



# **Promises and Challenges in Assimilation of IR/MW All-sky Satellite Radiances**

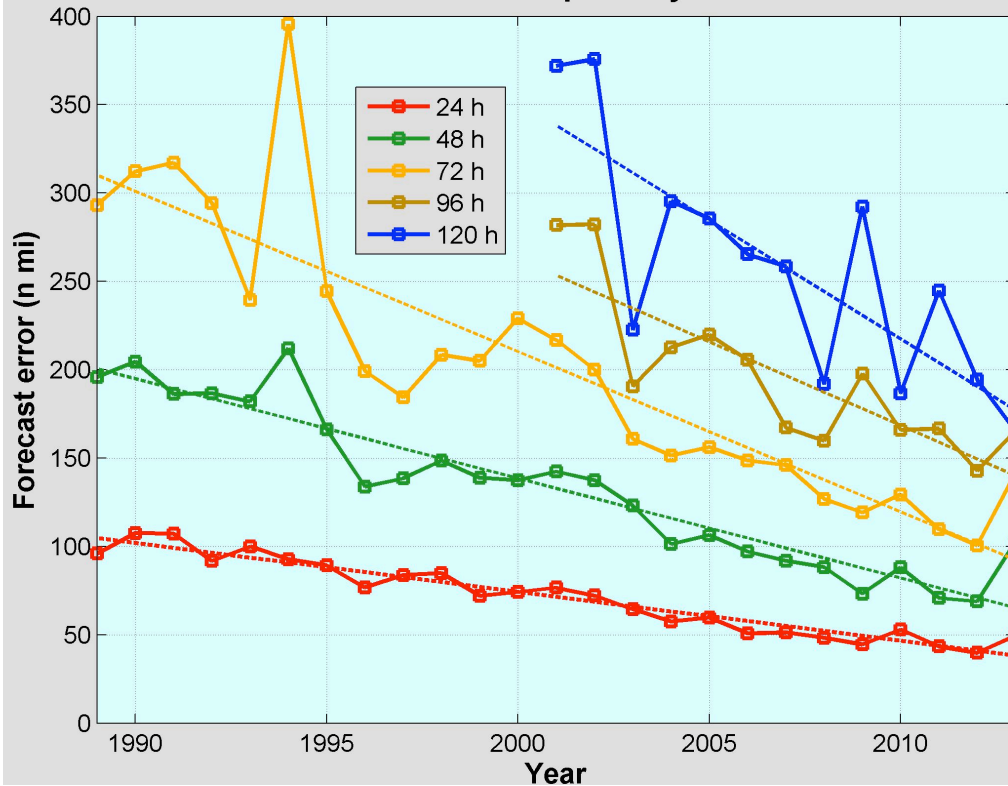
**Fuqing Zhang**  
**Penn State University**

**Masashi Minamide, Scott Sieron, Yunji Zhang, Yinghui Lu, Lei Zhu, Su Liu  
Robert Nystrom, Michael Ying, XC Chen, Eugene Clothiaux, David Stensrud**

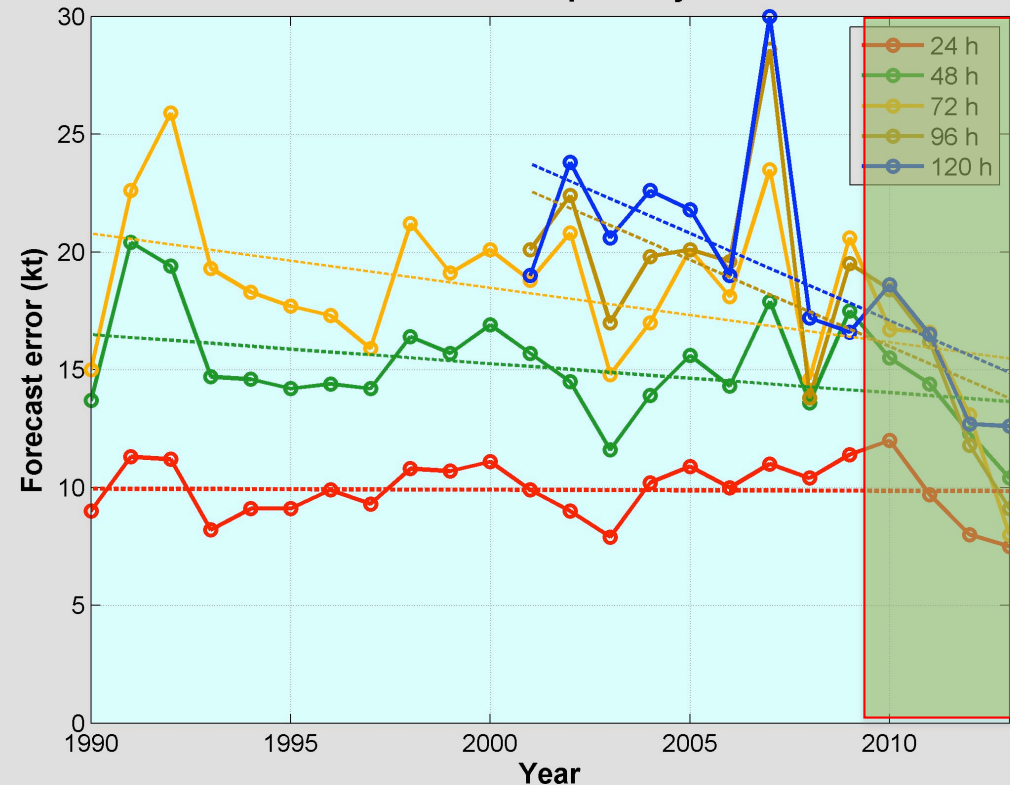


# National Hurricane Center Official TC Forecast Errors

NHC Official Annual Average Track Errors  
Atlantic Basin Tropical Cyclones



NHC Official Intensity Error Trend  
Atlantic Basin Tropical Cyclones



*Track forecasts have improved drastically over past 25 years: a 3 day forecast today is as accurate as a 1 day forecast was in 1989.*

*Intensity forecast accuracy has remained generally stagnant over that same period of time, except for the last few years.*

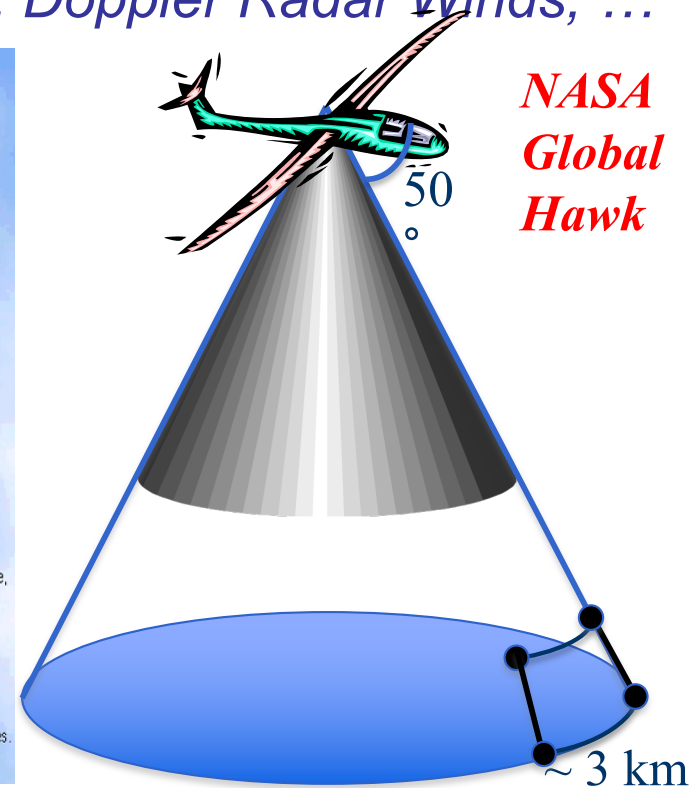
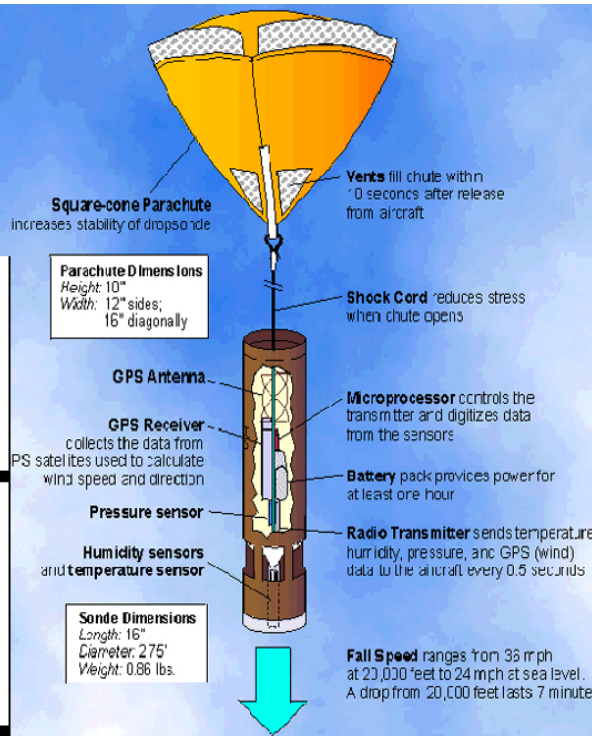
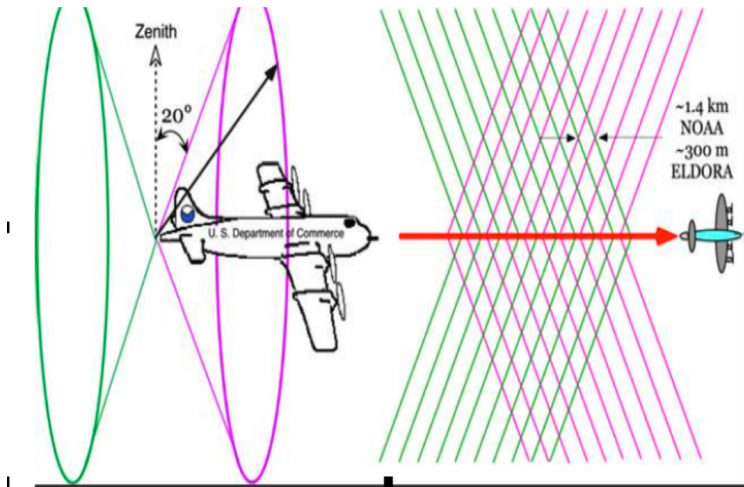
*What limits the predictability of tropical cyclone intensity?*

# How to make better input to the hurricane models?

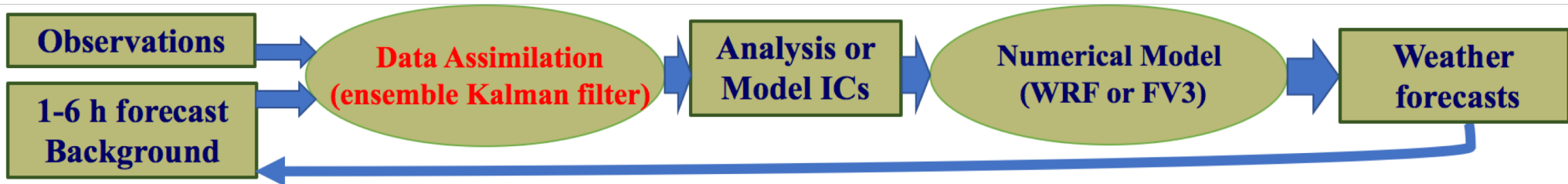
High-resolution observations from Hurricane Hunters and UAVs: *Provide crucial airborne inflight measurements, dropsondes, Doppler Radar Winds, ...*




**NOAA P3**



**NASA Global Hawk**



## REVIEW

 **Review of the Ensemble Kalman Filter for Atmospheric Data Assimilation**

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(Manuscript received 17 December 2015, in final form 6 June 2016)

## ABSTRACT

This paper reviews the development of the ensemble Kalman filter (EnKF) for atmospheric data assimilation. Particular attention is devoted to recent advances and current challenges. The distinguishing properties of three well-established variations of the EnKF algorithm are first discussed. Given the limited size of the ensemble and the unavoidable existence of errors whose origin is unknown (i.e., system error), various approaches to localizing the impact of observations and to accounting for these errors have been proposed. However, challenges remain; for example, with regard to localization of multiscale phenomena (both in time and space). For the EnKF in general, but higher-resolution applications in particular, it is desirable to use a short assimilation window. This motivates a focus on approaches for maintaining balance during the EnKF update. Also discussed are limited-area EnKF systems, in particular with regard to the assimilation of radar data and applications to tracking severe storms and tropical cyclones. It seems that relatively less attention has been paid to optimizing EnKF assimilation of satellite radiance observations, the growing volume of which has been instrumental in improving global weather predictions. There is also a tendency at various centers to investigate and implement hybrid systems that take advantage of both the ensemble and the variational data assimilation approaches; this poses additional challenges and it is not clear how it will evolve. It is concluded that, despite more than 10 years of operational experience, there are still many unresolved issues that could benefit from further research.

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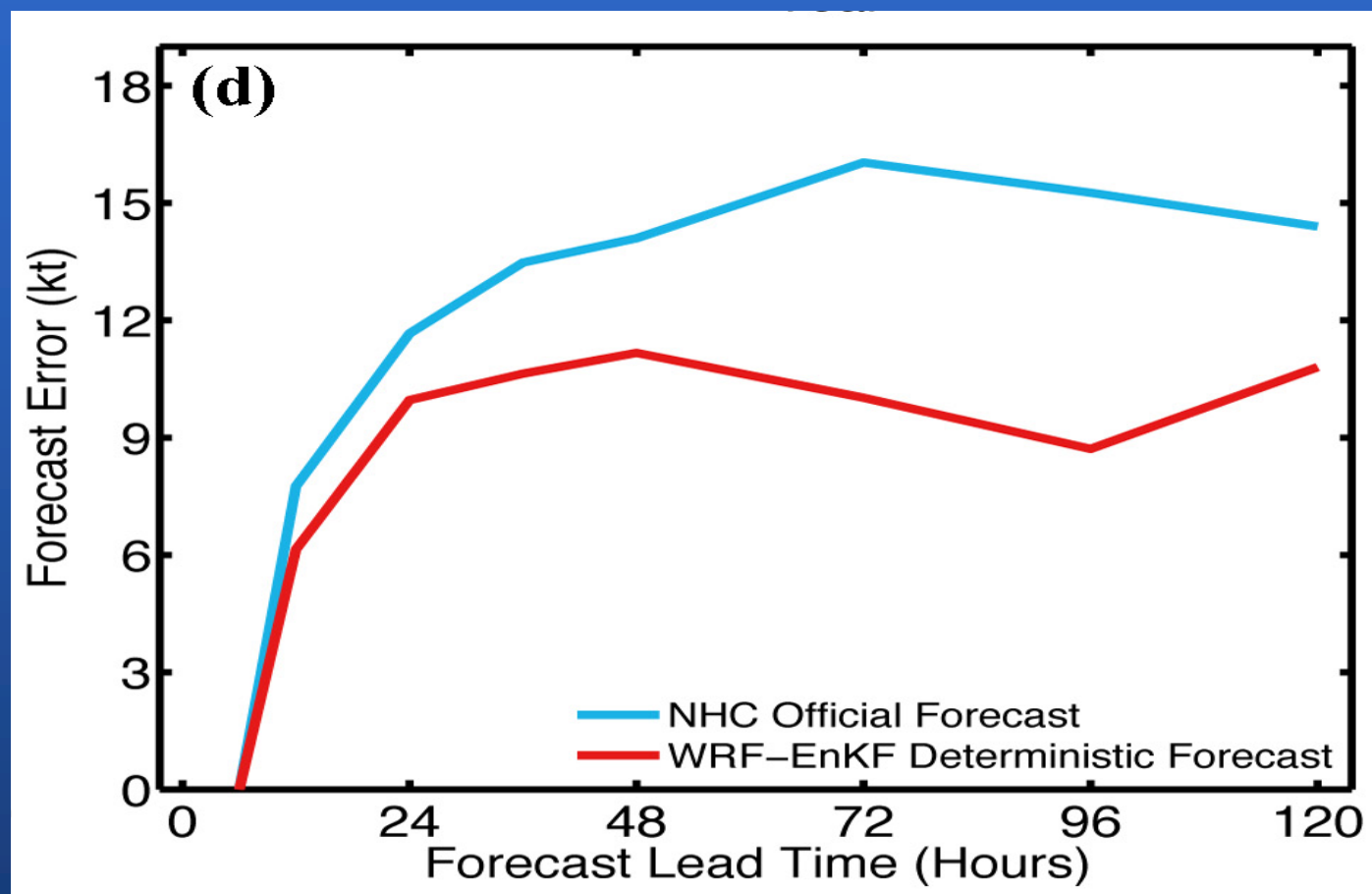
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# PSU WRF-EnKF Hurricane Analysis & Prediction System with advanced assimilation of airborne Doppler Radar Vr

*Evaluated for all 100+ P3 TDR missions during 2008-2012*

## PSU WRF-EnKF Hurricane Intensity error (knots)



*The TDR EnKF methodology is now adopted by NOAA for the operational HWRF model.*

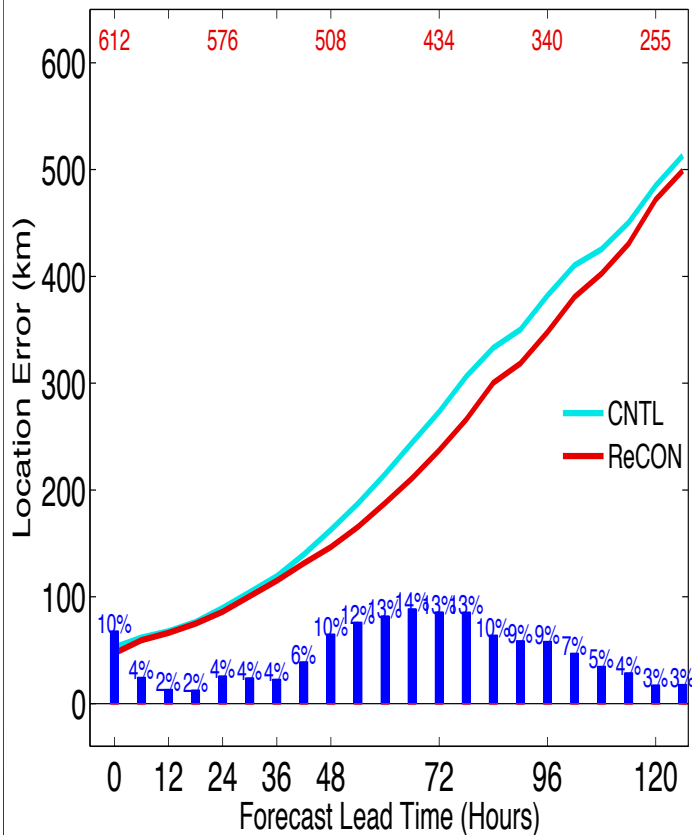
(F. Zhang and Y. Weng 2015, BAMS)

# WRF-EnKF Performance w/ versus w/o Aircraft OBS

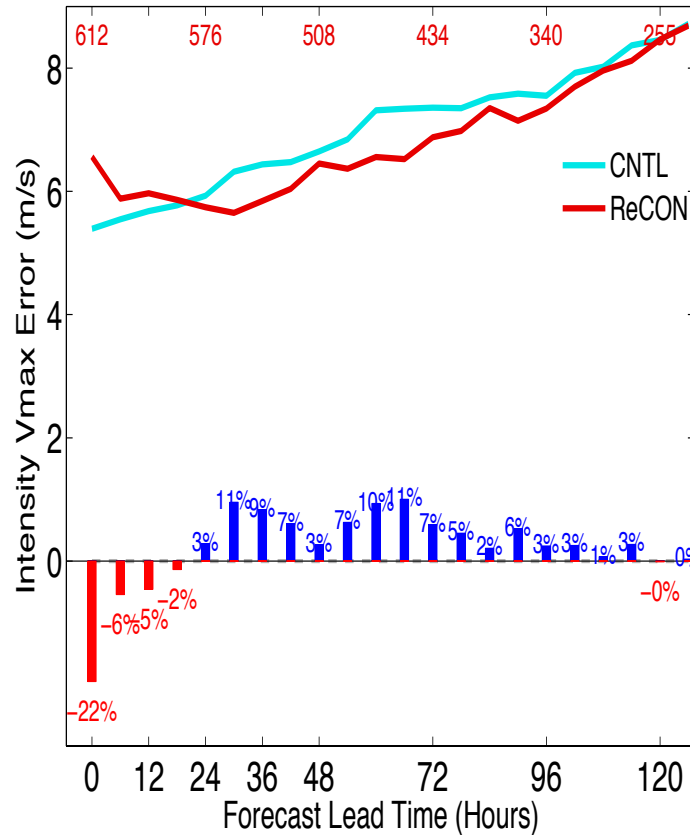
for HFIP/NHC selected RDITT cases w/o TDR during 2008-2012

WRF-EnKF: 3 domains (27, 9, 3km), 60-member ensemble, PSU TC flux scheme

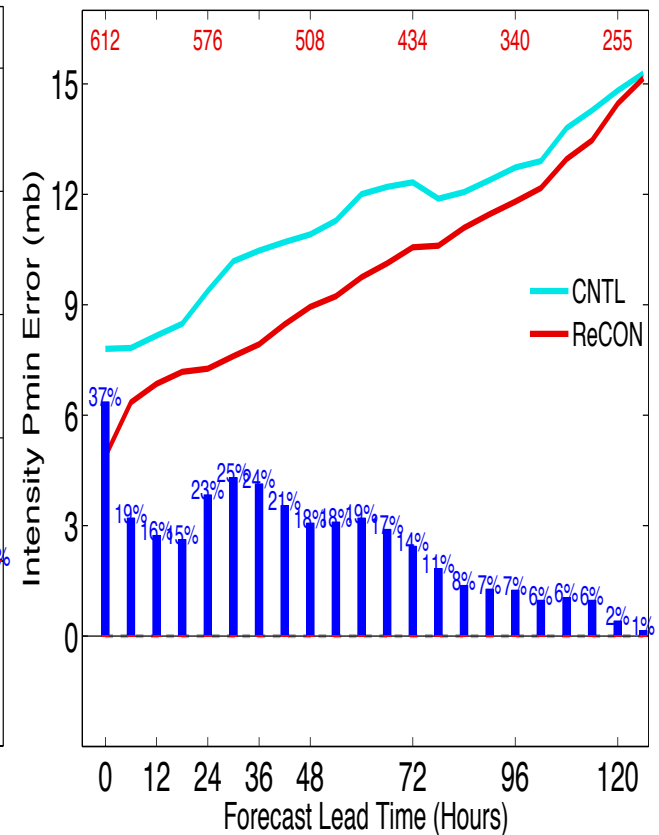
## Position error (km)



## Vmax error (knots)



## Pmin error (mb)



(Weng and Zhang, 2016 JMSJ)

# Next Frontier: Geostationary Satellite GOES-R

*from NASA to NOAA*

# GOES-R

## THE FUTURE OF FORECASTING

### 3X MORE CHANNELS



Improves every product from current GOES Imager and will offer new products for severe weather forecasting, fire and smoke monitoring, volcanic ash advisories, and more.

