-Artificial Intelligence.
- MIIDAPS-AI was built to allow NOAA to implement *proof of concept* artificial intelligence (AI) techniques in remote sensing.
  - Goal is to mimic the performance of the traditional remote sensing algorithms such as MIIDAPS/MiRS using *fewer computational resources*.
- MIIDAPS-AI is a next-gen, enterprise remote sounding algorithm. As an extension of MiRS and MIIDAPS, it can be applied to
  - IR, MW polar and geo sounders and imagers - valid for any CRTM sensor
  - Data assimilation pre-processing and data fusion (products optionally produced in GrIB2 for ingest into NAWIPS and AWIPS2).
- Algorithms for ~10 sensors and product generation (assessment/validation/monitoring) system built by a team of 2 people in less than 10 months.



## MIIDAPS-AI Remote Sounding Algorithm

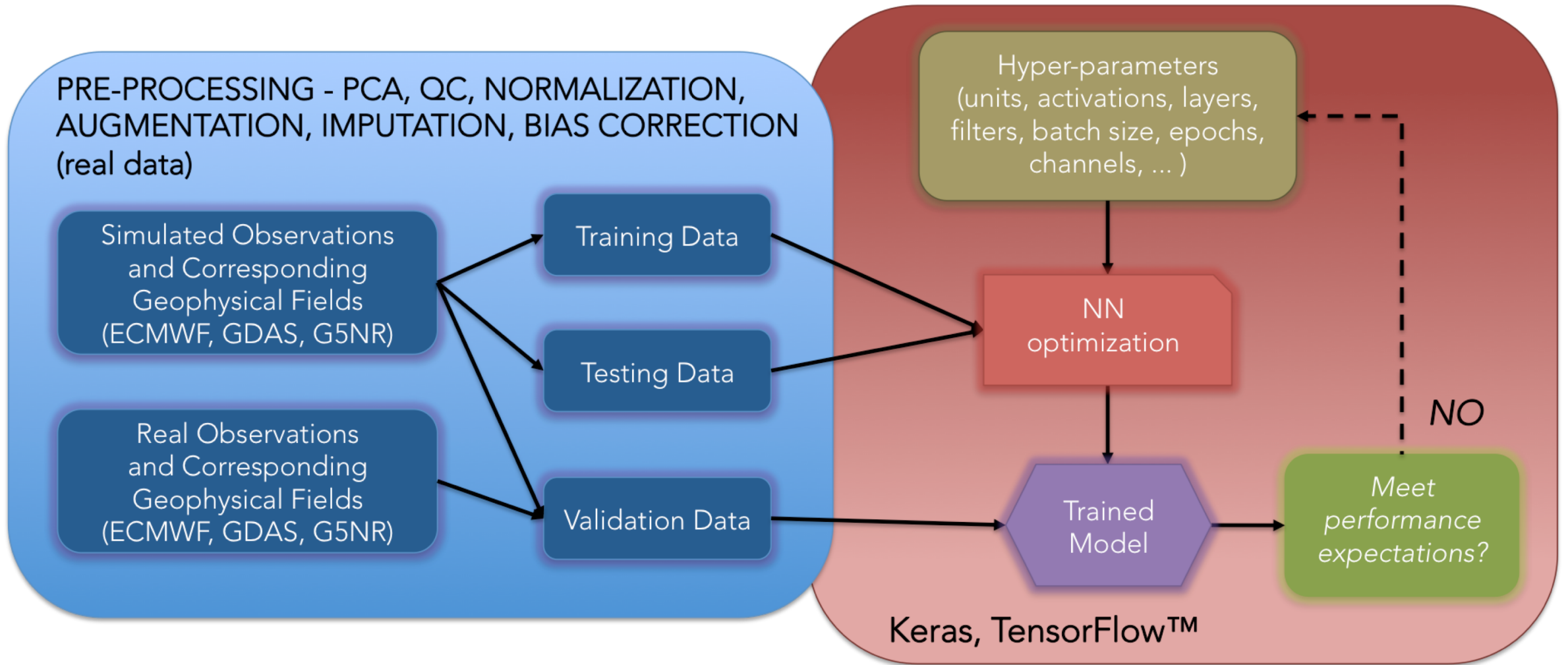
- Algorithms are deep feed forward (and locally-connected) neural networks trained in simulation and applied to real observations
- Network architecture and hyper parameters are tested and optimized using Google TensorFlow™ and Keras



## MIIDAPS-AI Sensor and Product Capabilities

	T(p)	Q(p)	SST/LST	TPW	Cld/Ice Amt.	Cld/Ice Top	Precip	Sfc Emis	Trace Gas Amt	Aerosol	QC
	L72 hybrid sigma				Total	Pressure	Total, RR		CO, CO <sub>2</sub> , O <sub>3</sub>	Pressure, Amt	$\chi^2$ ErEst
NOAA-18 AMSU-A/MHS											
MetOp-A AMSU-A/MHS											
MetOp-B AMSU-A/MHS											
MetOp-B IASI											
S-NPP ATMS											
S-NPP CrIS											
NOAA-20 ATMS											
GOES-East ABI											
HYPOTHETICAL/SMALL SAT SENSORS – NOT ALL SENSORS PROCESSED ON ROUTINE BASIS									Applicable		
MiCROMAS										Not Produced Regularly	
CiRAS										Possibly Applicable	
EON-MW										Not Applicable	

# MIIDAPS-AI Model Development Methodology



Training algorithms run on standalone CPU, GPU or HPC CPU/GPU clusters and generally take < 1hour for millions of training/testing cases

