Penn State Center for
Advanced Data Assimilation and Predictability Techniques

Advances and Challenges in Ensemble-based Convection-permitting Satellite Data Assimilation

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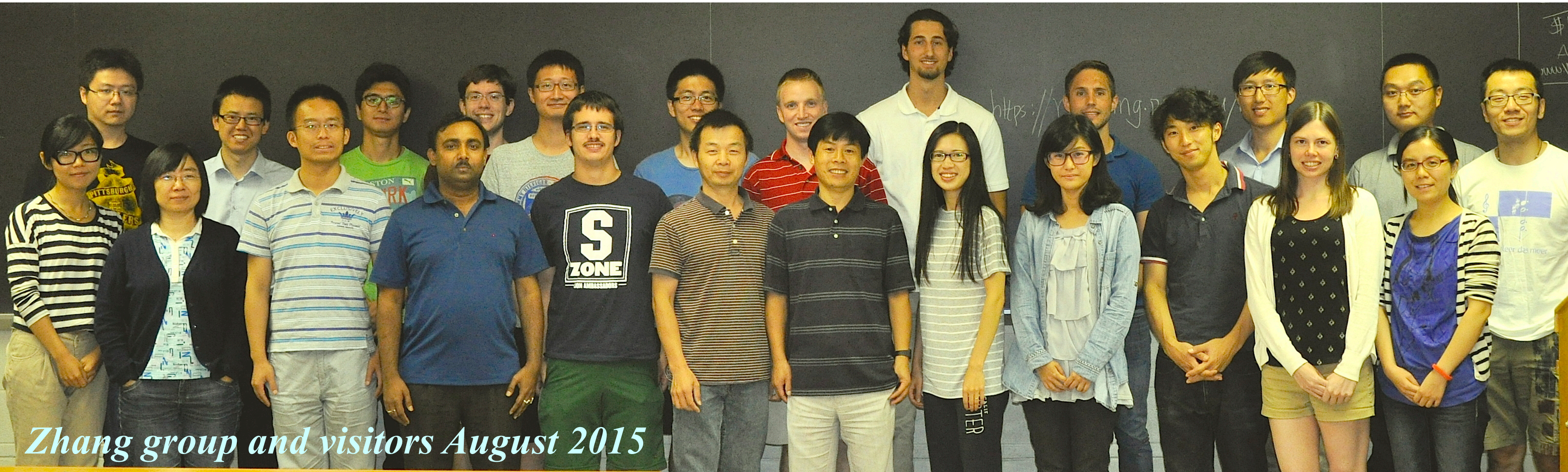
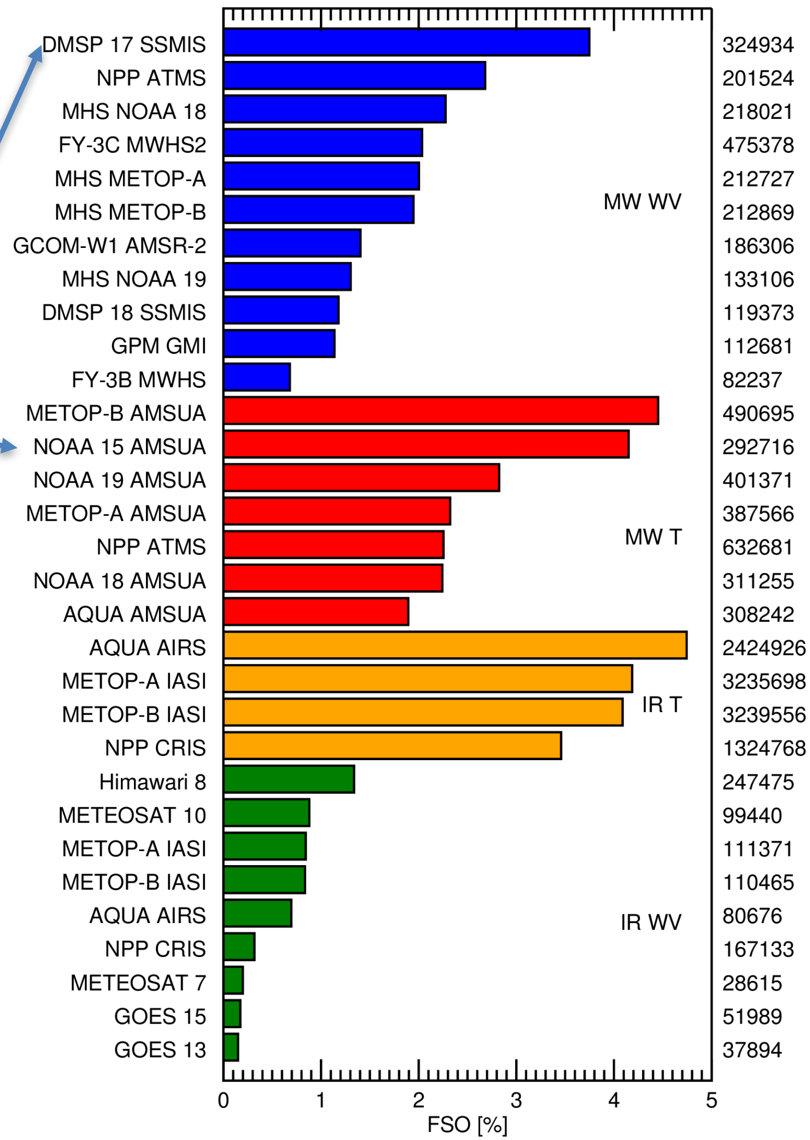
Sponsored by ONR, NASA, NSF and NOAA/HFIP


Zhang group and visitors August 2015

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%

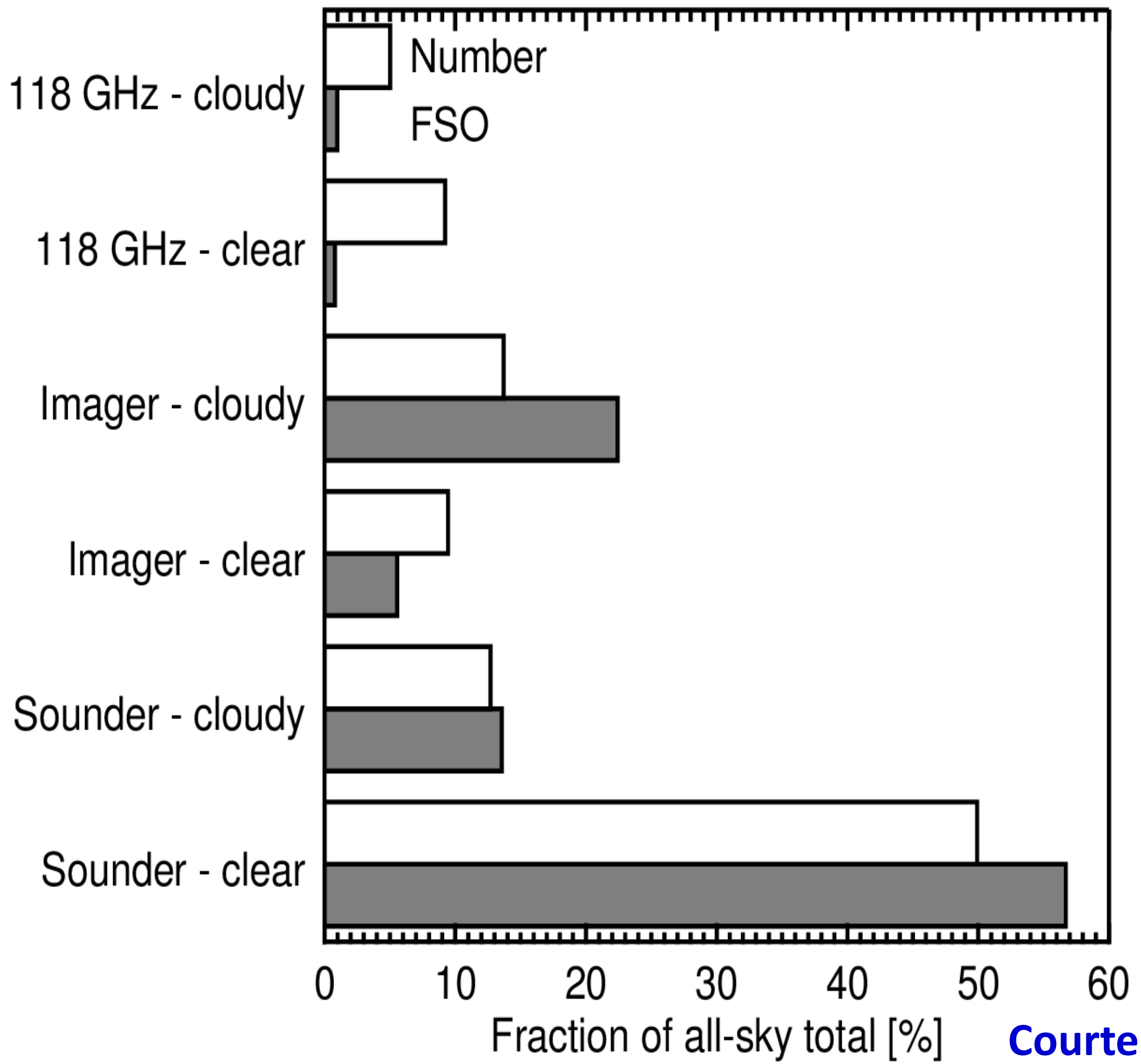
Amount of information coming from humidity/cloud/precipitation is equivalent to what's coming from T sounding

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

Courtesy of Alan Geer at ECMWF

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

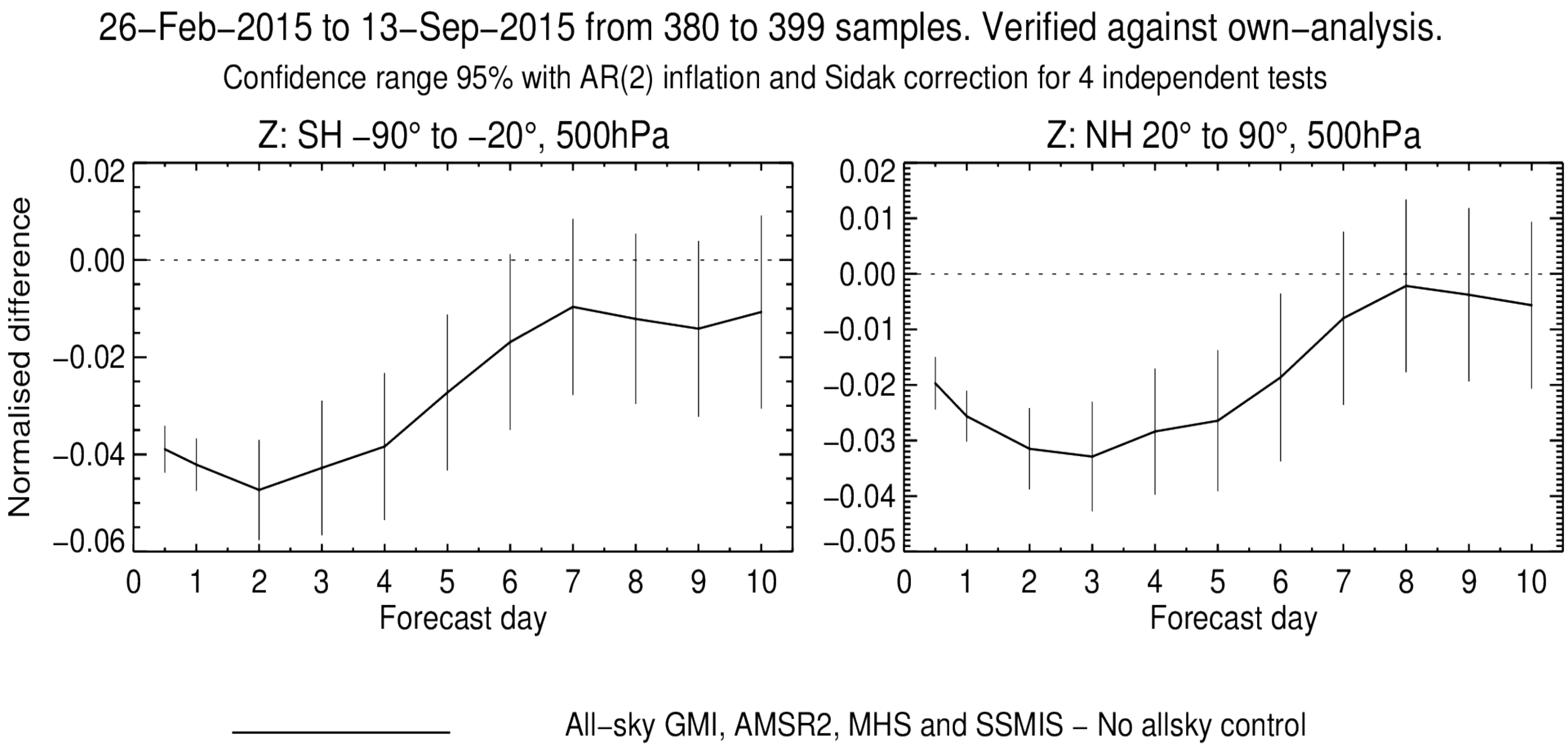
But don't forget all-sky gives a more optimal assimilation of "clear" scenes (going to all-sky at least doubled the forecast impact of MHS)

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*



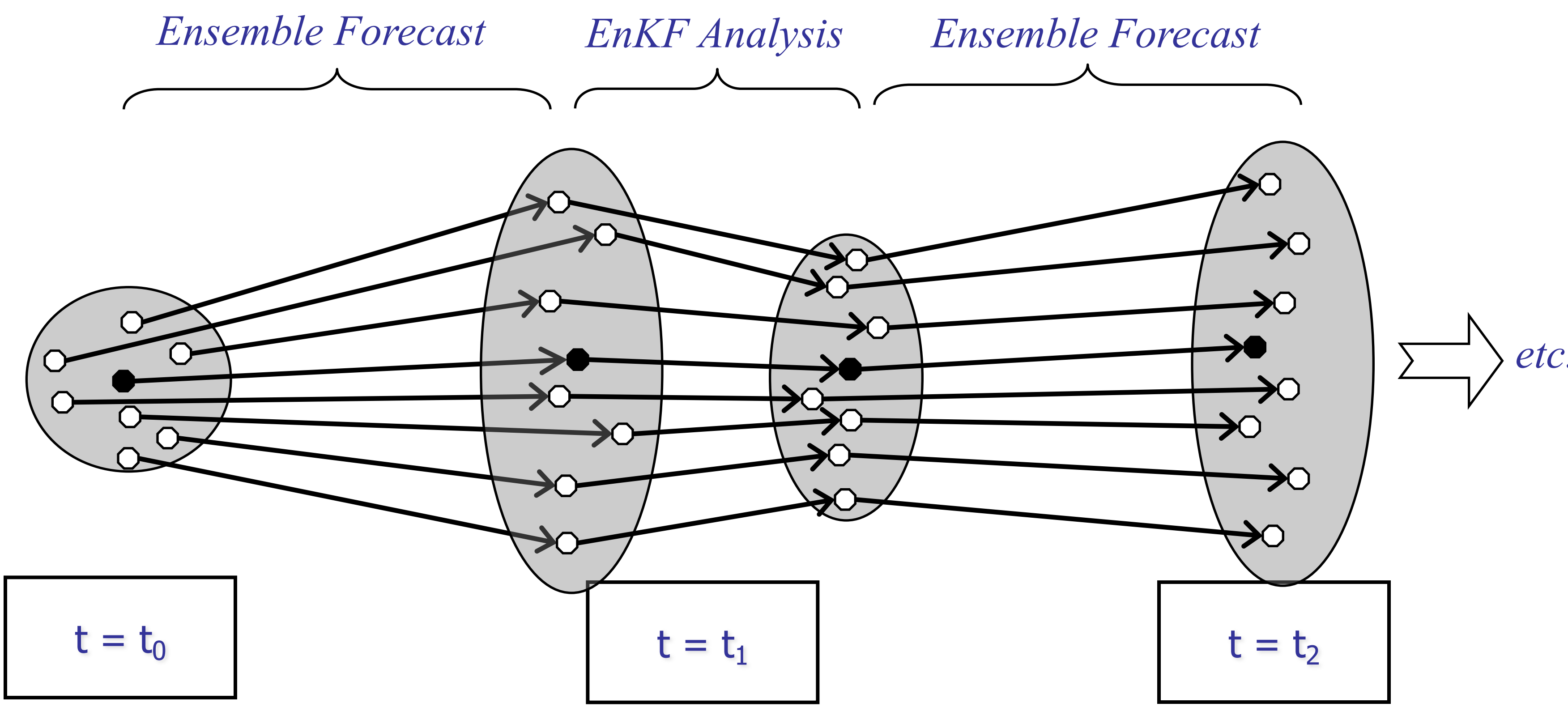
Courtesy of Alan Geer at ECMWF

EnKF: flow-dependent sample covariance from ensemble

(Kalman 1960; Evensen 1994; Houtekamer & Zhang 2016)

$$x^a = x^f + BH^T(HBH^T+R)^{-1}(y-Hx^f)$$

$$B = N_e^{-1}\Sigma\,(x_i^f-\underline{x})(x_i^f-\underline{x})^T$$



Equivalence to 4Dvar in linear systems; no adjoint or TLM; fully coupled with ensemble forecast; nonlinear dynamics included; adaptable to be coupled/hybrid with 3D/4DVar

REVIEW

Review of the Ensemble Kalman Filter for Atmospheric Data Assimilation

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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.

CONTENTS

PSU WRF-based multi-functional regional-scale ensemble and hybrid data assimilation system

DA methods included:

PSU **WRF-EnKF** (Zhang et al. 2009a; Weng & Zhang 2012): publically released

NCAR WRFDA-**3DVar** (Huang et al. 2009): publically released

NCAR WRFDA-**4DVar** (X Zhang et al. 2014): publically released

E3DVar/3DenVar (hybrid/coupling of EnKF & 3DVar) (Zhang et al. 2013)

E4DVar (coupling of EnKF & 4DVar) (Zhang et al. 2009b; Poterjoy & Zhang 2014)

4DEnVar (ensemble-based 4D hybrid) (Liu et al. 2008; Poterjoy & Zhang 2015)

Current DA plans at the leading NWP centers:

ECWMF: adjoint-based as an ensemble of 4DVar but with hybrid covariance

UK-Met: adjoint-based E4DVar in operation, better than ensemble-based 4DEnVar

NCEP: ensemble-based 4DEnVar

CMC: 4DEnVar for deterministic forecasts, EnKF for ensemble prediction

Regional-scale EnKF vs. 3DVar for Jun 2003

WRF/EnKF: 40-member multi-physics-scheme ensemble

Boundary conditions: D1 updated by 12 hourly GFS/FNL analyses

3DVar (Barker et al. 2005)**:** Updated B with May 2003 forecasts via NMC method (Parrish and Derber 1992; Xiao and Sun 2007)

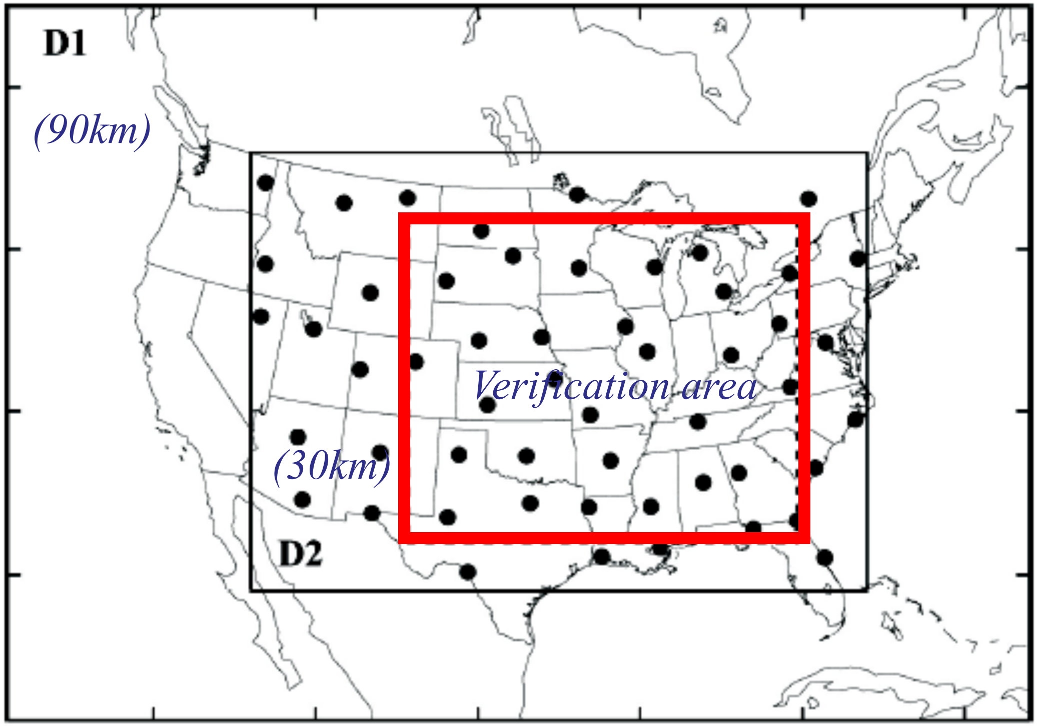
Observations: Soundings every 12h quality-controlled by 3DVar in D2, assuming observational errors of NCEP, assimilated on 30-km D2 only

Verification: against soundings 12-h forecast time and at standard pressure levels

Inflation: covariance relaxatio

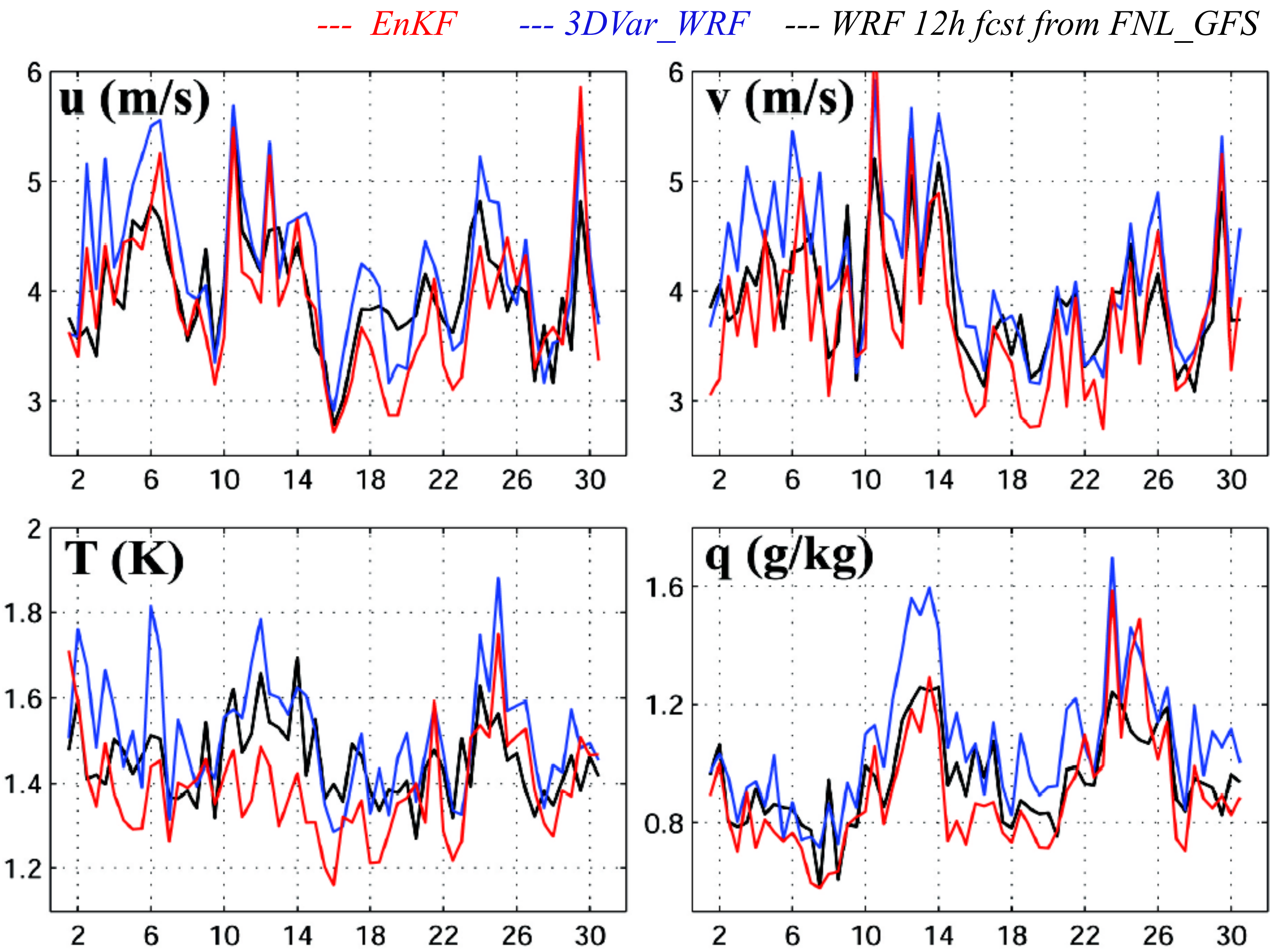
$$(\mathbf{x}^a_{new})' = (1 - \alpha)\,(\mathbf{x}^a)' + \alpha\,(\mathbf{x}^f)'$$

(Zhang et al. 2004 MWR)



(Meng and Zhang 2008a,b MWR)

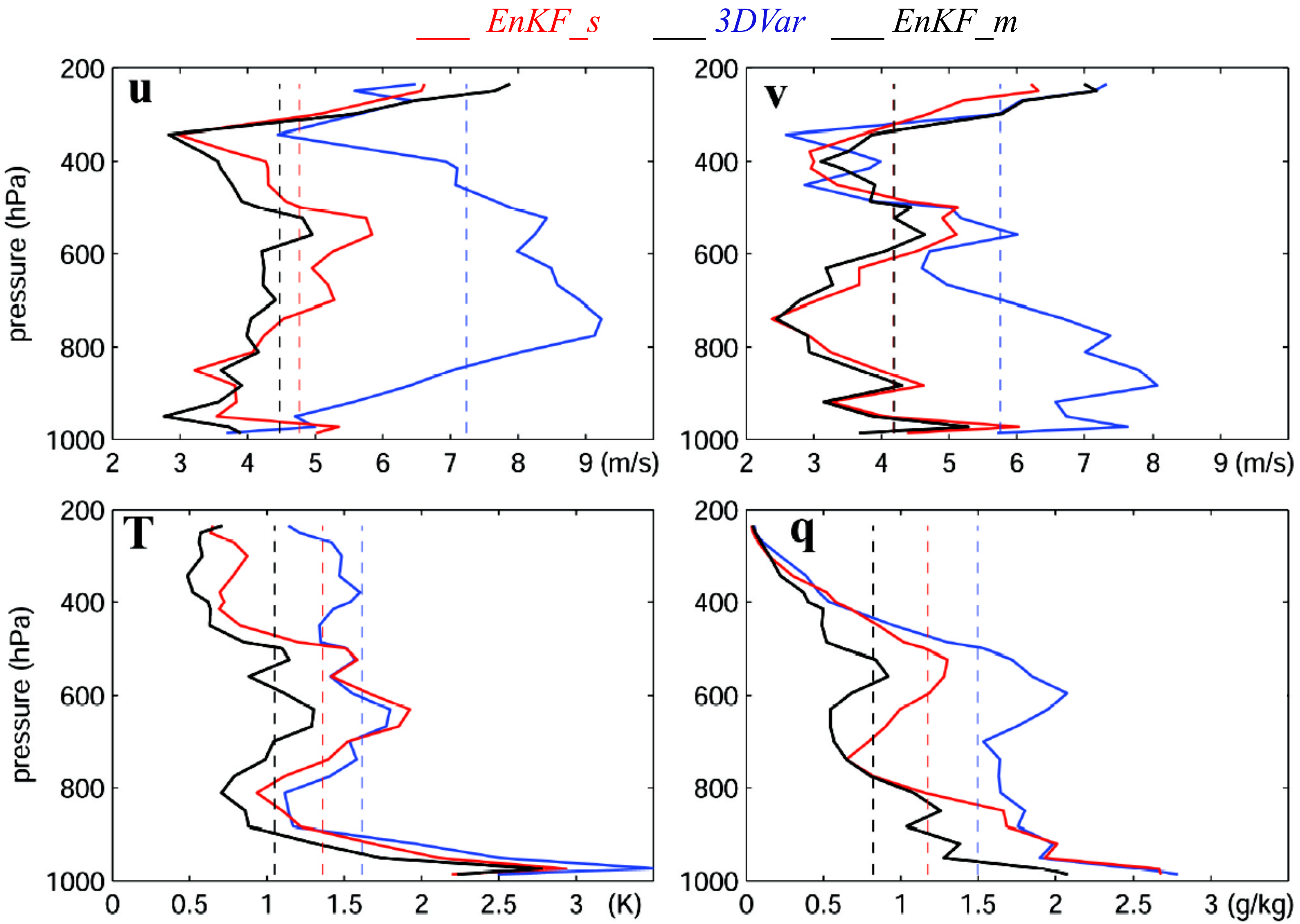
EnKF vs. 3DVar vs. FNL_GFS for June 2003



EnKF performs even better than FNL_GFS which assimilates many more data including satellite FNL_GFS has a generally smaller 12-h forecast error than WRF-3DVar.