### 4X BETTER RESOLUTION



The GOES-R series of satellites will offer images with greater clarity and 4x better resolution than earlier GOES satellites.

### 5X FASTER SCANS



Faster scans every 30 seconds of severe weather events and can scan the entire full disk of the Earth 5x faster than before.

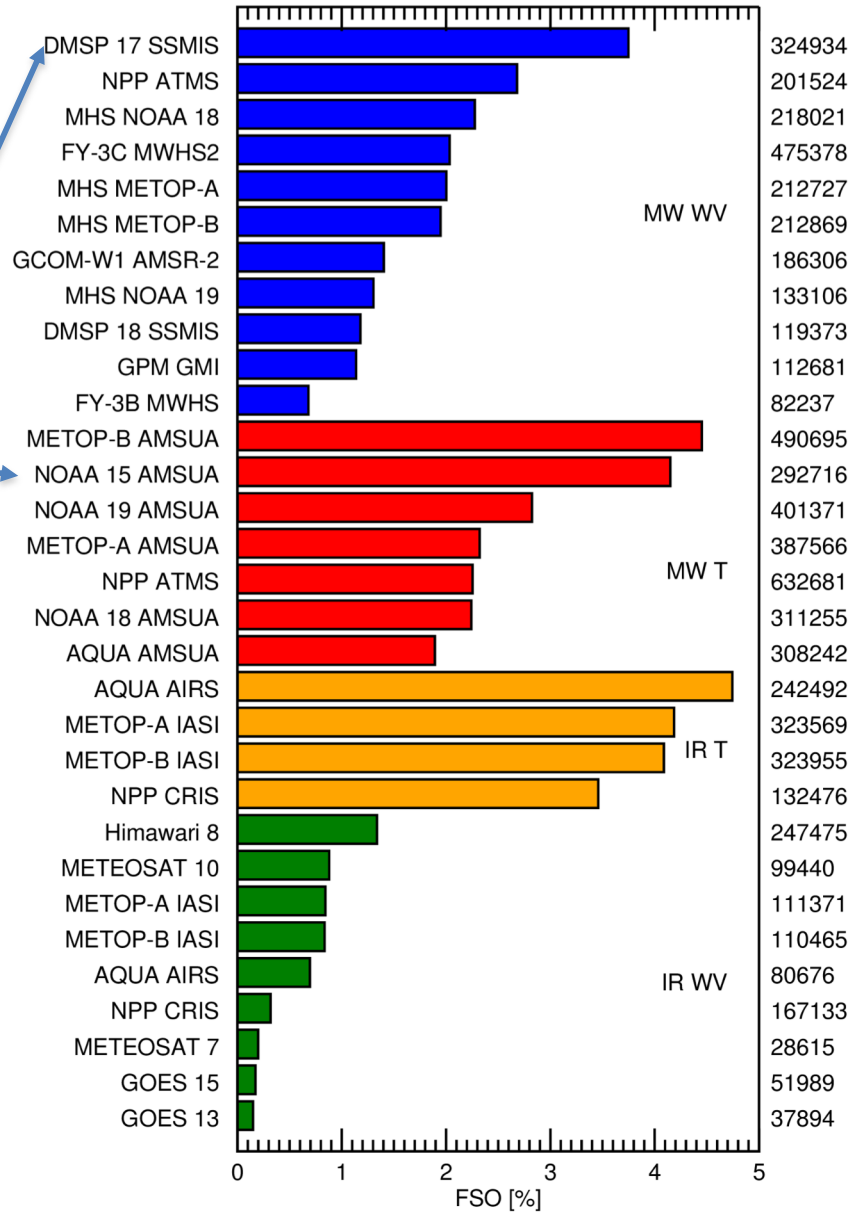
GOES  
2005



# State-of-the-Science: Importance of All-sky Radiances from ECMWF Operations

## FSO of satellite radiances, August 2016 (100% = full operational observing system)

An SSMIS (combining imaging and humidity sounding channels) is nearly equivalent to the best of the temperature-sounding AMSU-As



Microwave WV 20.4%

Microwave T 20.1%

Infrared T 16.5%

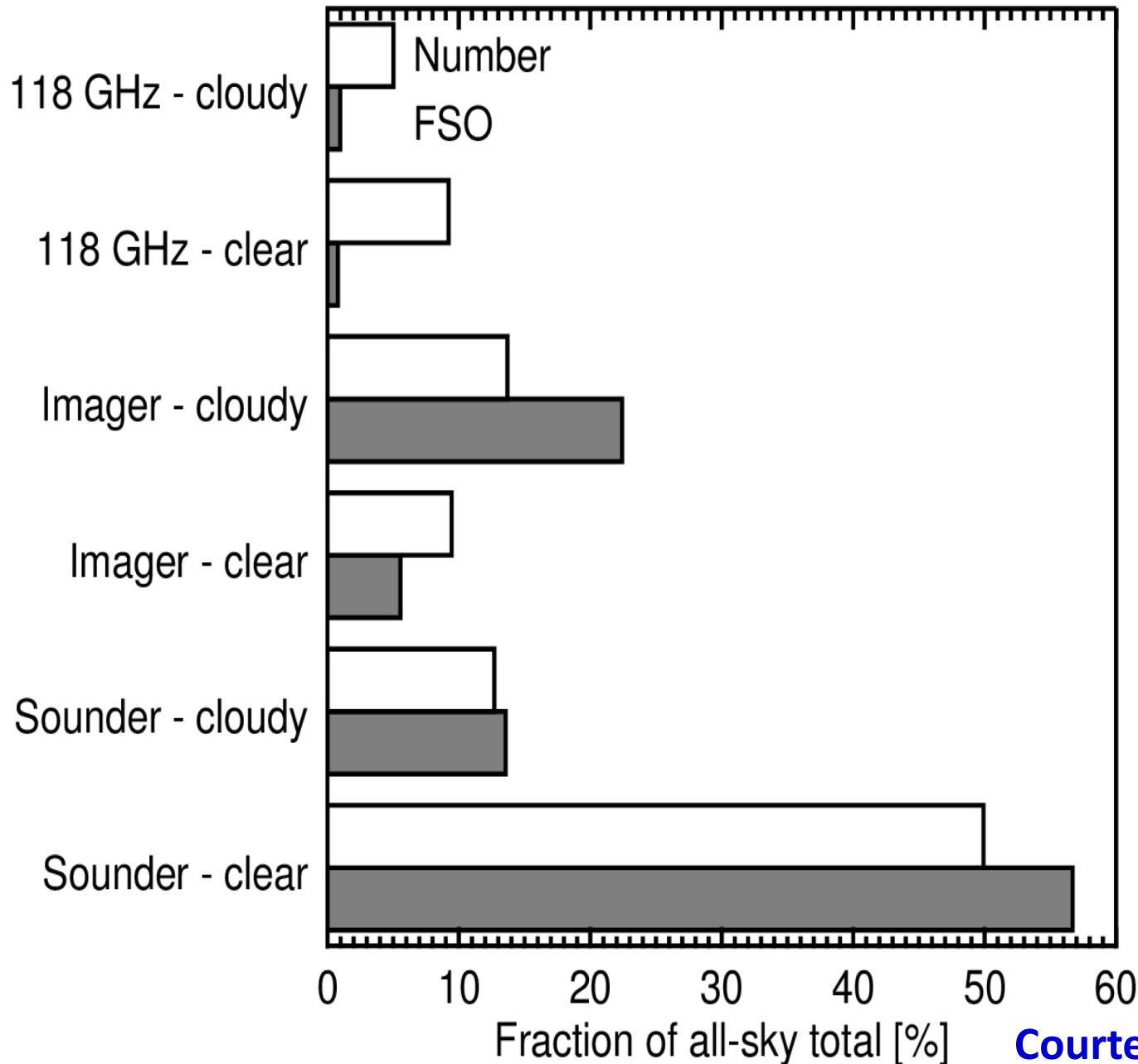
Infrared WV 5.4%

Amount of information coming from humidity/cloud/precipitation is equivalent to what's coming from T sounding

There is great potential to get more from the infrared water vapour channels by going to all-sky

# State-of-the-Science: Importance of Cloudy and Precipitating Scenes

FSO of satellite radiances, August 2016 (100% = 9 all-sky satellite radiance measurements)



**Imagers: Cloudy and precipitating scenes give more FSO than clear-sky scenes**

**Sounders: Cloudy and precipitating scenes have same per-obs FSO as clear-sky scenes**

**But don't forget all-sky gives a more optimal assimilation of "clear" scenes (going to all-sky at least doubled the forecast impact of MHS)**

**Courtesy of Alan Geer at ECMWF**



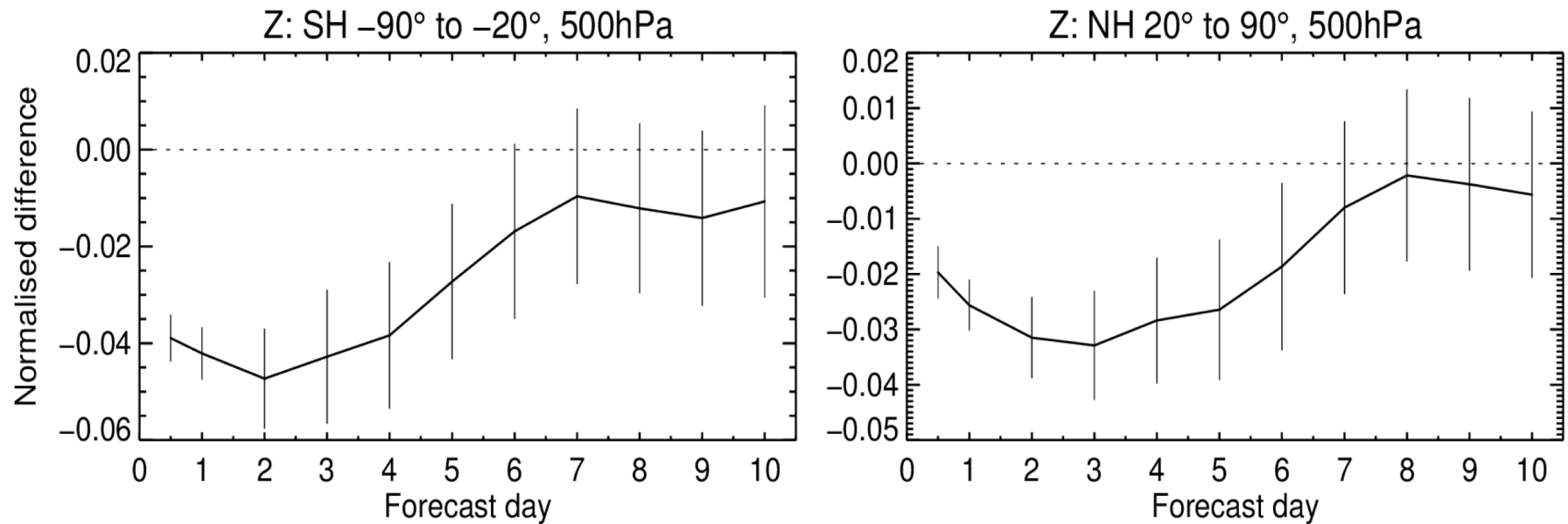
# State-of-the-Science: Importance of Cloudy and Precipitating Scenes

**High FSO => real improvements in medium-range synoptic forecasts**

***Mechanism:** 4D-Var can infer dynamical initial conditions from observed WV, cloud and precipitation*

26-Feb-2015 to 13-Sep-2015 from 380 to 399 samples. Verified against own-analysis.

Confidence range 95% with AR(2) inflation and Sidak correction for 4 independent tests



————— All-sky GMI, AMSR2, MHS and SSMIS – No allsky control

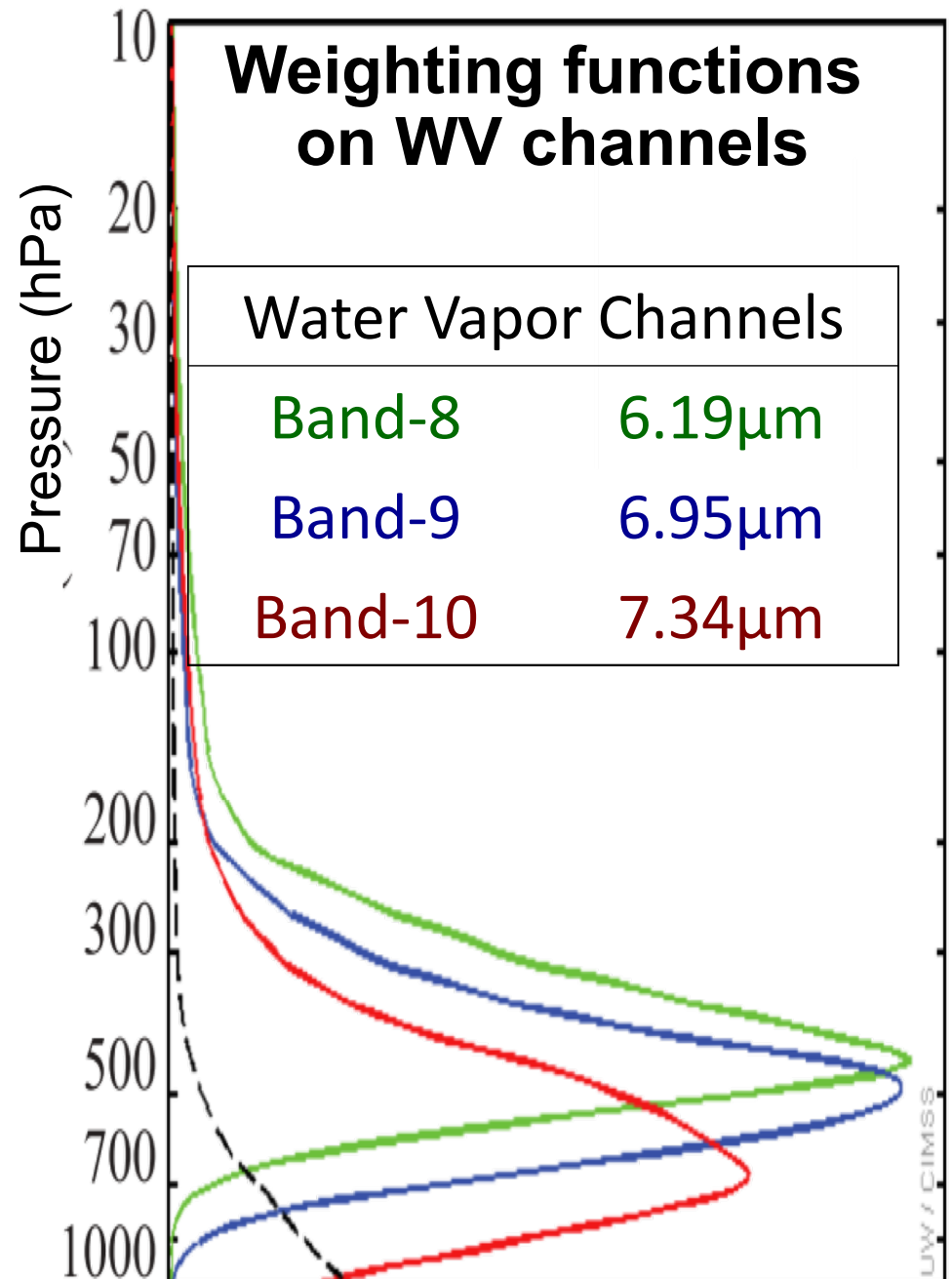
# New Generation of Geostationary IR Satellites



Launch Dates:

- Oct 2014 (Himawari-8, Japan)
- Nov 2016 (Himawari-9, Japan)
- **Nov 2016 (GOES-R/16, USA)**
- Dec 2016 (FY-4, China)
- **Mar 2018 (GOES-S/17, USA)**

Resolution: 10-15 minutes; 2-4 km

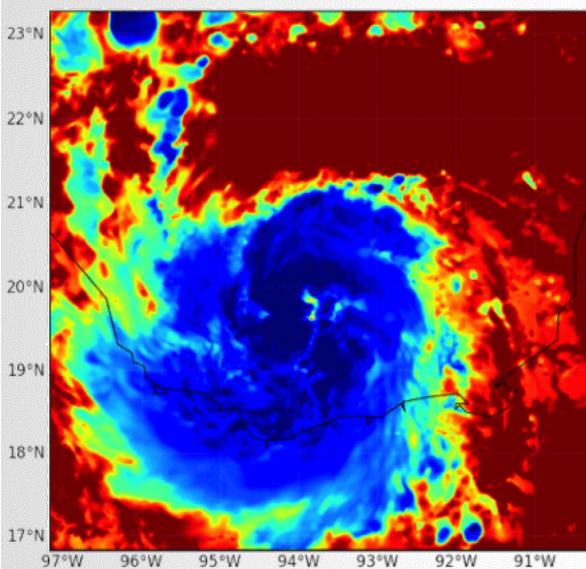




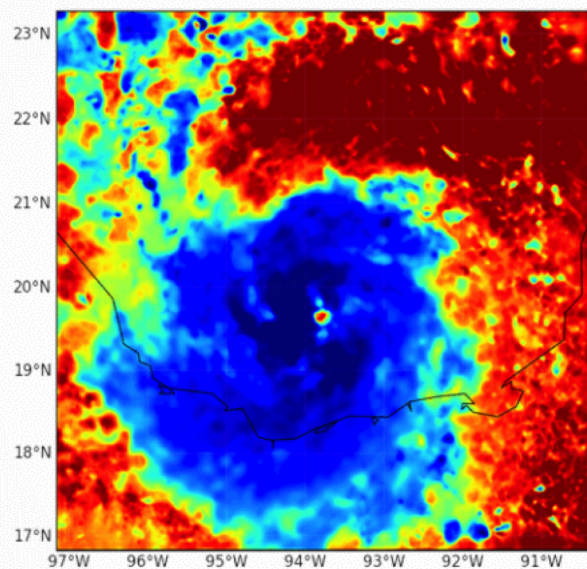
# EnKF Performance assimilating simulated radiance

Truth versus EnKF-analyzed Infrared Radiance of GOES-R ABI ch14 (11.2  $\mu\text{m}$ )

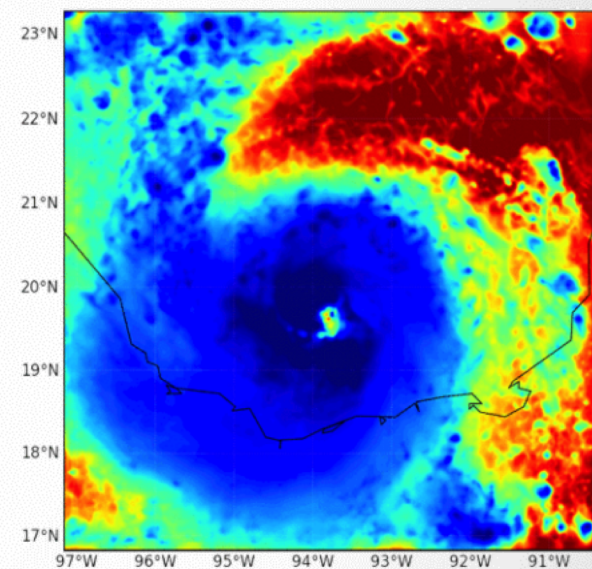
[2010-09-16\_22:00]



Verifying truth



EnKF analysis  
with radiance &  
minimum SLP



EnKF analysis  
with minimum  
SLP only



(Zhang, Minamide & Clothiaux, 2016 GRL)



# Adaptive Observation Error Inflation (AOEI)

Problem: erroneous analysis increments

If Model (**clear** / **cloudy**)  $\neq$  Observation (**cloudy** / **clear**)

$$\text{In updating SLP, } \frac{12.5 [hPa \times K]}{3^2 + 5^2 [K^2]} \times 40 [K] \sim \mathbf{15 [hPa]}$$

**AOEI: inflating observation error variance**

$$\sigma_{o-AOEI}^2 = \max \left\{ \sigma_o^2, [y_o - h(x_b)]^2 - \sigma_{h(x_b)}^2 \right\}$$

$$\text{With AOEI, } \frac{12.5 [hPa \times K]}{40^2 [K^2]} \times 40 [K] \sim \mathbf{0.3 [hPa]}$$

AOEI

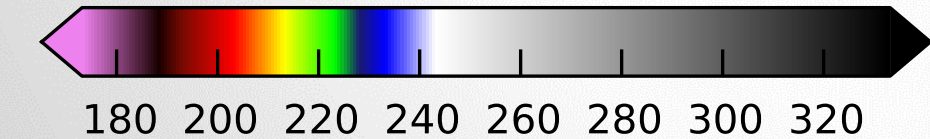
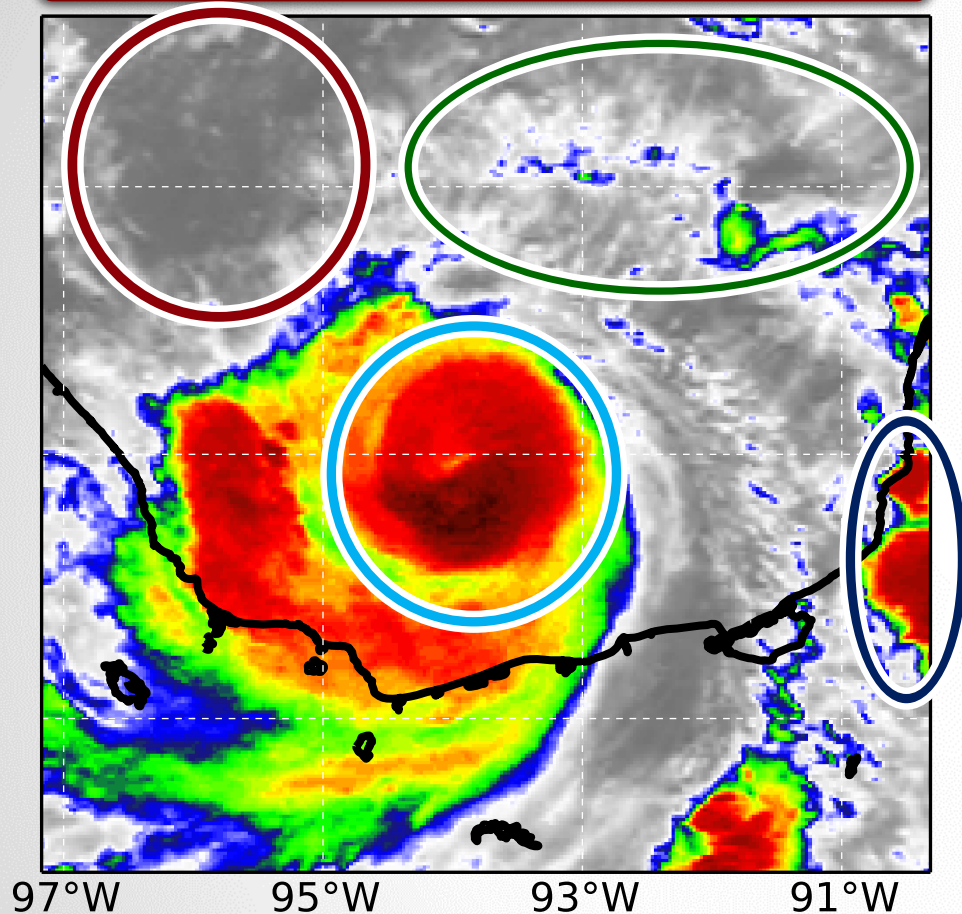
suppresses erroneous analysis increments,  
relieves the issues of representativeness & sampling,  
& contributes to maintaining balance.