# MIIDAPS-AI Product Generation System

## PRE-PROCESSING

- Data reformatting, footprint matching, observation QA/QC
- NWP (ECMWF/GDAS) co-location
- CRTM simulation using NWP<sup>+</sup>, noise, augmentation, ...
- Algorithm training and assessment<sup>+</sup>

## PRODUCT GENERATION

- Serial processing of retrieved parameter groups
  - Atmosphere – T, Q, T<sub>skin</sub>
  - Cloud - liquid, ice, rain
  - Surface (spectral emis)
  - Trace Gas (O<sub>3</sub>, CO, CO<sub>2</sub>)<sup>#</sup>

## POST-PROCESSING

- Product QC (negative values, out of range)<sup>#</sup>
- L3 products
- Product assessment versus NWP
  - Statistics and plotting
- Web posting of results
- CRTM simulation using retrieved products<sup>+</sup>

### MIIDAPS-AI system:

- Is *sensor agnostic* (file driven). Same code runs 8 polar/geo IR and MW sensors each day.
- Leverages *MiRS/MIIDAPS* and *CRTM* development– *valid for any sensor with CRTM coefficients, any atmospheric variable that CRTM can simulate (cloud, trace-gas, aerosol, etc.)*
- Has *small computational footprint* (most required steps utilize fewer than 20CPUs, product generation requires ~2CPUs/retrieved parameter groups)
- Runs interactively via crontab/shell scripts or via SLURM, PBS/Torque scheduling system
- Is software *version controlled* in gitlab

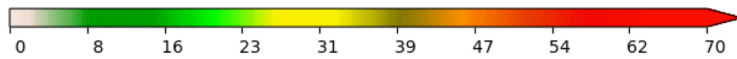
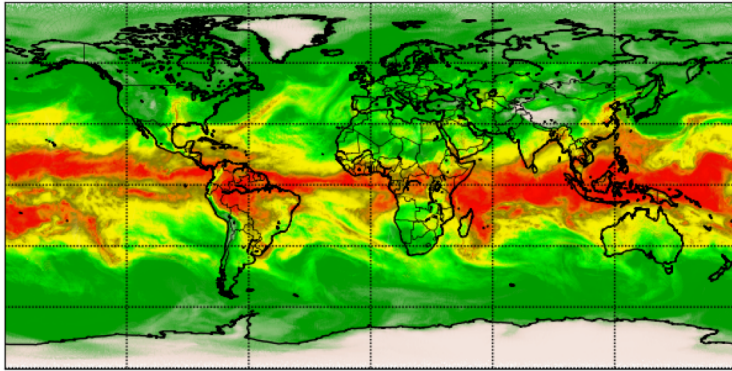
<sup>+</sup> Optional steps – only for training

<sup>#</sup> Work in progress. System does not currently produce on regular basis.

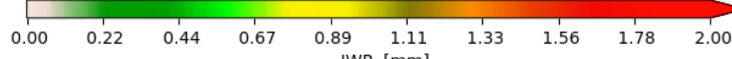
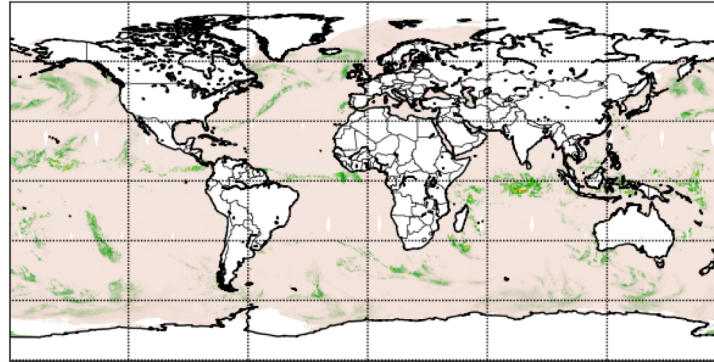


# MIIDAPS-AI Product Examples – Real Polar Geo IR and MW Observations

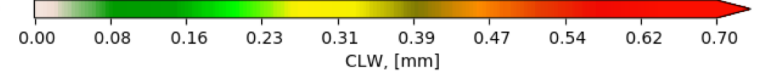
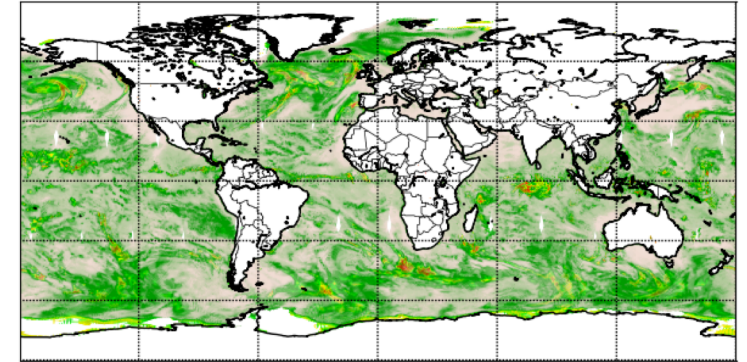
SNPP ATMS 04/21/2018  
MIIDAPS-AI TPW



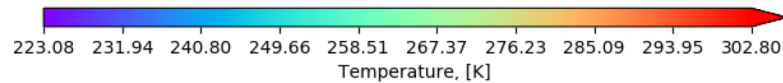
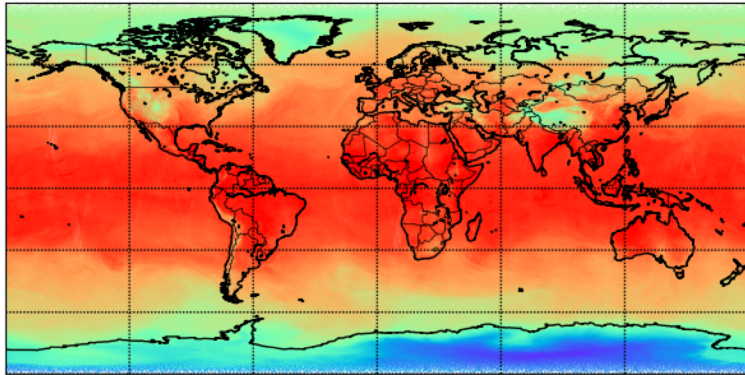
NOAA-18 AMSU-A/MHS 04/21/2018  
MIIDAPS-AI IWP