(Meng and Zhang 2008a,b)

Multi-scheme EnKF: verified against independent dropsondes



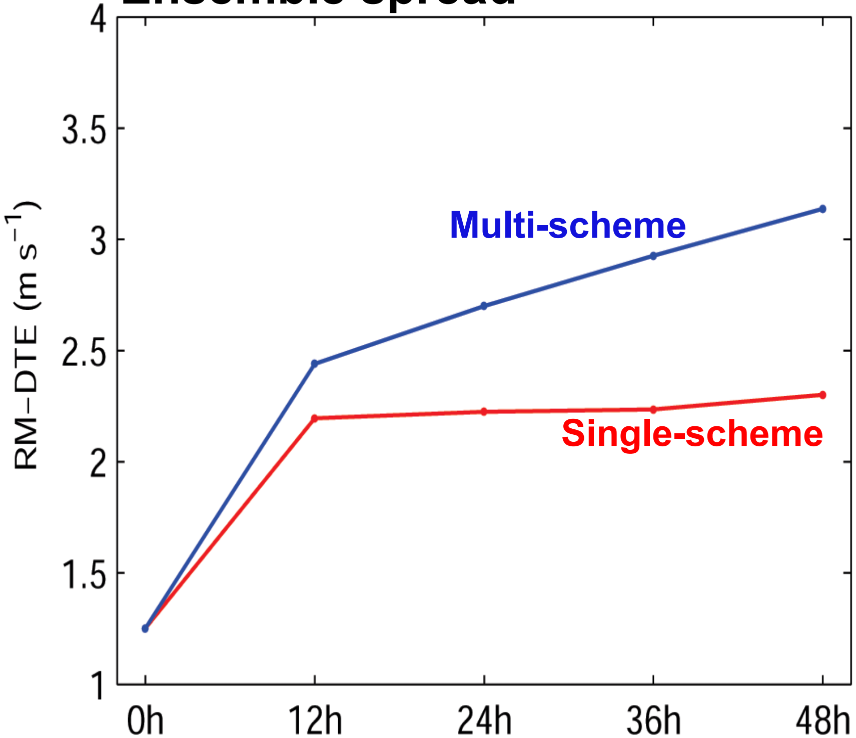
The multi-physics-scheme EnKF_m performs better than WRF 3DVar

EnKF_m also performs better than single-physics-scheme EnKF_s especially for T and q

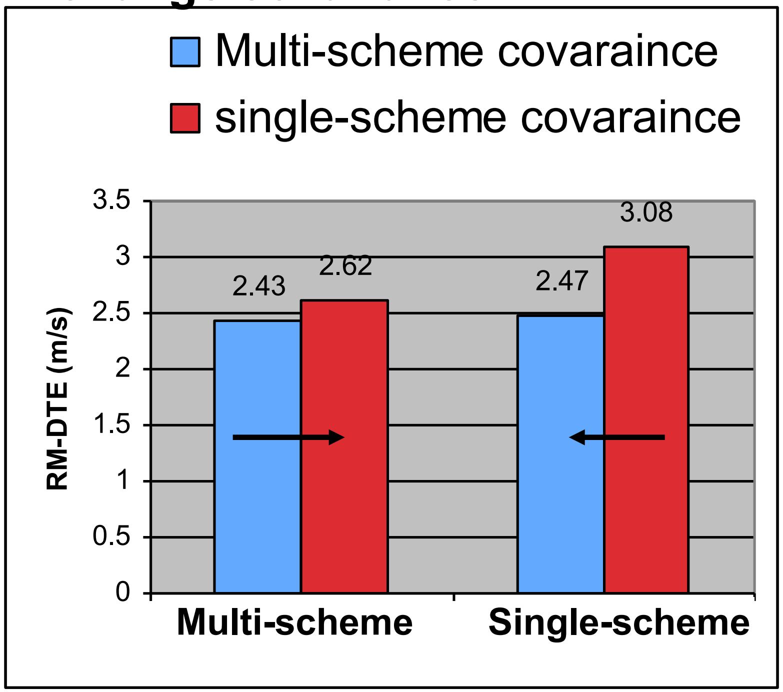
(Meng and Zhang 2008a)

Model Error in EnKF: Why multi-scheme is better?

Ensemble spread



Exchange covariance

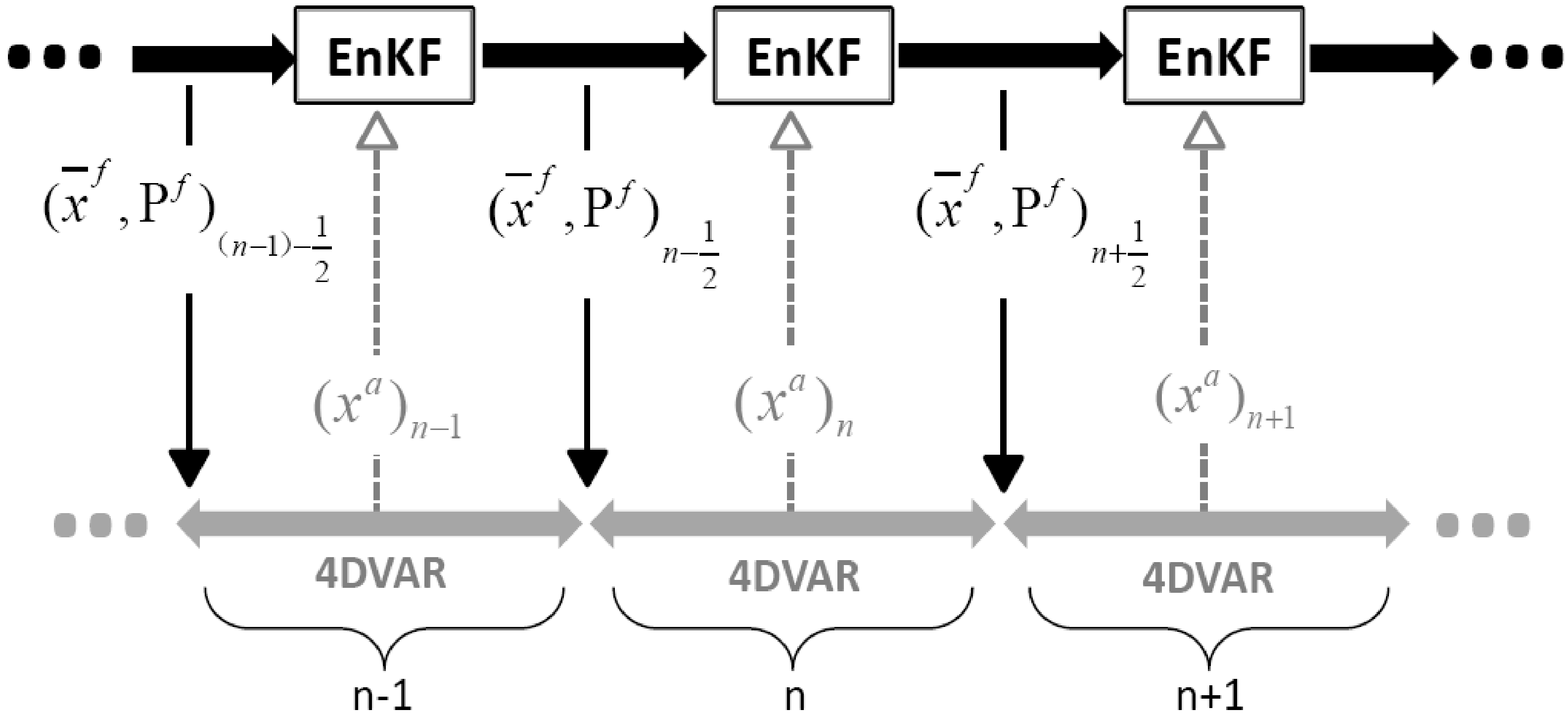


Multi-scheme is less vulnerable to filter divergence due to larger ensemble spread

Multi-scheme has a better background error covariance structure

(Meng and Zhang 2007 MWR)

E4DVar: 2-way Full Coupling of EnKF with 4DVar



Necessary Variable Changes:

EnKF provides ensemble-based background error covariance (P^f) for 4DVar

EnKF provides the prior ensemble mean ($\overline{x}^f$) as the first guess for 4DVar

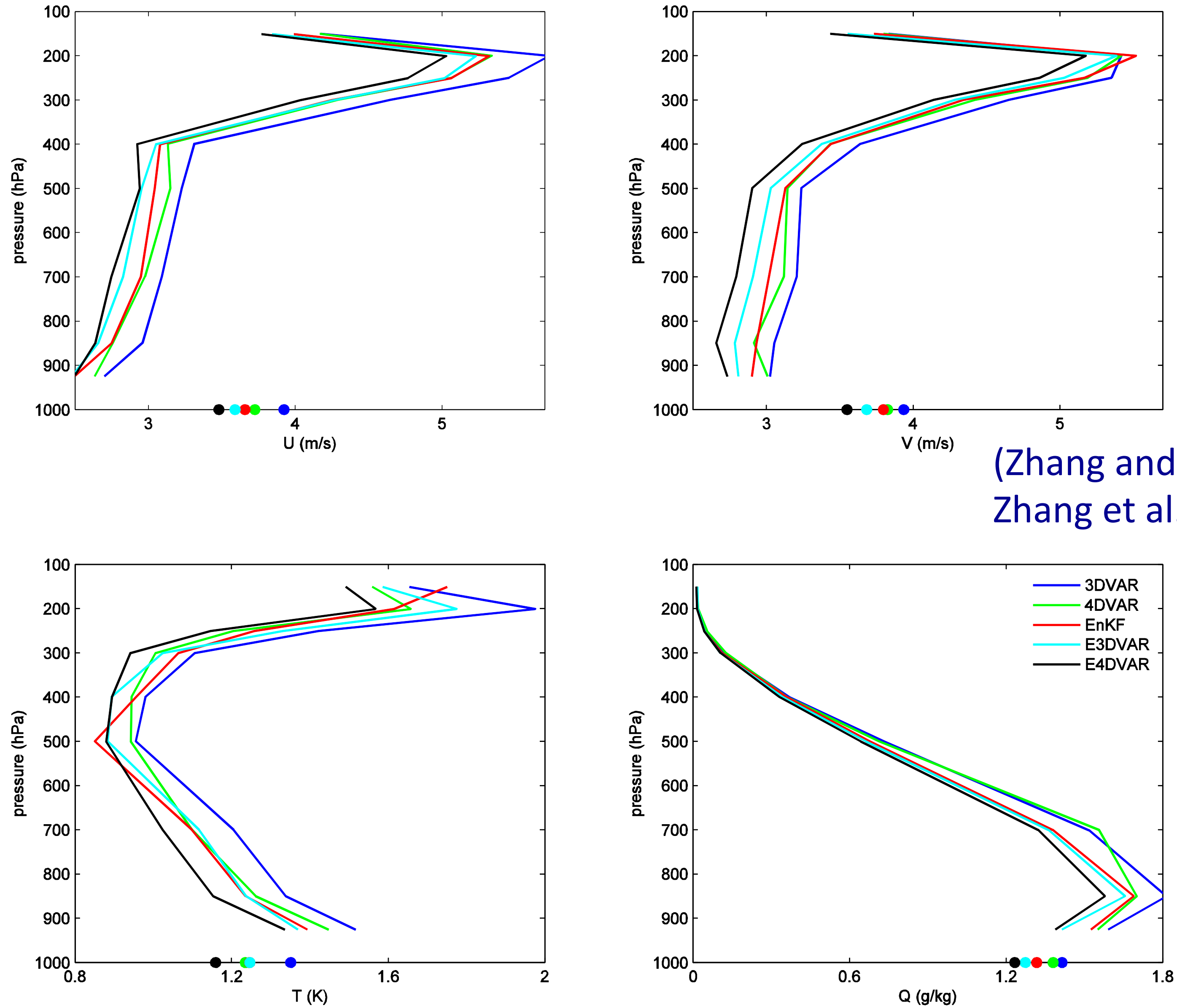
4DVar provides deterministic analysis ($\overline{x}^a$) to replace the posterior ensemble mean for the next ensemble forecast

1st proof-of-concept in Zhang, Zhang and Hansen (2009 AAS)

Real-data experiments in Zhang&Zhang (2012) and Poterjoy&Zhang (2014)

E4DVar, E3DVar vs. EnKF, 3DVar, 4DVar

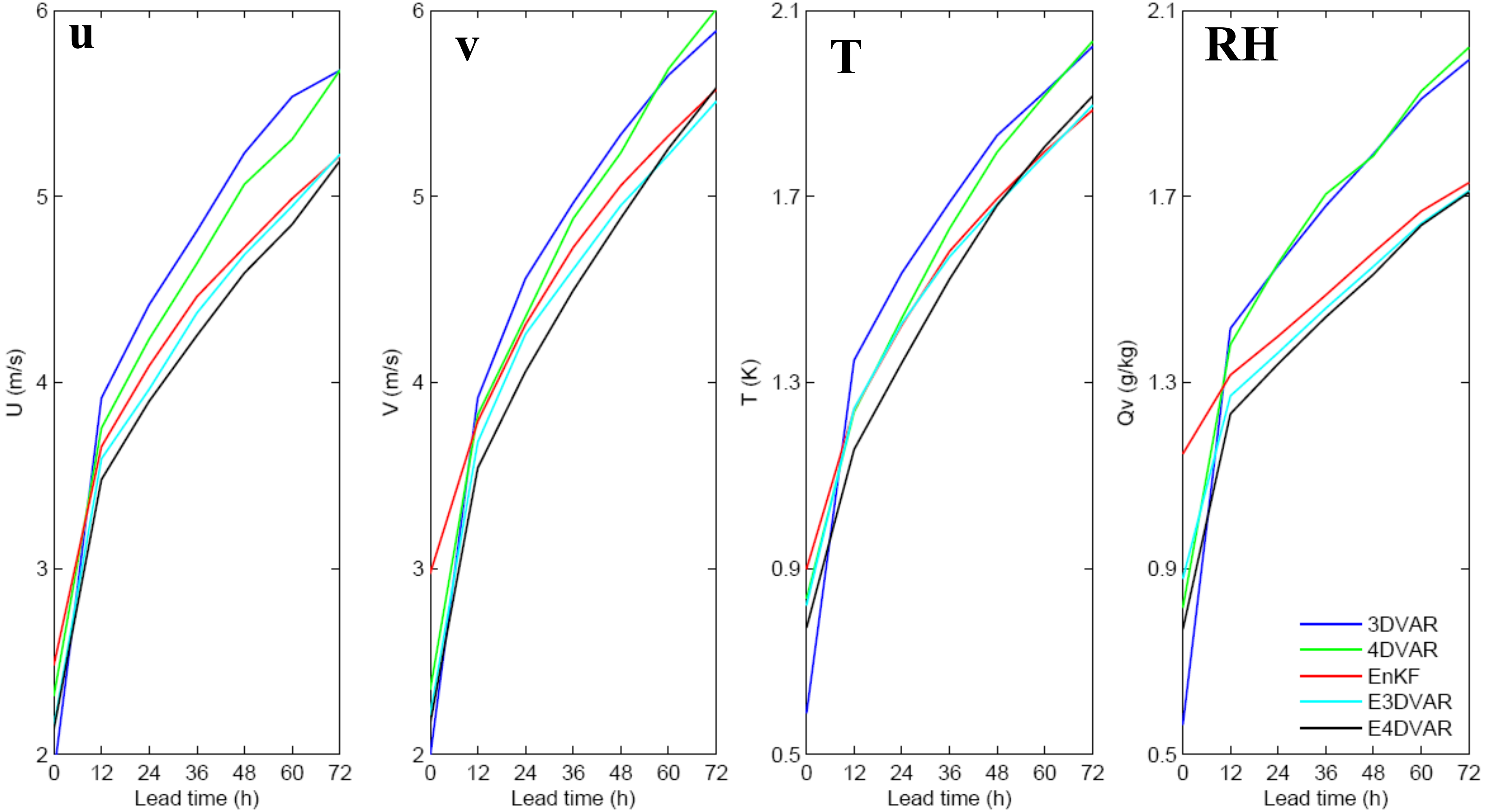
Mean vertical profiles of month-averaged 12-h forecast RMSE over CONUS



(Zhang and Zhang 2012; Zhang et al. 2013)

Inter-comparison of E4DVar, E3DVar vs. EnKF, 3DVar, 4DVar

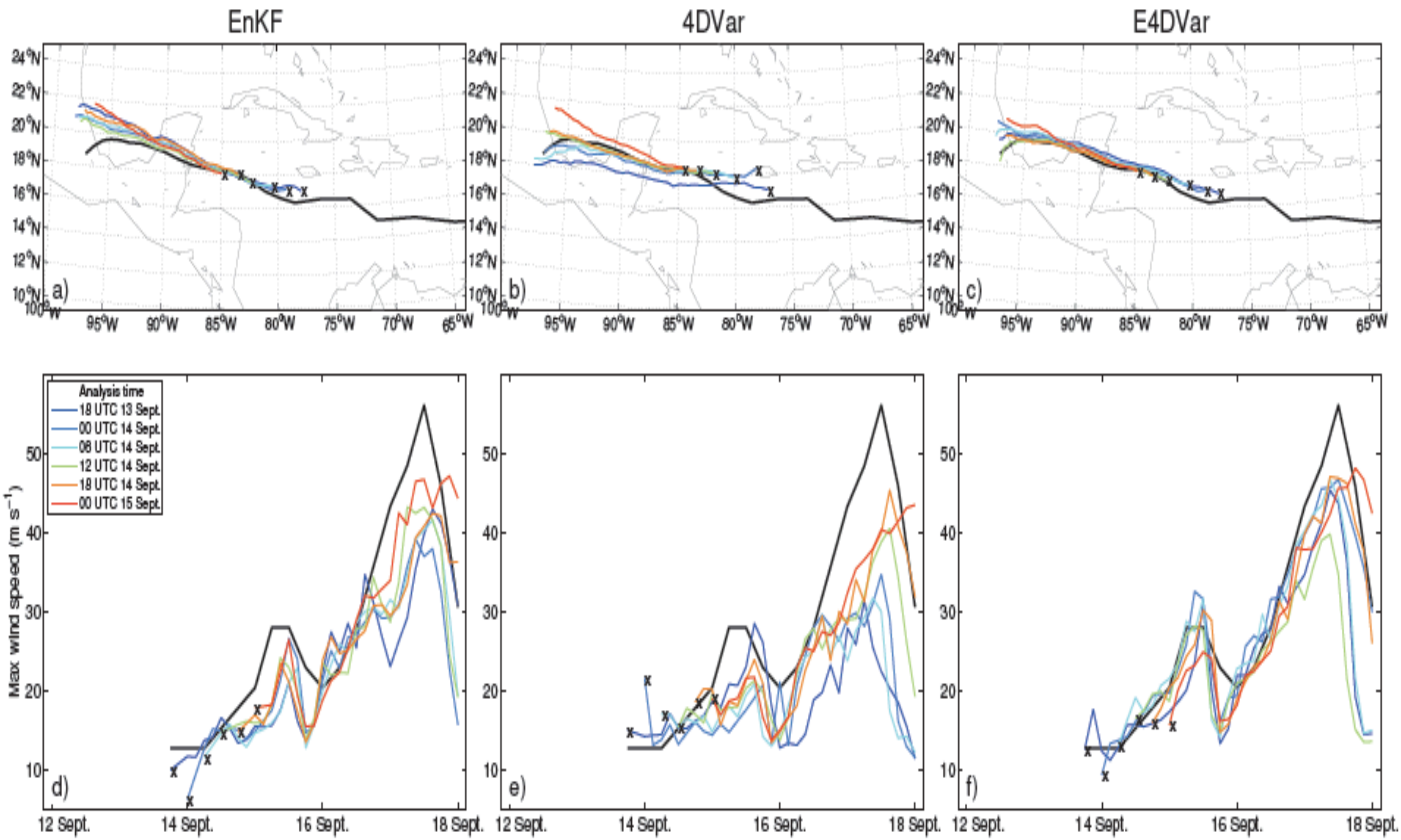
Total RMSE of U, V, T and Q with 0~72 lead time



(Zhang and Zhang 2012; Zhang et al. 2013 MWR)

Inter-comparison of E4DVar vs. EnKF & 4DVar for TCs

Deterministic forecast for Track & Intensity: w/ field sondes



(Poterjoy and Zhang, 2014 MWR)

E4DVar (Zhang et al. 2009) vs. 4DEnVar (Liu et al. 2008)

(Poterjoy and Zhang 2015, 2016 MWR)

The primary difference between E4DVar and 4DEnVar is how covariance is approximated in the assimilation window.

E4DVar uses $\mathbf{M}_\tau$ to approximate time-dependent covariance, starting from static covariance $\mathbf{P}^s$ and ensemble covariance $\mathbf{P}_0^f$

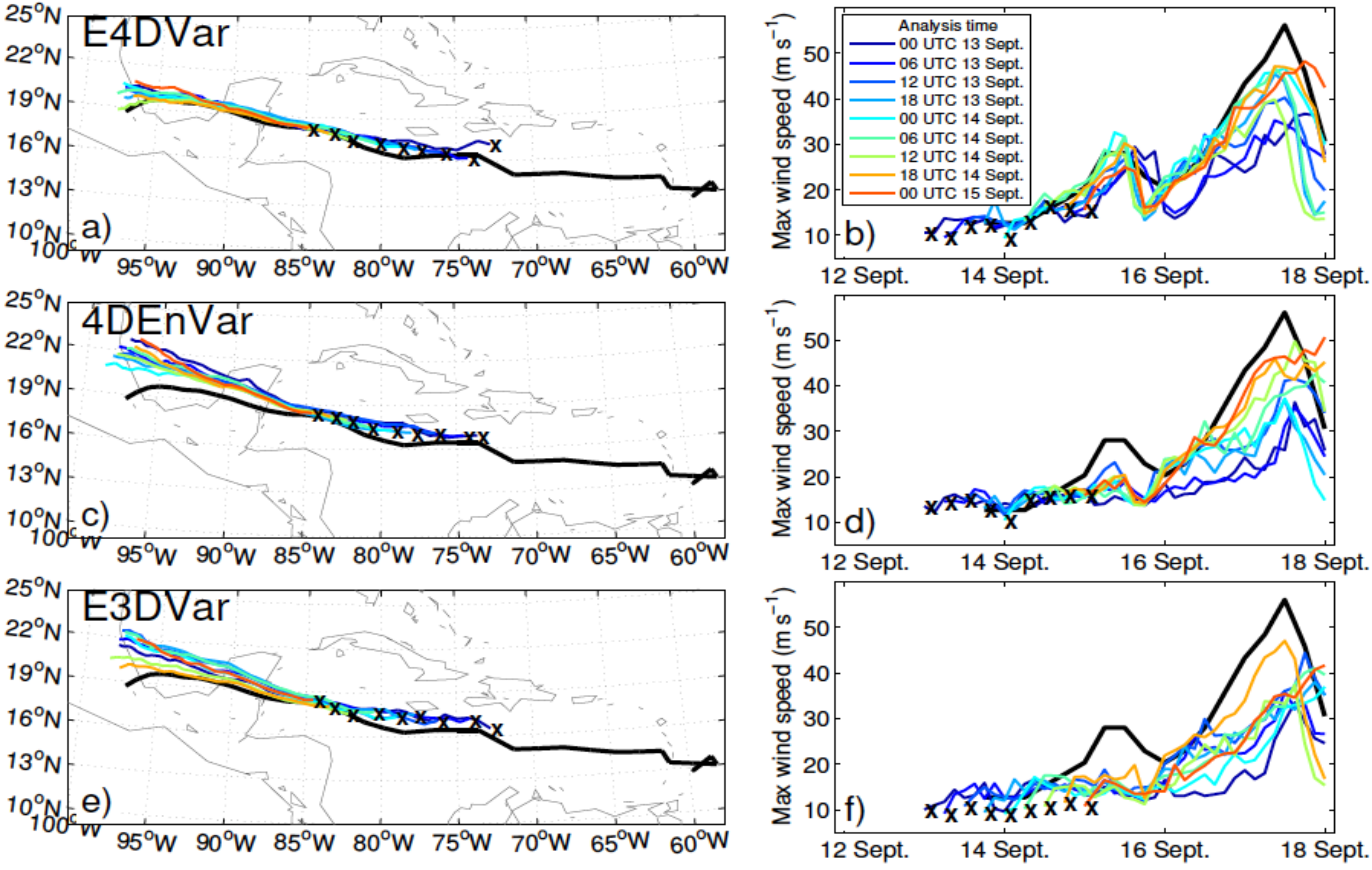
$$
\begin{aligned}
\mathbf{P}_{0,\tau} &\approx [\mathbf{M}_\tau \mathbf{P}_0^b]^T \\
&= \{\mathbf{M}_\tau[\beta \mathbf{P}^s + (1-\beta)\mathbf{P}_0^f]\}^T \\
&= \beta[\mathbf{M}_\tau \mathbf{P}^s]^T + (1-\beta)[\mathbf{M}_\tau \mathbf{P}_0^f]^T
\end{aligned}
$$