(Minamide & Zhang, MWR, 2017)



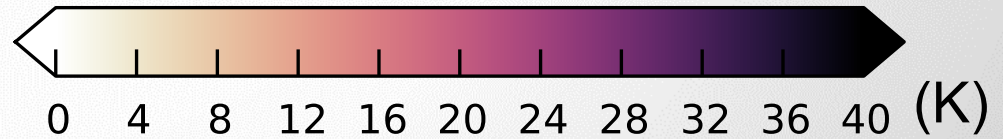
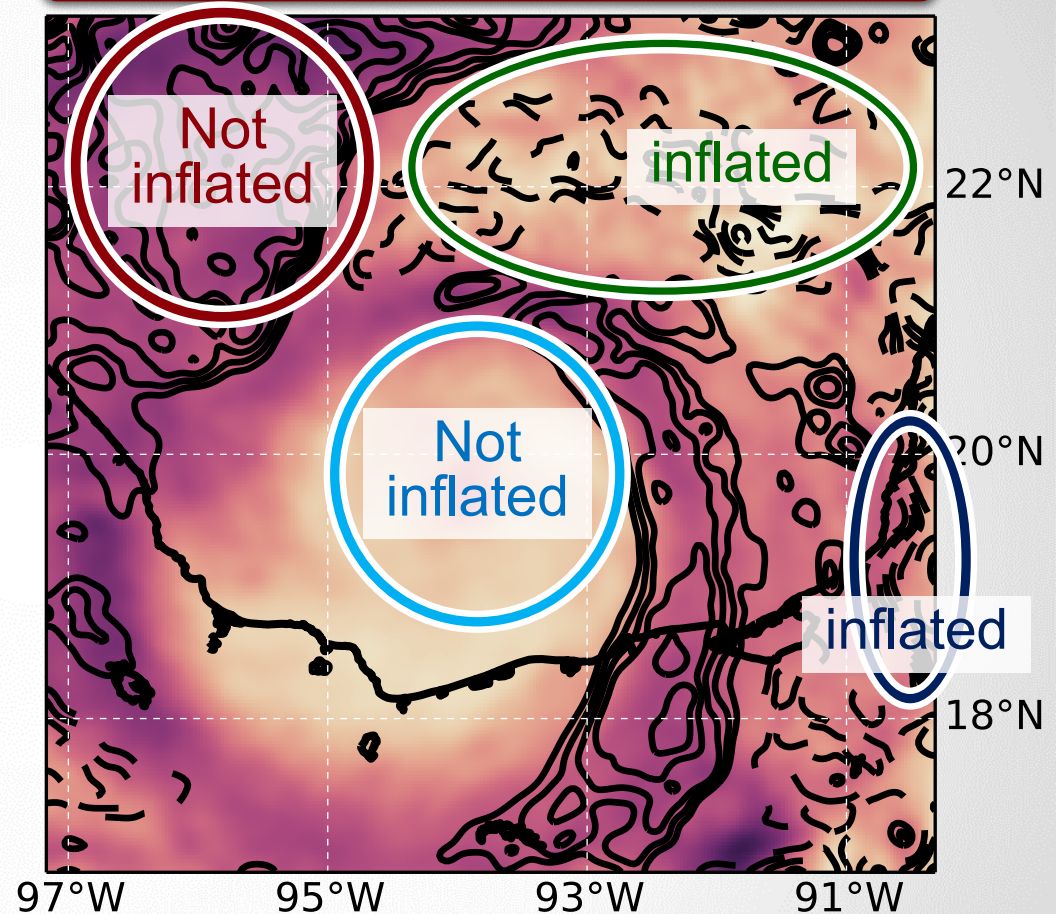
# Adaptive Observation Error Inflation (AOEI)

## GOES-13 Observation



Color: observed brightness temperature

## Background Error / Spread



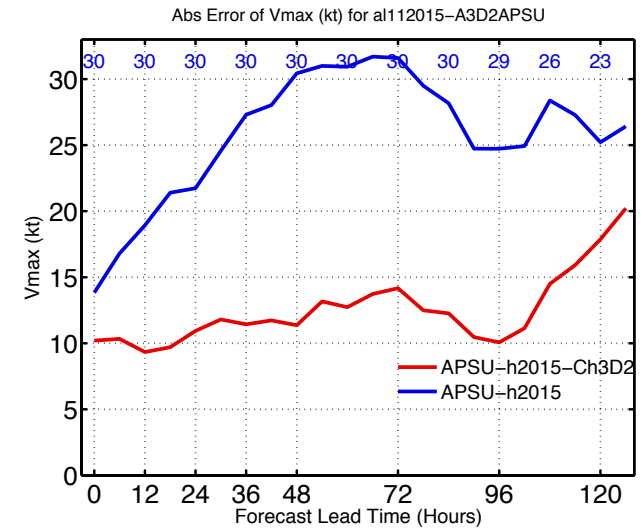
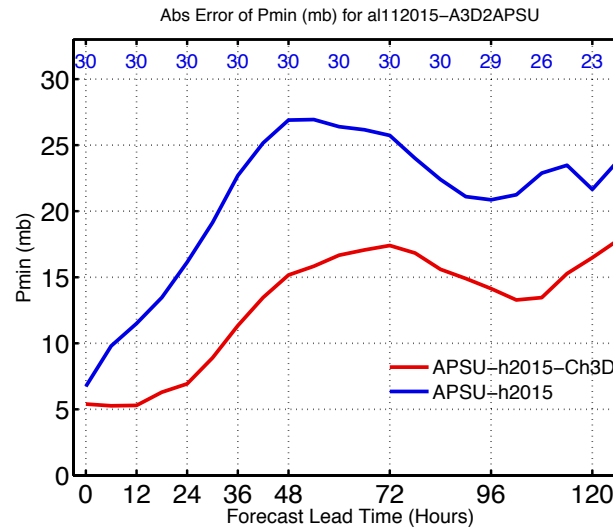
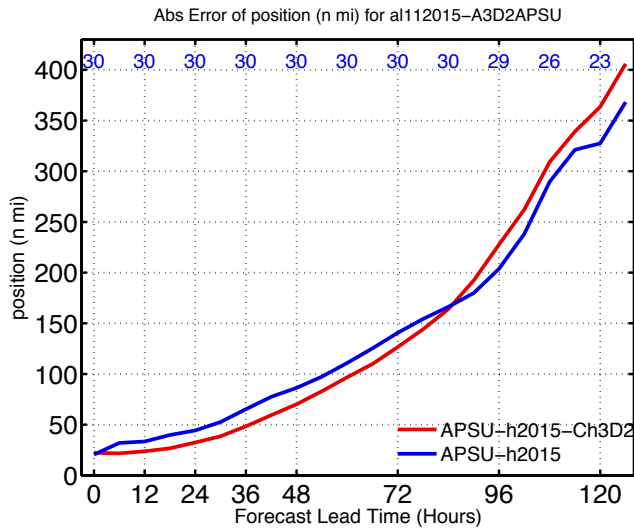
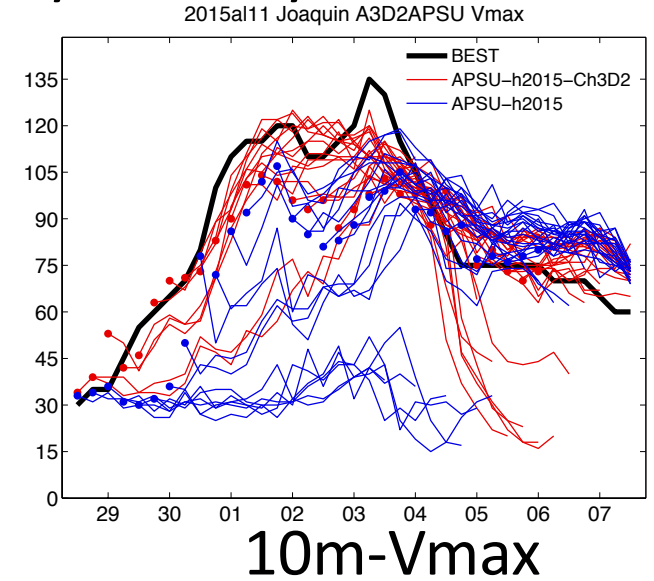
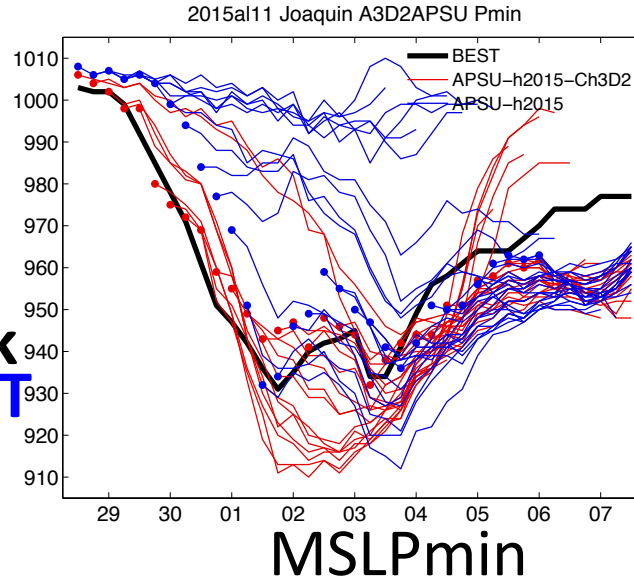
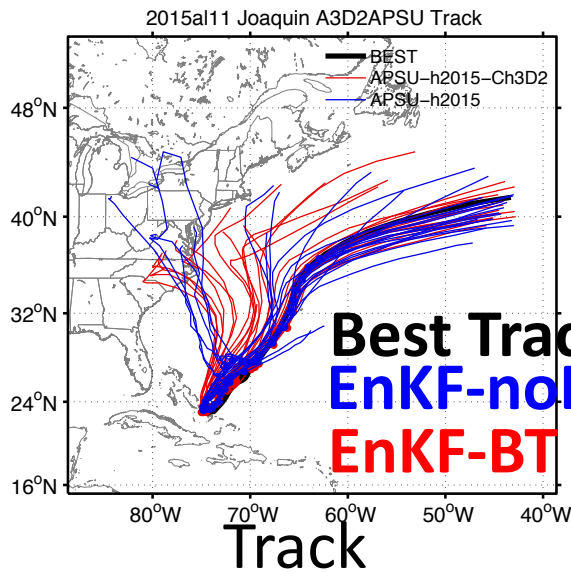
Contour: Background error

Color: ensemble spread

# Convection-permitting EnKF Assimilation of All-sky Radiance: GOES-13

Deterministic Forecasts for Hurricane Joaquin (2015) : w/ & w/o Radiance

Deterministic forecasts from EnKF analysis every 6 hours



Averaged absolute error reference to Best Track

(Lei, Weng, Meng and Zhang, in internal review)



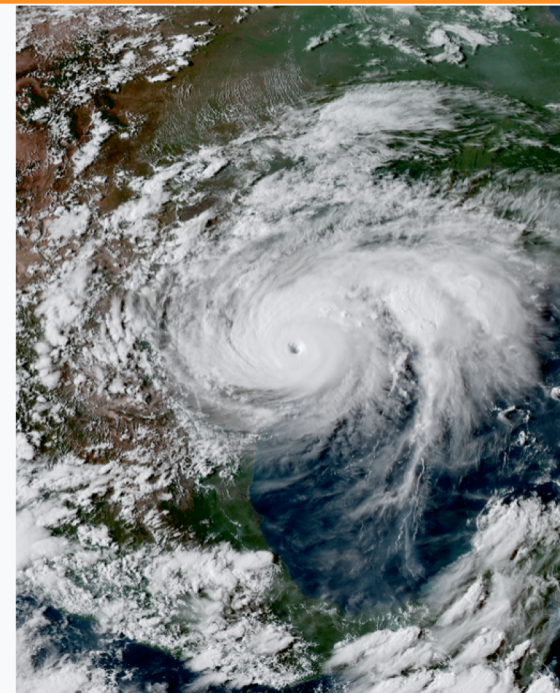
# Hurricane Harvey (2017): first GOES-R full disk

**Hurricane Harvey** is tied with [Hurricane Katrina](#) as the costliest [tropical cyclone](#) on record, inflicting \$125 billion (2017 USD) in damage, primarily from catastrophic rainfall-triggered flooding in the [Houston metropolitan area](#). It was the first [major hurricane](#)<sup>[nb 1]</sup> to make [landfall](#) in the [United States](#) since [Wilma](#) in 2005, ending a record 12-year span in which no hurricanes made landfall at such an intensity in the country. In a four-day period, many areas received more than 40 inches (1,000 mm) of rain as the system slowly meandered over eastern Texas and adjacent waters, causing unprecedented flooding. With peak accumulations of 60.58 in (1,539 mm), Harvey was the [wettest tropical cyclone on record in the United States](#). The resulting floods inundated hundreds of thousands of homes, displaced more than 30,000 people, and prompted more than 17,000 rescues.

The eighth [named storm](#), third [hurricane](#), and the first major hurricane of the extremely active [2017 Atlantic hurricane season](#), Harvey developed from a [tropical wave](#) to the east of the [Lesser Antilles](#), reaching [tropical storm](#) status on August 17. The storm crossed through the [Windward Islands](#) on the following day, making landfall on the southern end of [Barbados](#) and a second landfall on [Saint Vincent](#). Upon entering the [Caribbean Sea](#), Harvey began to weaken due to moderate [wind shear](#), and degenerated into a tropical wave north of [Colombia](#), early on August 20. The remnants were monitored for regeneration as it continued west-northwestward across the Caribbean and the [Yucatán Peninsula](#), before redeveloping over the [Bay of Campeche](#) on August 23. Harvey

## Hurricane Harvey

**Category 4 major hurricane (SSHWS/NWS)**



Hurricane Harvey near peak intensity prior to landfall in southern [Texas](#) on August 25

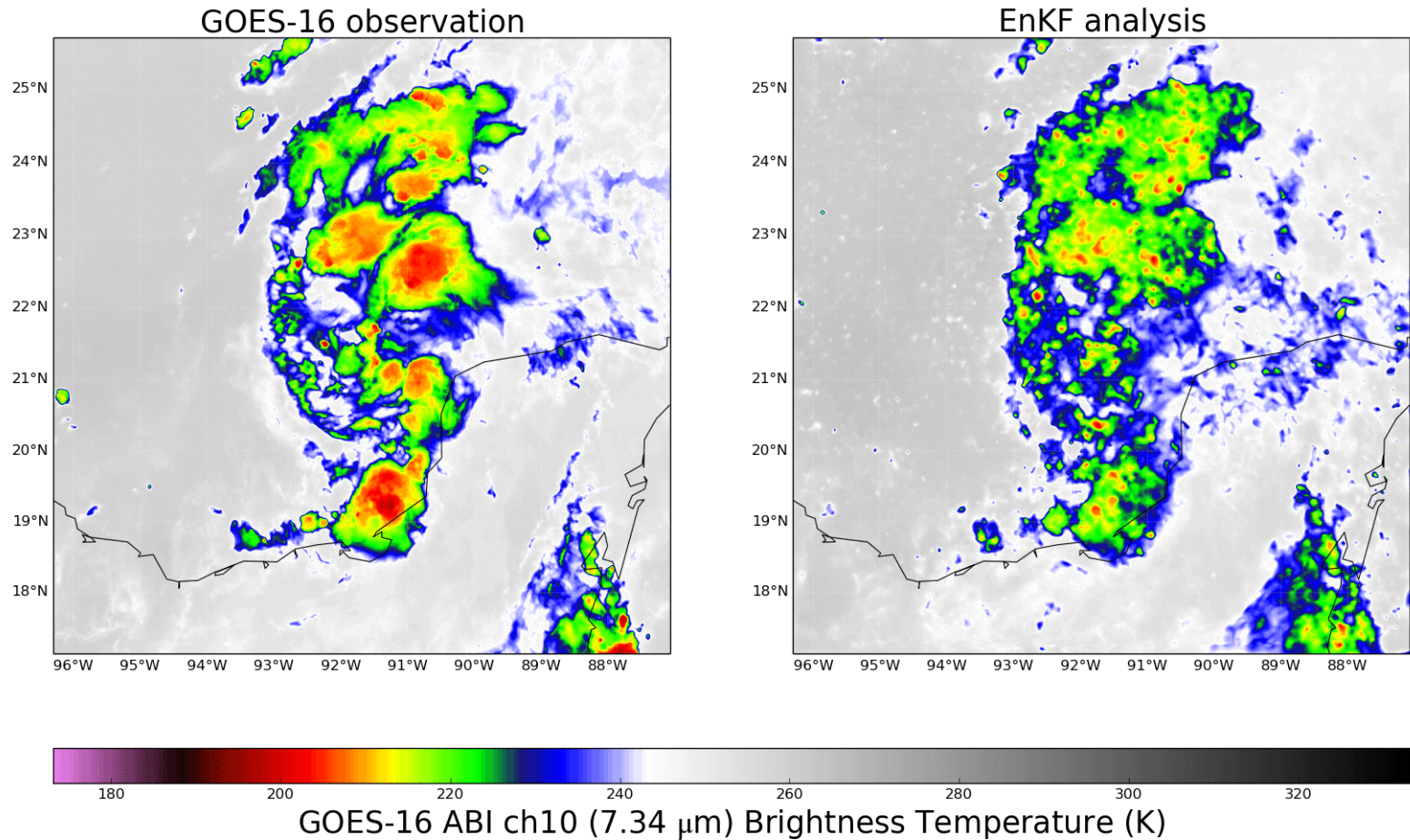
<b>Formed</b>	August 17, 2017
<b>Dissipated</b>	September 2, 2017 ( <a href="#">Extratropical</a> after September 1)
<b>Highest winds</b>	<i>1-minute sustained:</i> 130 mph (215 km/h)
<b>Lowest pressure</b>	937 <a href="#">mbar (hPa)</a> ; 27.67 <a href="#">inHg</a>
<b>Fatalities</b>	68 direct, 39 indirect
<b>Damage</b>	\$125 billion (2017 <a href="#">USD</a> ) ( <a href="#">Tied as costliest tropical cyclone</a> )



# Assimilating All-sky GOES-R Radiances: Harvey (2017)

PSU WRF-EnKF,  $\Delta x=3\text{km}$ , ensemble size=60, channel 8, every 1h

## Independent observations vs. EnKF analysis of channel 10

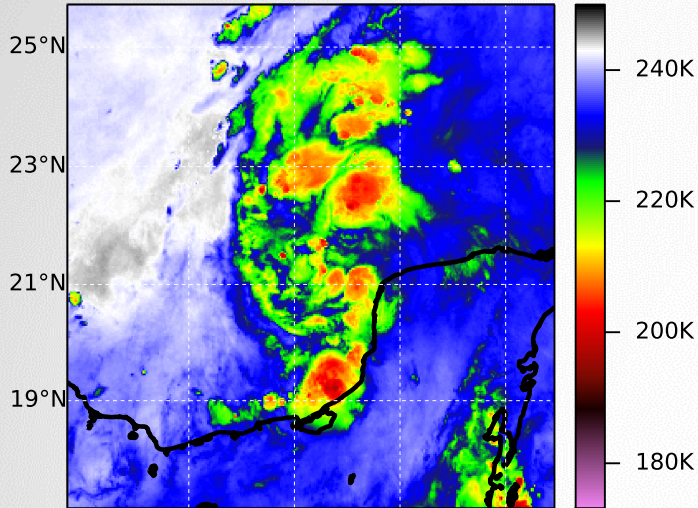


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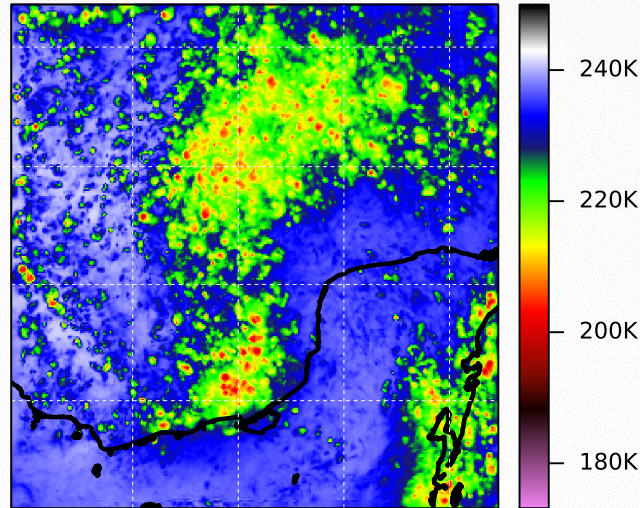