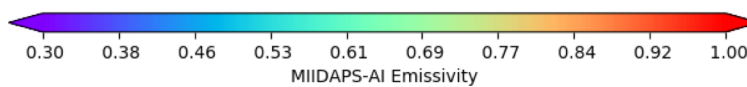
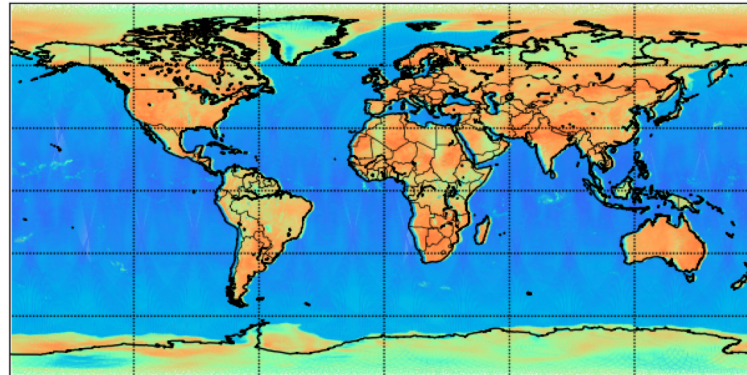
NOAA-18 AMSU-A/MHS 04/21/2018  
MIIDAPS-AI CLW



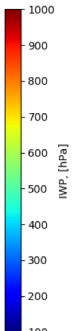
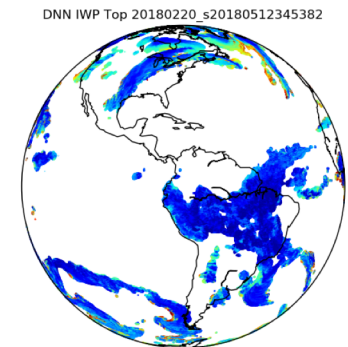
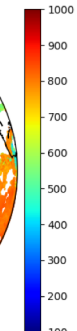
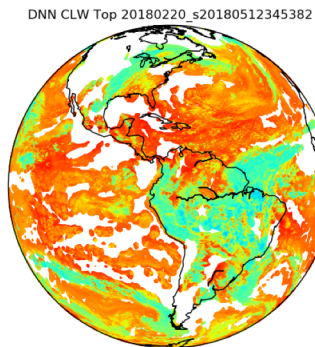
SNPP ATMS 04/21/2018  
MIIDAPS-AI Temperature(level=70)