4DEnVar uses the full nonlinear model to estimate ensemble covariance, but cannot evolve $\mathbf{P}^s$ in time.

$$
\mathbf{P}_{0,\tau} \approx \beta \mathbf{P}^s + (1-\beta)\left[\frac{1}{N_e-1}\sum_{n=1}^{N_e} \mathbf{x}'^f_{0,n}(\mathbf{x}'^f_{\tau,n})^T\right]
$$

Inter-comparison of E4DVar vs. 4DEnVar and E3DVar

Deterministic forecast for Track & Intensity: w/ field sondes



(Poterjoy and Zhang, 2016 MWR)

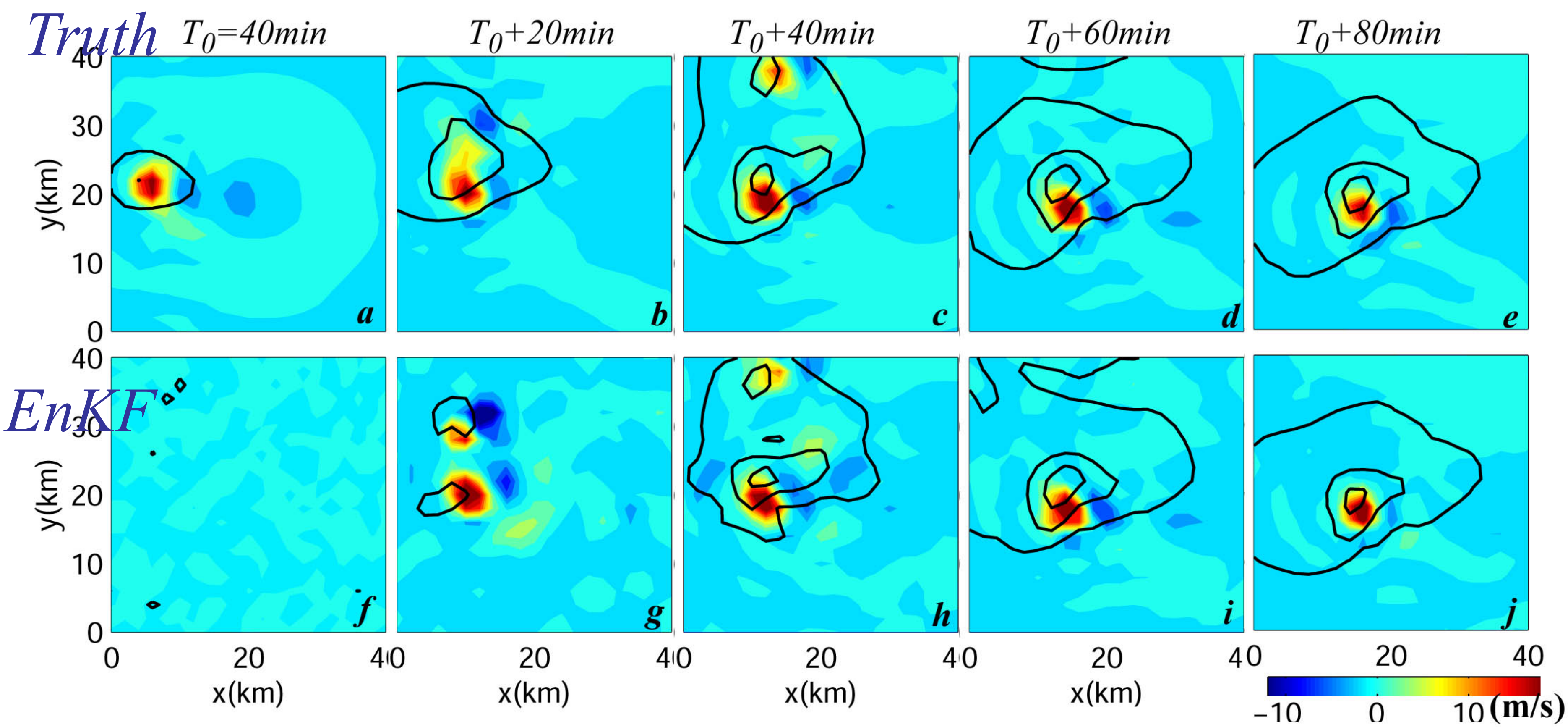
First Test of EnKF for Convection-permitting NWP

Assimilation of Radar Vr for Supercells

(Snyder and Zhang 2003; Zhang, Snyder and Sun 2004; Dowell, Zhang et al. 2004; all in MWR)

Observations: radial velocity V_r only, available every 5 minutes where reflectivity dBZ>12

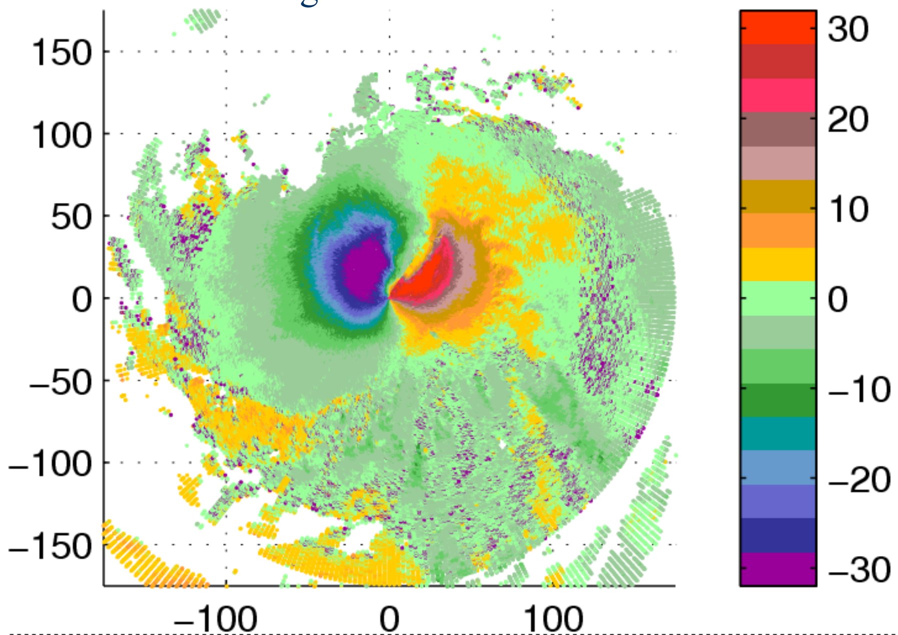
Vertical velocity at 5km (colored) and surface cold pool (black lines, every 2K)



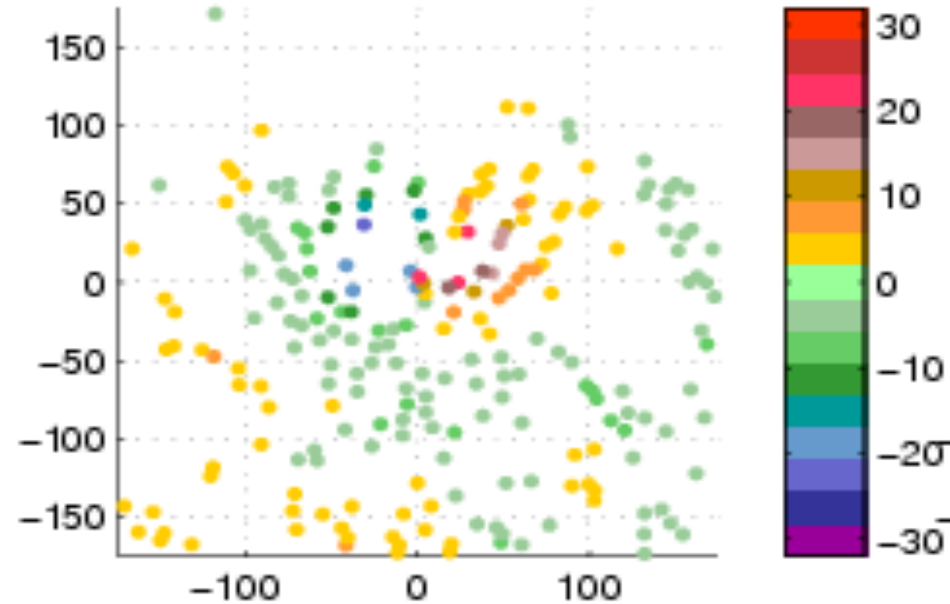
Super-Obs: QC and thinning of WSR-88D Vr Obs

(Zhang et al. 2009 MWR; Weng et al 2011 CiSE)

0.5degree RAW data



0.5degree SO



•Define SO position depended on the radial distance

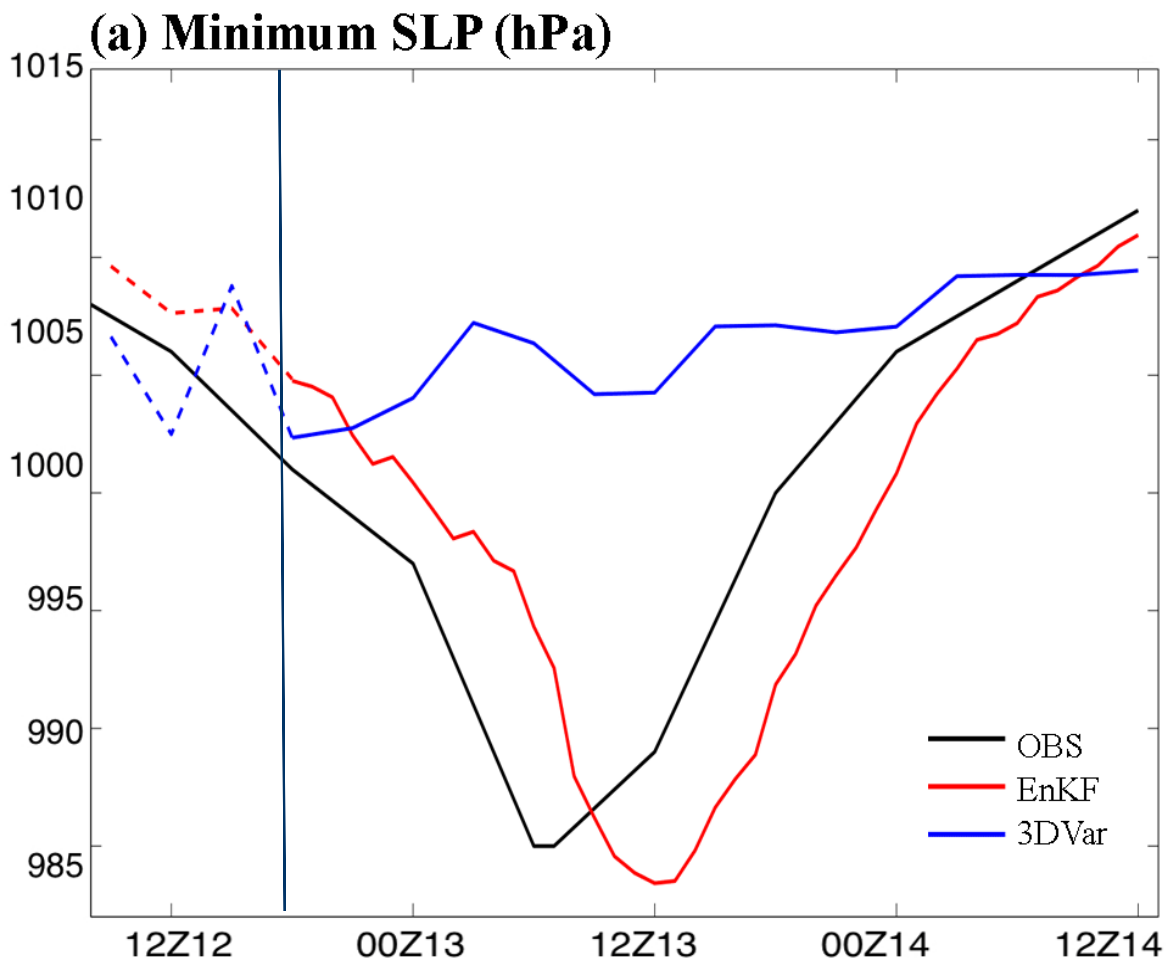
•Average10 nearest data points in the raw polar scan to create a SO

•Averaging bin is 5km max radial range and 5° max azimuthally resolution

•There are at least 4 valid velocity data within an averaging bin.

Assimilate W88D Doppler Vr for Humberto'05

WRF/EnKF Forecast vs. Observations vs. 3DVAR



The WRF/3DVAR (as a surrogate of operational algorithm) assimilates the same radar data but without flow-dependent background error covariance, its forecast failed to develop the storm despite fit to the best-track observation better initially

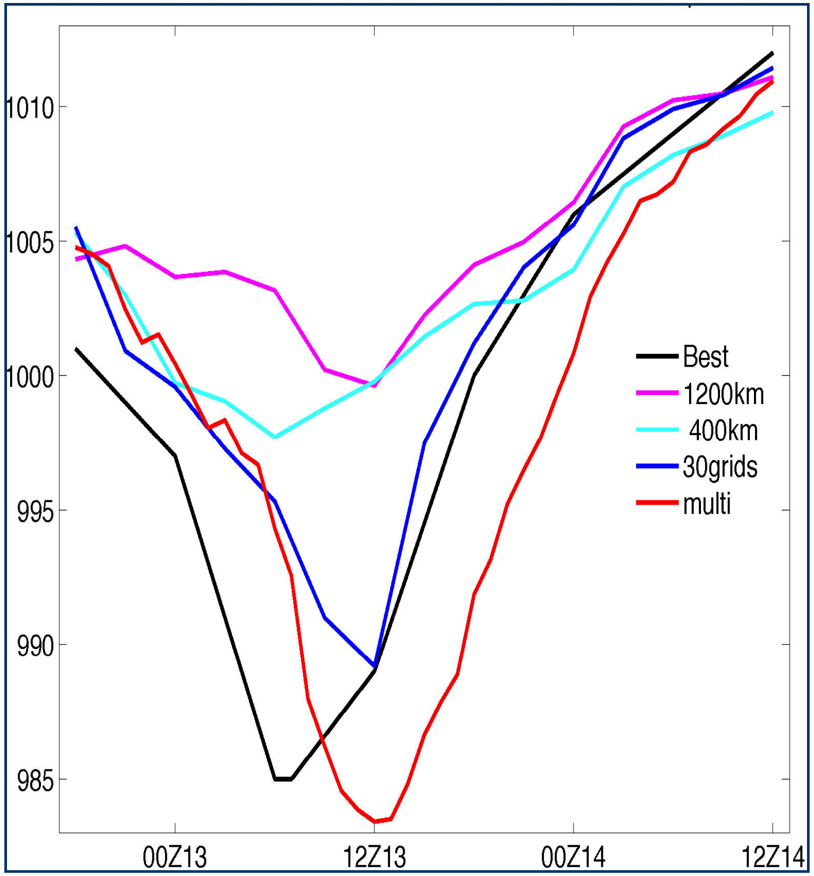
(Zhang et al. 2009 MWR)

How/if we can perform adaptive localization in multiscale systems?

Multiscale ROI: Successive Covariance Localization (SCL)

(Zhang et al. 2009 MWR)

- Dense observations contain information of the state at different scales, e.g., hurricanes.
- Rationale: larger-scale errors have larger correlation length scales thus need fewer observations, large radii of influence; more observations with smaller radius of influence are needed to constrain small-scale errors (Zhang et al. 2006).
- SCL has some similarity to successive correction method (SCM) used in some earlier empirical objective analysis schemes (e.g., Barnes 1964), though subgrouping of observations is used in the EnKF so the same observation not used twice.



Adaptive covariance localization: known truth

Kalman gain update with known true covariance:

$$\Delta x_i^a = r_i^t \Delta y$$

$$r_i^t = \frac{(B^{true} h^\top)_i}{R + h B^{true} h^\top}$$

Kalman gain update with known localized sampling covariance:

$$\Delta x_i^a = r_i^s \rho_i \Delta y$$

Optimum localization radius (ROI) is to minimize the following cost function F0:

$$F_0(ROI) = \sum_{i=1}^{n} (r_i^s \rho_i - r_i^t)^2$$

Zhen and Zhang (2014 MWR, December issue)

Adaptive covariance localization: unknown truth

Distribution of true covariance from a given sampling covariance:

$$p(B|B^s) = \frac{p(B, B^s)}{p(B^s)} = \frac{p(B^s|B)p(B)}{p(B^s)}$$

Average of cost function F with ROI over all possible true covariance:

$$\int \sum_{i=1}^{n} F(r_i^t, r_i^s, d_i, ROI) \frac{p(B^s|B)p(B)}{p(B^s)} dB$$

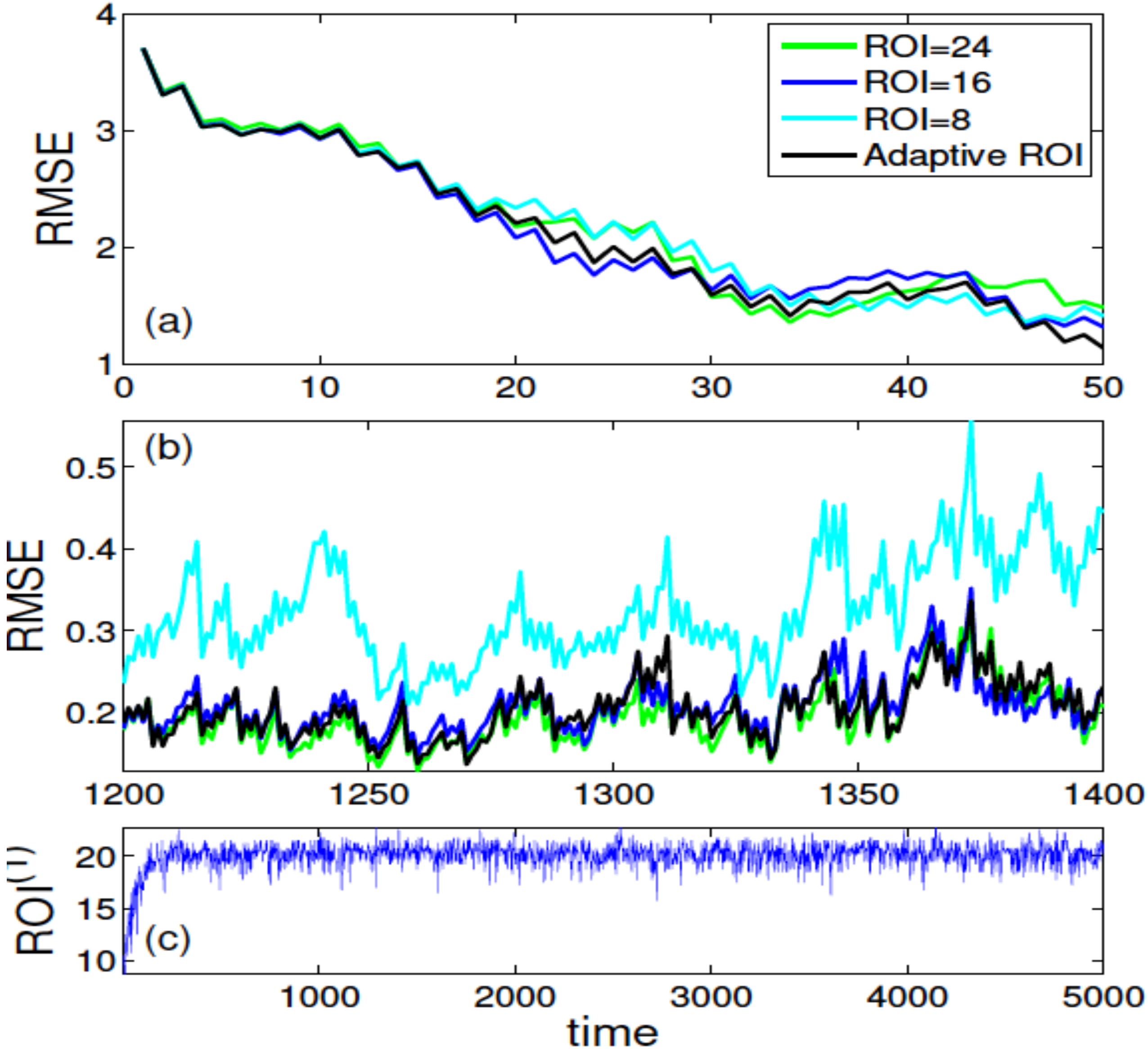
Modified cost function for unknown truth:

$$F(ROI) = \int \left\{ \sum_{d_i < ROI} \left[(\rho_i r_i^s - r_i^t)^2 - (r_i^t)^2 \right] + \sum_{d_i < ROI} \rho_i^2 (r_i^s - r_i^t)^2 \right\} \frac{p(B_{Loc}^s|B_{Loc})p(B_{Loc})}{p(B_{Loc}^s)} dB_{Loc}$$

Refer to Zhen and Zhang (2014 MWR, December issue) for detailed math; Alternative empirical ACL: Li and Anderson 2014, Anderson 2012, Jun et al. 2011, Bishop et al. 2011, Bishop and Hodyess 2007

Tests of ACL with Lorenz-96 perfect model

Performance in terms of RMSE for N=61

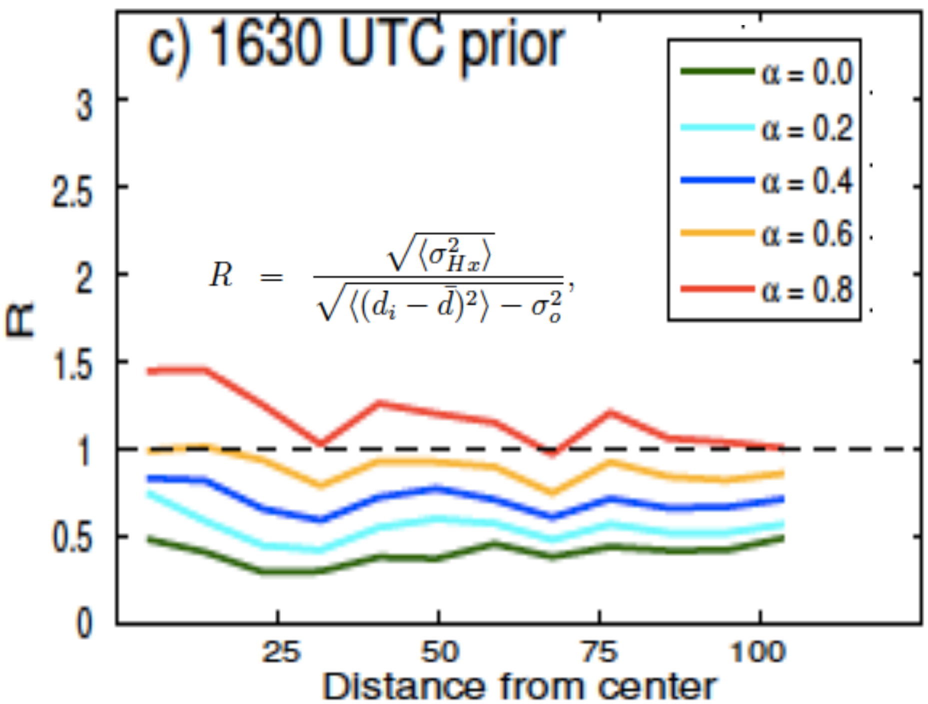


Covariance Relaxation: Inflation through Relaxation to Prior

$$(x'^a)_{new} = \alpha\, x'^f + (1-\alpha)\, x'^a$$

(Zhang, Snyder and Sun 2004 MWR)

- **α is the relaxation or mixing coefficient**
- Treats sampling issues with respect to both model error and ensemble size
- More inflation in the area of denser observations while no inflation if no obs
- The method is adopted from the commonly used relaxation method in interactive numerical solver
- **An simple adaptive covariance inflation method but α is still empirically chosen**



(Poterjoy, Zhang & Weng, 2014 MWR)

Adaptive Covariance Relaxation (ACR)

(Ying and Zhang, QJ, 2014)

1. Estimate inflation factor from innovation statistics in observation space (use posterior statistics since it's an relaxation):

$$\lambda = \sqrt{\langle d^{o-a} d^{a-b} \rangle} / \bar{\sigma}^a$$

2. Smooth the inflation factor in time to reduce sampling bias:

$$\lambda_{\text{smth},t} = \lambda_{t-1} + (\lambda_t - \lambda_{t-1})/\tau$$

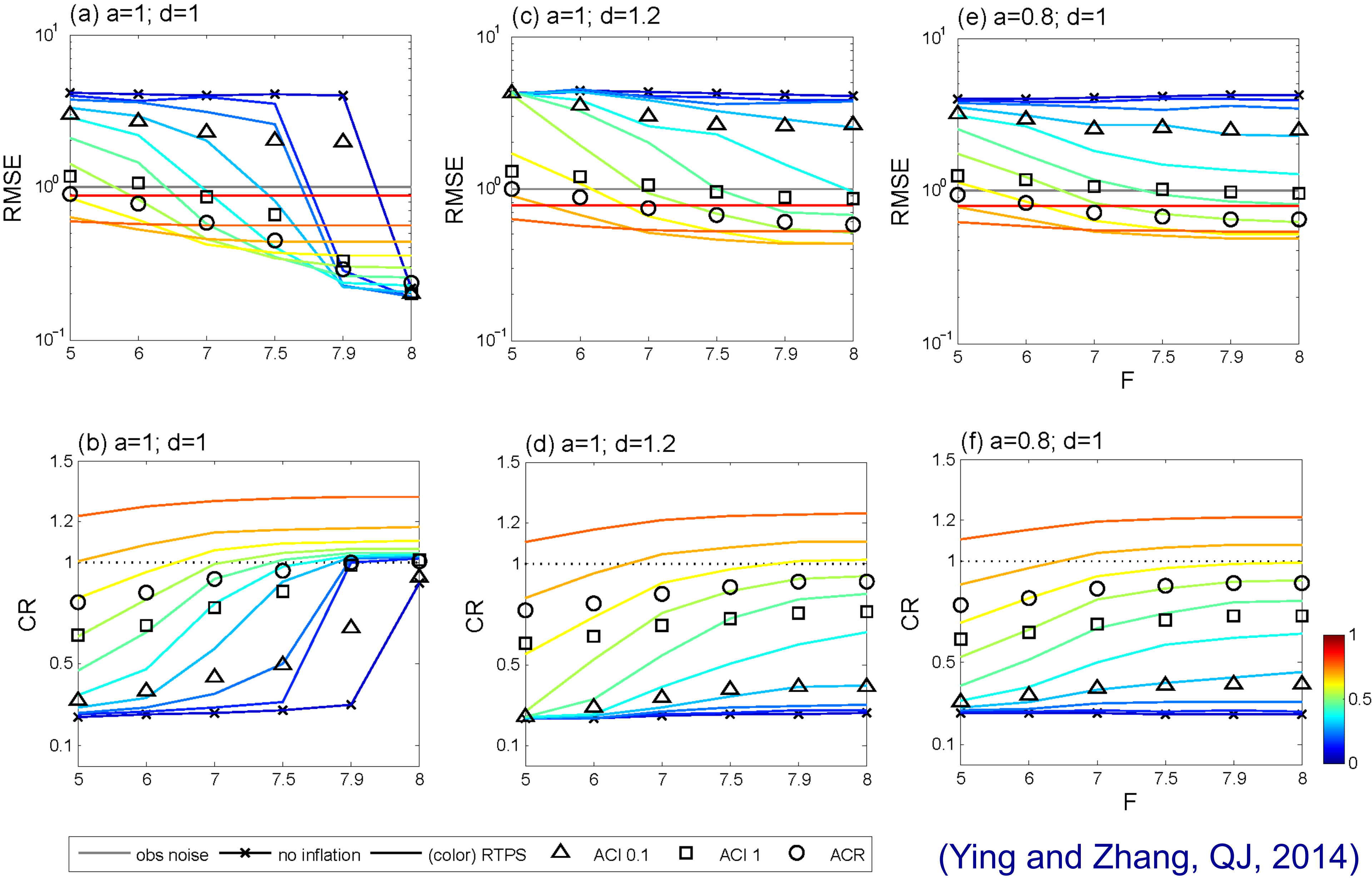
3. To account for spatially inhomogeneous observations, instead of treating a spatially independent inflation factor (Anderson 2009, Miyoshi 2011), we use relative reduction in ensemble spread (Whitaker and Hamill 2012) to provide a spatial mask, and derive α in observation space:

$$\frac{(1-\alpha)\bar{\sigma}^a + \alpha\bar{\sigma}^b}{\bar{\sigma}^a} = \lambda_{\text{smth}}$$