# Adaptive Background Error Inflation (ABEI)<sup>14</sup>

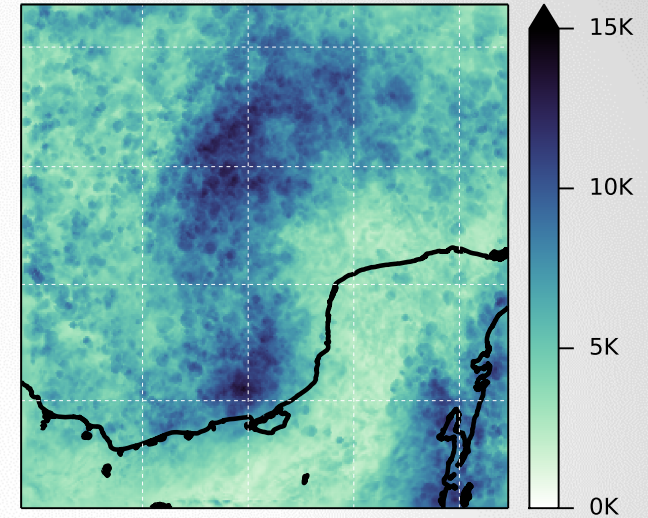
(a) Observation:  $Y_o$



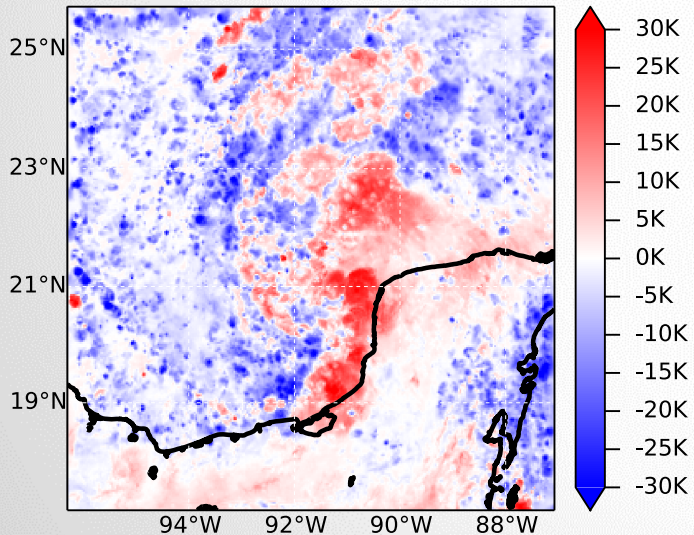
(b) EnKF background:  $h(x_b)$



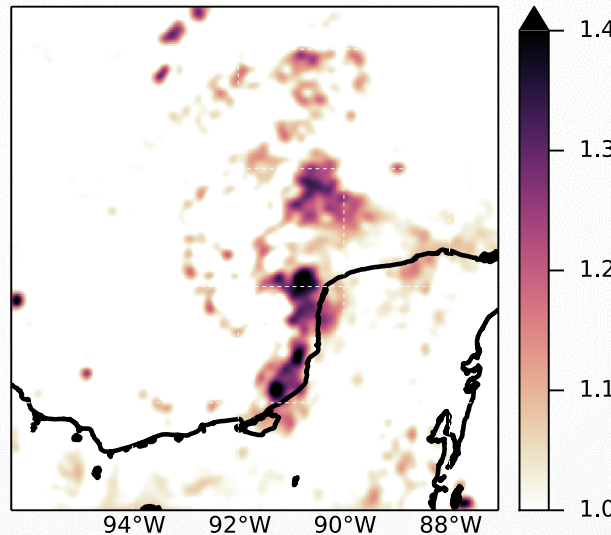
(c) Ensemble spread:  $\sigma_{h(x_b)}$



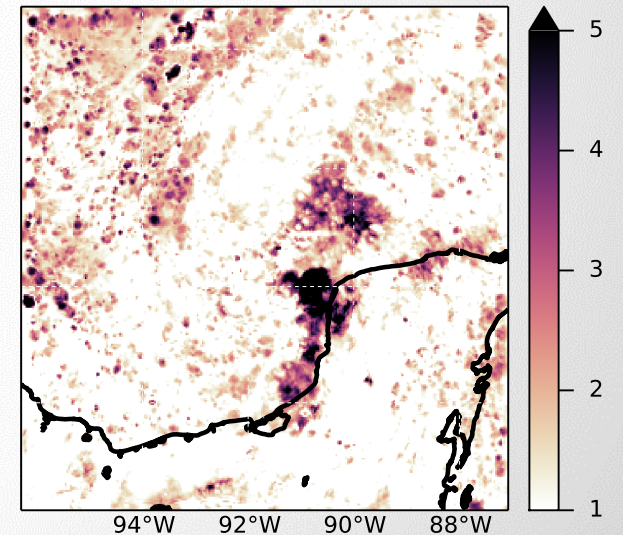
(d) Asymmetric cloud parameter:  $C_A$



(e) Inflation factor:  $\lambda_{(C_A)}$



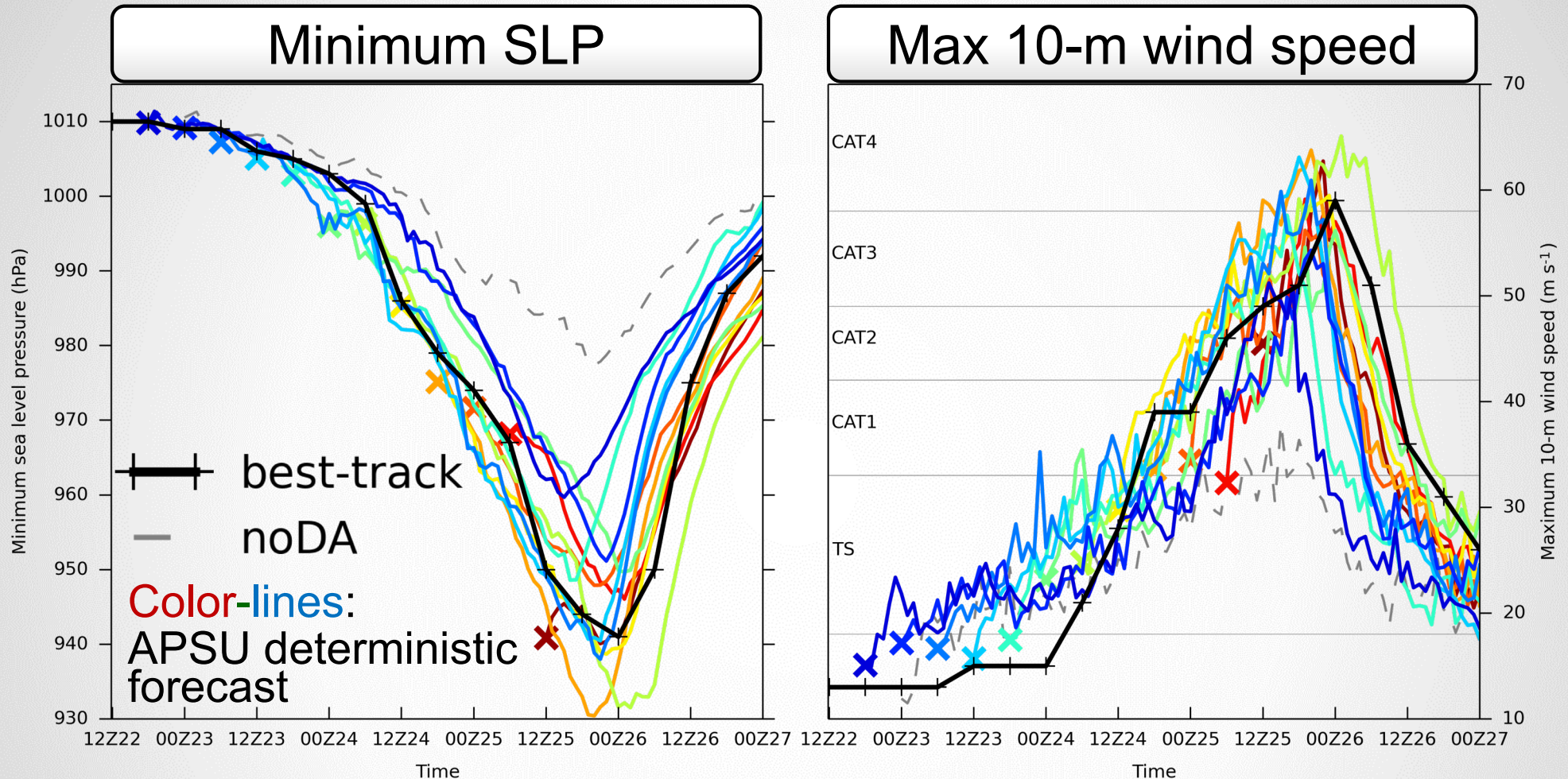
(f) Individual  $CR_y: \frac{|Y_o - h(x_b)|}{\sigma_{h(x_b)}}$



(Minamide & Zhang, MWR, 2018 in review)



# EnKF Performance on deterministic forecast

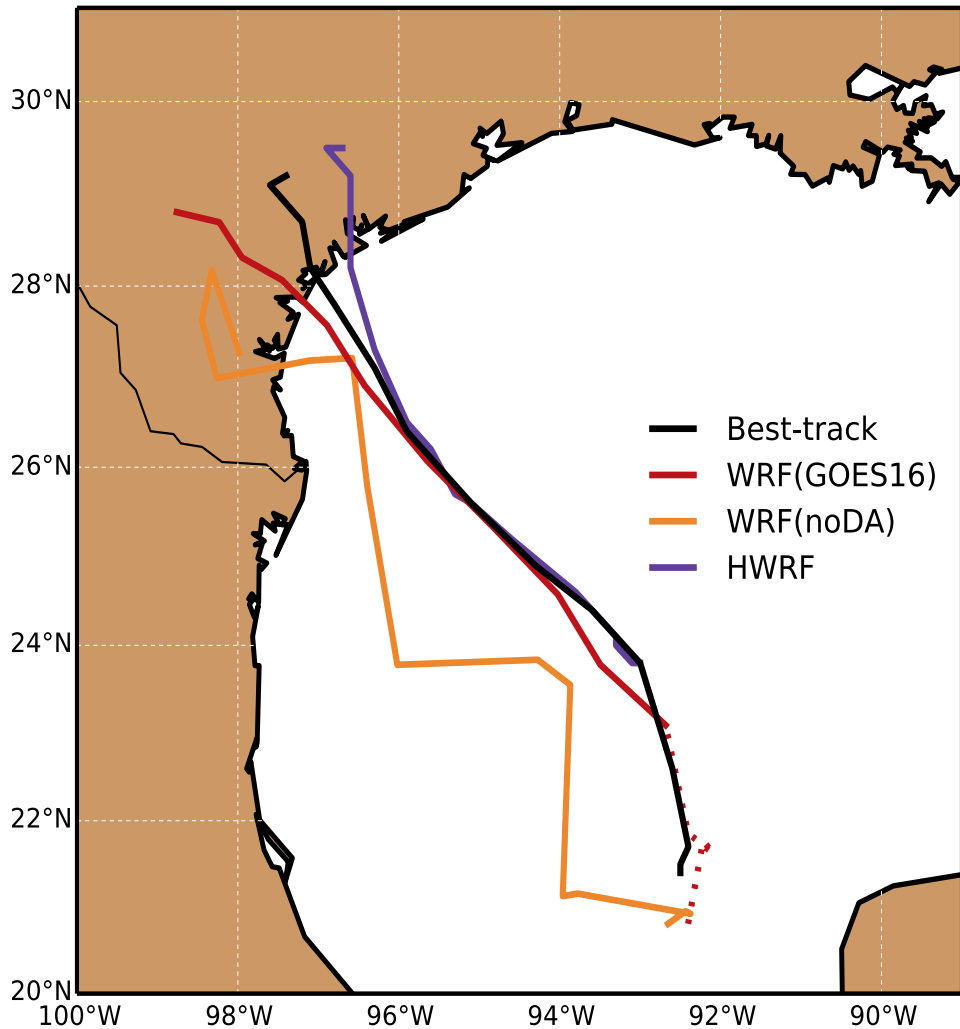


- All deterministic forecast accurately capture the RI of Harvey, which is largely improved from noDA forecast.

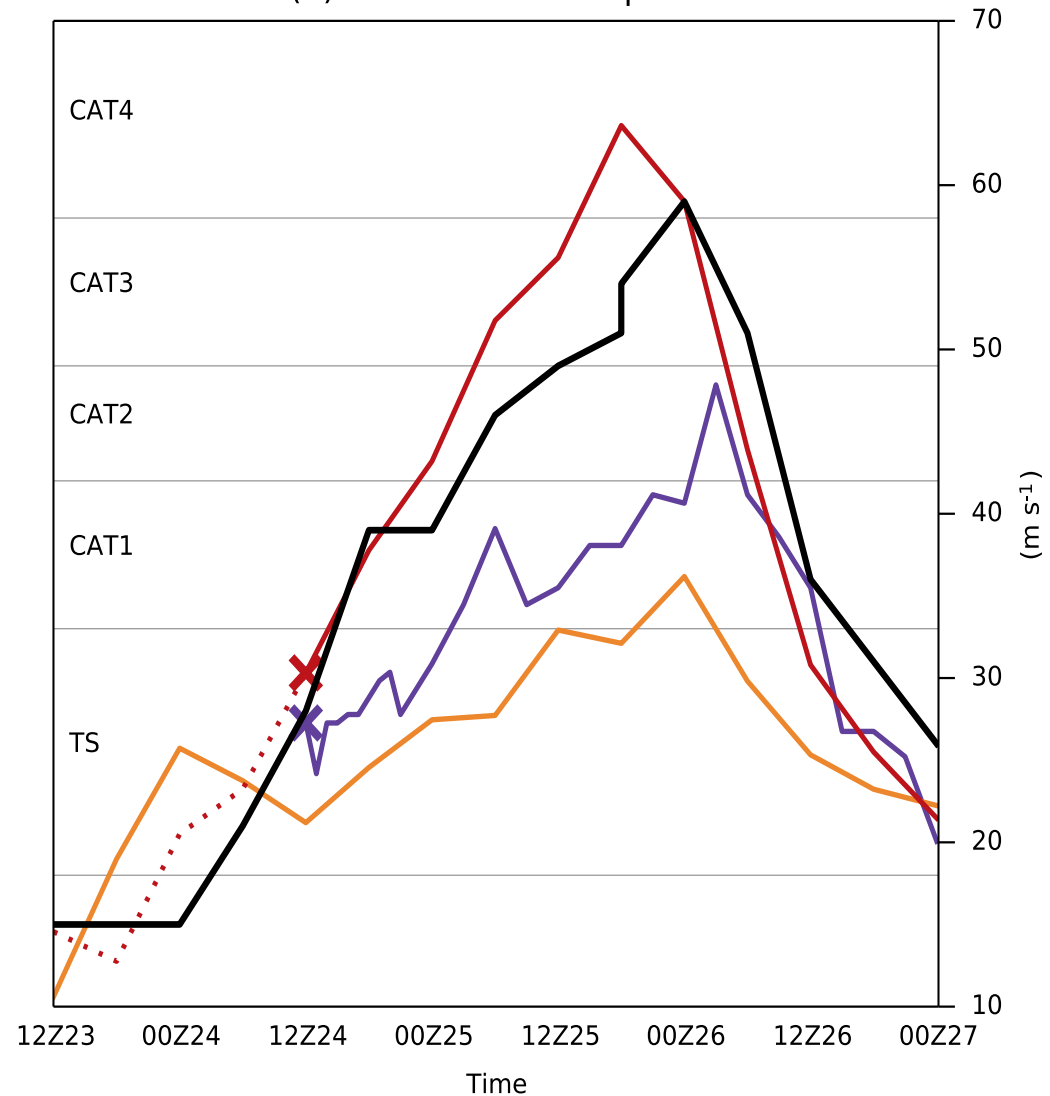
*(Masashi Minamide's Ph.D. Dissertation research)*

# PSU WRF-EnKF Harvey Forecast with GOES-R Assimilation in comparison with *WRF(NoDA)*, *operational HWRF* & *best track*

(a) TC Track



(b) Maximum wind speed



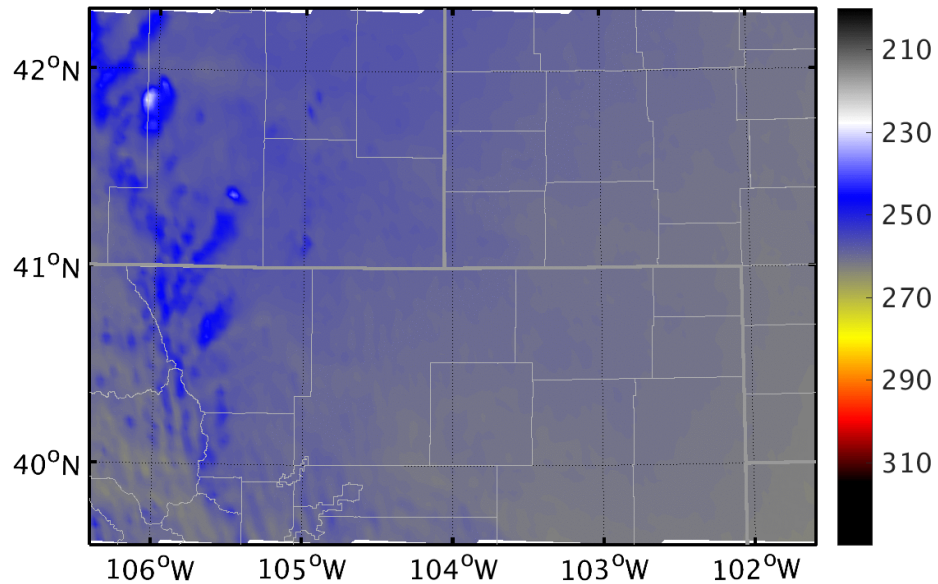
*Research Supported by ONR, NASA, NOAA and NSF*



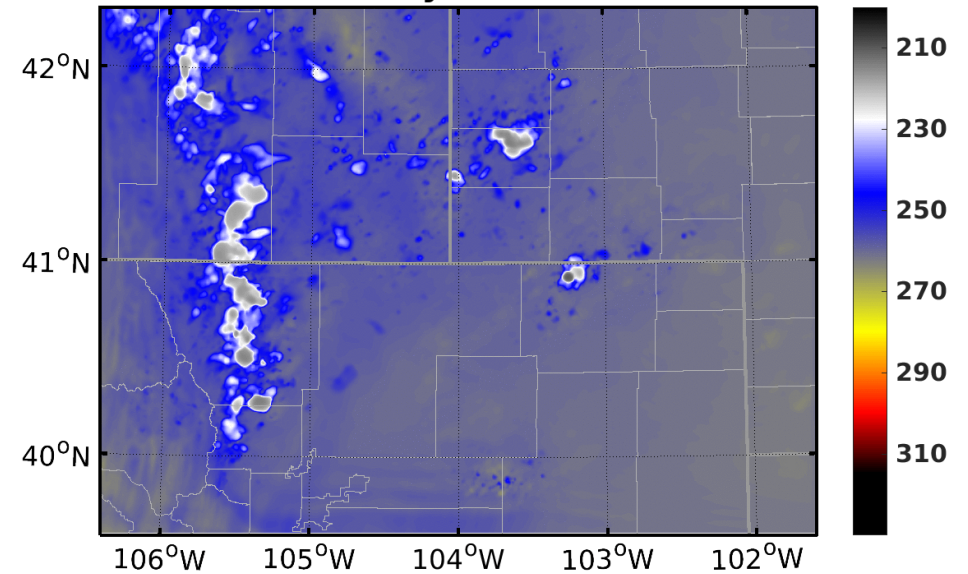
# GOES-R Assimilation for Tornadic Storms