SNPP ATMS 04/21/2018  
MIIDAPS-AI Emissivity, Channel = 1



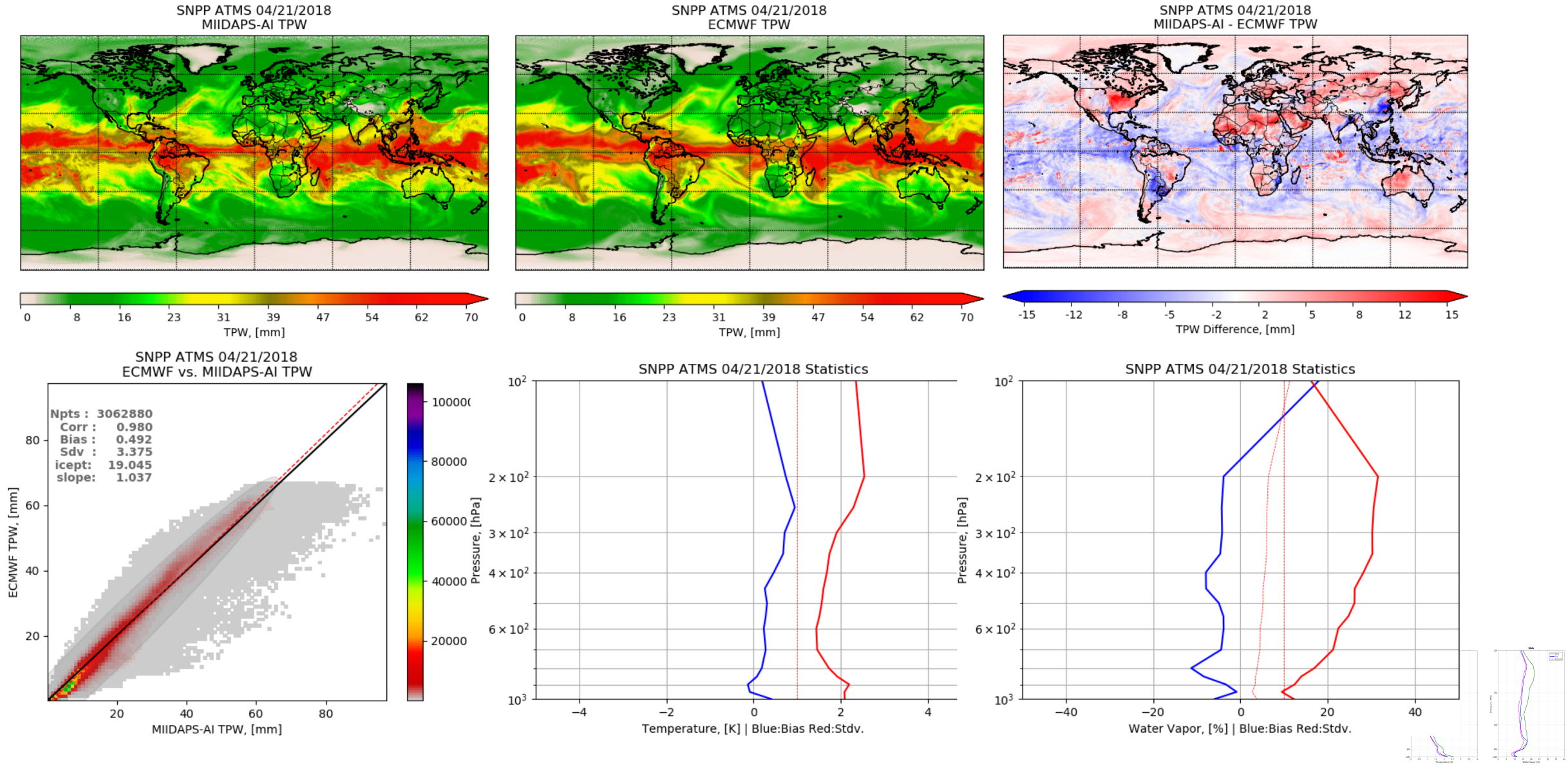
GOES-EAST ABI LIQUID and ICE CTP





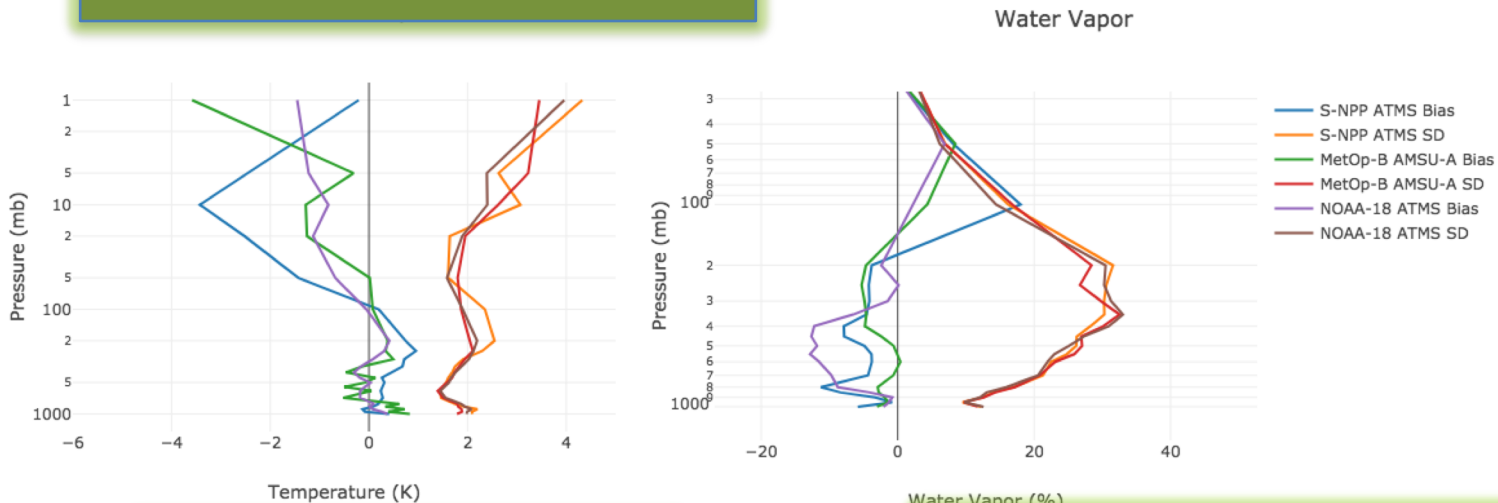
# MIIDAPS-AI $T(p)$ and $Q(p)$ Product Assessment