4. Apply relaxation in state space:

$$(x^a)'_{\text{new}} = (x^a)' \frac{(1-\alpha)\sigma^a + \alpha\sigma^b}{\sigma^a}$$

Sensitivity to model error: fully-observed



(Ying and Zhang, QJ, 2014)

ACR improves result for a wide range of model error severity

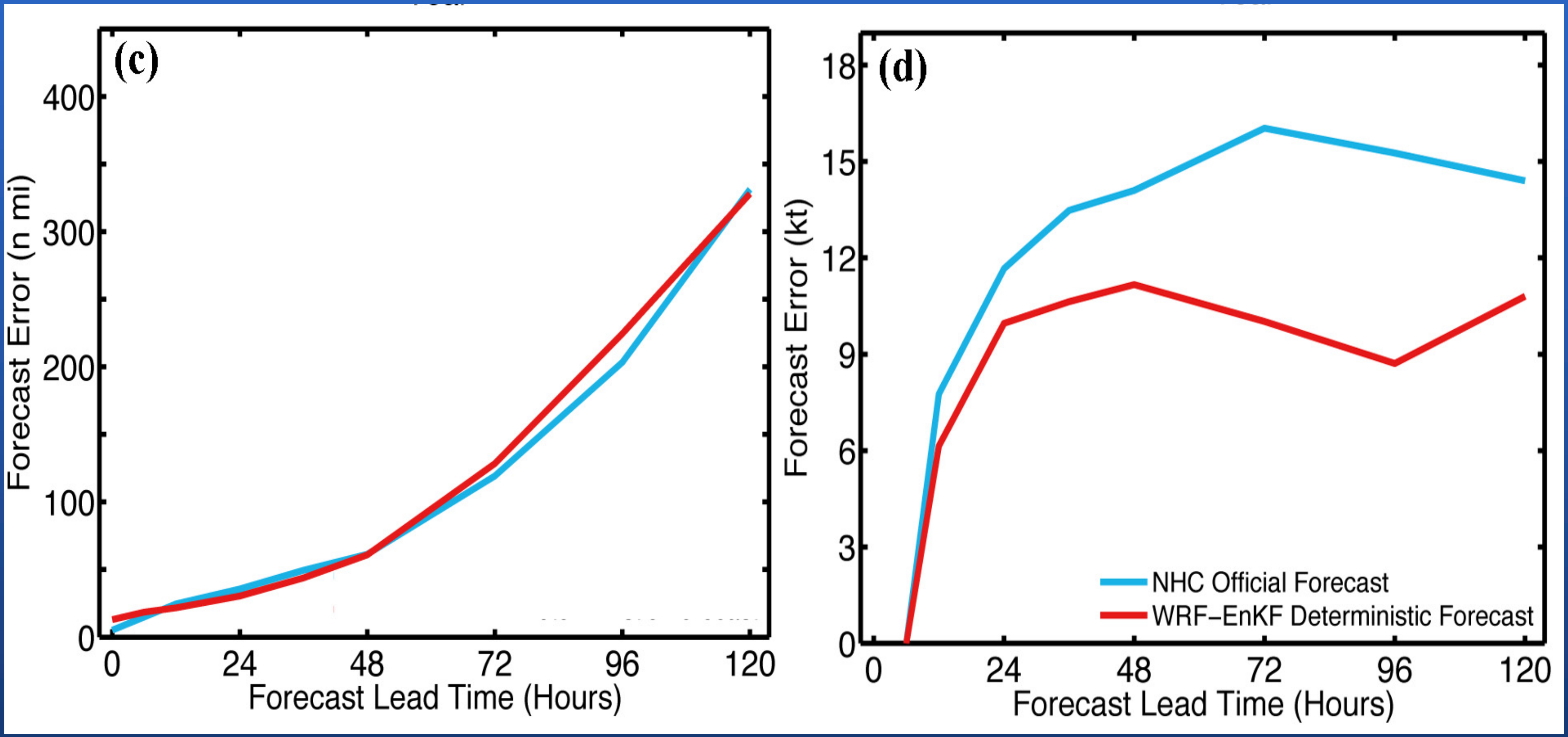
WRF-EnKF Performance Assimilating Airborne Vr

all 100+ P3 TDR missions during 2008-2012

Quasi-operational evaluation by NOAA/NHC since 2011 as stream 1.5 run

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

Position error (km) **Intensity error (knots)**



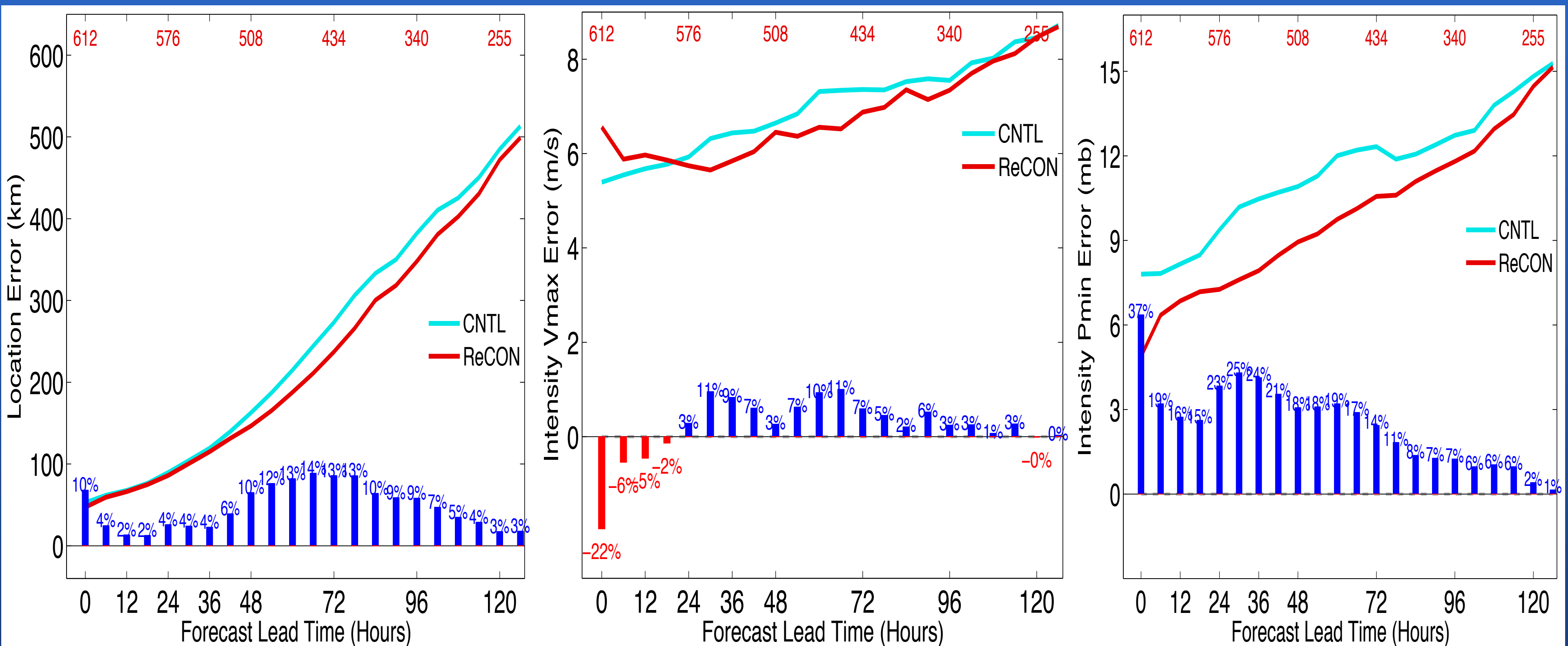
(Zhang et. 2011 GRL; Zhang and Weng, 2015 BAMS)

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)

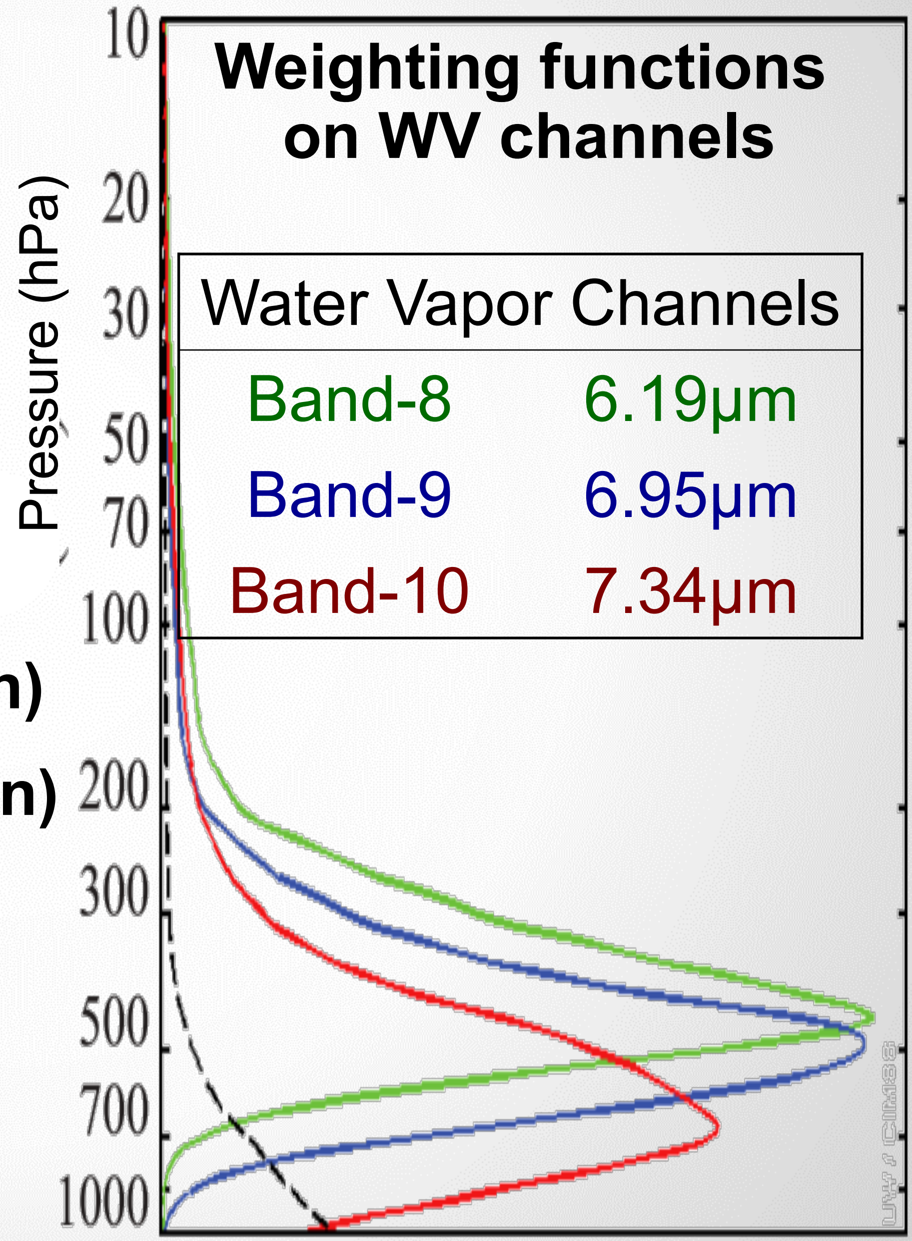
New Generation of Geostationary IR Satellites

Launch Dates:

- **Oct 2014 (Himawari-8, Japan)**
- **Nov 2016 (Himawari-8, Japan)**
- **Nov 2016 (GOES-R, USA)**
- **Dec 2016 (FY-4, China)**

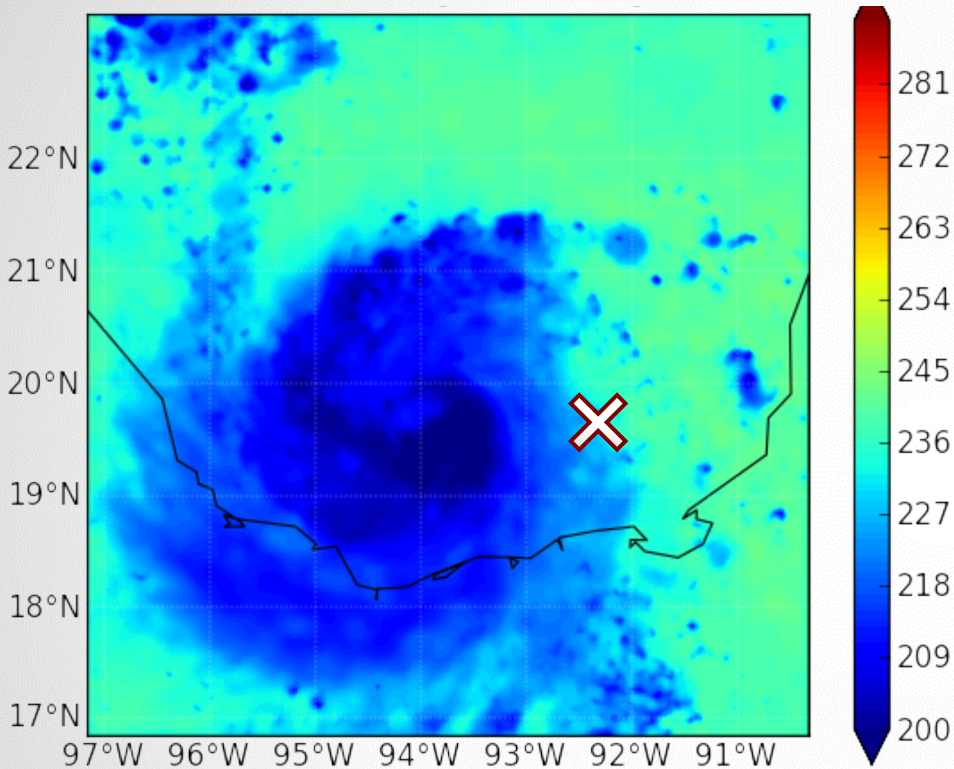
High spatiotemporal resolutions:

➢ **10-15 minutes; 2-4 km**

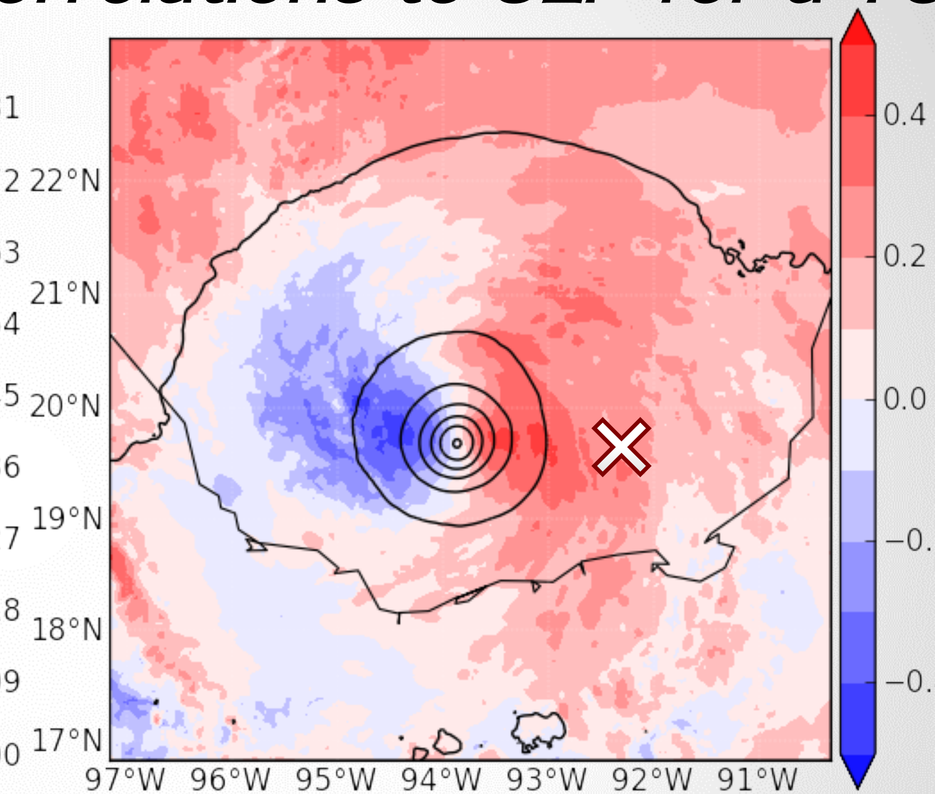


EnKF Assimilation of All-sky Radiance from GOES-R

Simulated Radiance and Correlations to SLP for a TC



Simulated GOES-R ABI Ch8 (6.19 μm) radiance

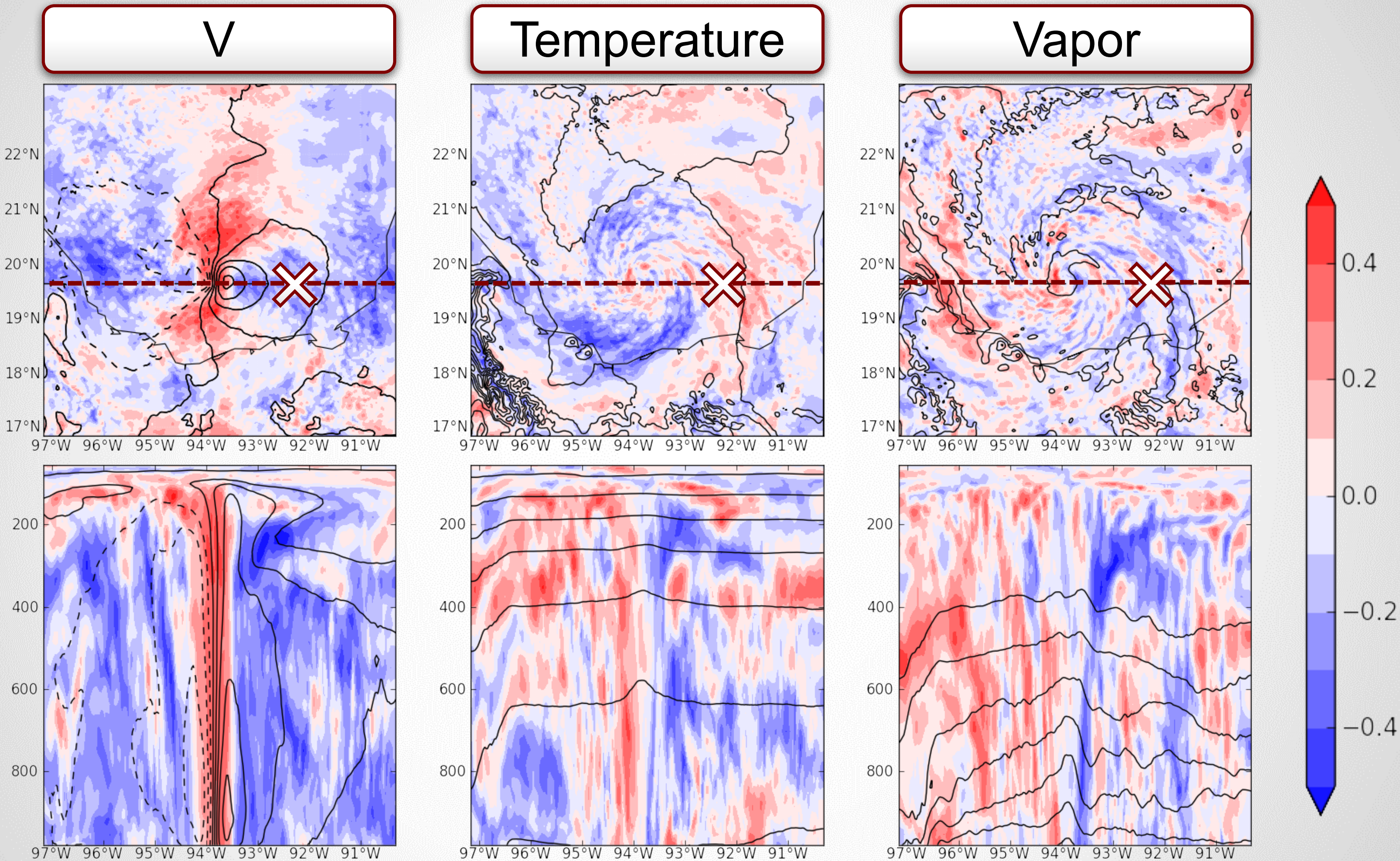


Colors: ensemble correlation of SLP to radiance at 'X'

Contours: ensemble mean SLP

(Zhang, Minamide & Clothiaux, 2016 GRL)

Correlations of Radiance to Model State Variables

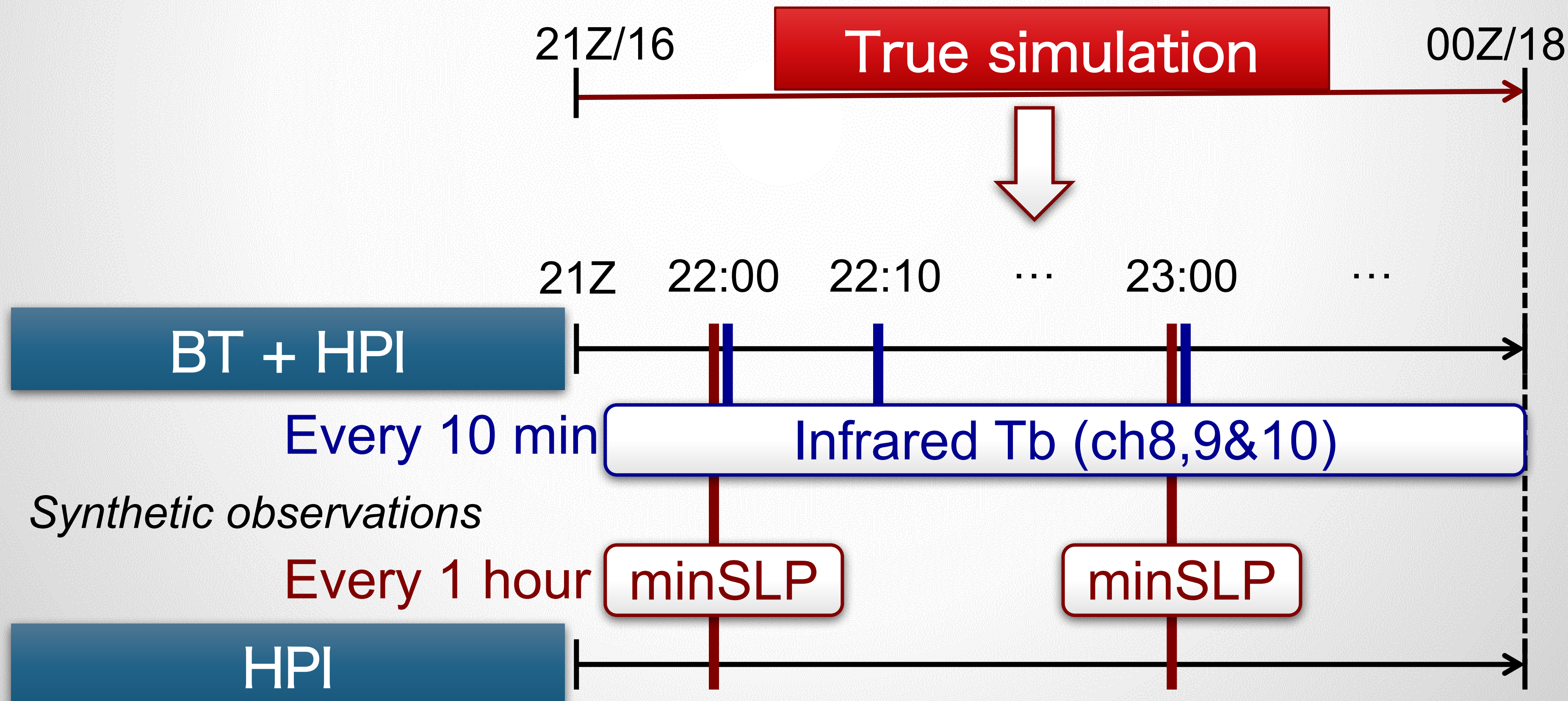


Colors: ensemble correlation to radiance (6.19 μm) at ‘x’ ,

Contours: ensemble mean at 930 hPa (top) & 19.6 N (below)

Observing System Simulation Experiments (OSSE)