*(see Y. Zhang's talk later this session)*

GOES-16 CH-10: 2017-06-12T18:57:19.0Z

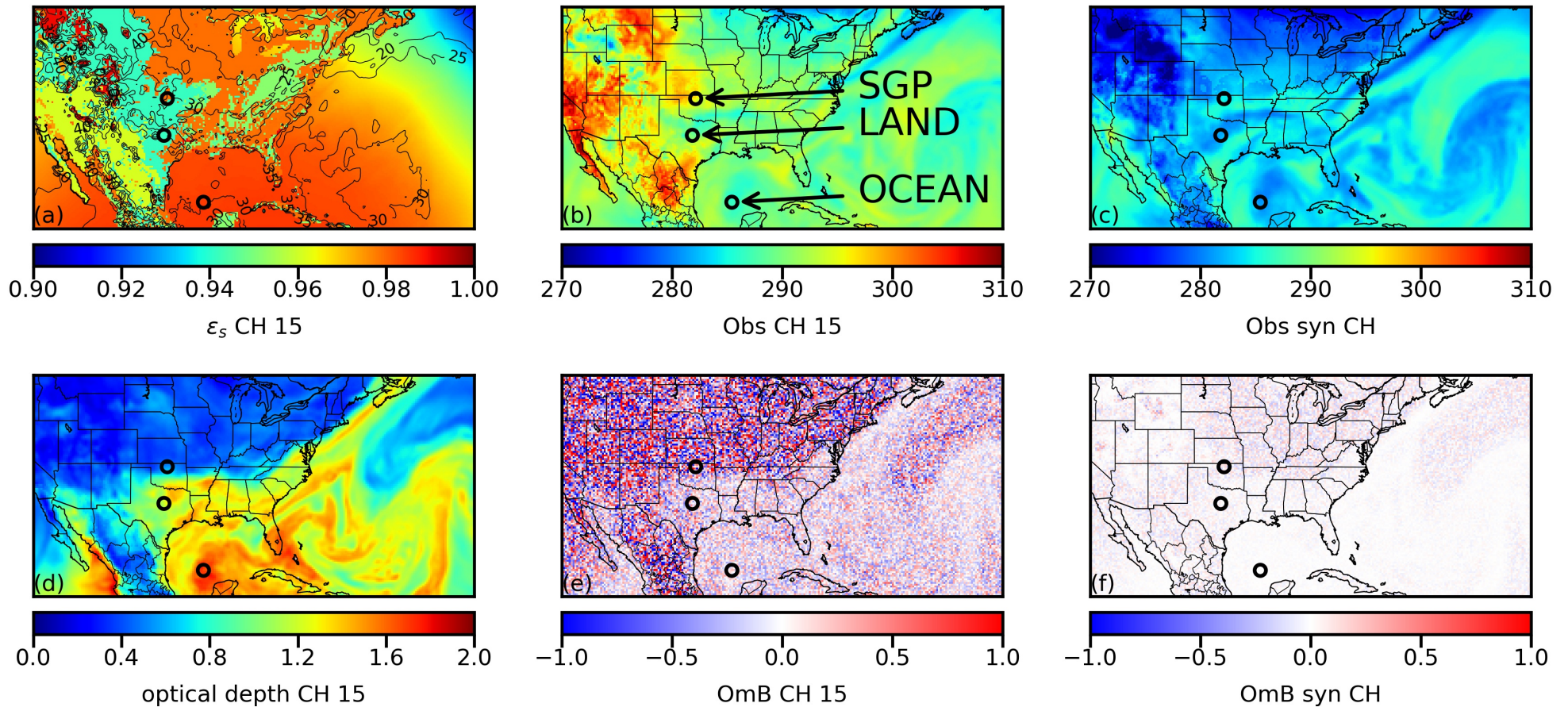


ENKF CH10 Analysis: 201706121900

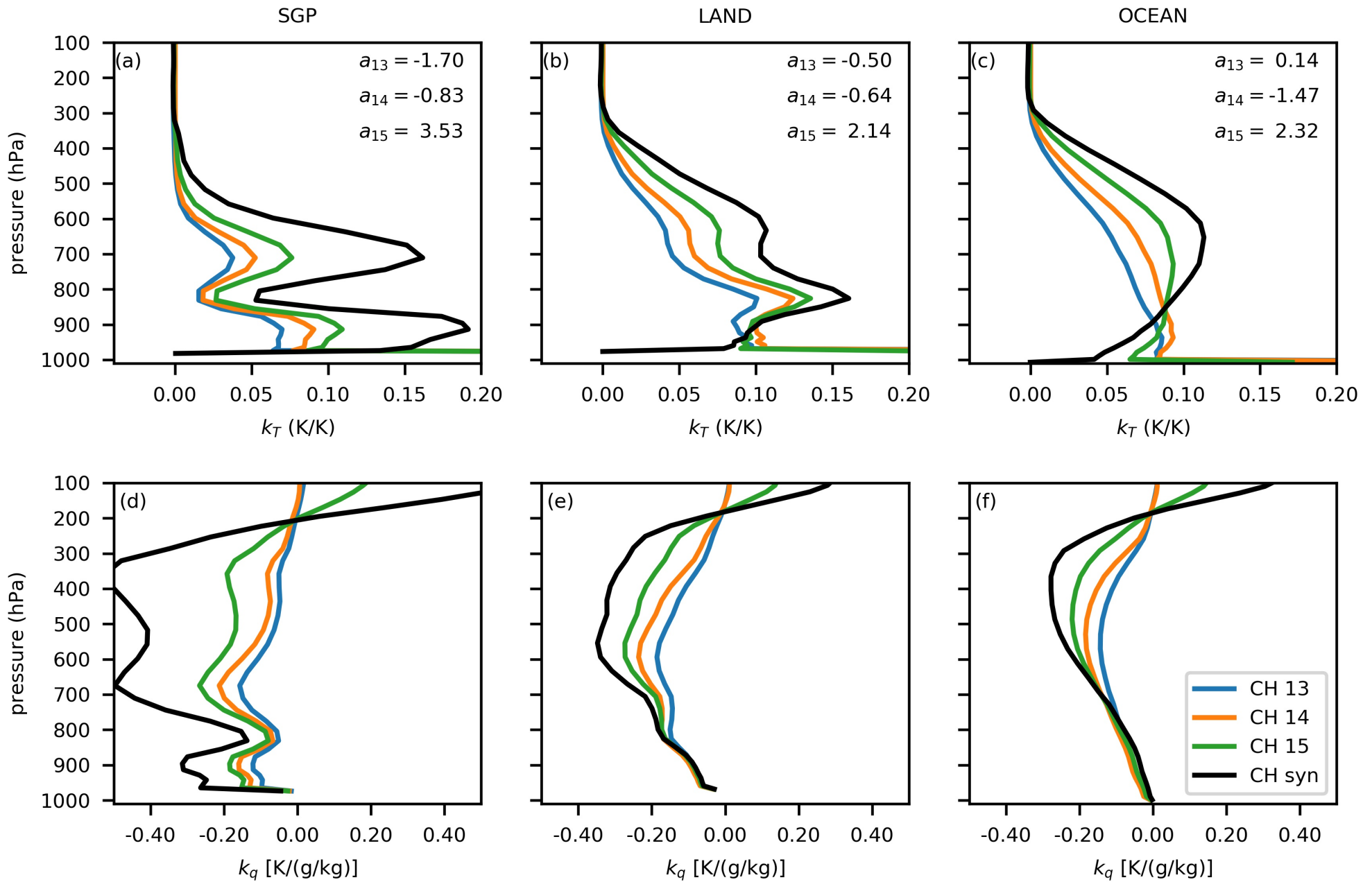


# Beyond simple data thinning, channel selection and superrobbing

*Channel-synthesizing for reducing uncertainties in satellite radiative transfer modeling*

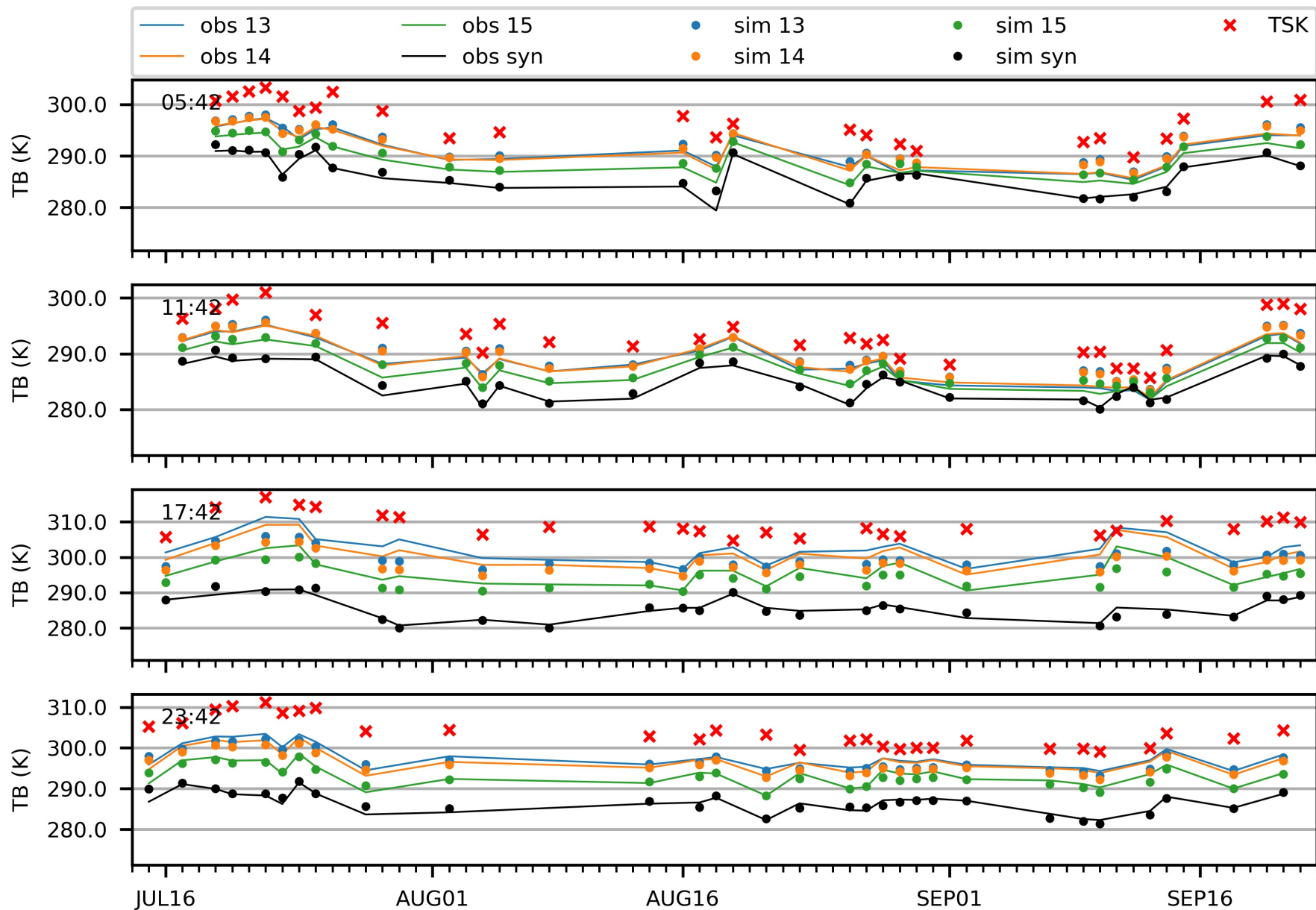


# channel-synthesizing for reducing uncertainties in satellite radiative transfer modeling

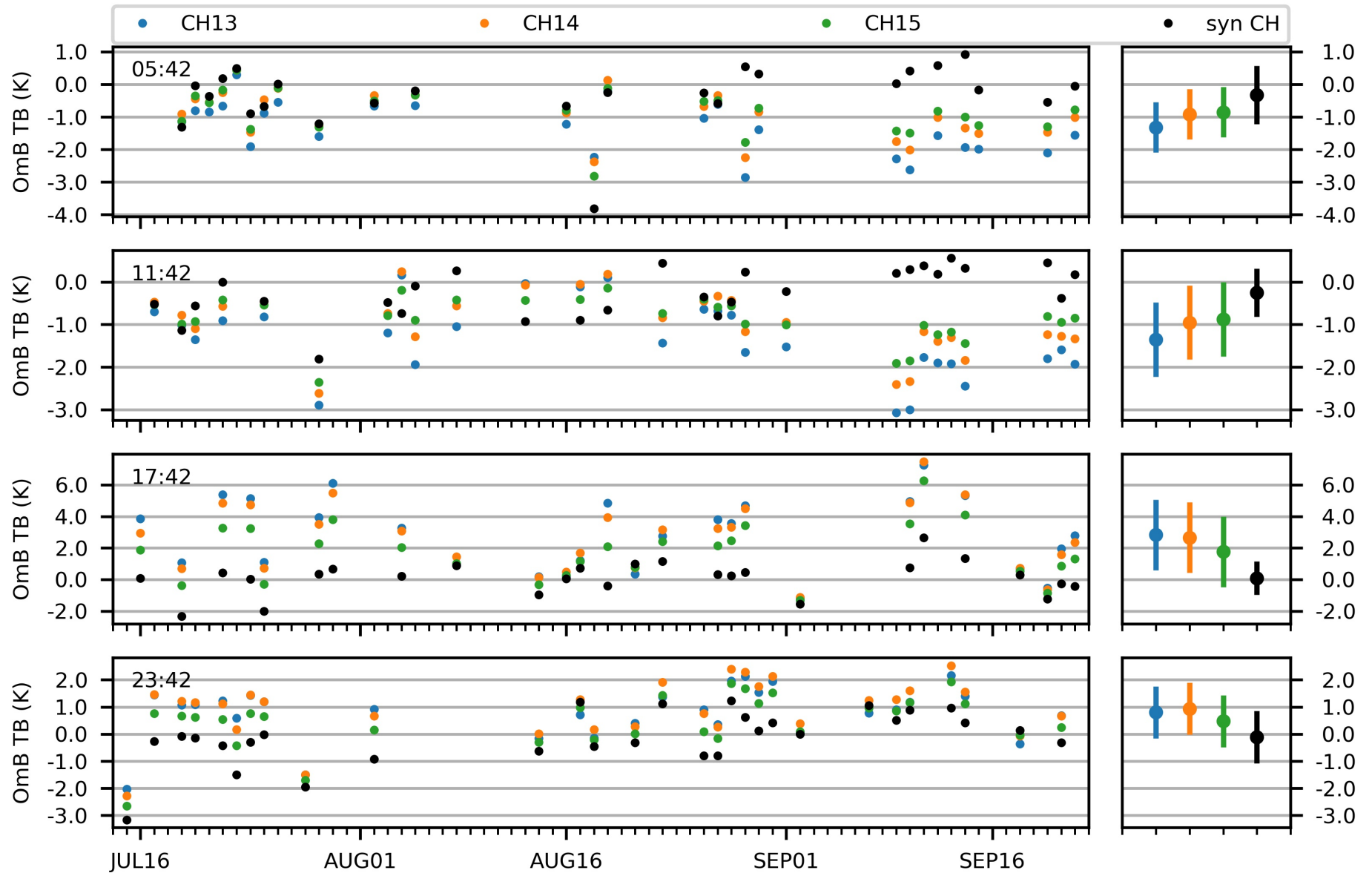




# channel-synthesizing for reducing uncertainties in satellite radiative transfer modeling

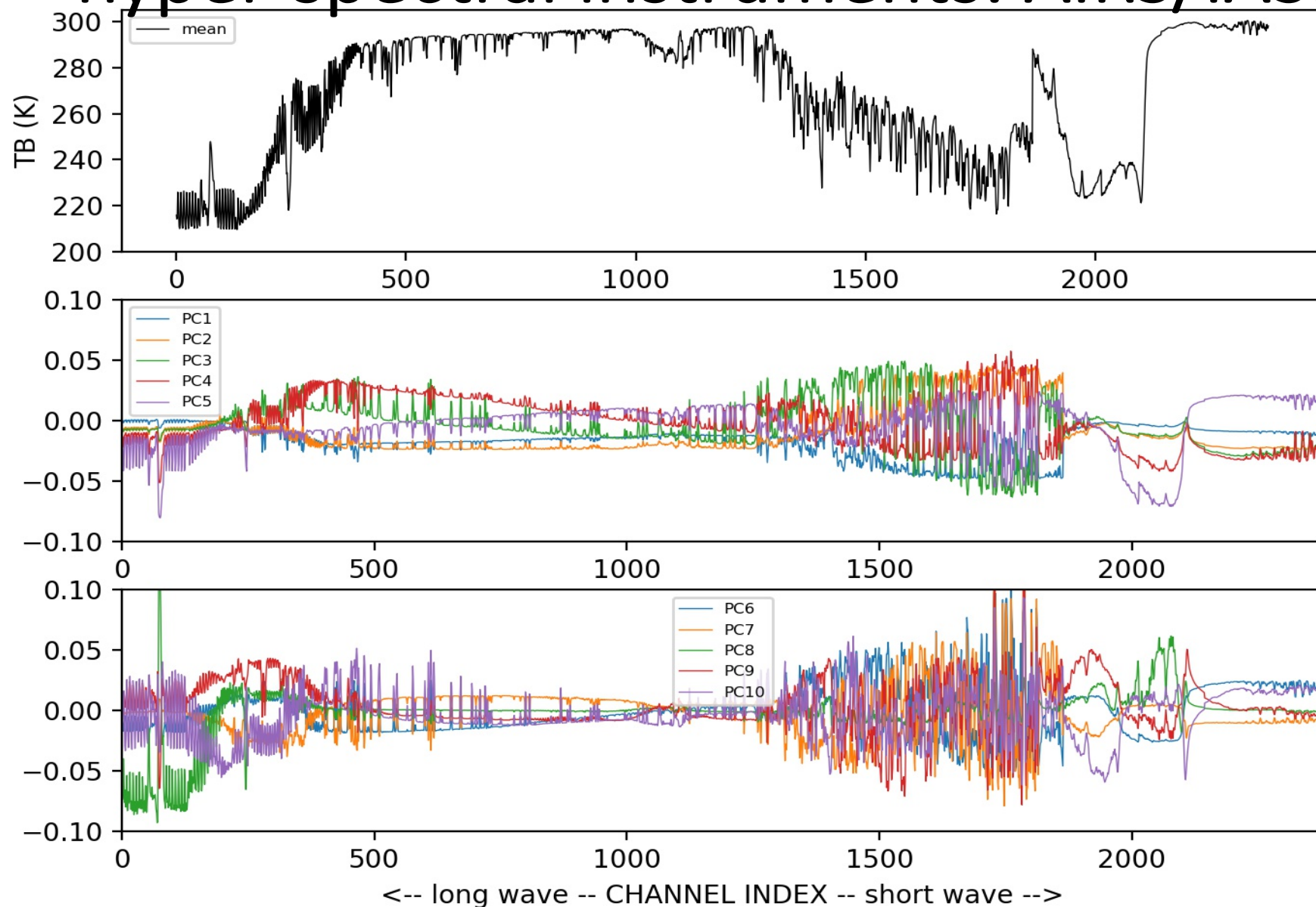


# channel-synthesizing for reducing uncertainties in satellite radiative transfer modeling



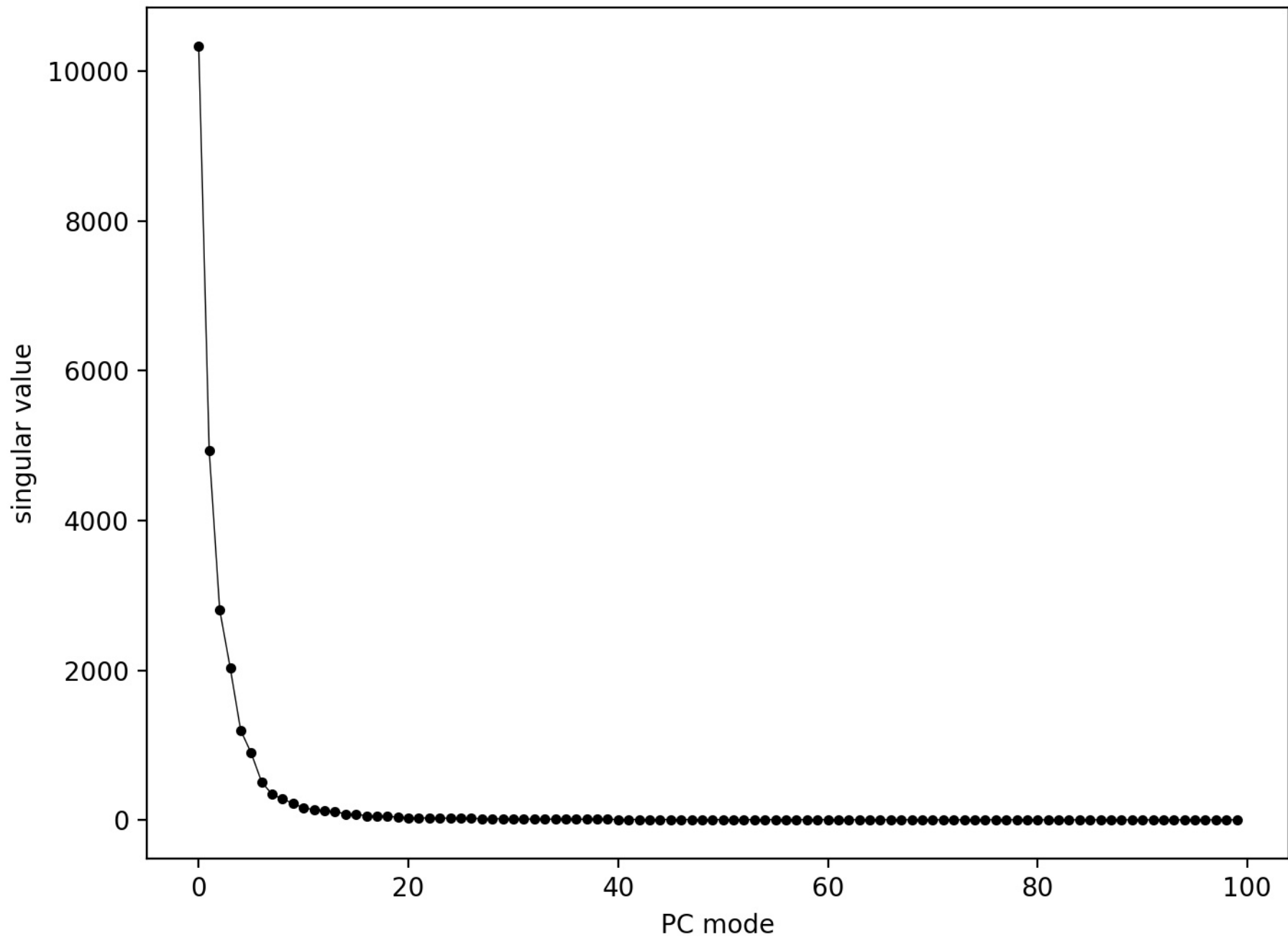


# Principal component based RTM and DA for hyper-spectral instruments: AIRS/IASI

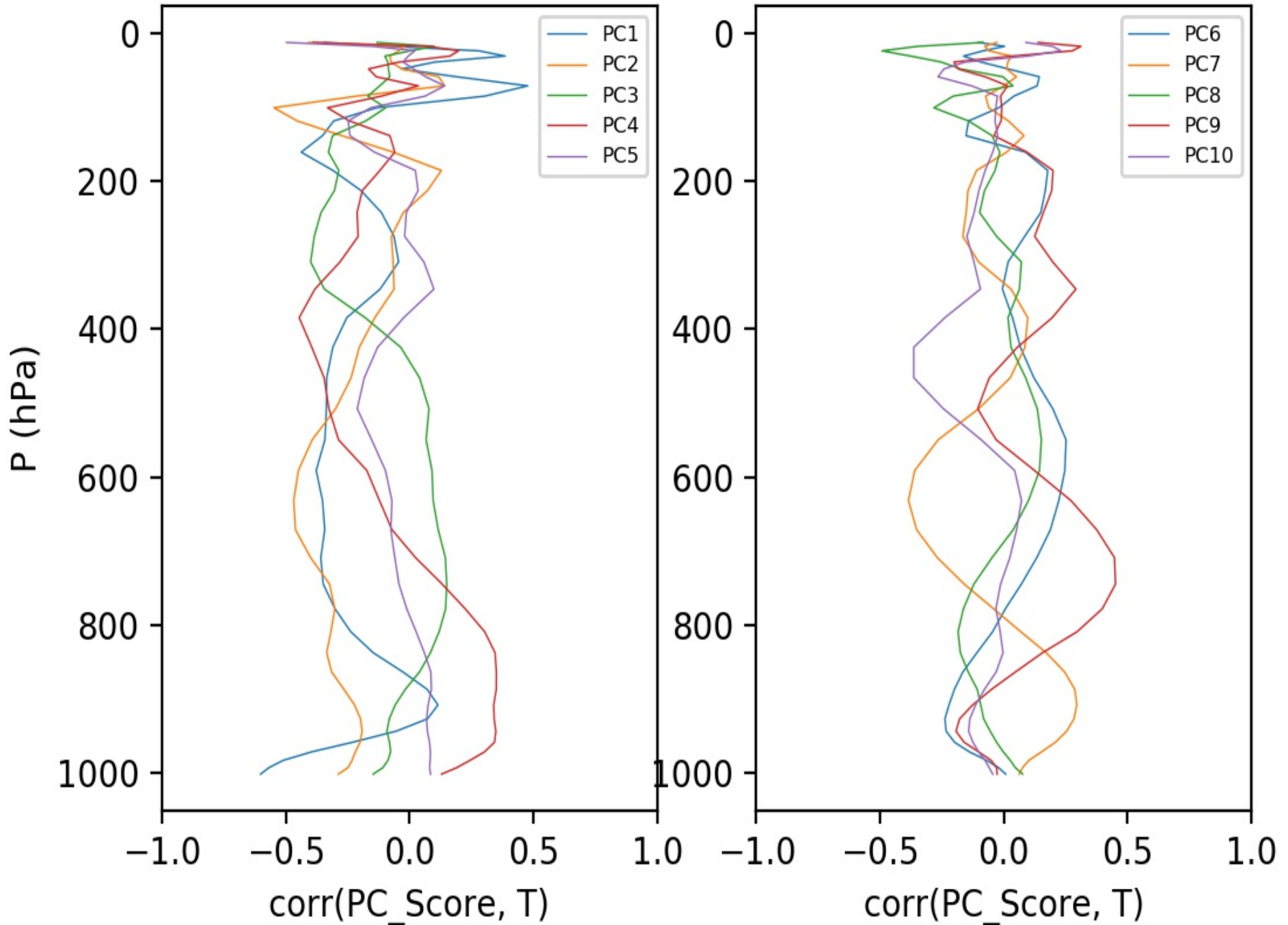


Ongoing work by Yinghui Lu

# Singular values corresponding to the PC modes (singular vectors of SVD)



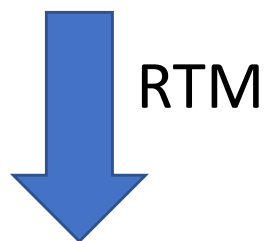
# “Climatological” correlations of leading PC modes to temperature and Moisture



# Work Plan: Principal component based RTM and DA for hyper-spectral instruments

Climatological data

Atm, sfc, .....