## 2018-04-21 S-NPP ATMS Comparison to ECMWF – >95% yield

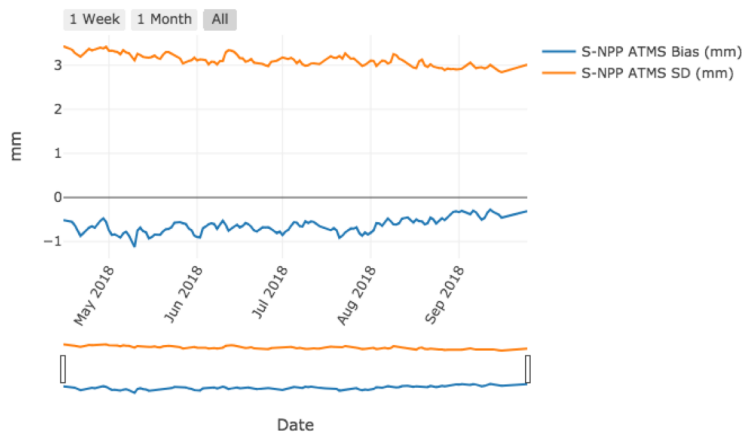


# MIIDAPS-AI Product Assessments versus ECMWF – >95% yield

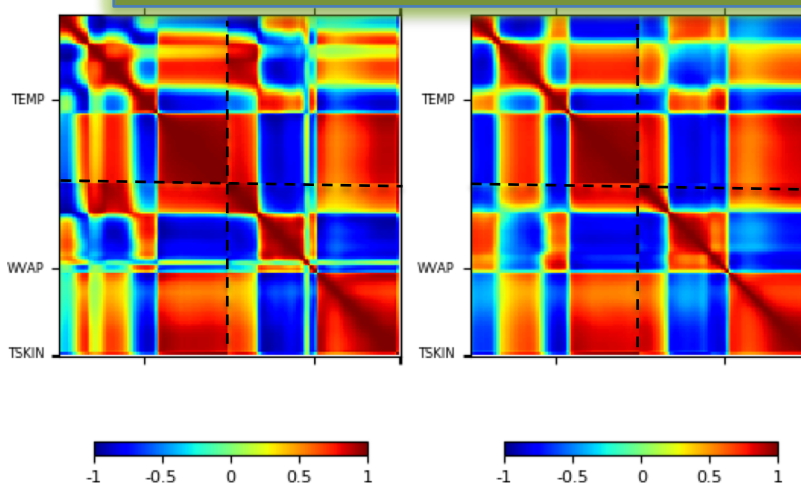
## Inter-sensor statistics comparison



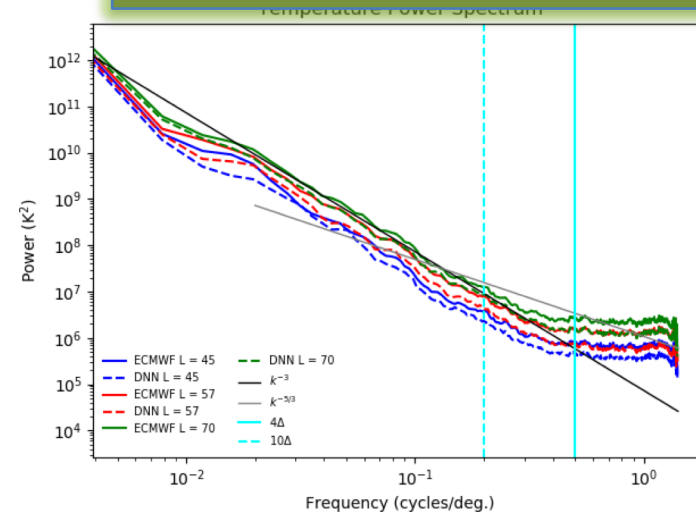
## Statistical Timeseries



## Product and Reference Inter-parameter Correlation

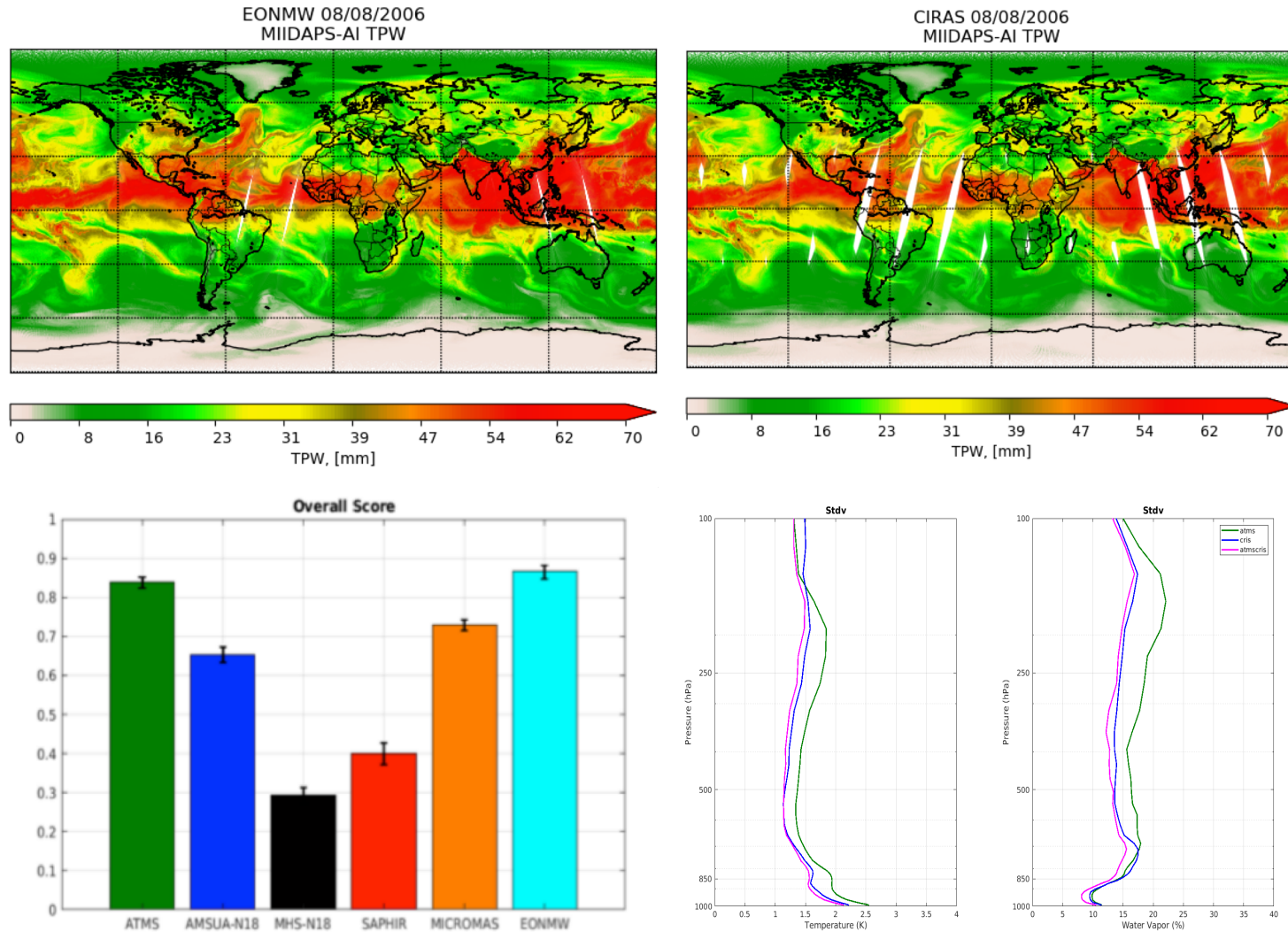


## Spatial coherence (1-D PSD)



- Monitoring enables diagnosis of temporal trends and degradation in sensor products
  - Working toward “adaptive” or on-line training of algorithms as new data comes in.
- Inter-parameter correlation and spatial coherence to ECMWF indicates products are consistent with model fields except at high frequencies (highest resolutions)