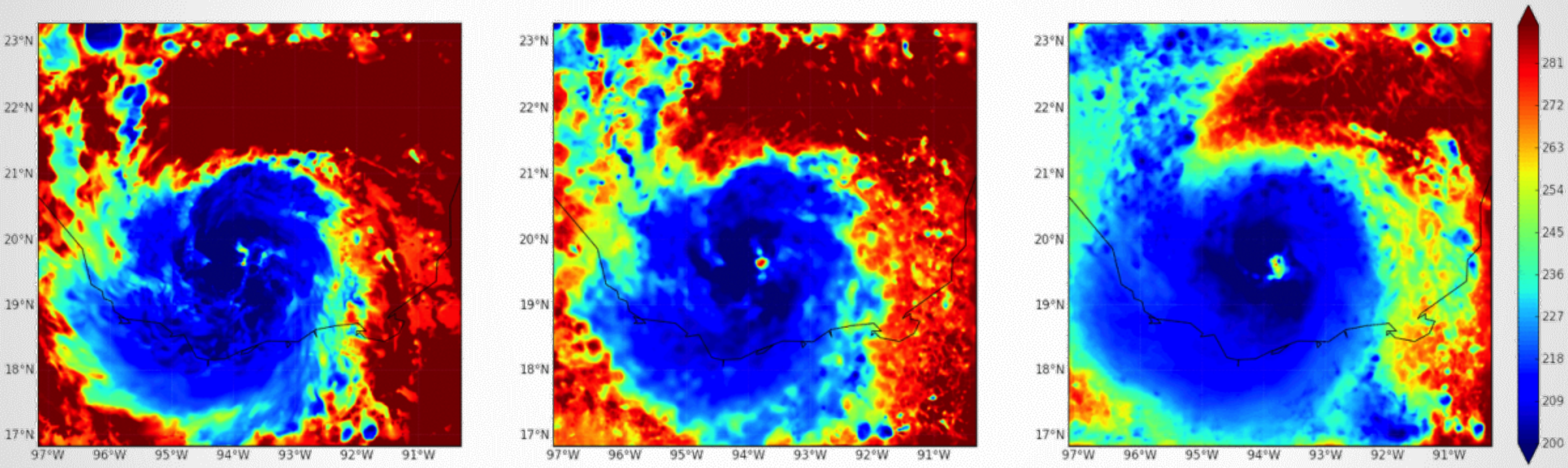
WRF truth run: **Hurricane Karl**, 21Z/16–00Z/18 Sep 2010; 27, 9, 3km (D1-3)
PSU WRF-EnKF: 60-mem ensemble (Zhang et al. 2009; Weng & Zhang 2012)
Covariance inflation: relaxation to prior perturbation (RTPP, Zhang et al. 2004)
Successive covariance localization (SCL, Zhang et al. 2009)
Adaptive observation error inflation (AOEI, Minamide & Zhang 2016)



EnKF Performance assimilating simulated radiance

Truth versus EnKF-analyzed Infrared Radiance
of GOES-R ABI ch14 (11.2 μm)

[2010-09-16_22:00]



Verifying truth

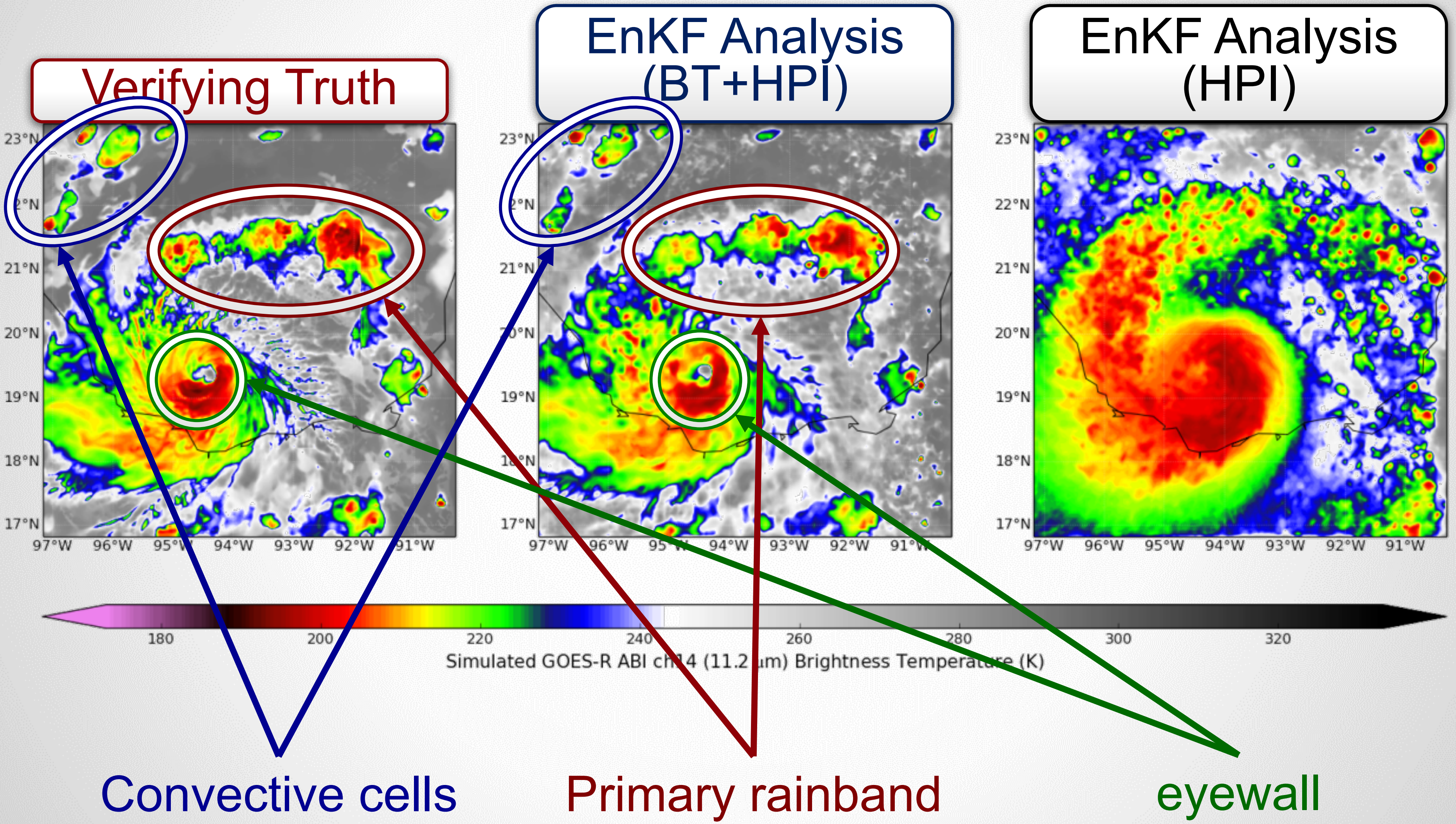
EnKF analysis
with radiance & minimum SLP

EnKF analysis
with minimum SLP only

(Zhang, Minamide & Clothiaux, 2016 GRL)

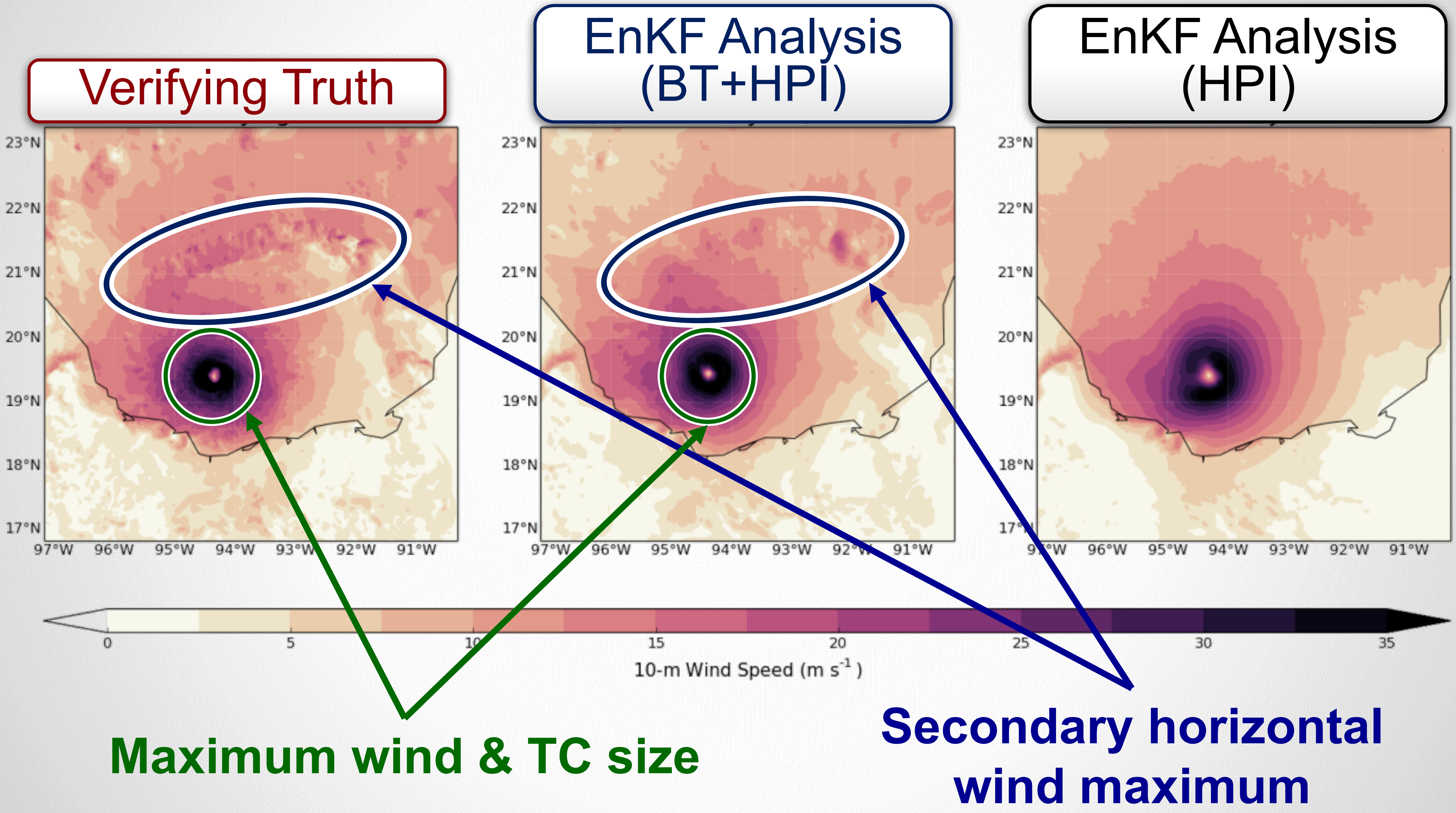
EnKF Performance on IR Brightness Temperature

Brightness Temperature of GOES-R ABI Ch14 (11.2 μm)



Zhang et al. (2016) GRL

EnKF Performance on 10-m wind speeds



Zhang et al. (2016) GRL

Adaptive Observation Error Inflation (AOEI)

Problem: **erroneous analysis increments**

If **Model (clear / cloudy) ≠ Observation (cloudy / clear)**

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

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

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

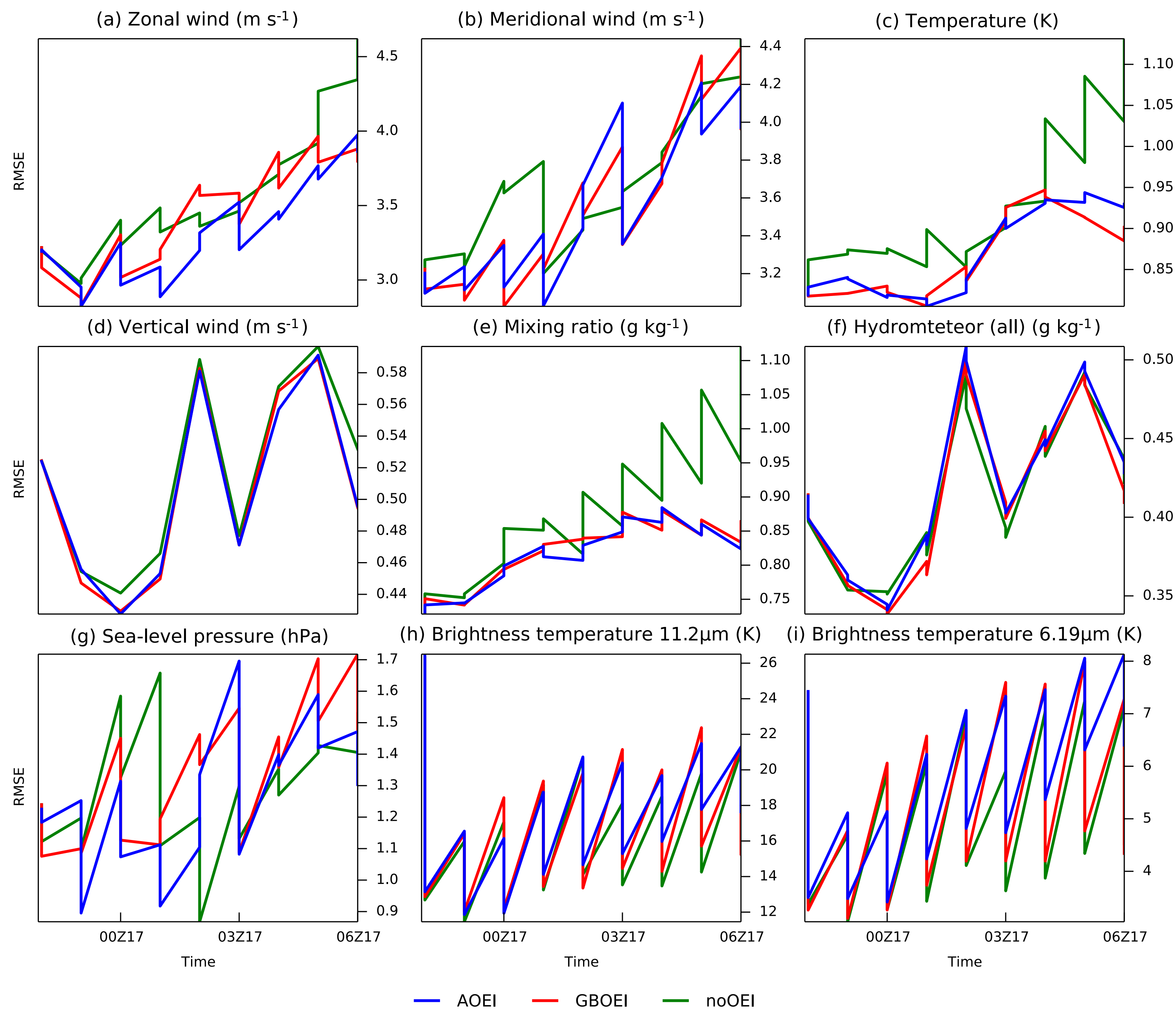
AOEI

suppresses erroneous analysis increments,

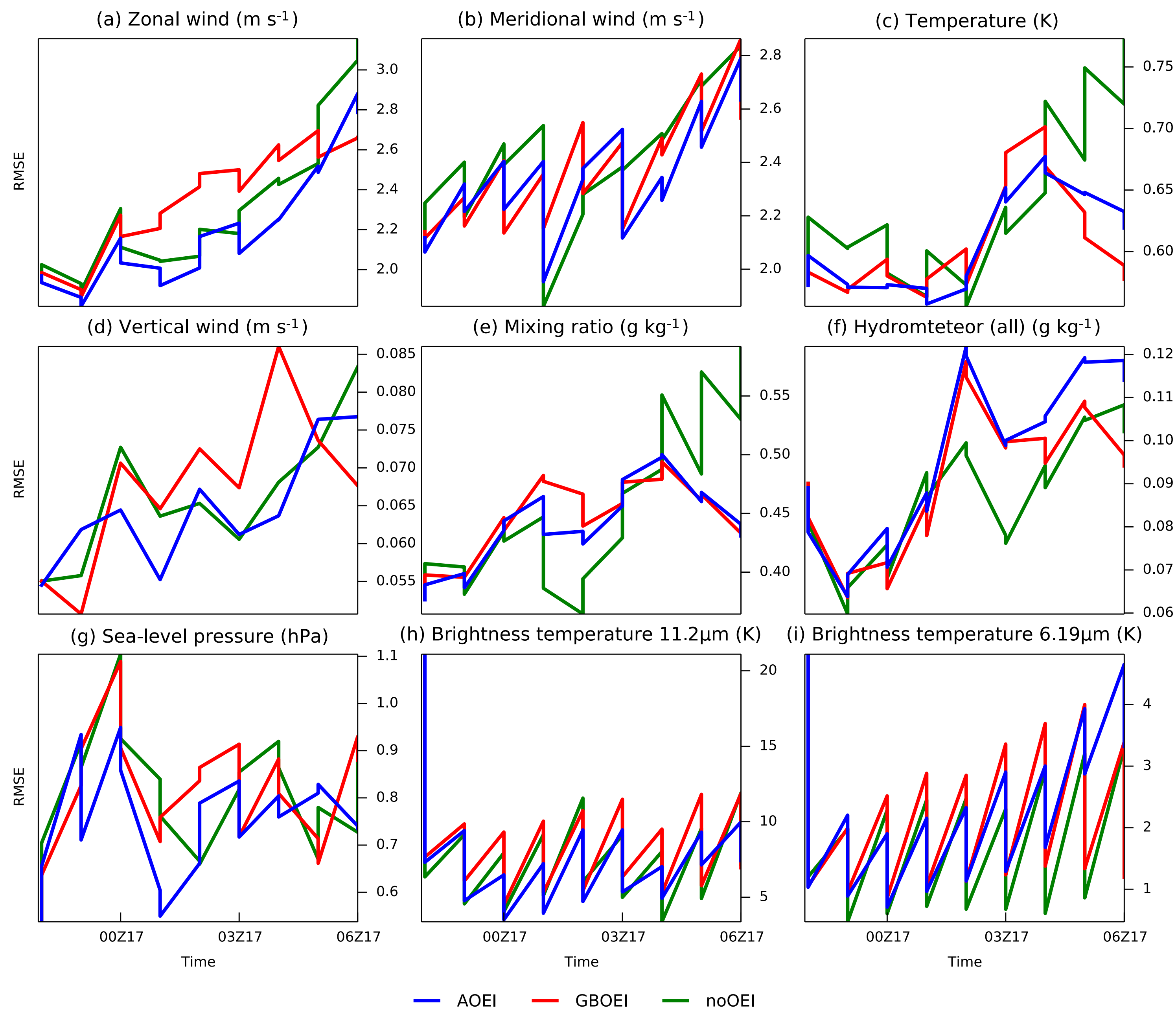
relieves the issues of representativeness & sampling,

& contributes to maintaining balance.

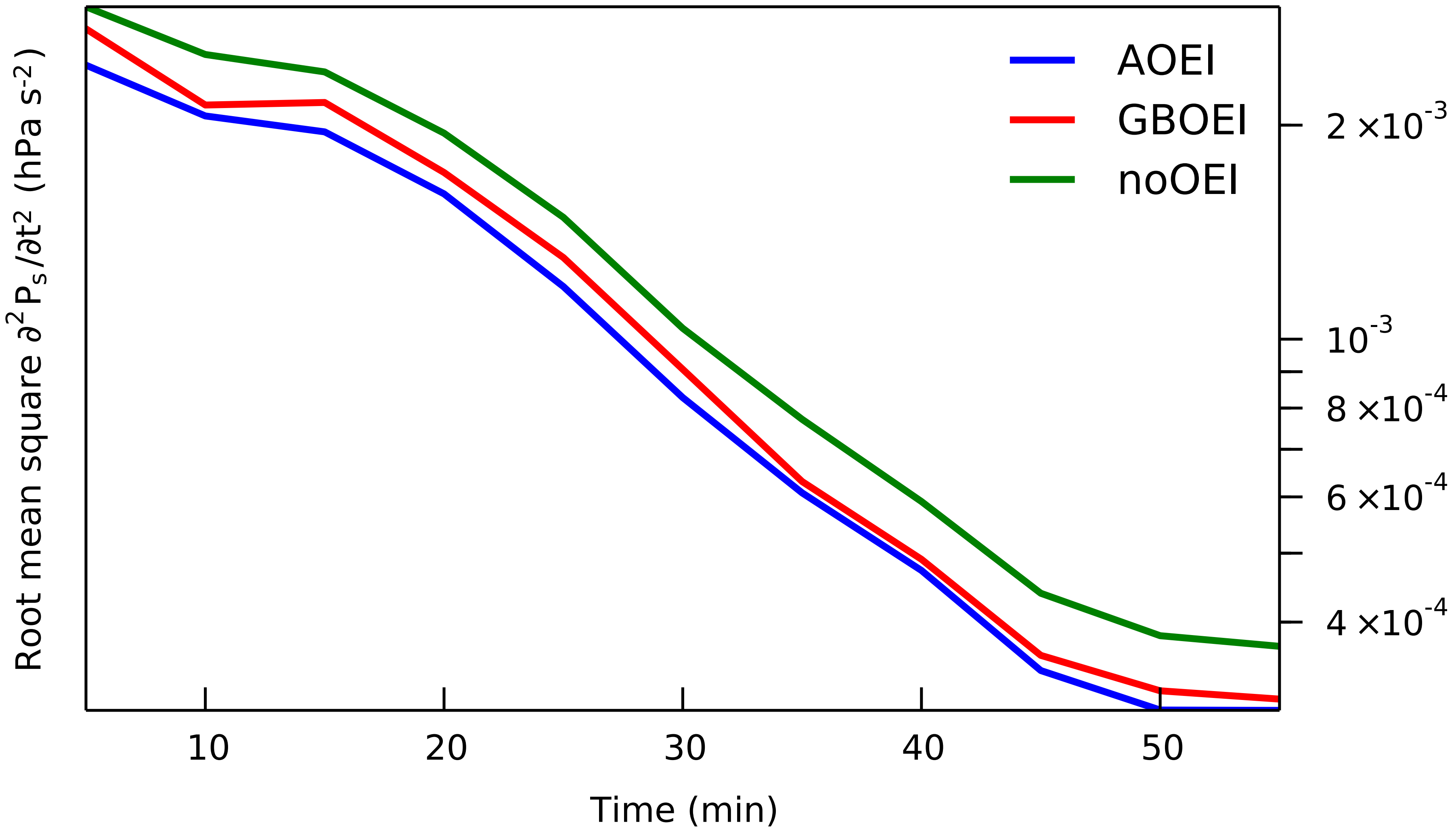
(Minamide & Zhang, MWR, accepted)



Temporal evolution of domain-averaged EnKF RMSEs with AOEI, GBOEI and noOEI



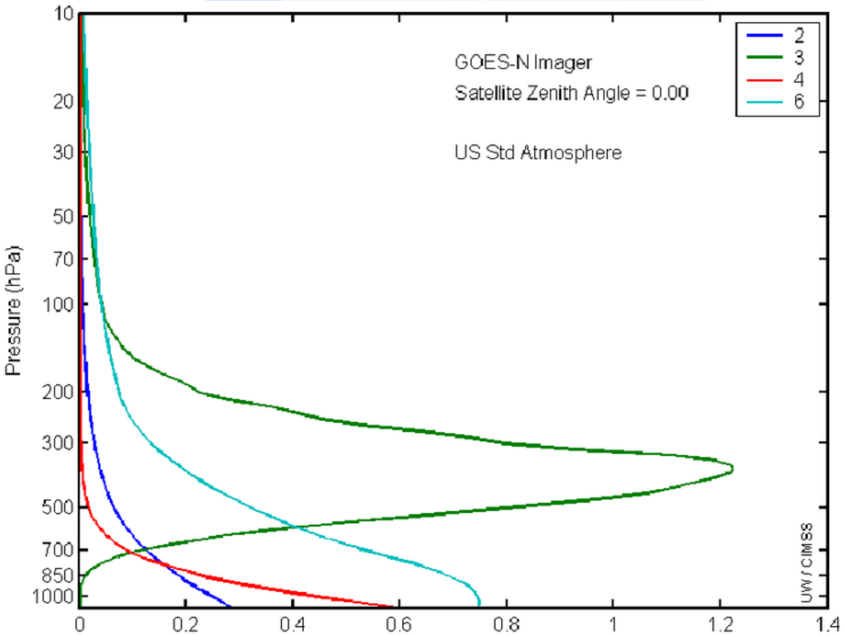
Temporal evolution of domain-averaged EnKF RMSEs for wavelenghs > 300km



Flow imbalance in forecasts after the EnKF analysis

Existing IR Radiances from GOES-13 Imager

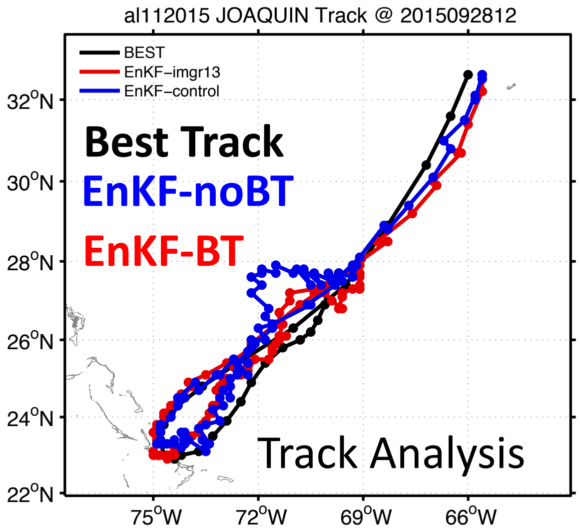
- **GOES-13: Geostationary orbit; altitude = 35786 km; lon = 75W;**
- **IMAGER:**
  - ➢ **5 channels covering VIS, MWIR and TIR**
    - ✓ **0.65µm (0.55-0.75);**
    - ✓ **3.90µm (3.80-4.00);**
    - **6.55µm (5.80-7.30);**
    - **10.70µm (10.2-11.2);**
    - **13.25µm (13.0-13.7)**
  - ➢ **4.0 km for IR channels; 1.0 km for the VIS channel;**
  - ➢ **Full disk every 30 min.**
- **Only assimilates Channel 3 by considering to reduce the impact of clouds.**

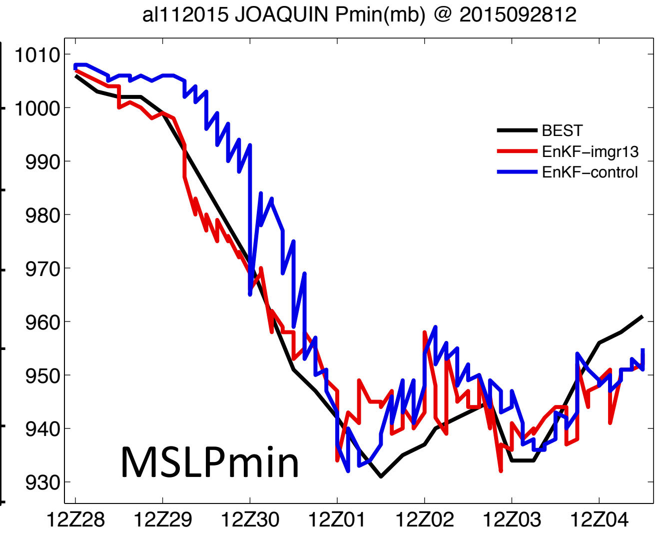


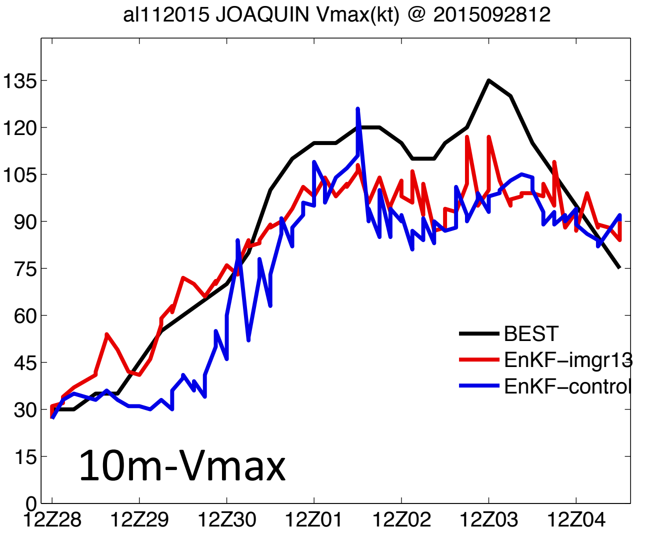
GOES-13 Imager Waiting Functions

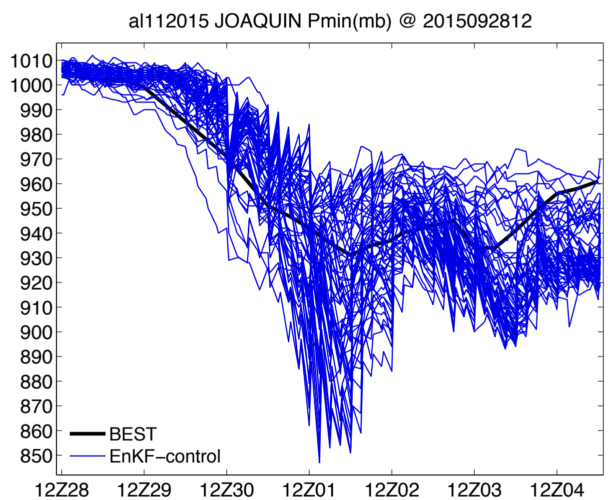
(Weng and Zhang, in preparation)