TB



Mean TB,  
PC modes

Ensemble modeling

Atm, sfc, .....

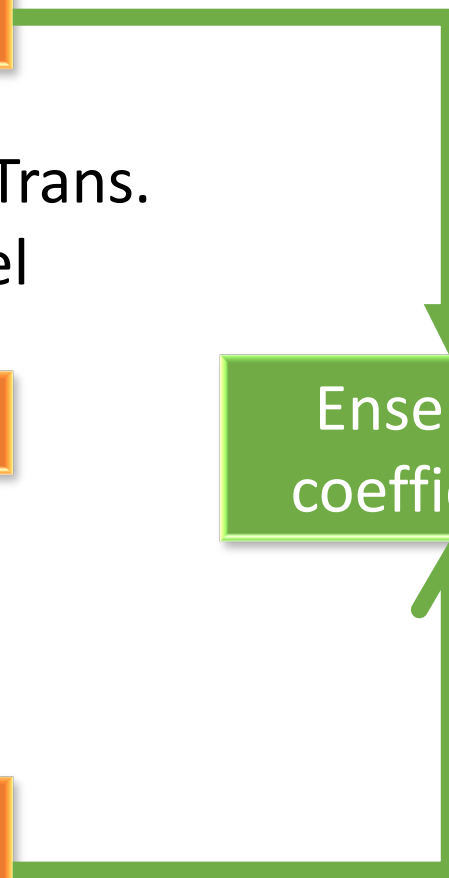


TB

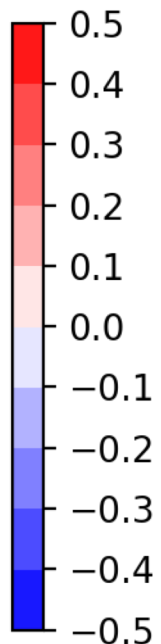
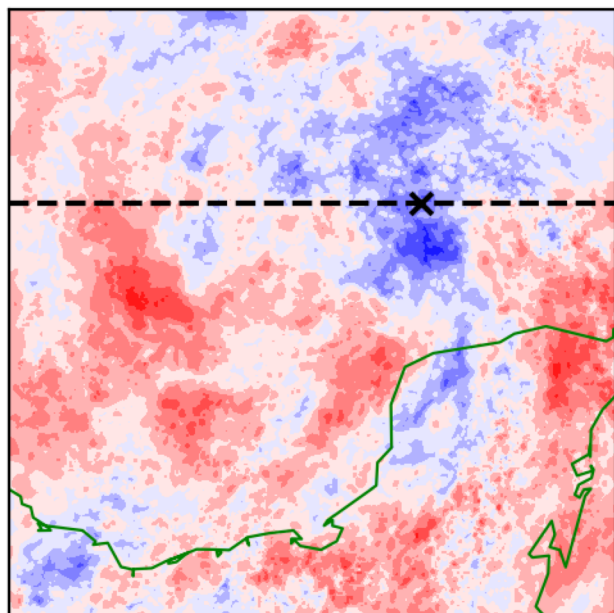


PC scores

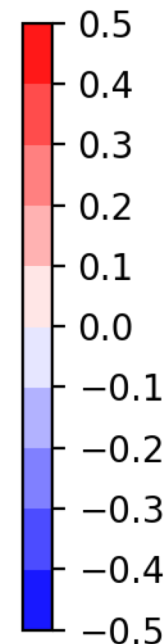
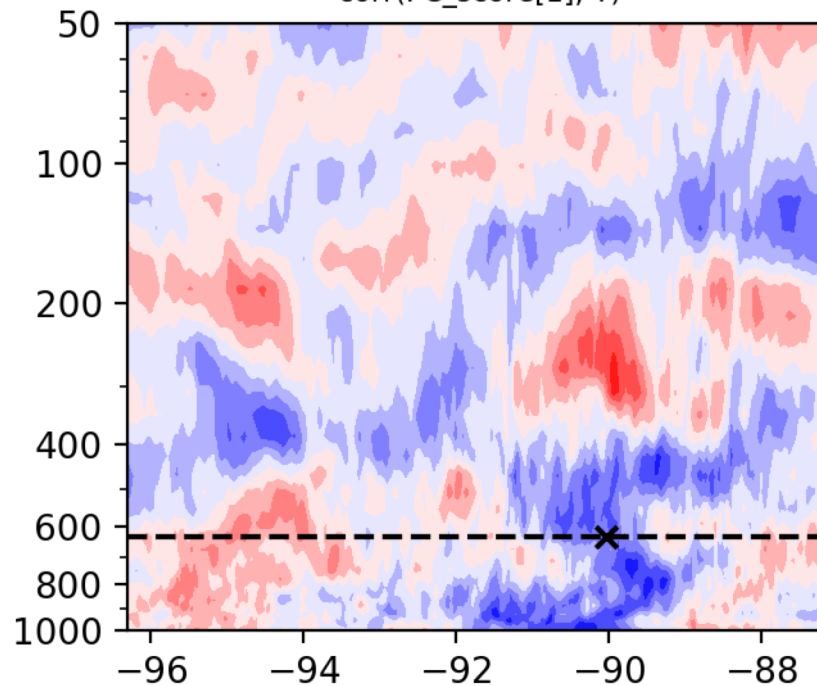
Ensemble  
coefficients



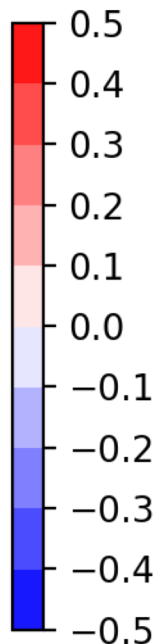
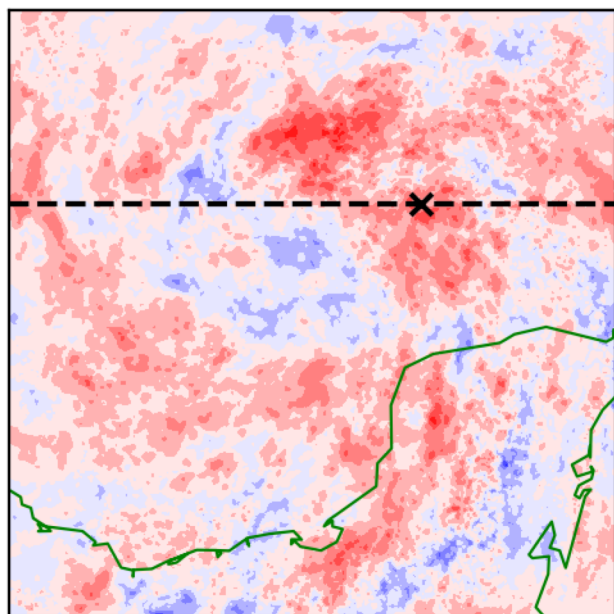
corr(PC\_score[1], T)



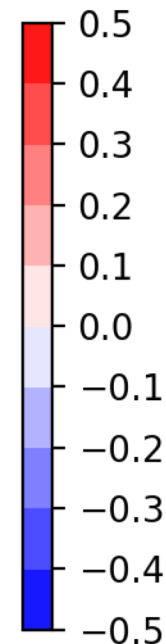
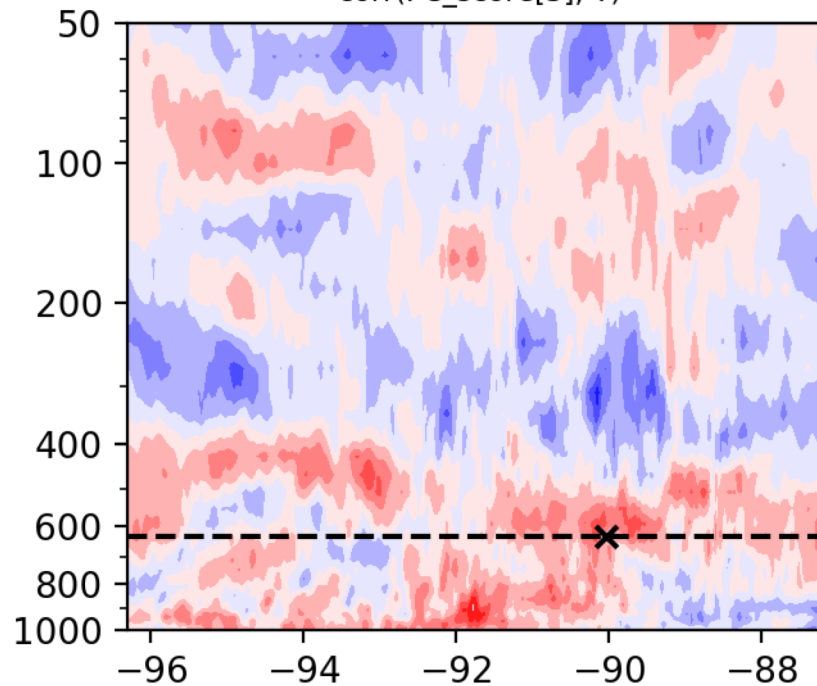
corr(PC\_score[1], T)



corr(PC\_score[3], T)

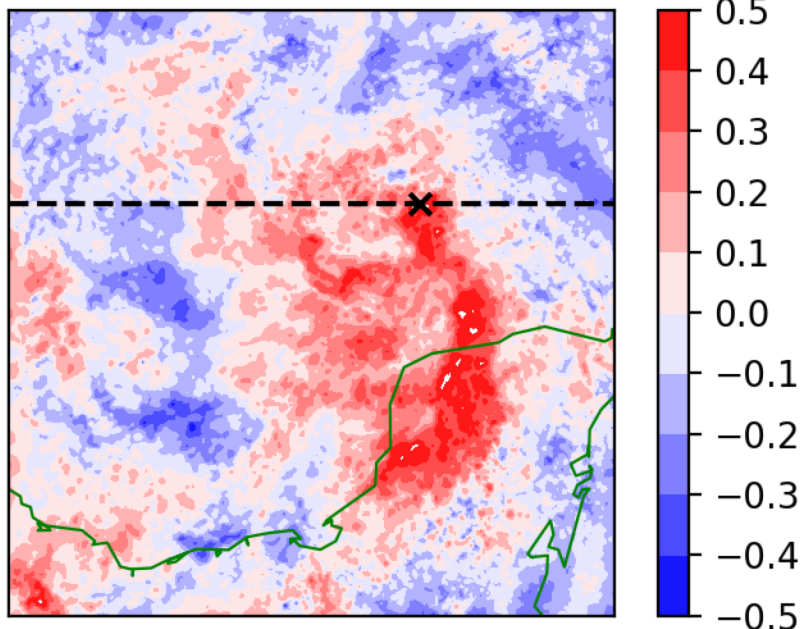


corr(PC\_score[3], T)

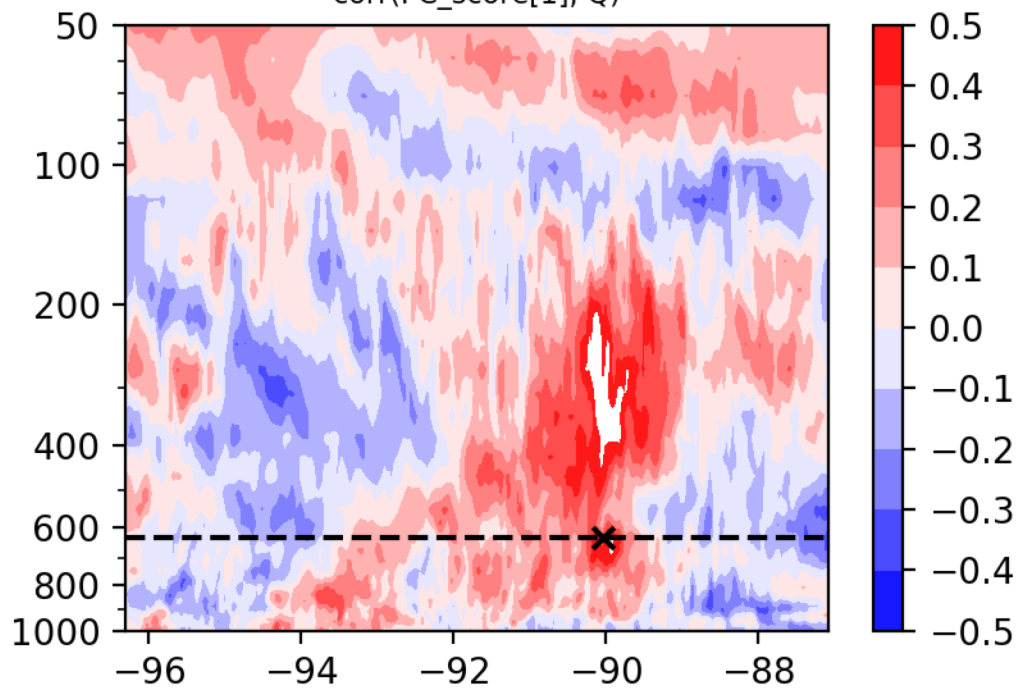




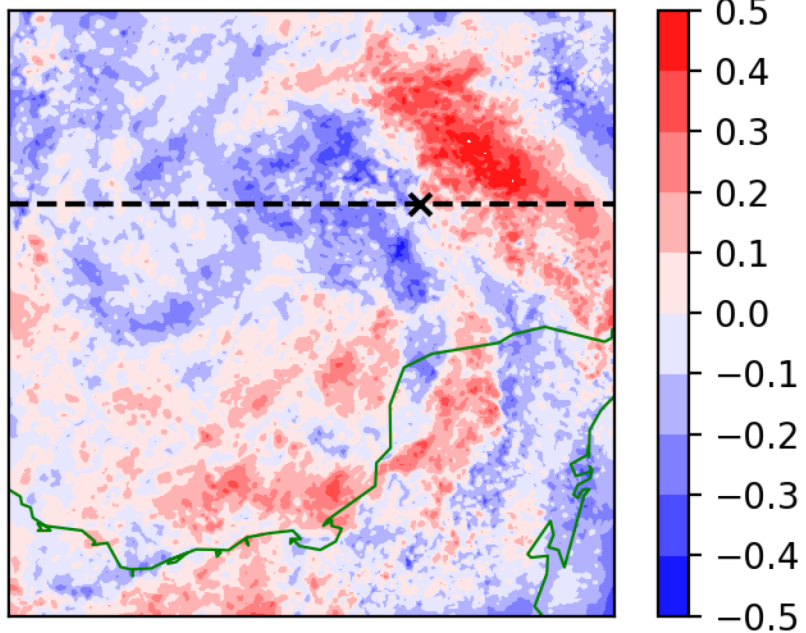
corr(PC\_score[1], Q)



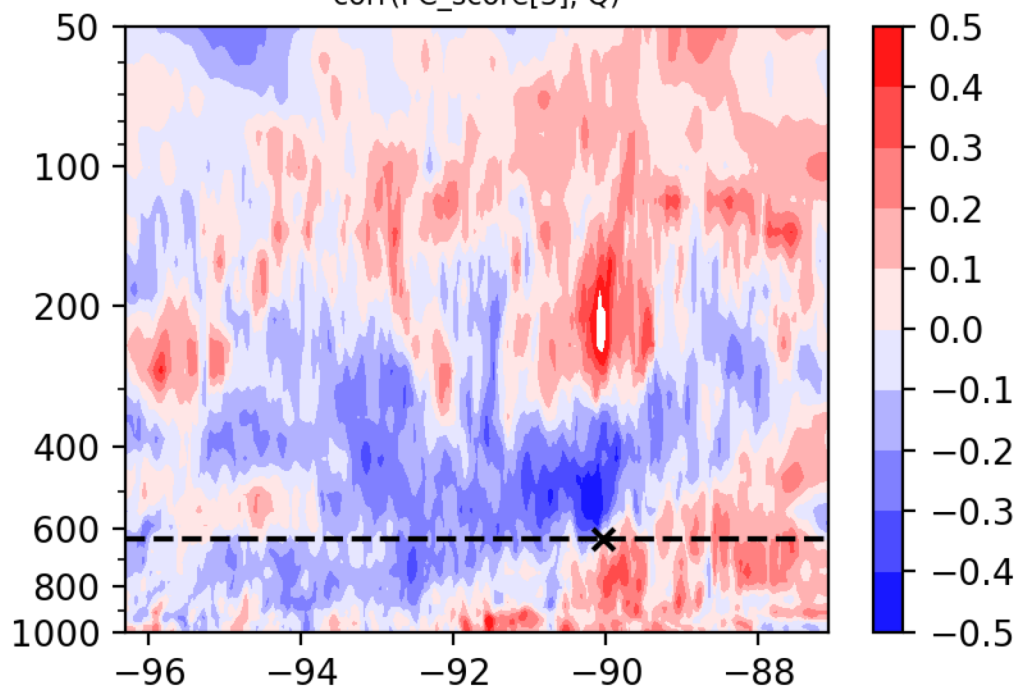
corr(PC\_score[1], Q)

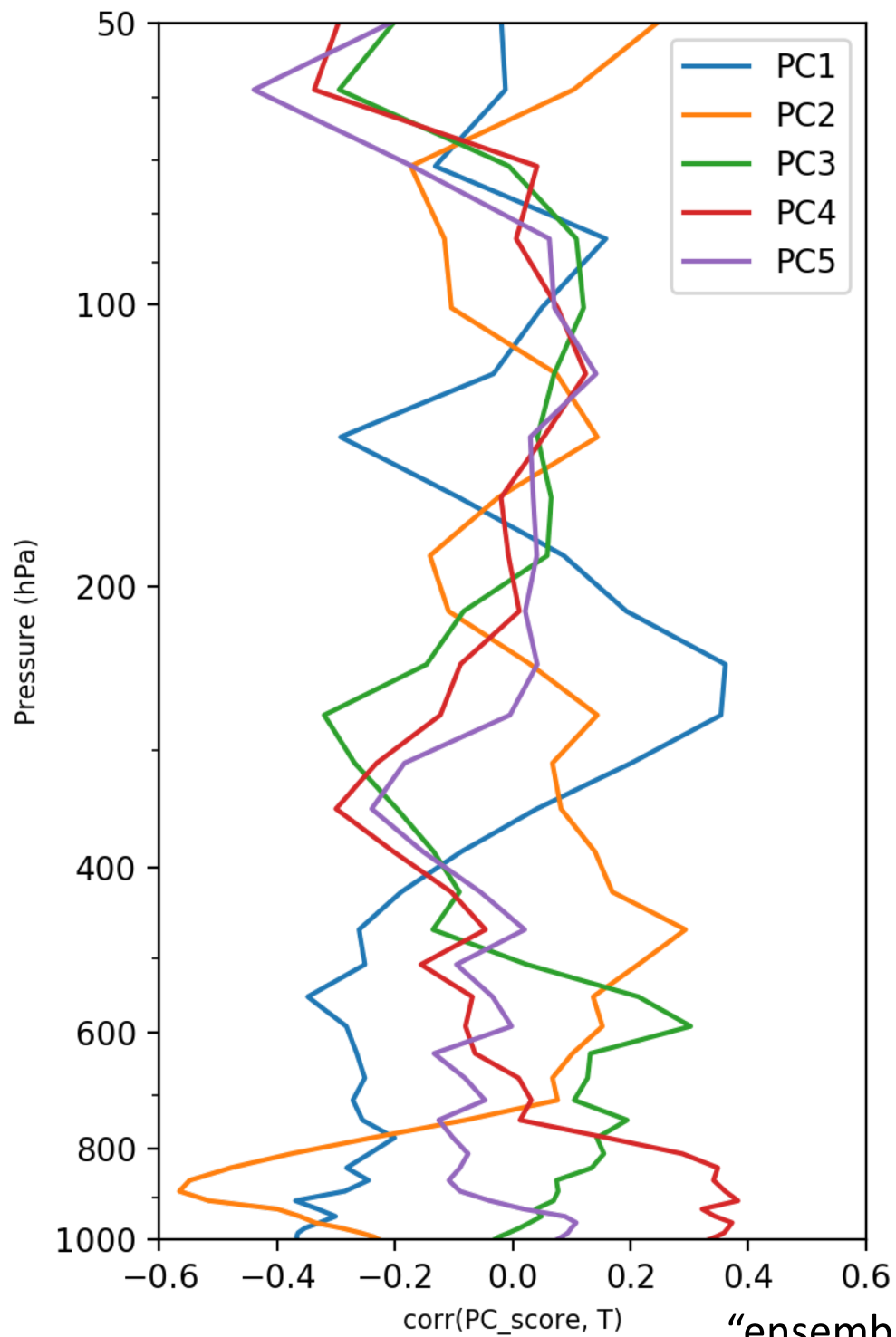


corr(PC\_score[3], Q)