# MIIDAPS-AI $T(p)$ and $Q(p)$ Sensor Assessment for Current and Hypothetical Instruments Using G5NR-based Simulation

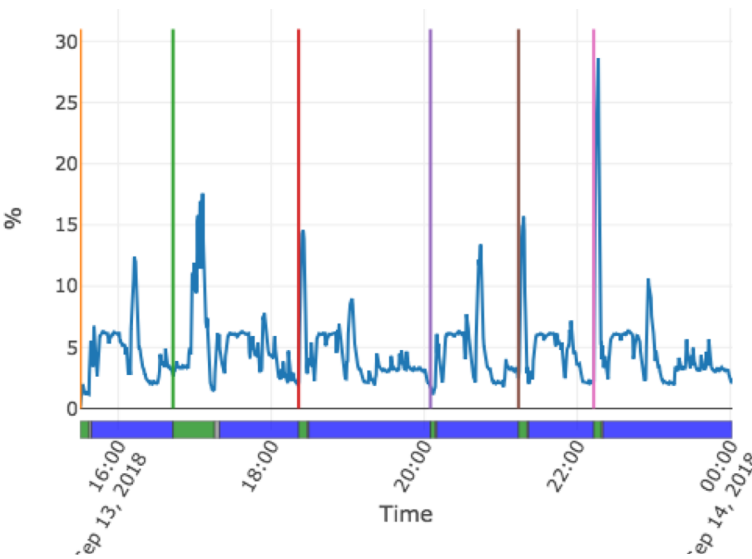


- **Top:** MIIDAPS-AI algorithms applied to EONMW and CIRAS in simulated all-surface/all-sky conditions
- **Lower left:** Value of current and hypothetical sensors summarized in normalized  $T(p)$ ,  $Q(p)$ ,  $Cloud$  RMSE and Correlation relative to G5NR
- **Lower right:** Assessment of IR, MW and combined IR+MW  $T(p)$  and  $Q(p)$  performance with ATMS and CrIS.

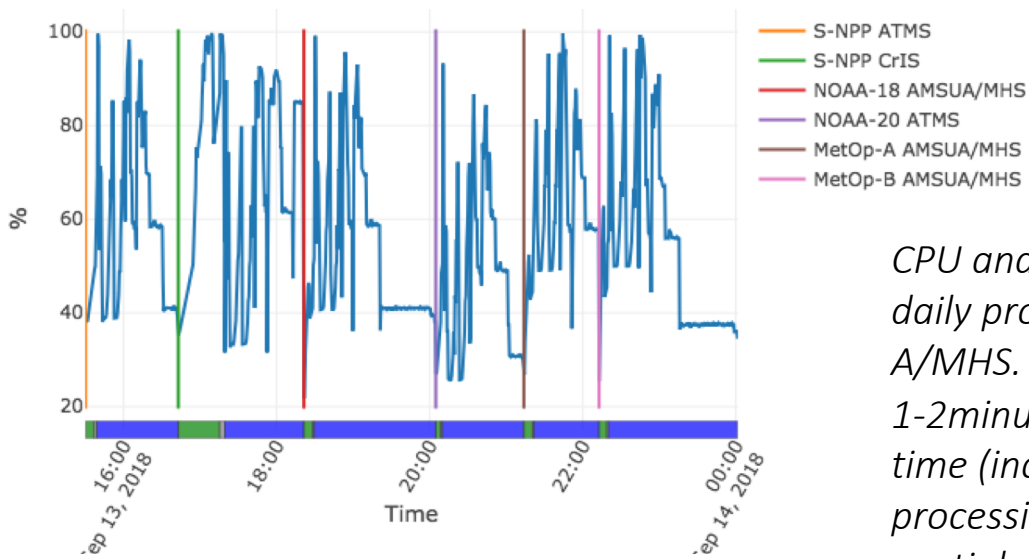


# MIIDAPS-AI Production System Web-Monitoring and Timing Comparison to Traditional Algorithms

CPU Used



Memory Used



CPU and memory usage of MIIDAPS-AI over daily processing of ATMS, CrIS, AMSU-A/MHS. Product generation takes roughly 1-2minutes per sensor. Total algorithm time (including pre-processing and post-processing steps) for all sensors at full spatial resolution < 70 minutes/full day.