Cycling Assimilation for Joaquin (2015)

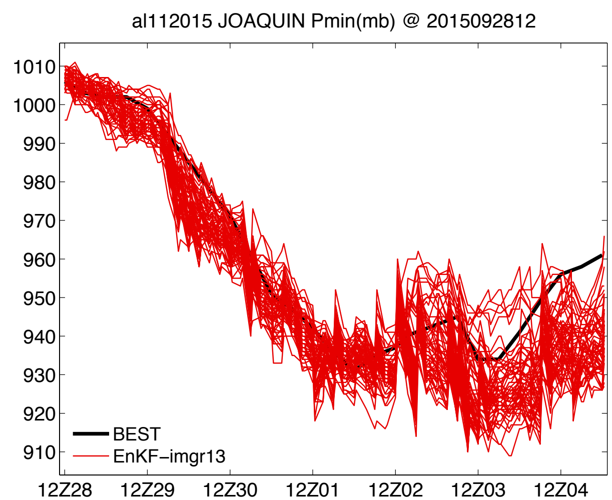




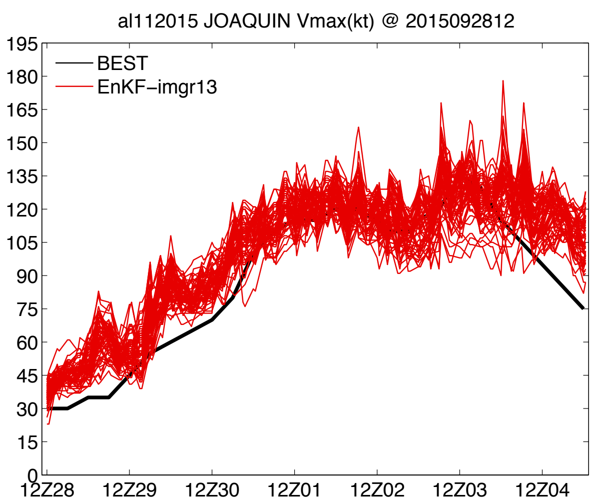




MSLPmin of EnKF members without BT

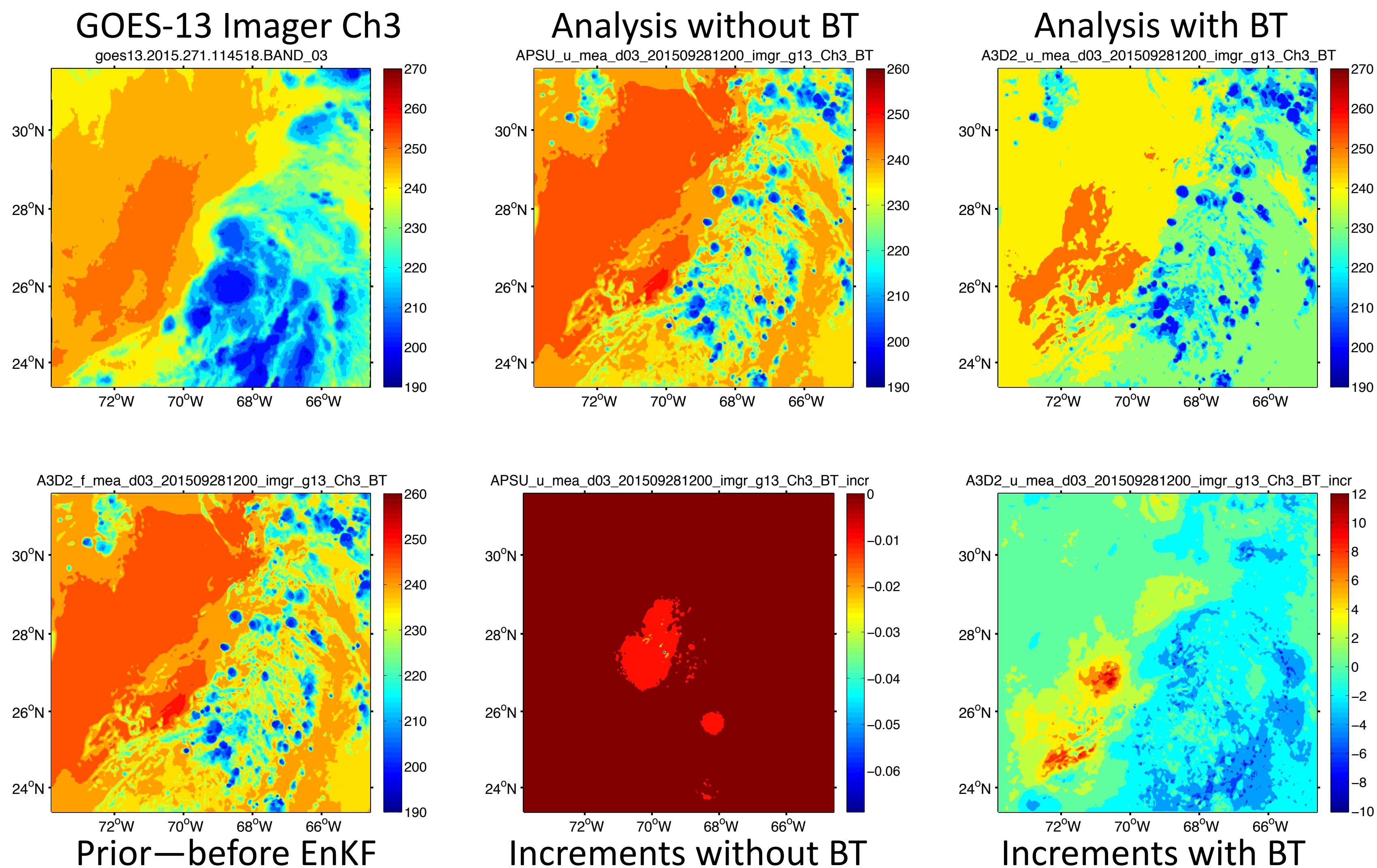


MSLPmin of EnKF members with BT



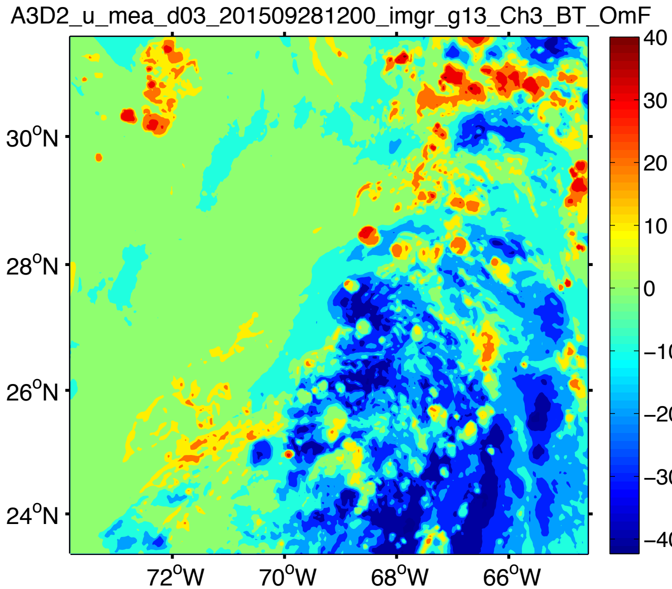
10m-Vmax of EnKF members with BT

EnKF increments @ BT

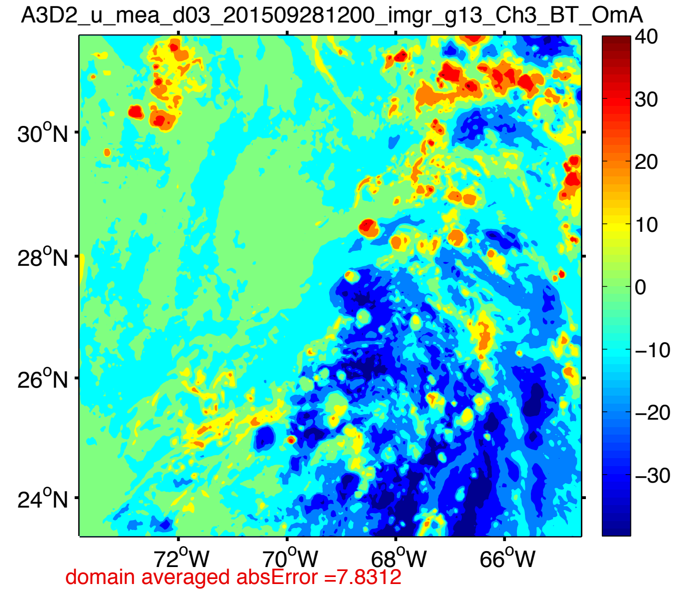


Forecast and Analyses Biases Against OBS

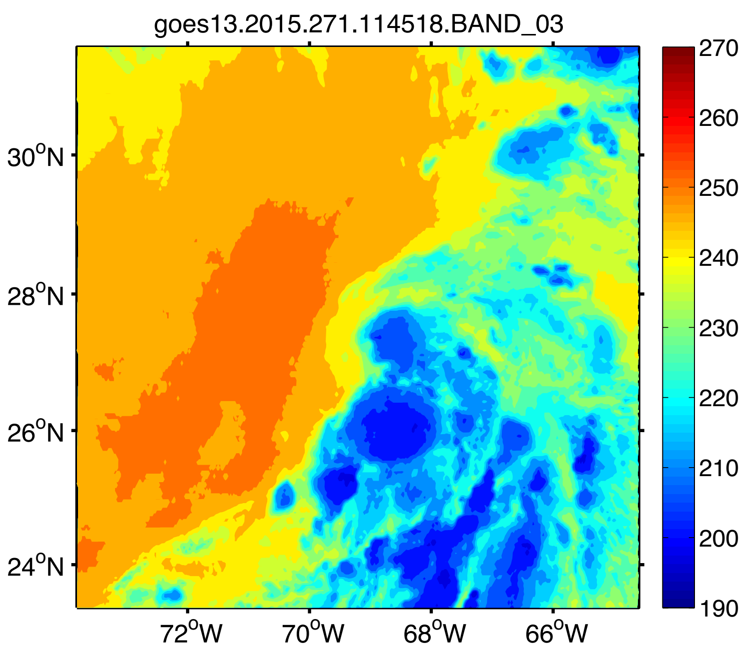
OmF

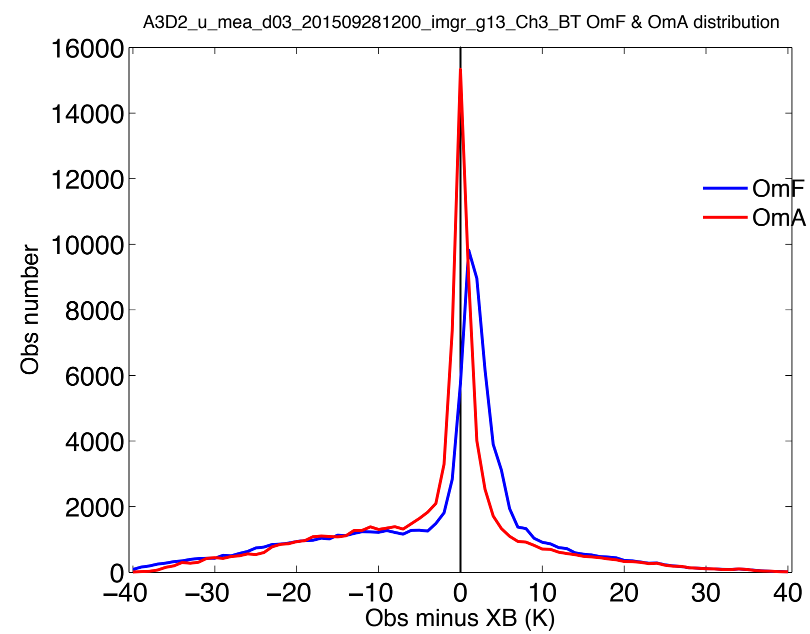


OmA



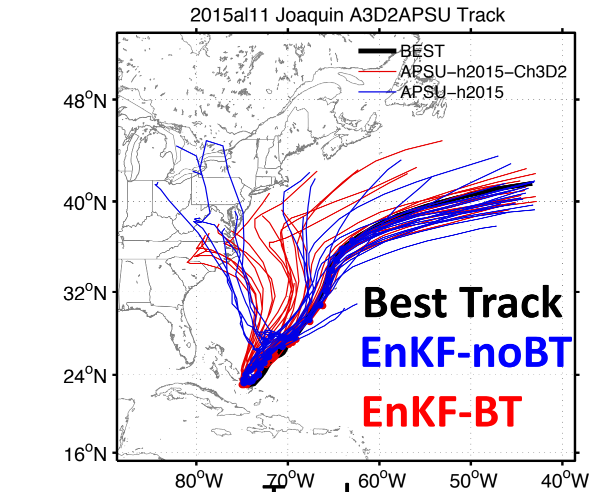
GOES-13 Imager Ch3



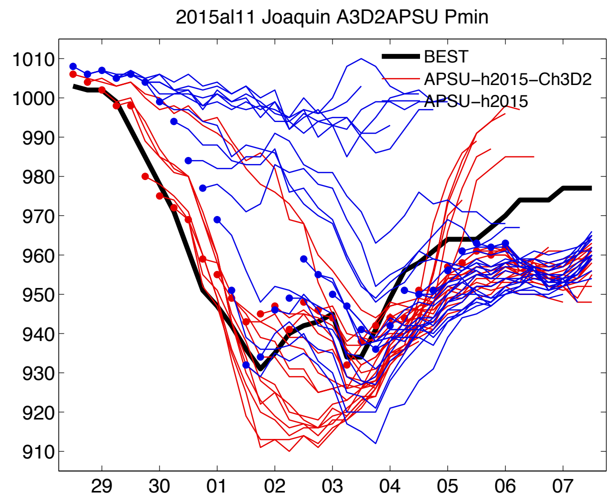


Deterministic Forecasts for Joaquin (2015)： w/ & w/o Radiance

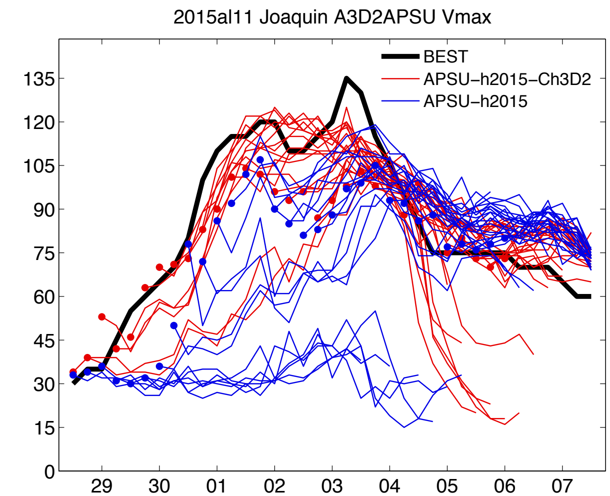
Deterministic forecasts from EnKF analysis every 6 hours



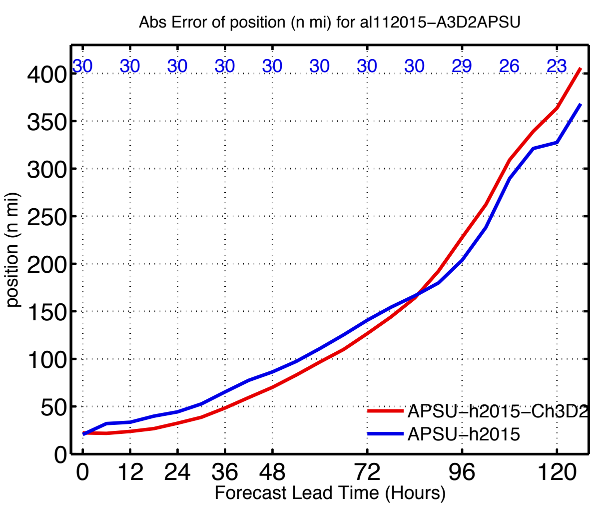
Track

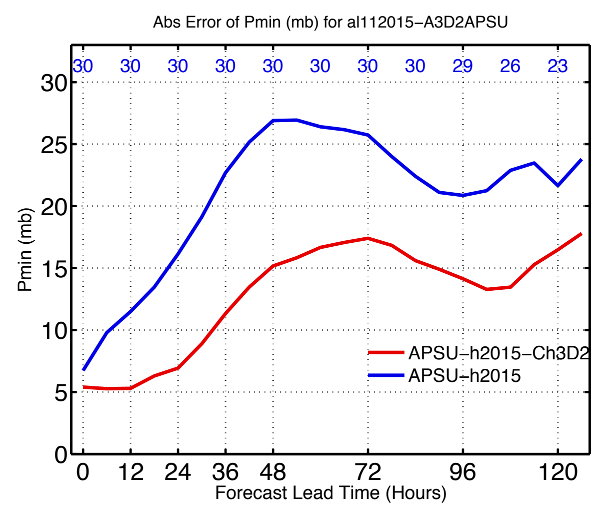


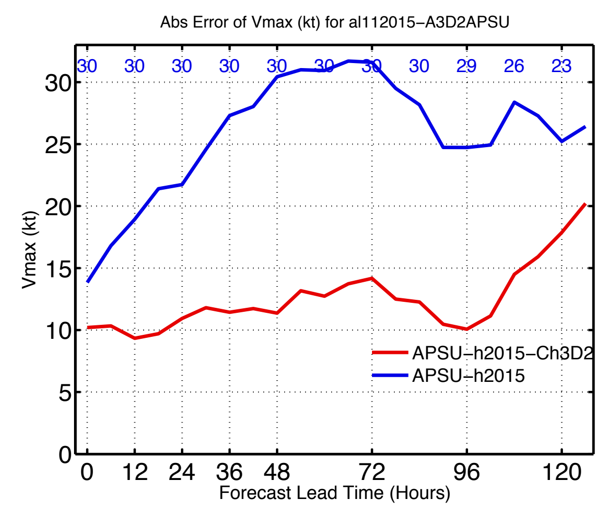
MSLPmin



10m-Vmax



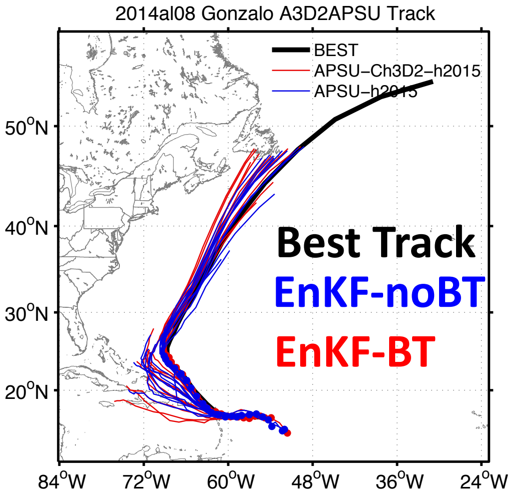




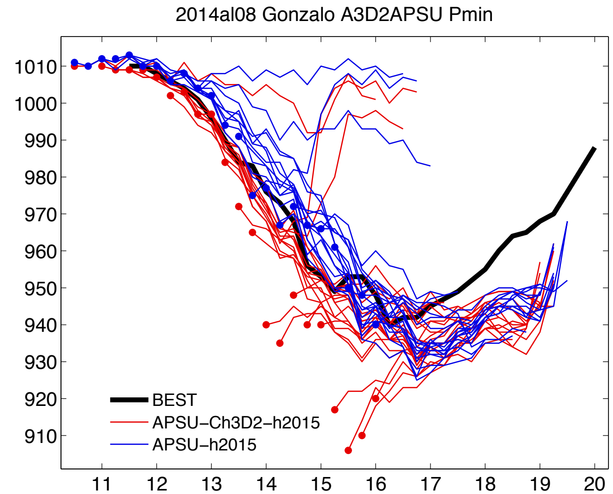
Averaged absolute error reference to Best Track

Deterministic Forecasts for Gonzalo (2014)： w/ & w/o Radiance

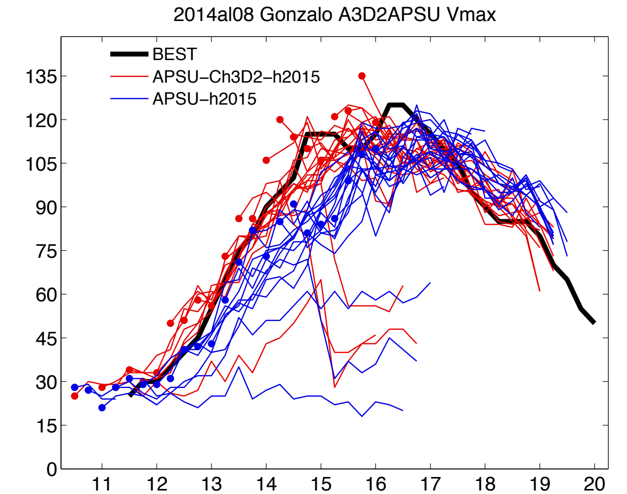
Deterministic forecasts from EnKF analysis every 6 hours



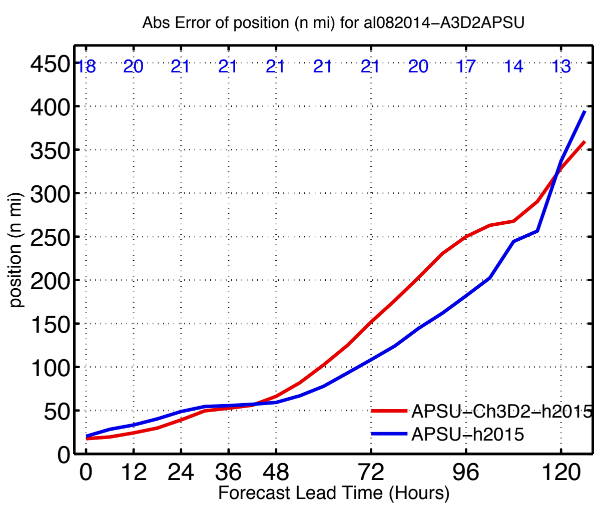
Track

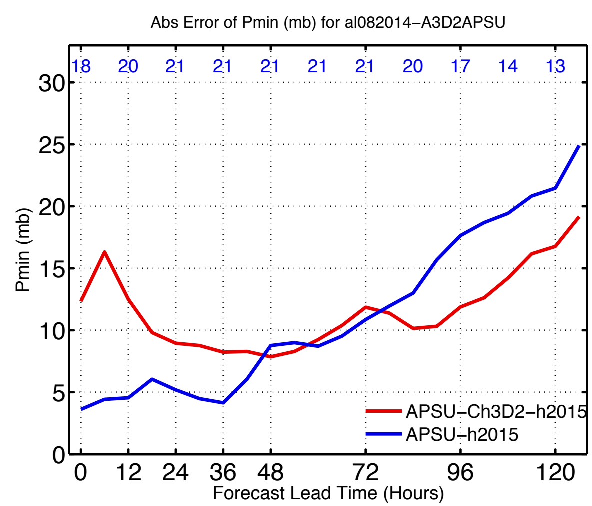


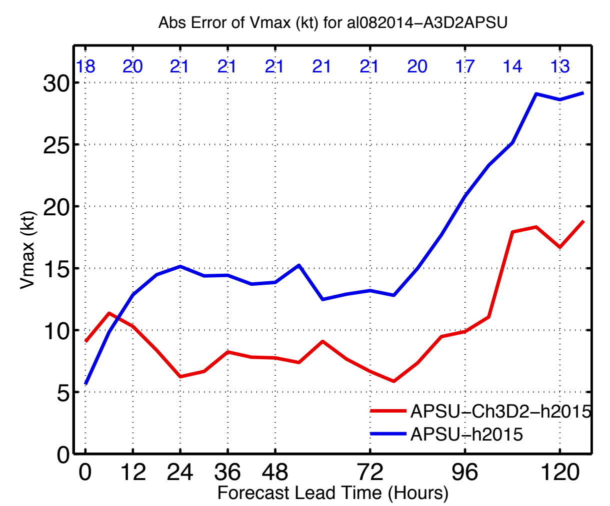
MSLPmin



10m-Vmax



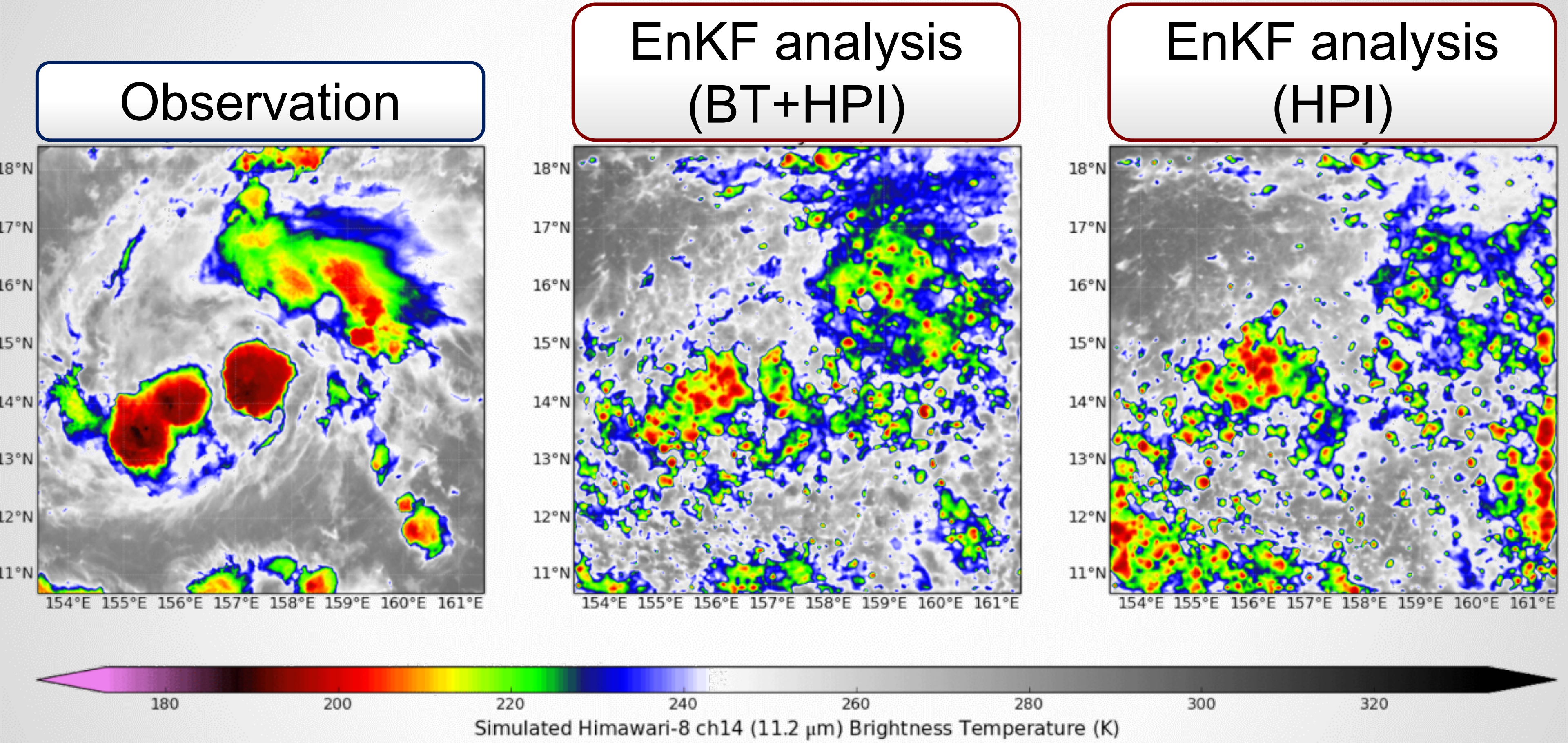




Averaged absolute error reference to Best Track

EnKF Performance W/ Assimilating Himawari-8 BT

Himawari-8 **Infrared** Channel (ch14: 11.2 μm)