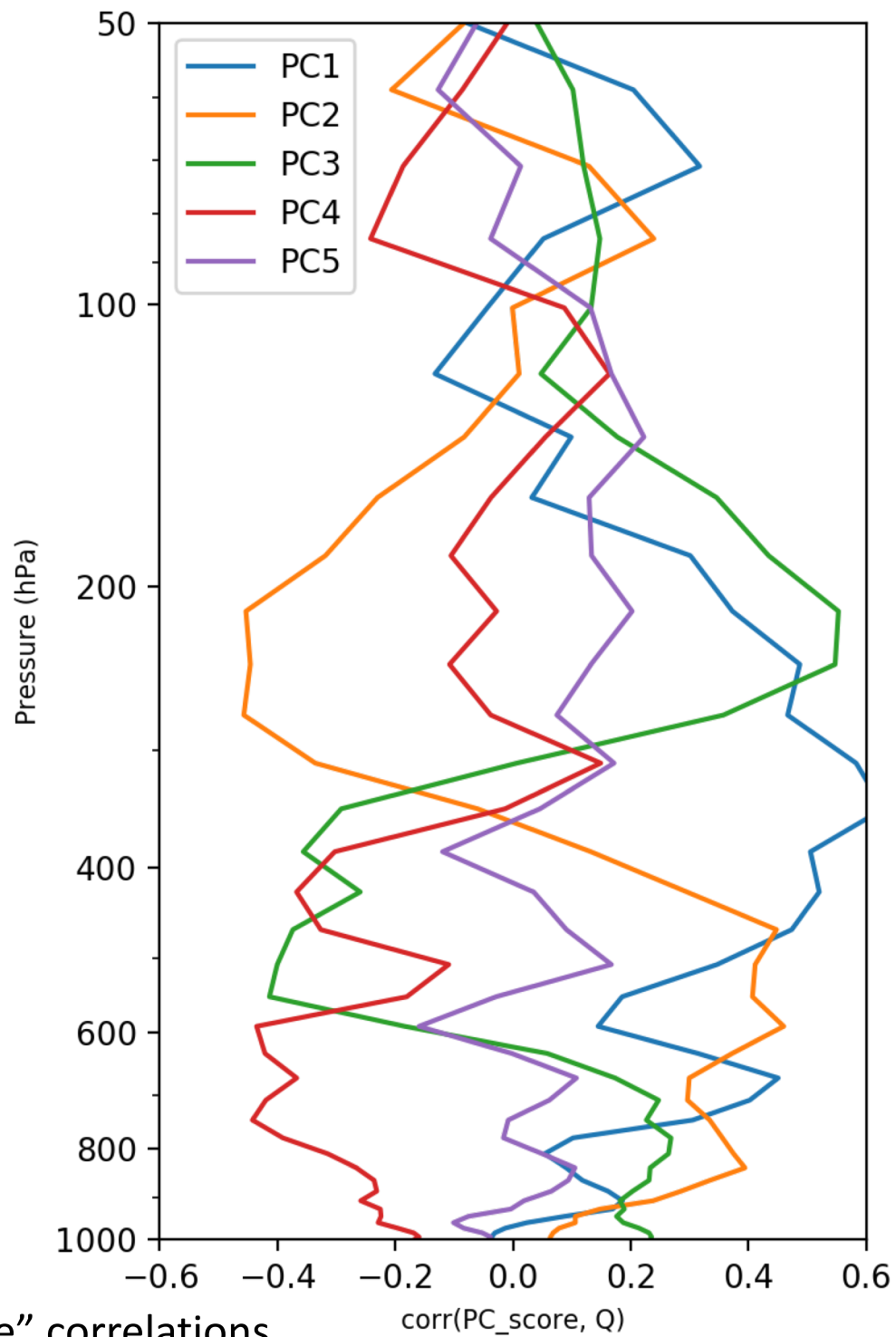


corr(PC\_score[3], Q)





“ensemble” correlations



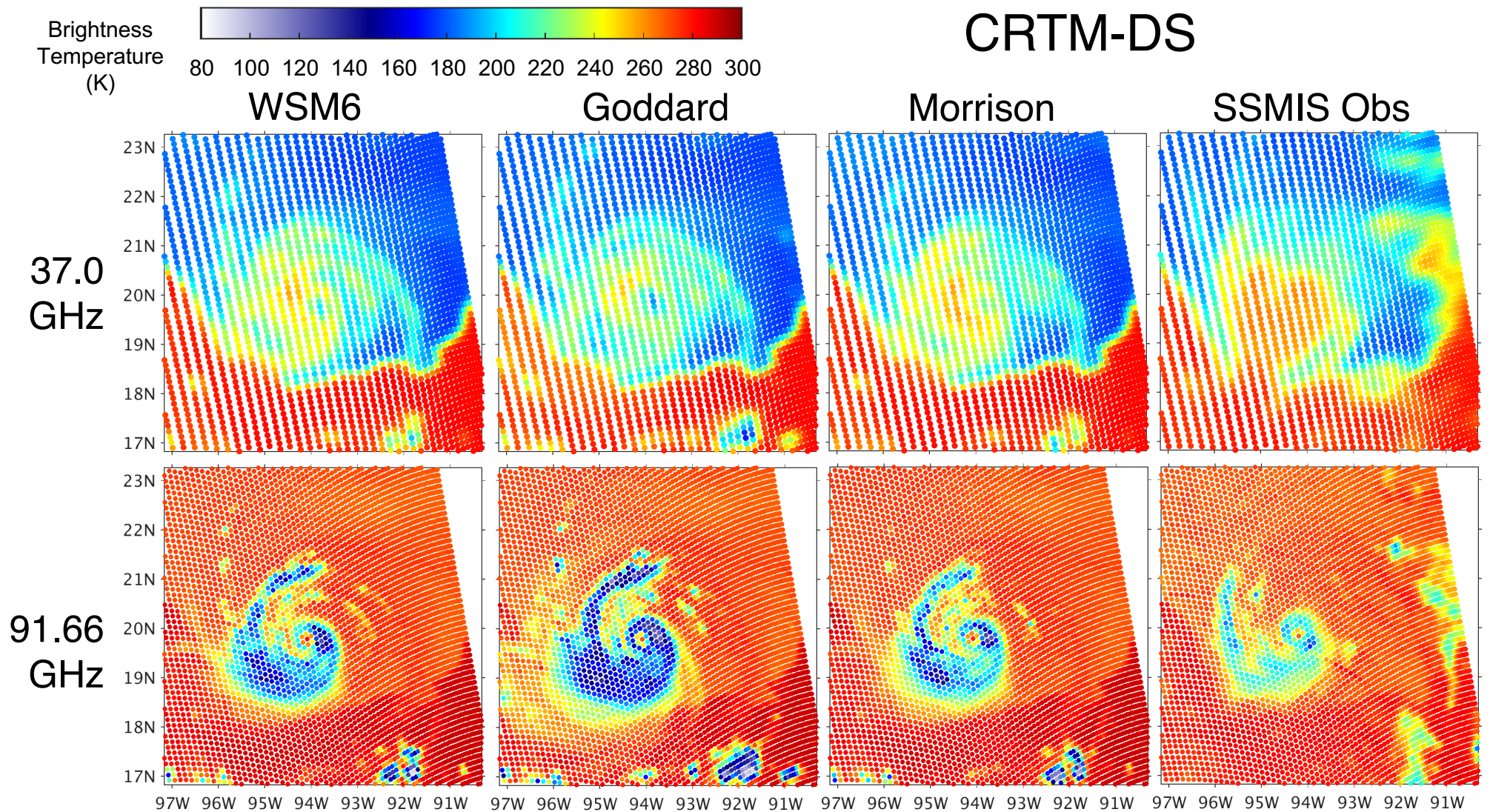
# Towards Assimilation of Cloudy MW Radiances

## *Modifying CRTM for microphysics consistency*

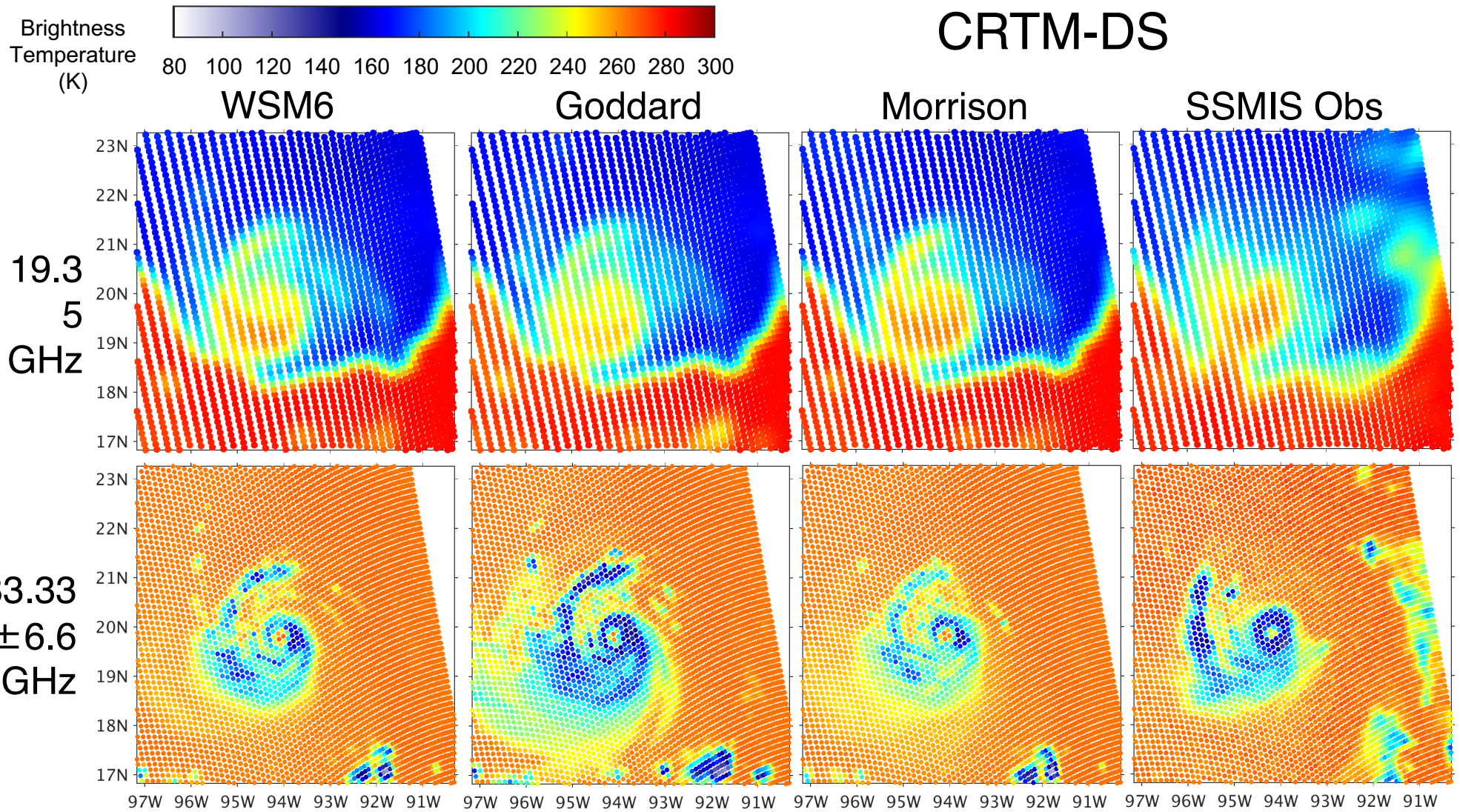
- “Distribution-Specific,” CRTM-DS:
  - New cloud scattering property lookup tables
  - Construct with MP scheme particle properties and size distributions
    - Very high resolution (1  $\mu\text{m}$  radius)
- Single particles modeled as soft spheres
  - These MP schemes specify hydrometeors as spheres
  - Maxwell-Garnett mixing formula for ice dielectric constants
  - Liquid dielectric constants from Tuner et al. (2016)



# CRTM-Simulated vs. SSMIS-observed All-sky Radiance

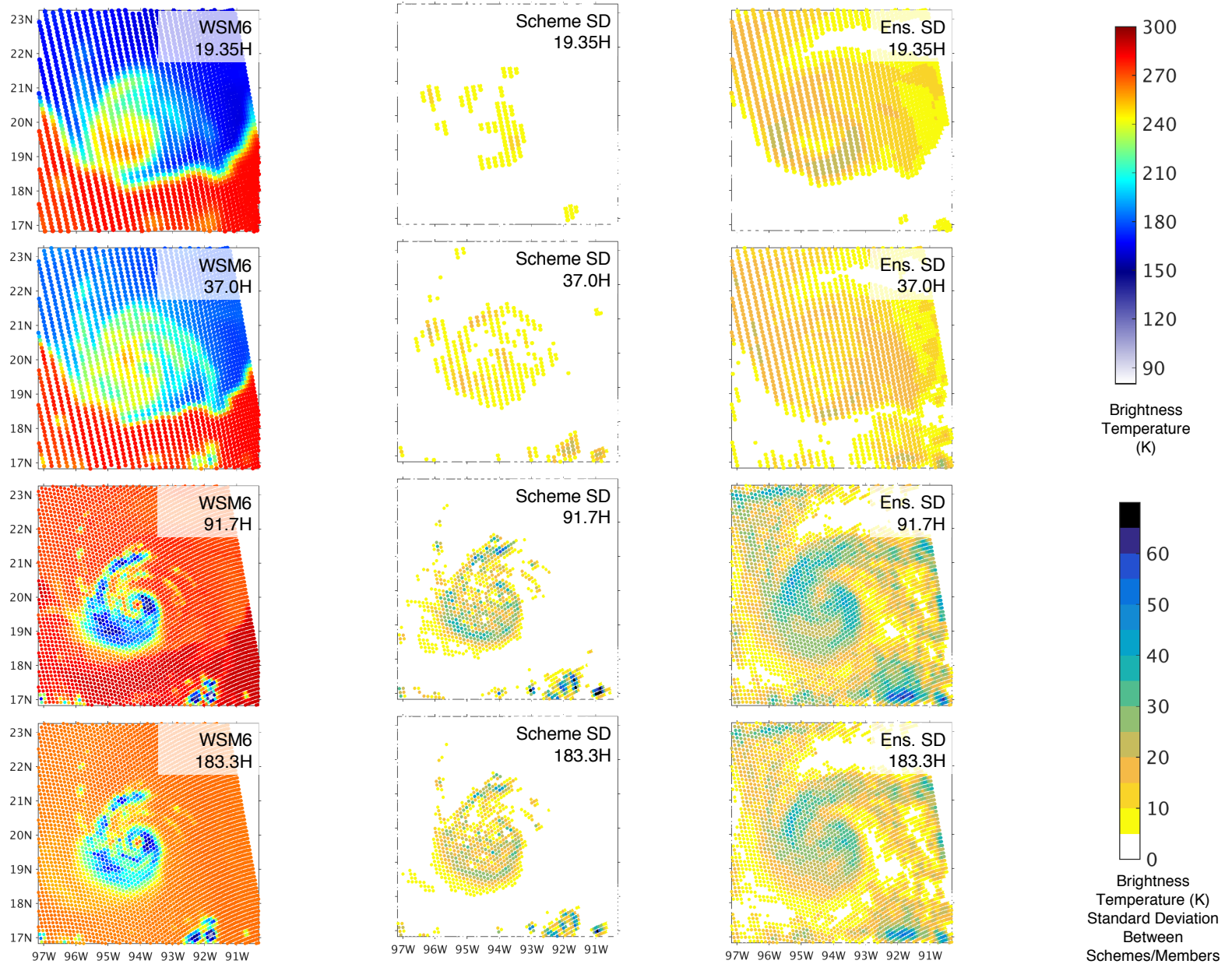


# CRTM-Simulated vs. SSMIS-observed All-sky Radiance





# CRTM Simulated: initial condition vs. physics uncertainty



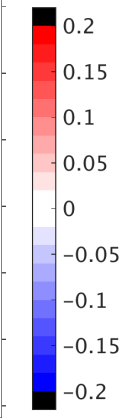
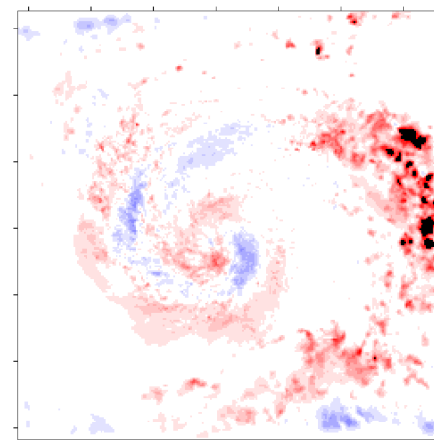
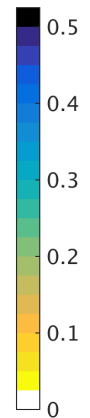
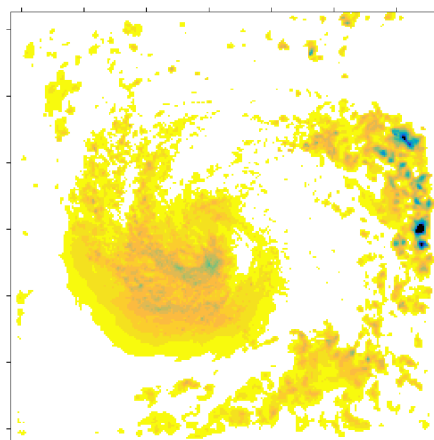
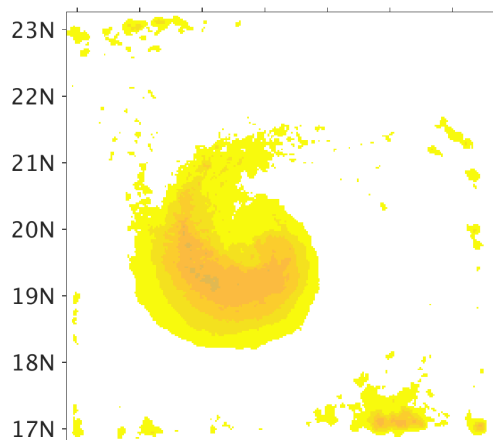
# CRTM-DS WSM6 Assimilating 19.35 GHz

$\overline{x_b}$

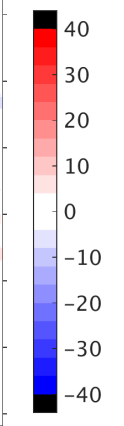
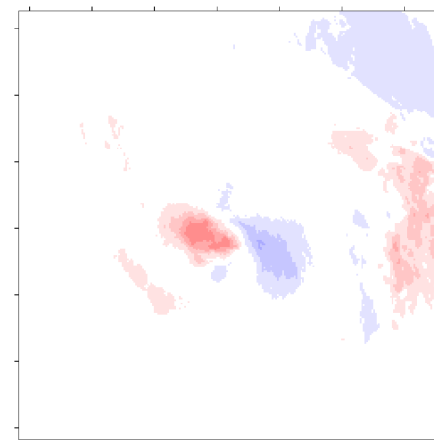
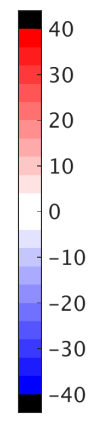
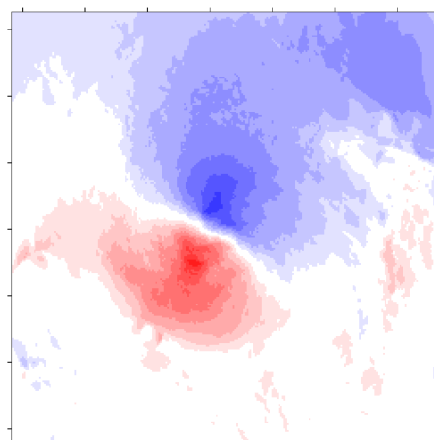
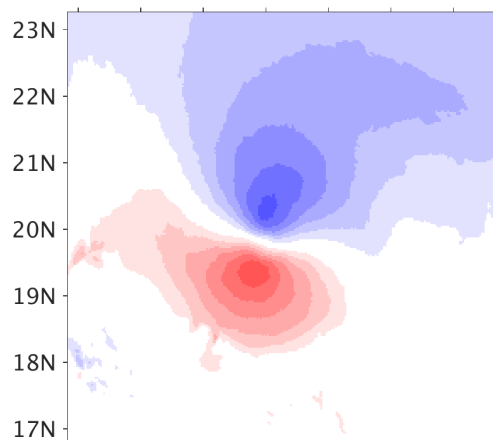
$\overline{x_a}$

$\overline{x_a} - \overline{x_b}$

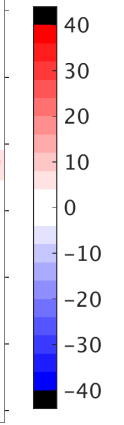
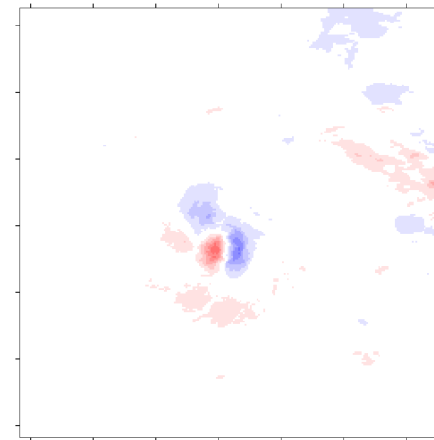
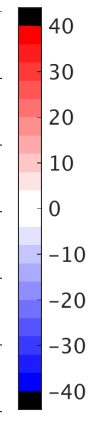
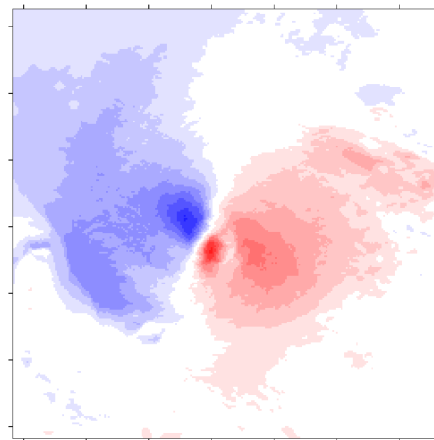
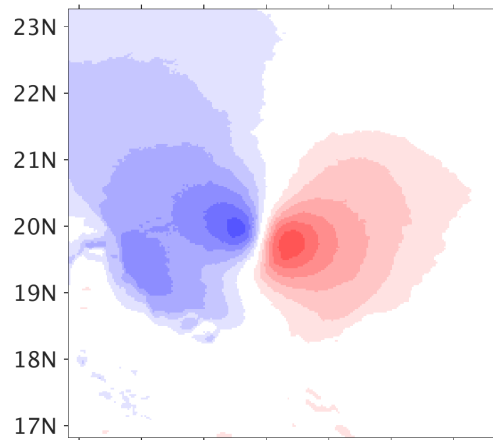
Water Path of  
All Precip