Pre-processing, AI-Based Product Generation, Post-processing

Comparison of number of days that can be processed per day using the same computing resources and using either the next generation (MIIDAPS-AI) algorithm or traditional variational approaches (MIIDAPS, MiRS, or NUCAPS)

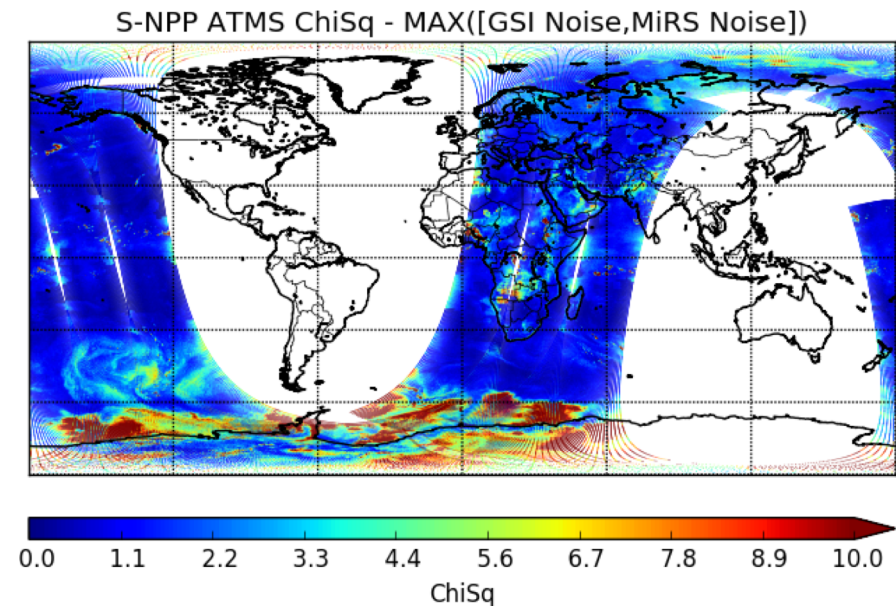
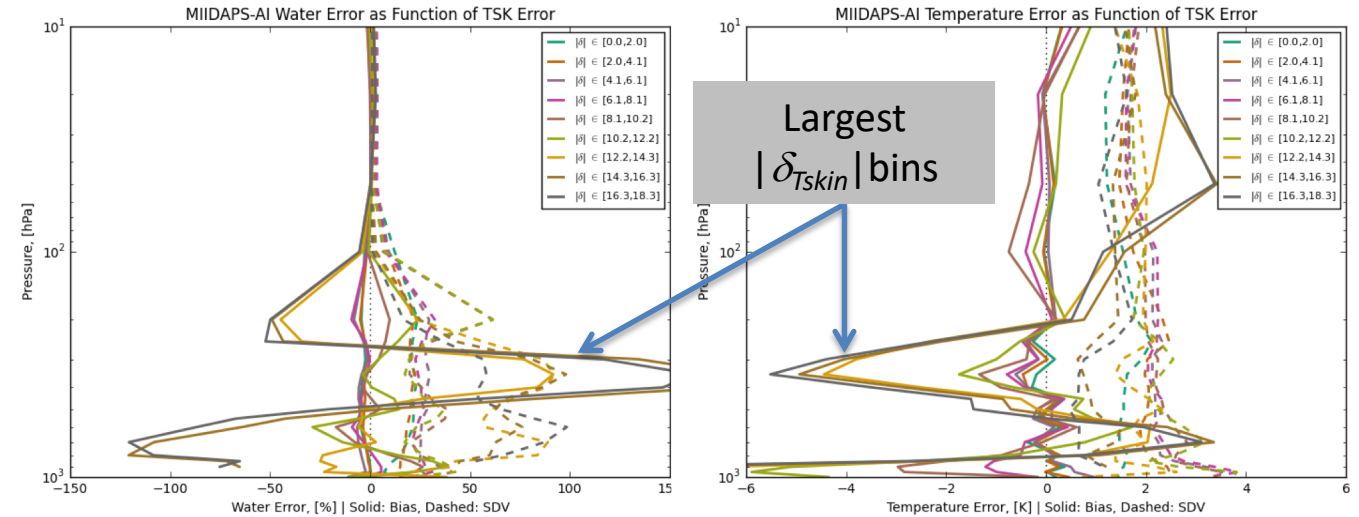
	ATMS		CrIS		ABI	
	MIIDAPS-AI	MiRS	MIIDAPS-AI	NUCAPS**	MIIDAPS-AI	MIIDAPS
Algorithm (days/day)	720	3.6	400	3.9	30	0.15

\*\*ESTIMATED FROM A VERY OLD RUN I HAD



# MIIDAPS-AI QC and error estimates – work in progress

- **Top:** Example of product performance as a function of binned error predictions  $|\delta_{T_{skin}}|$ 
  - Estimate product uncertainty based on observed  $T_{bs}$ .
- **Bottom:** Example of S-NPP ATMS MIIDAPS-AI  $\chi^2$  (inverse/forward radiance closure)
  - MIIDAPS-AI product fed back into CRTM and compared to  $T_{bs}$ .



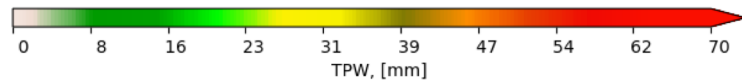
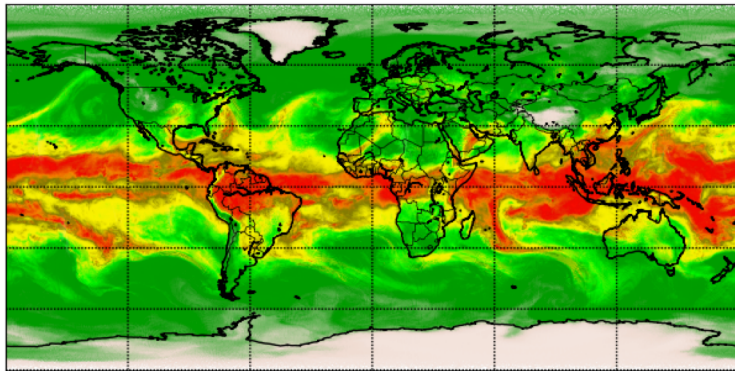
# Future Work and Wrap-up