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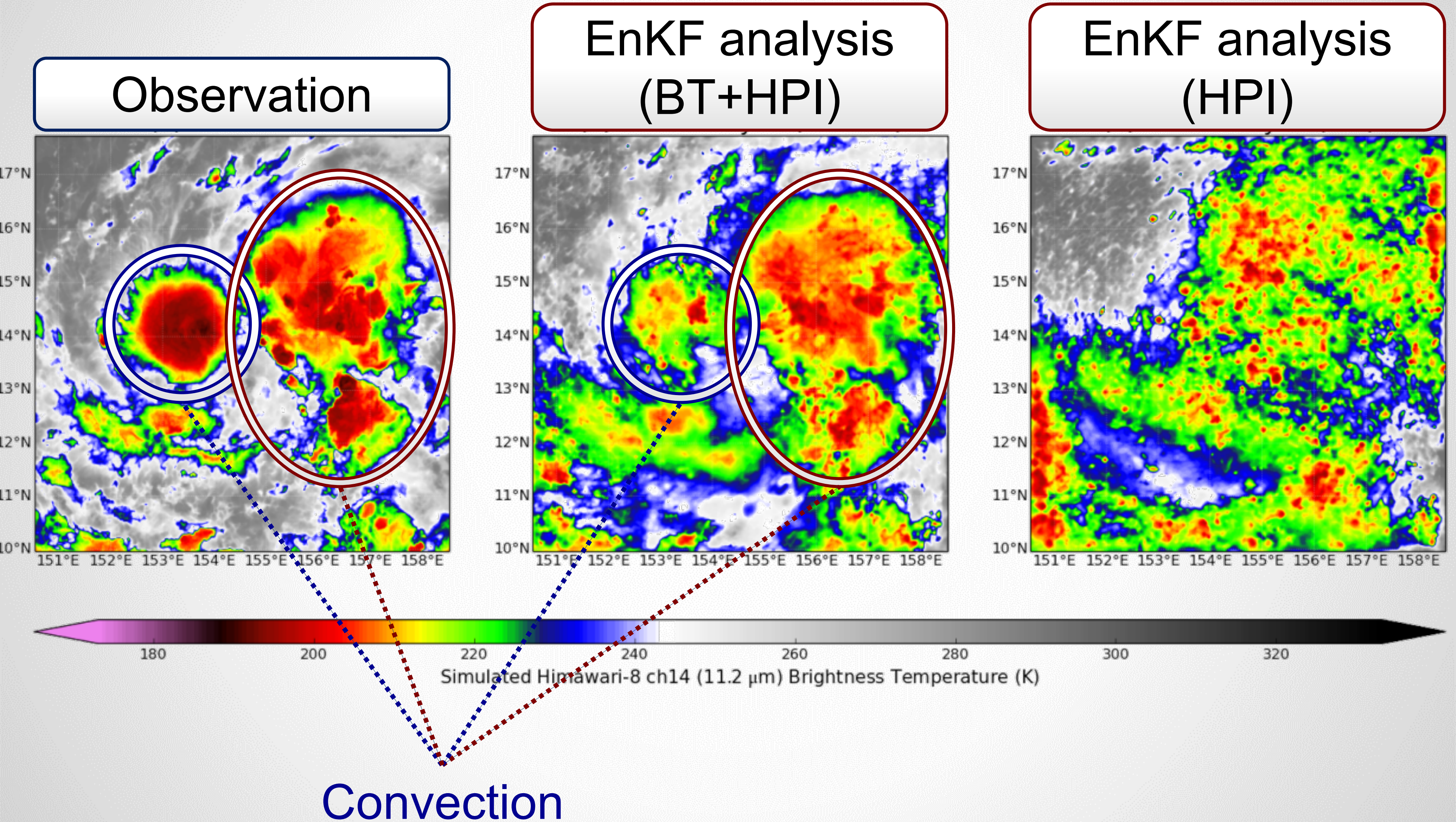
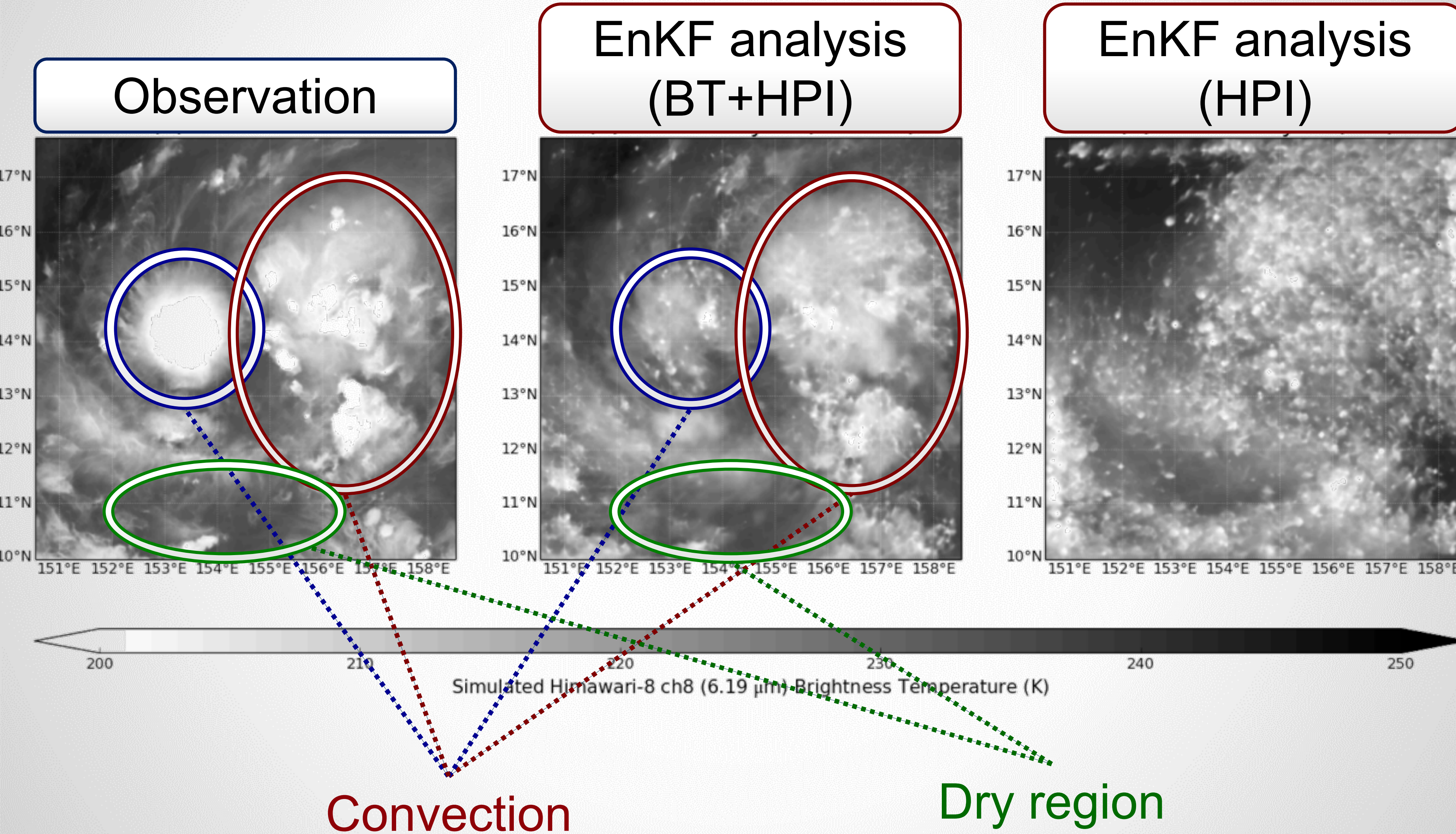
EnKF Performance W/ Assimilating Himawari-8 BT

Himawari-8 **Infrared** Channel (ch14: 11.2 μm)

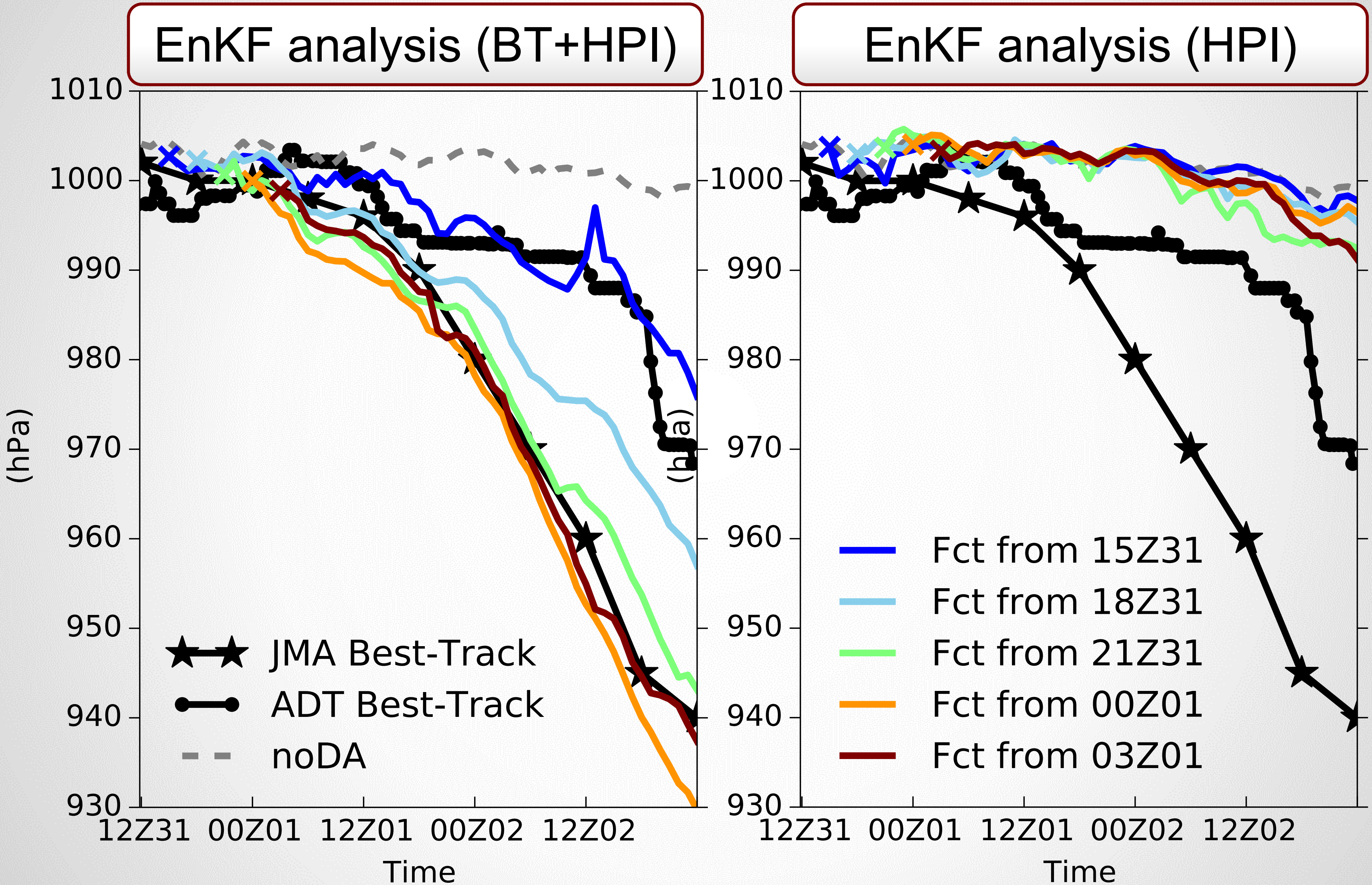


EnKF Performance W/ Assimilating Himawari-8 BT

Himawari-8 **Water Vapor** Channel (ch8: 6.19 μm)

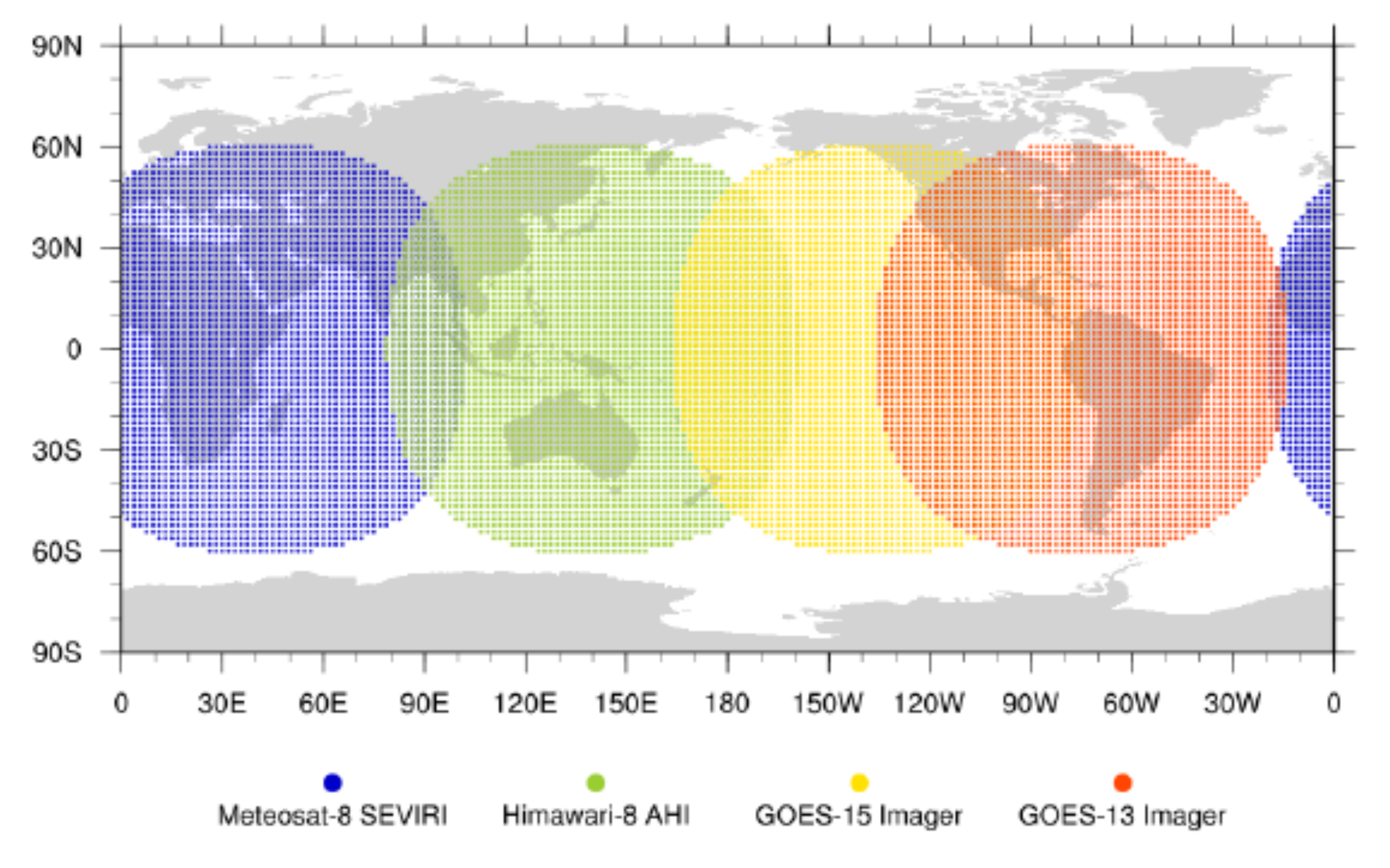


EnKF Performance: Forecasts of Minimum SLP



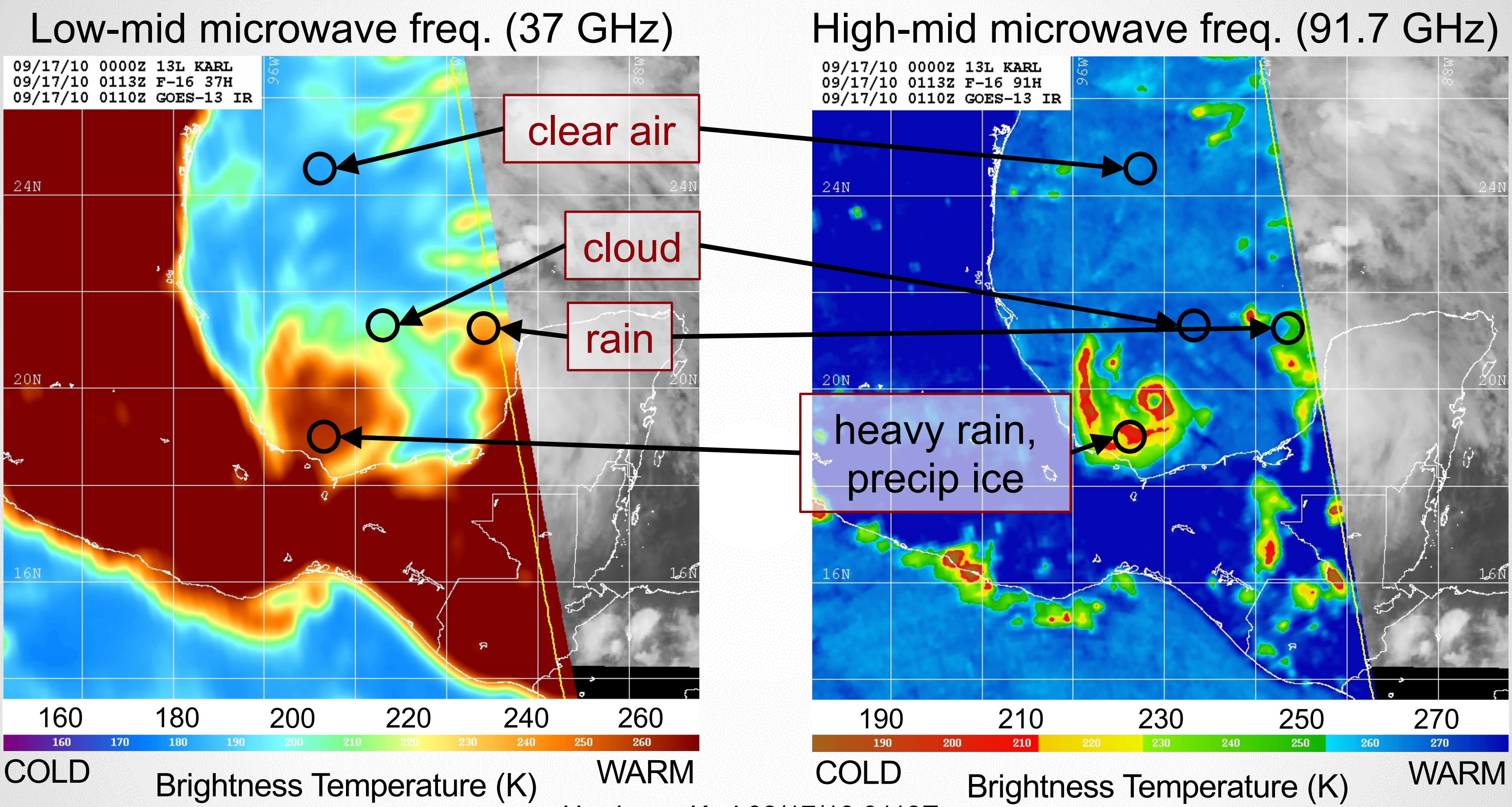
- Assimilation of BT greatly helps the forecasts to capture RI

Global IR coverage & ongoing GFS/GSI-LETKF OSSE



On going work with Da Cheng and Eugenia Kalnay at UMD

Microwave Radiometers and Precipitation



Hurricane Karl 09/17/10 0113Z
(SSMI/S image courtesy NRL)

- Rain and cloud liquid net add to low emission by water
- Some scattering by precipitation ice
- Scattering by precipitation ice dominates the signal

On going work with Scott Sieron and Eugene Clothiaux

Mesoscale NWP Microphysics

- Most bulk species are assumed either monodisperse, or having a generalized gamma particle size distribution (PSD):

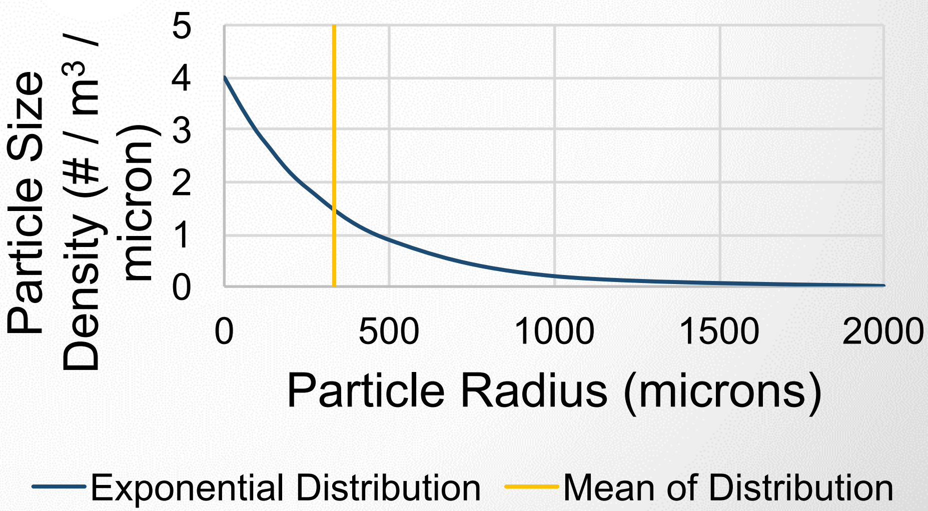
$$N(r) = N_0 r^{\mu} \exp(-\lambda r),$$

  - Common is Marshall-Palmer distribution: $\mu = 0$

- Most frozen species assumed to be homogeneous "soft spheres"
  - Mie theory well-represents scattering and absorption

- Schemes differ by some PSD parameter values and particle properties

WSM6 graupel λ = 3000 m^{-1} (0.078 g m^{-3})



Current ECMWF model: cloud liquid, cloud ice, rain – Mie sphere; snow – Liu sector snowflake

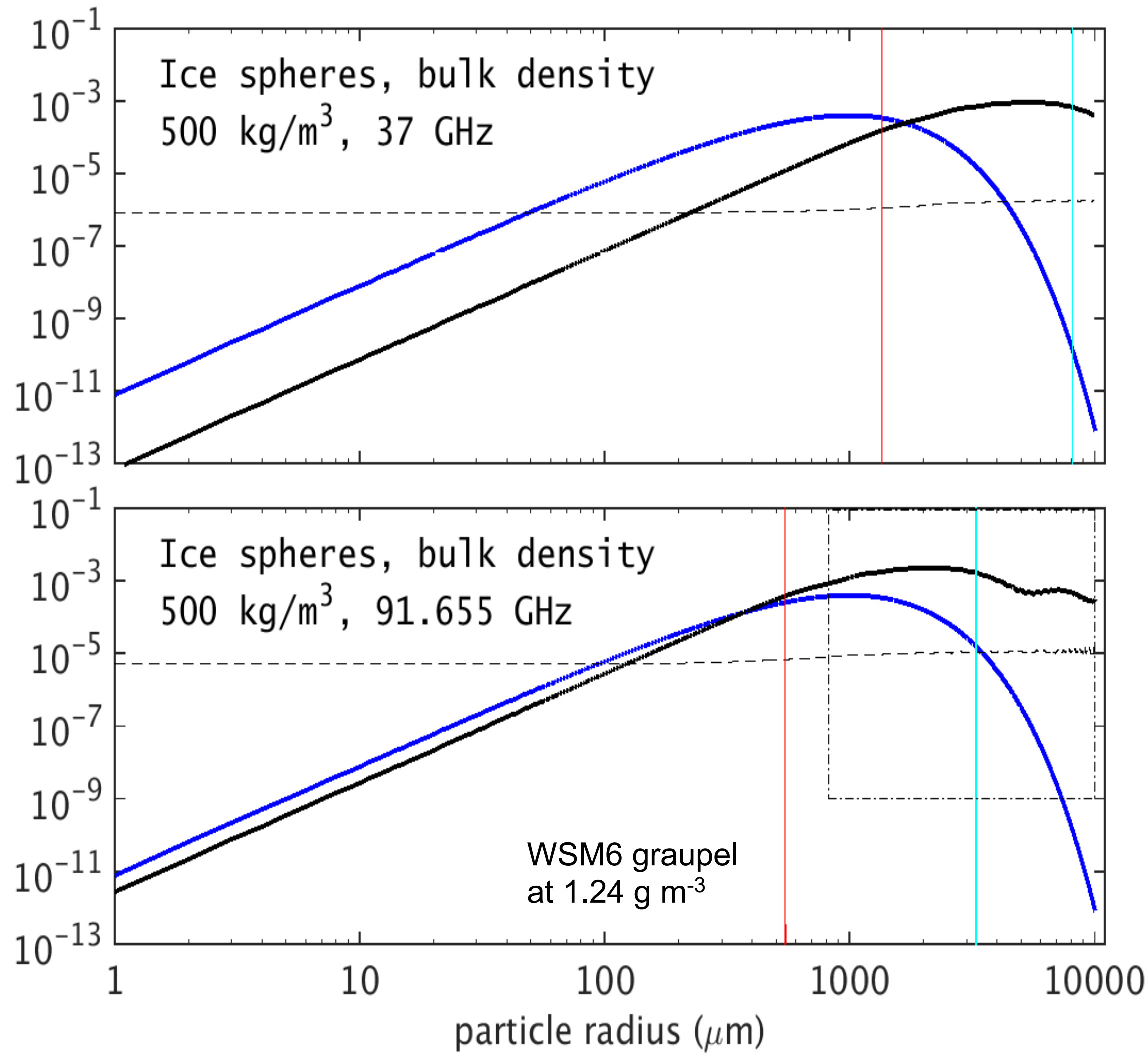
Potential Issue with Default CRTM Using Effective Radius