U wind



V wind



97W 96W 95W 94W 93W 92W 91W

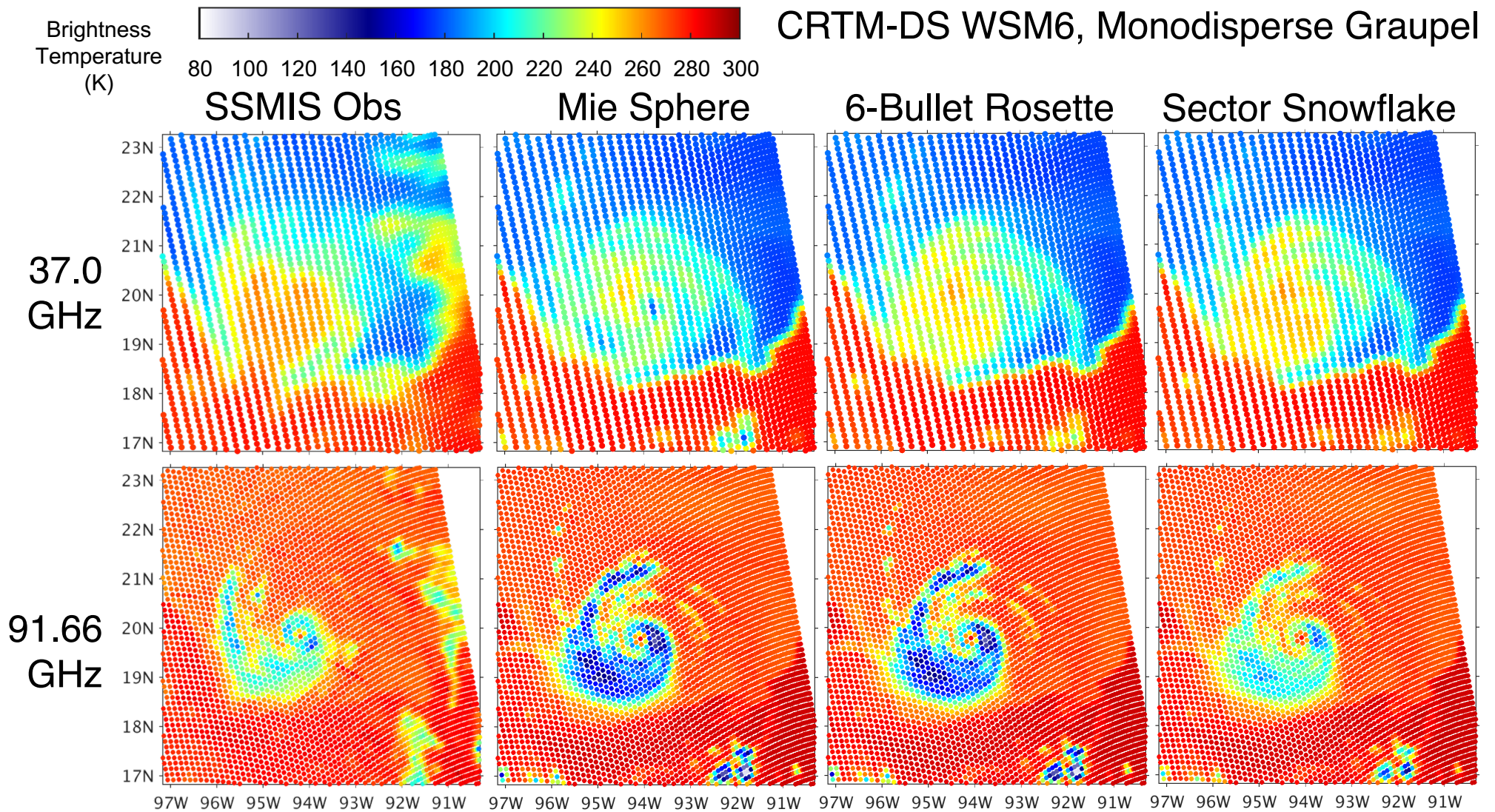
97W 96W 95W 94W 93W 92W 91W

97W 96W 95W 94W 93W 92W 91W



# Towards Assimilation of Cloudy MW Radiances

## *Further inclusion of non-spherical snow*



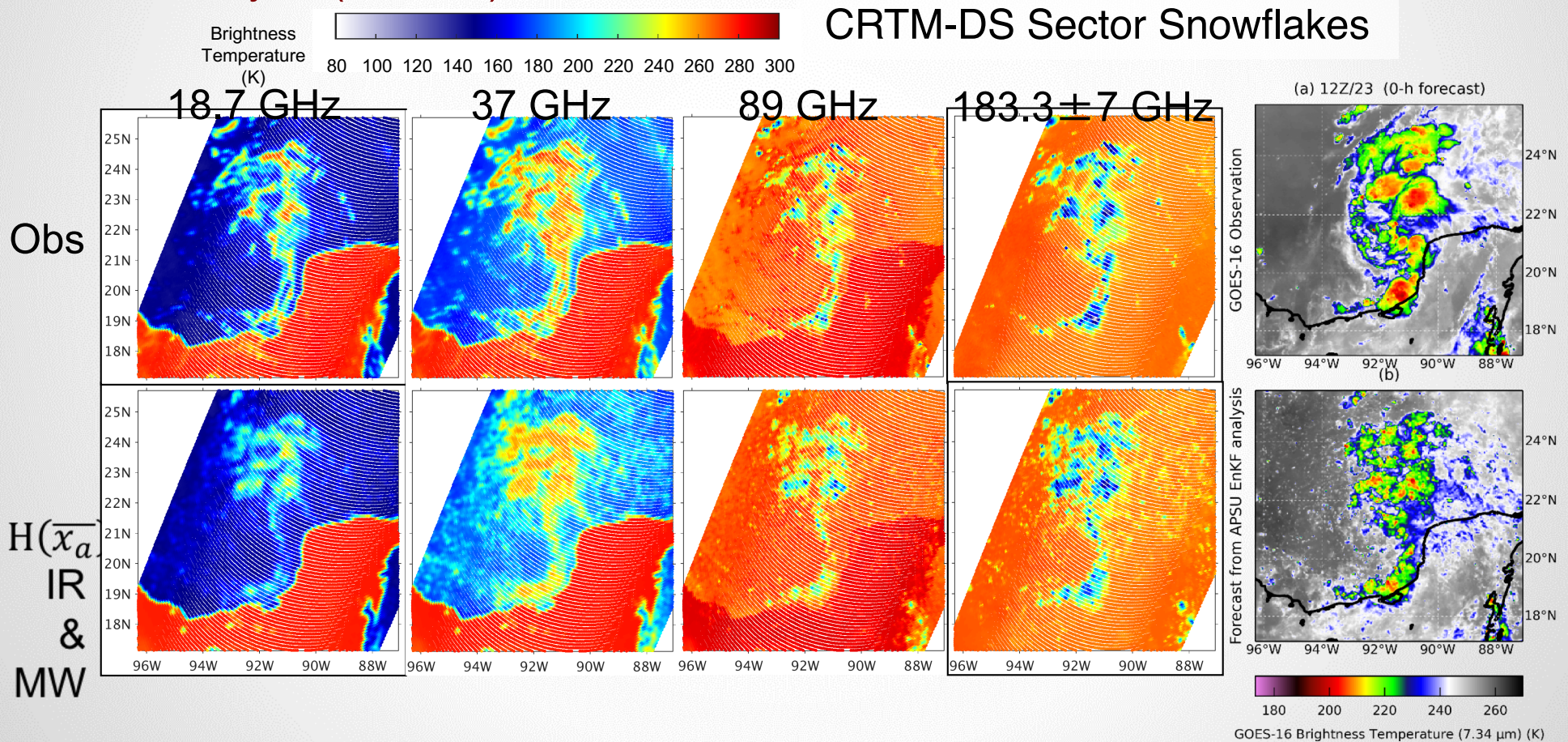
(Sieron, Zhang, et al. 2018 JAMES)



# Assimilating All-sky Satellite Radiances: Harvey (2017)

WRF/CRTM simulated MW radiance, 1<sup>st</sup> cycle (IR & MW)

Analysis (12 UTC) vs. 12 UTC GPM observations



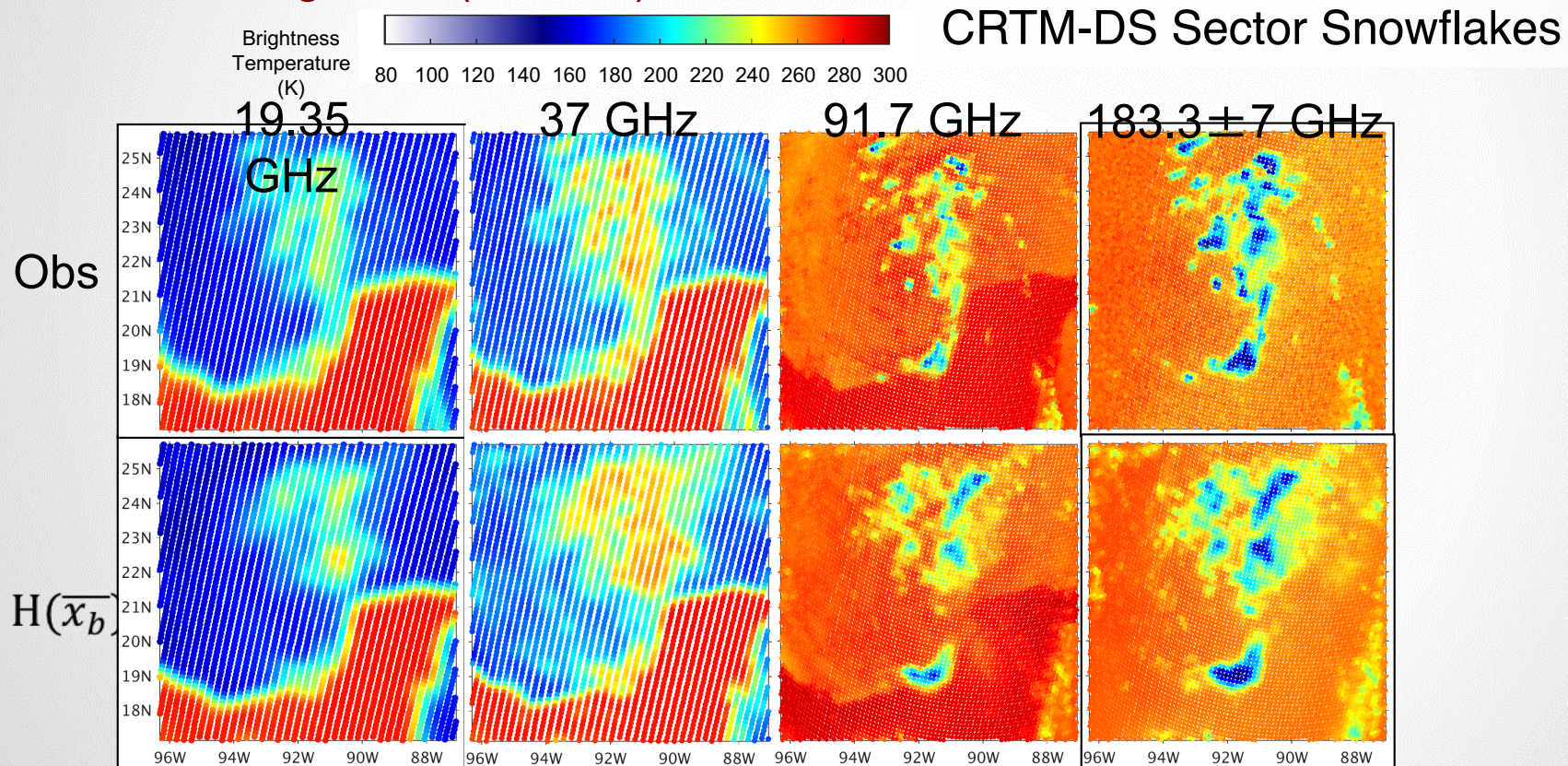
Ongoing Dissertation Research by Scott Sieron



# Assimilating All-sky Satellite Radiances: Harvey (2017)

WRF/CRTM simulated MW radiance, 2<sup>nd</sup> cycle (IR & MW)

Background (13 UTC) vs. 13 UTC SSMIS observations



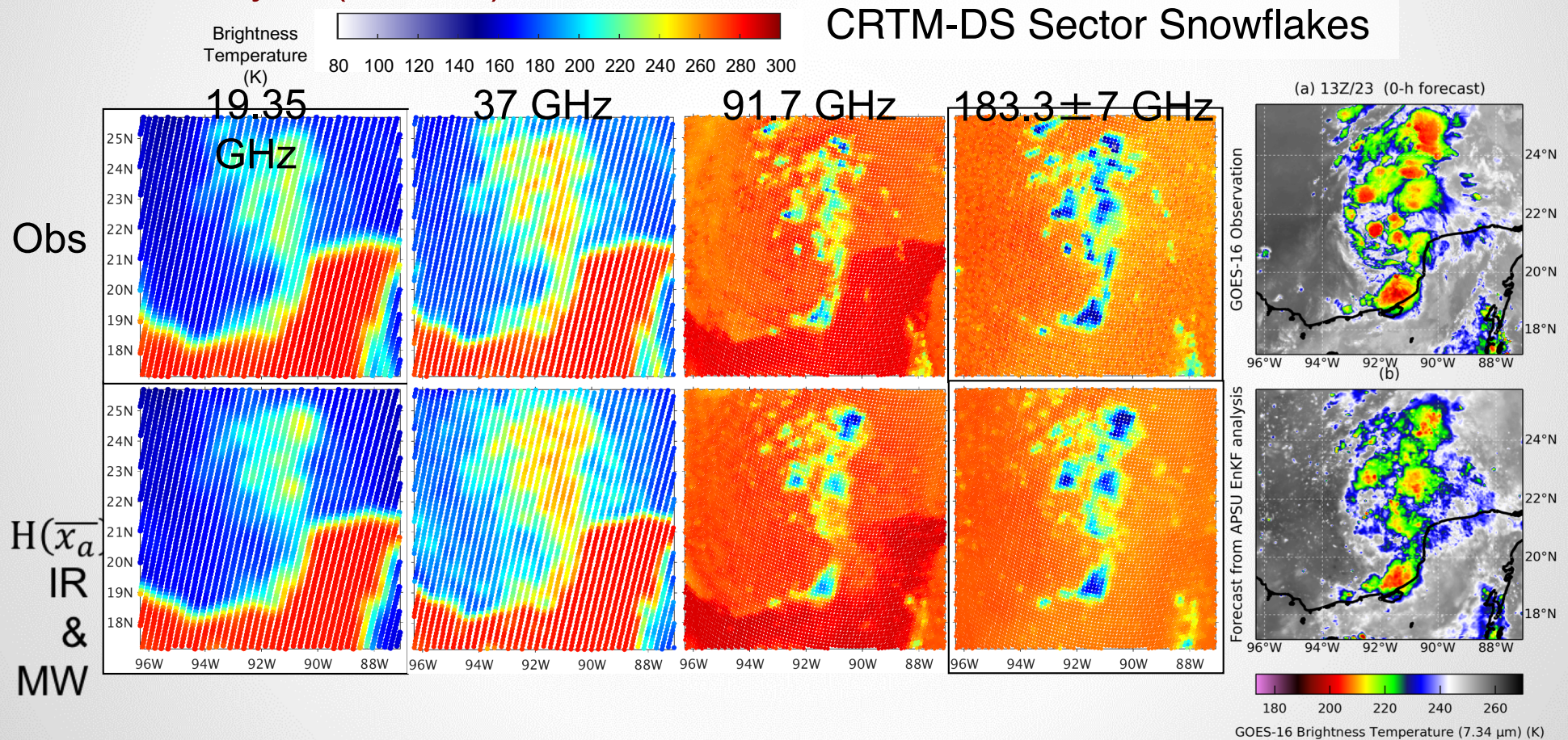
Ongoing Dissertation Research by Scott Sieron



# Assimilating All-sky Satellite Radiances: Harvey (2017)

WRF/CRTM simulated MW radiance, 2<sup>nd</sup> cycle (IR & MW)

Analysis (13 UTC) vs. 13 UTC SSMIS observations

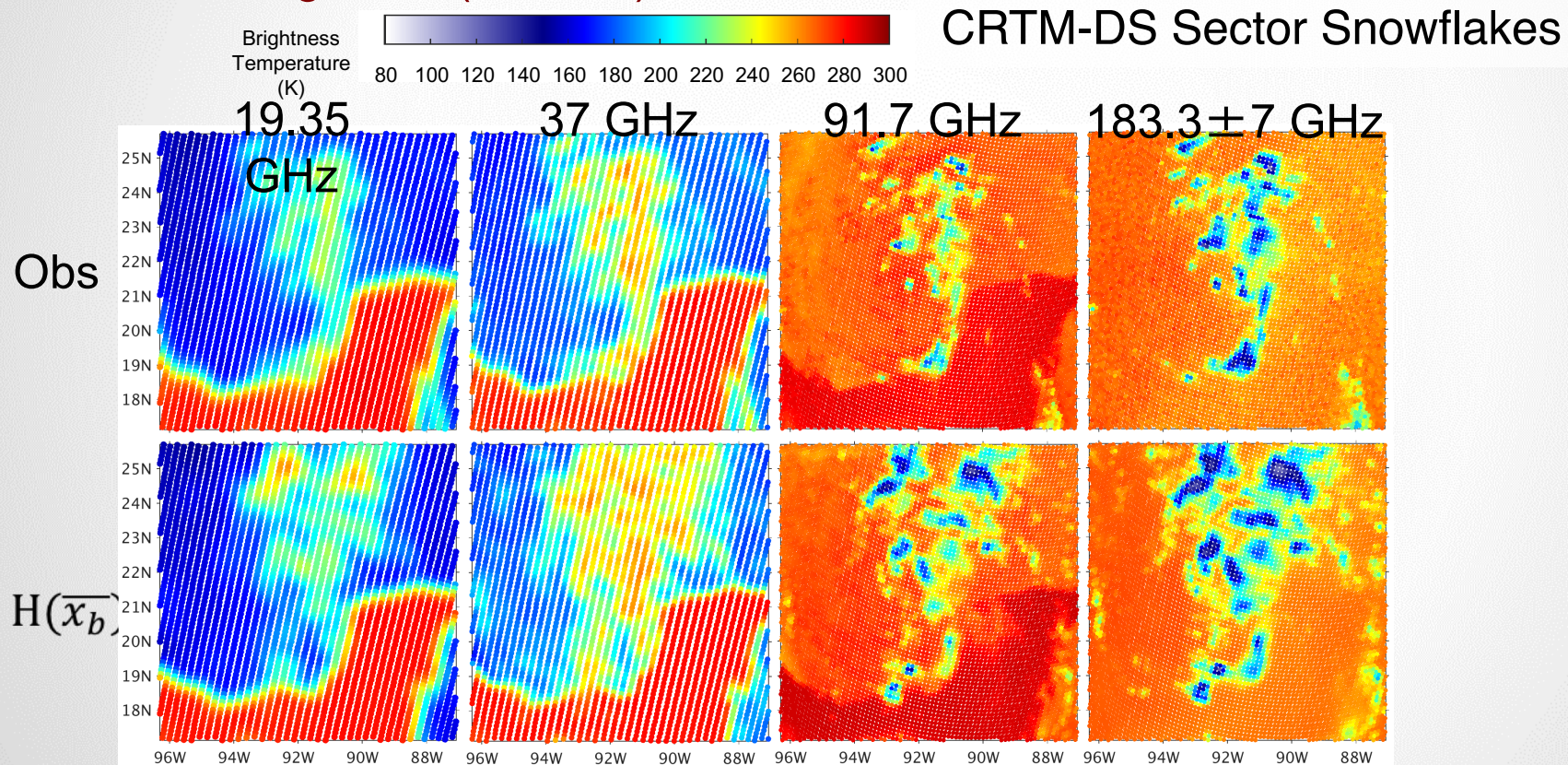




# Assimilating All-sky Satellite Radiances: Harvey (2017)

WRF/CRTM simulated MW radiance, 3<sup>rd</sup> cycle (IR only)

Background (14 UTC) vs. 13 UTC SSMIS observations







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NEWS • 02 MARCH 2018

# Latest US weather satellite highlights forecasting challenges

*Researchers begin to tackle the technical obstacles to incorporate observations from space into weather models.*

Jeff Tollefson

The Geostationary Operational Environmental Satellite-17 (GOES-17) will assume a position above the equatorial Pacific Ocean. When its data are combined with those from the identical GOES-16, which is already parked over the Atlantic Ocean, they will monitor the Earth from Africa to New Zealand. Weather forecasters around the world use such geostationary satellites to monitor storms, and their models incorporate limited data on atmospheric moisture and wind speed and direction.

“There is this huge treasure trove of information,” says Fuqing Zhang, a meteorologist at Pennsylvania State University in University Park. He has experimented with incorporating some of that unused data from satellites into his models, with promising results. “We can show dramatic improvements in weather prediction, but you do need a dedicated research effort.”

In a study currently in review at the *Bulletin of the American Meteorological Society*, Zhang and his colleagues show that incorporating high-resolution data from GOES-16 into an experimental weather model bolstered predictions of the early development and intensity of Hurricane Harvey, which struck Texas in August.

The lesson for the United States is that satellites and models aren't enough, Zhang says. “Our nation has put so much money into launching beautiful satellites, but we haven't really put as much effort into how to put the satellite information into the models.”



# Concluding Remarks

- Convection-permitting EnKF assimilation of GOES all-sky IR radiance show great promises for hurricane analysis & prediction
- Assimilation of cloudy microwave radiances is also promising but more challenging with key issues such as:
  - how to maintain consistency between model microphysics, CRTM and the wild nature of hydrometer distribution and shape
  - how to have microphysics distribution-specific radiative transfer for nonspherical particles given soft-sphere model microphysics
  - how to more effectively assimilate large volumes of data
  - how to deal with strong nonlinearity and non-Gaussianity
- Time is now to holistically integrate all-sky IR/MW radiances