- MIIDAPS-AI is a next-gen, computationally efficient, enterprise remote sounding algorithm and processing system
  - Algorithm has been applied to current and hypothetical polar and geo MW and IR sounders and imagers.
  - Daily processing of 7 sensors (multiple-ATMS, multiple-AMSU-A/MHS, CrIS, ABI) produce sounding, hydrometeor and surface products using far fewer computational resources compared to traditional approaches.
- We are currently looking at
  - Algorithm and training refinement to mitigate trends and biases and to produce QC/Error Estimates for all parameters
  - Assessing more complicated deep-learning architectures to incorporate:
    - Spatial and temporal information
    - Multi-spectral sensor and multi-product information - data fusion
  - Evaluation of MIIDAPS-AI versus RaOB and more traditional algorithms such as MiRS and NUCAPS

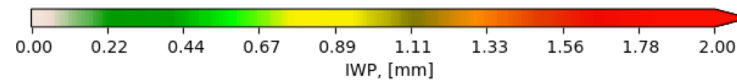
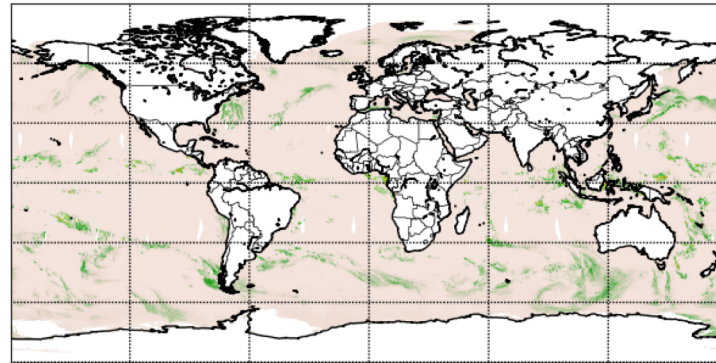
THANKS! QUESTIONS?

# MIIDAPS-AI and MiRS Product Examples – Real Polar Geo IR and MW Observations

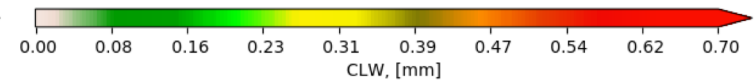
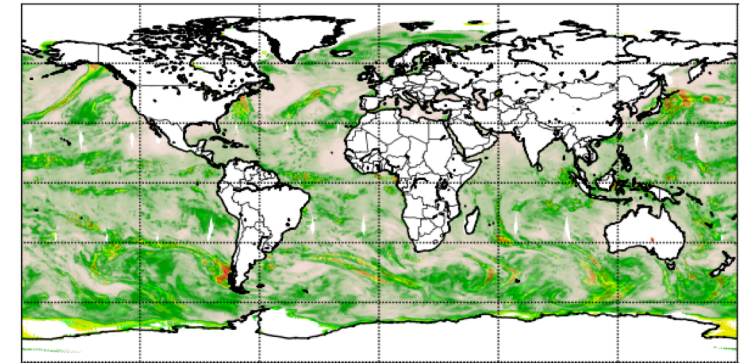
SNPP ATMS 04/25/2018  
MIIDAPS-AI TPW



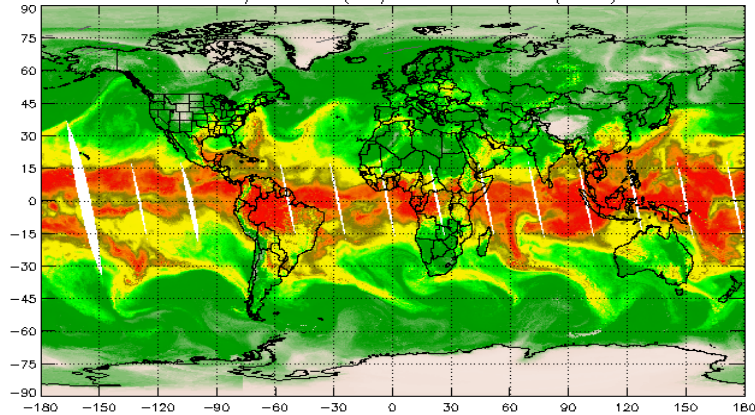
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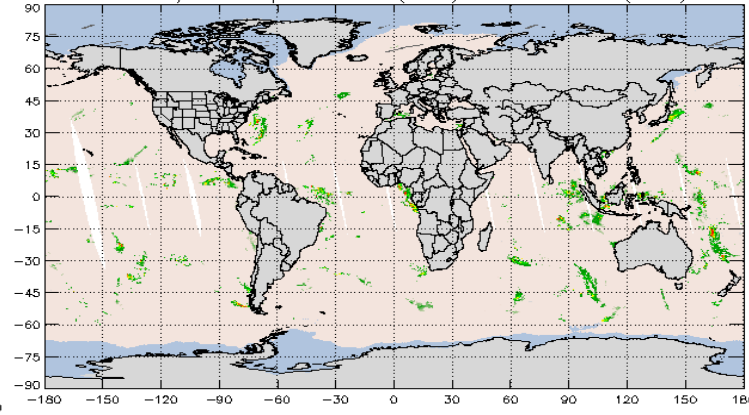
NOAA-18 AMSU-A/MHS 04/25/2018  
MIIDAPS-AI CLW



MIRS NPP/ATMS TPW (mm) 2018-04-25 Asc (V3783)



MIRS NPP/ATMS Graupel Water Path (mm) 2018-04-25 Asc (V3783)



MIRS NPP/ATMS CLW (mm) 2018-04-25 Des (V3783)