- The community defines effective radius as

$$r_{eff} = \frac{\int_{r2}^{r1} r^3 N(r) dr}{\int_{r2}^{r1} r^2 N(r) dr}$$

  - This is "mean radius for scattering" for <u>scattering by a particle $\propto r^2$</u> (Hansen and Travis 1974)

- For precipitation in microwave, scattering by particles is NOT $\propto r^2$
  - <u>Scattering $\propto r^6$</u> for particles much smaller than wavelength
  - Large fraction of mass in particle sizes ~wavelength
- Effective radius fails



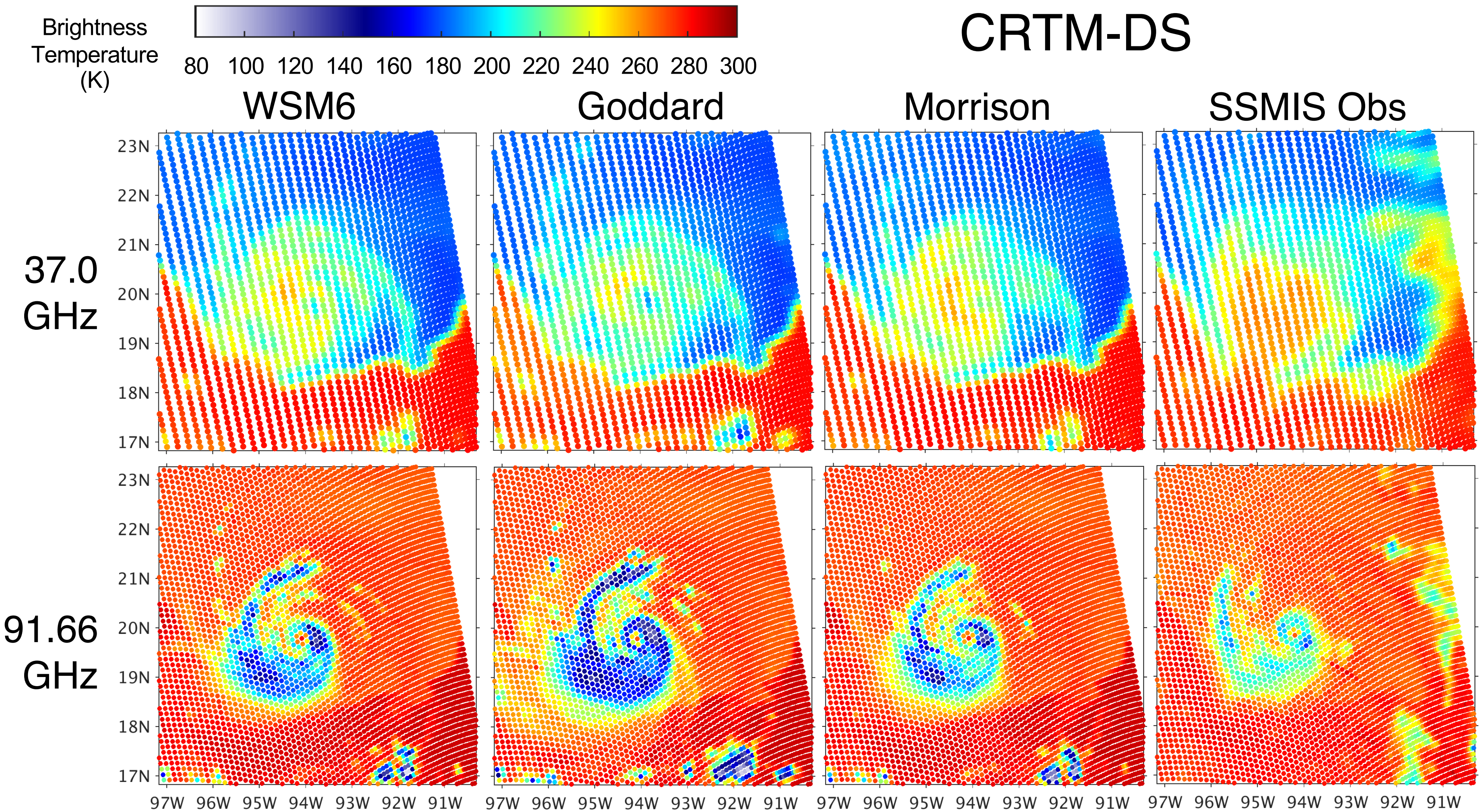
Black: scattering coeff. (m^2 kg^{-1})
Dashed: absorption coeff. (m^2 kg^{-1})
Blue: sample particle mass distribution (kg m^{-3} μm^{-1}) of graupel-like ice spheres

Modifying the CRTM for All-sky MW Radiances

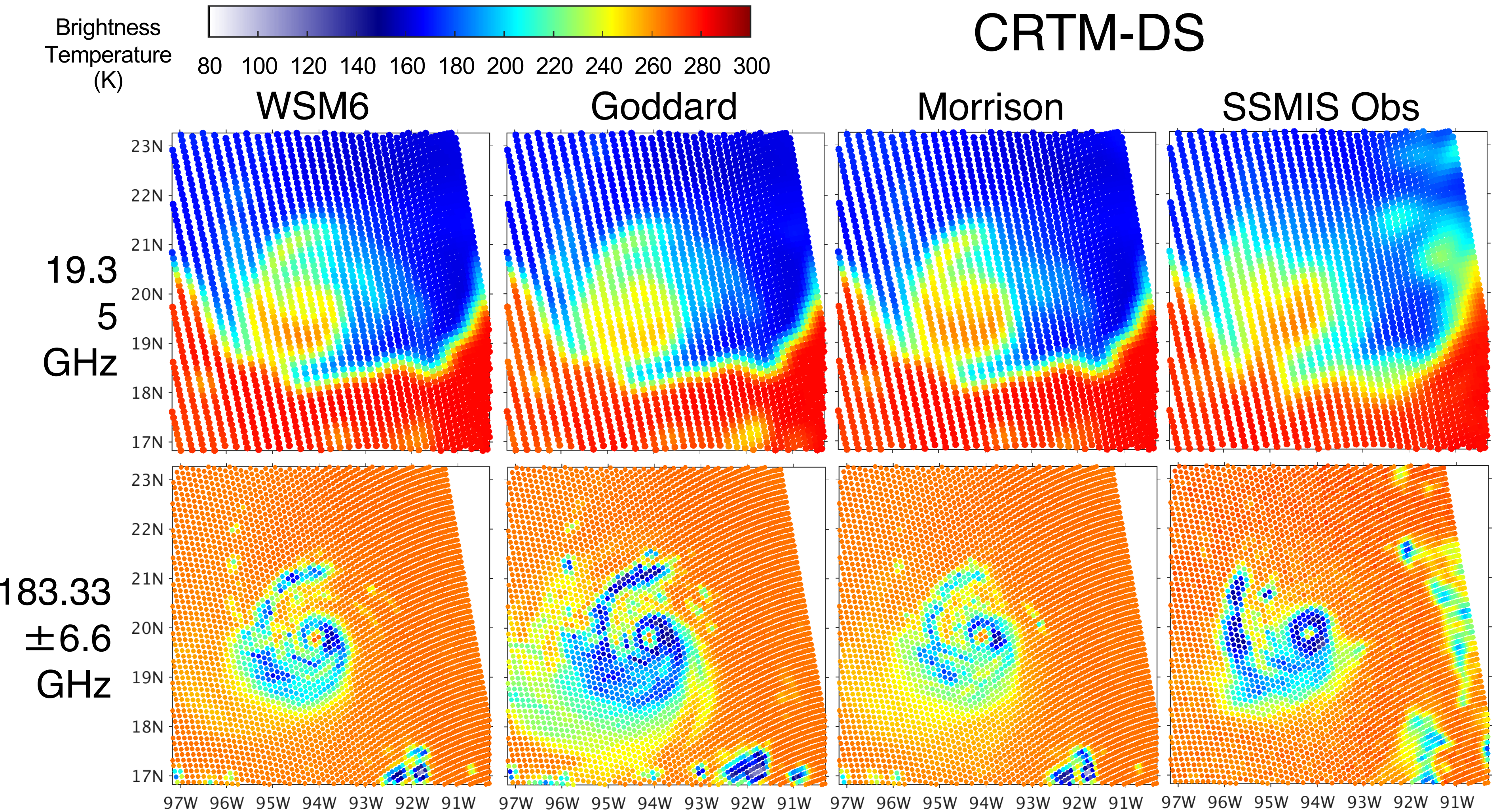
- "Distribution-Specific," CRTM-DS:
  - New cloud scattering property lookup tables
  - Construct with MP scheme particle properties and size distributions
    - Very high resolution (1 μm radius)

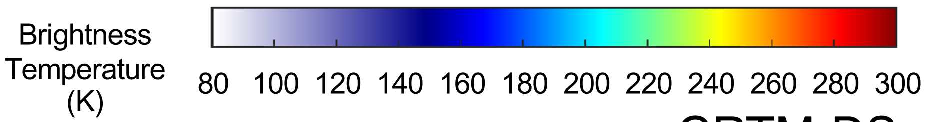
- Single particles modeled as soft spheres
  - These MP schemes specify hydrometeors as spheres
  - Maxwell-Garnett mixing formula for ice dielectric constants
  - Liquid dielectric constants from Tuner et al. (2016)

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



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

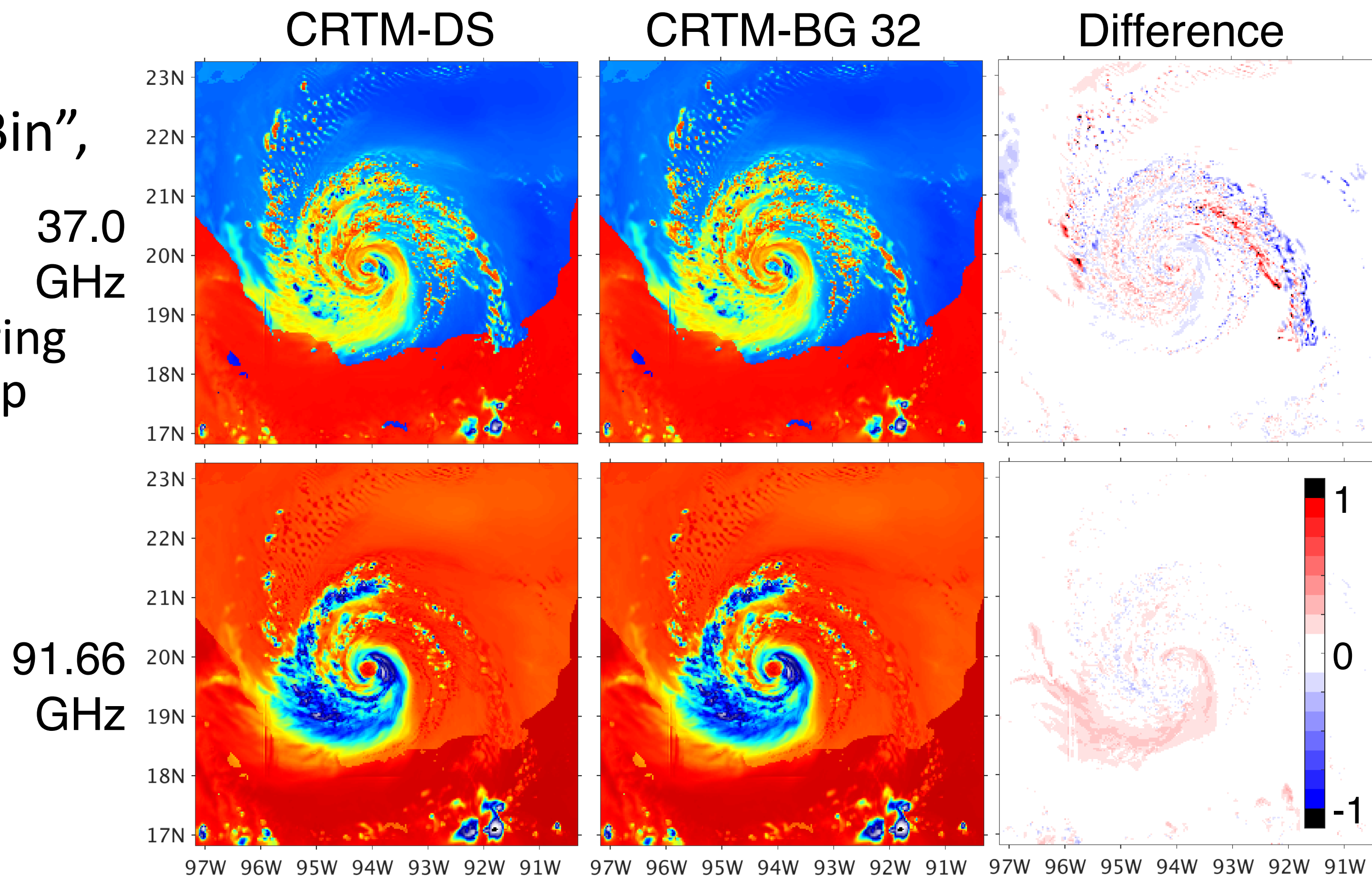




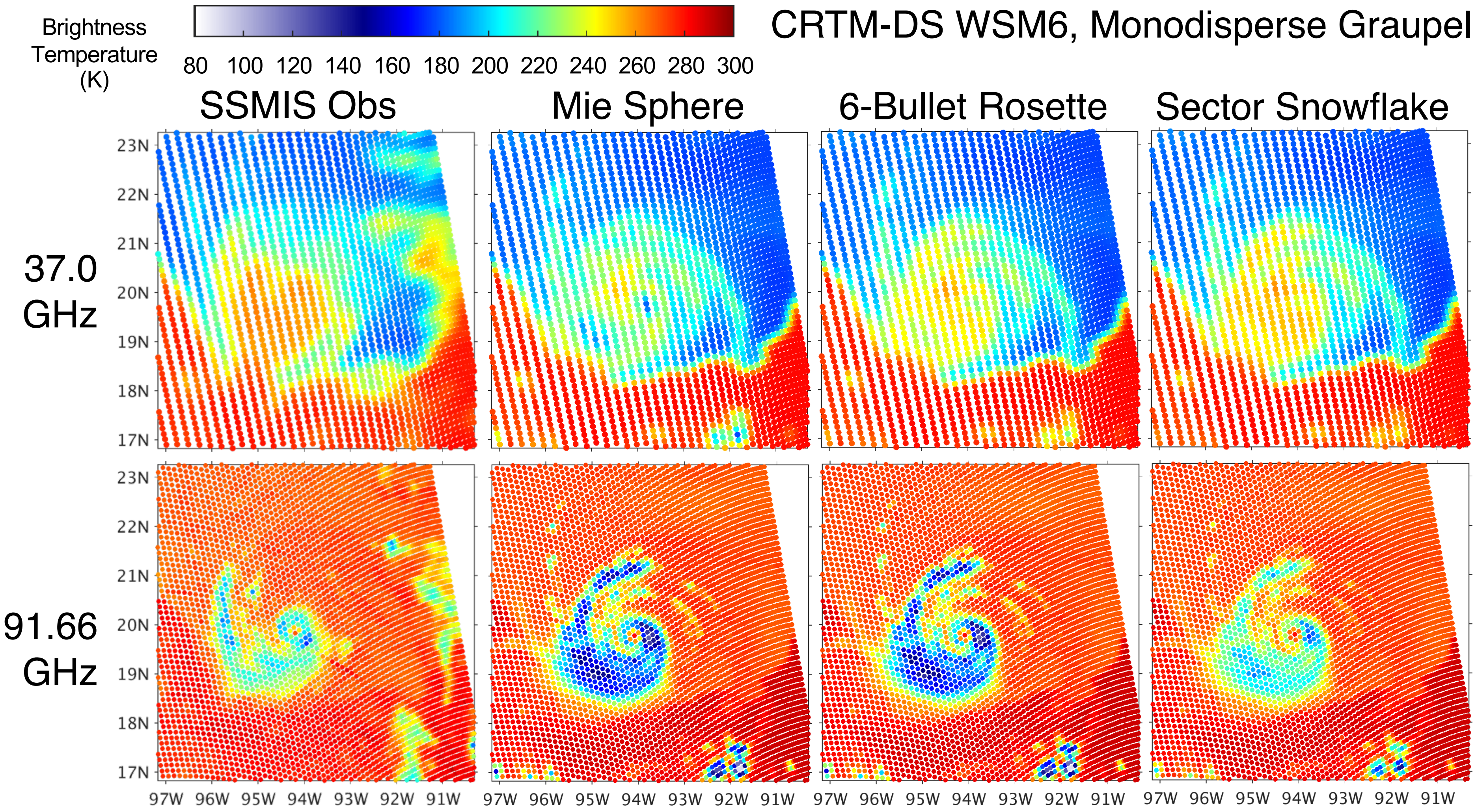
WSM6

“Generalized Bin”, CRTM-BG:

- particle scattering property lookup tables
- MP scheme information managed within CRTM
- More flexible than CRTM-DS

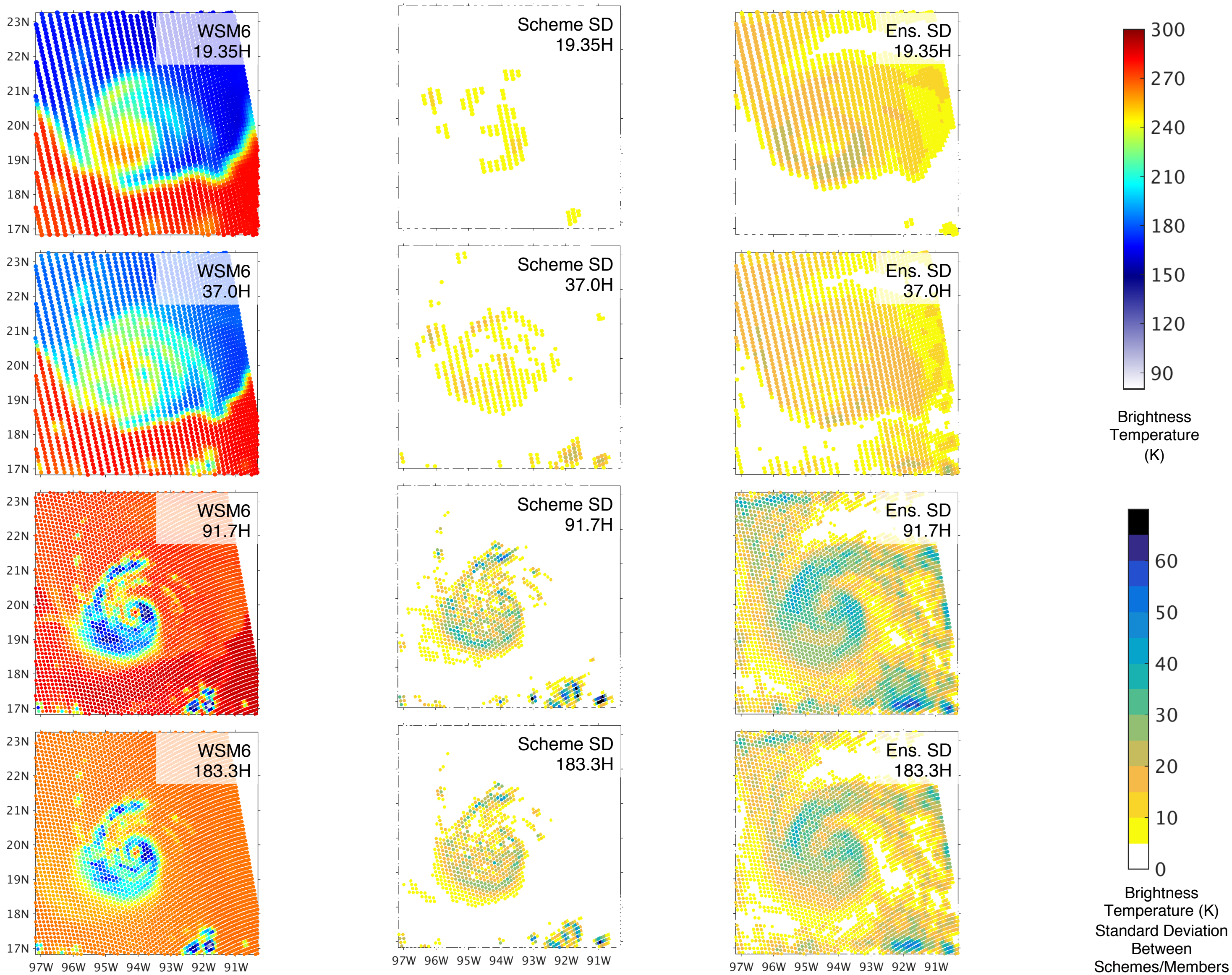


CRTM-Simulated vs. SSMIS-observed: non-spherical?



Current ECMWF model: cloud liquid, cloud ice & rain – Mie sphere; snow – Liu sector snowflake

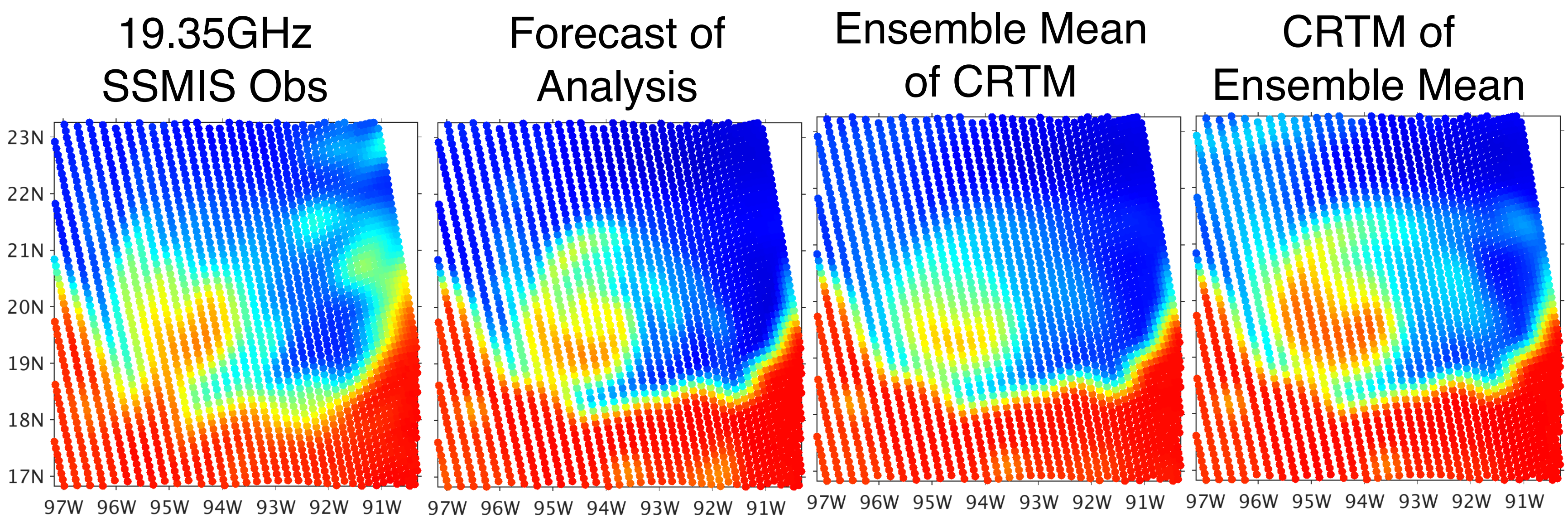
CRTM Simulated: initial condition vs. physics uncertainty



Standard deviation of brightness temperatures at each location between either different schemes or ensemble members

First Convection-permitting EnKF Experiment Assimilating Real-data SSMIS BTs for Karl (2010)

First only assimilate the 19.35-GHZ channel which is very rain sensitive

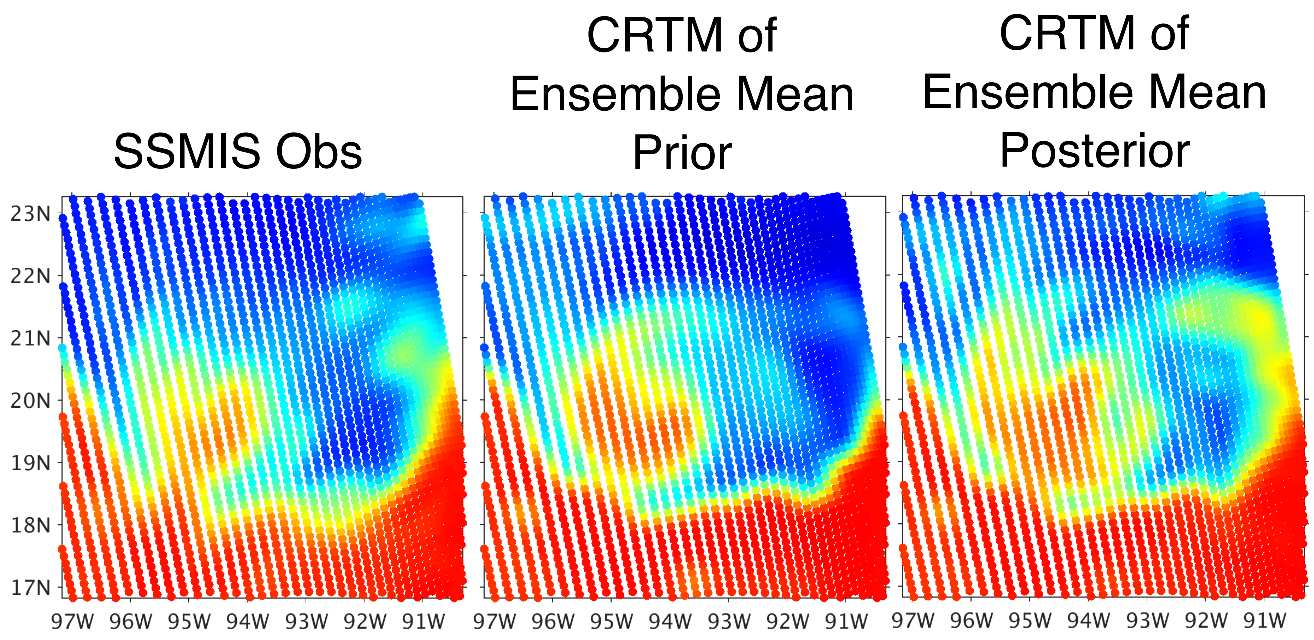


What should be the EnKF prior that is used for calculate innovation?

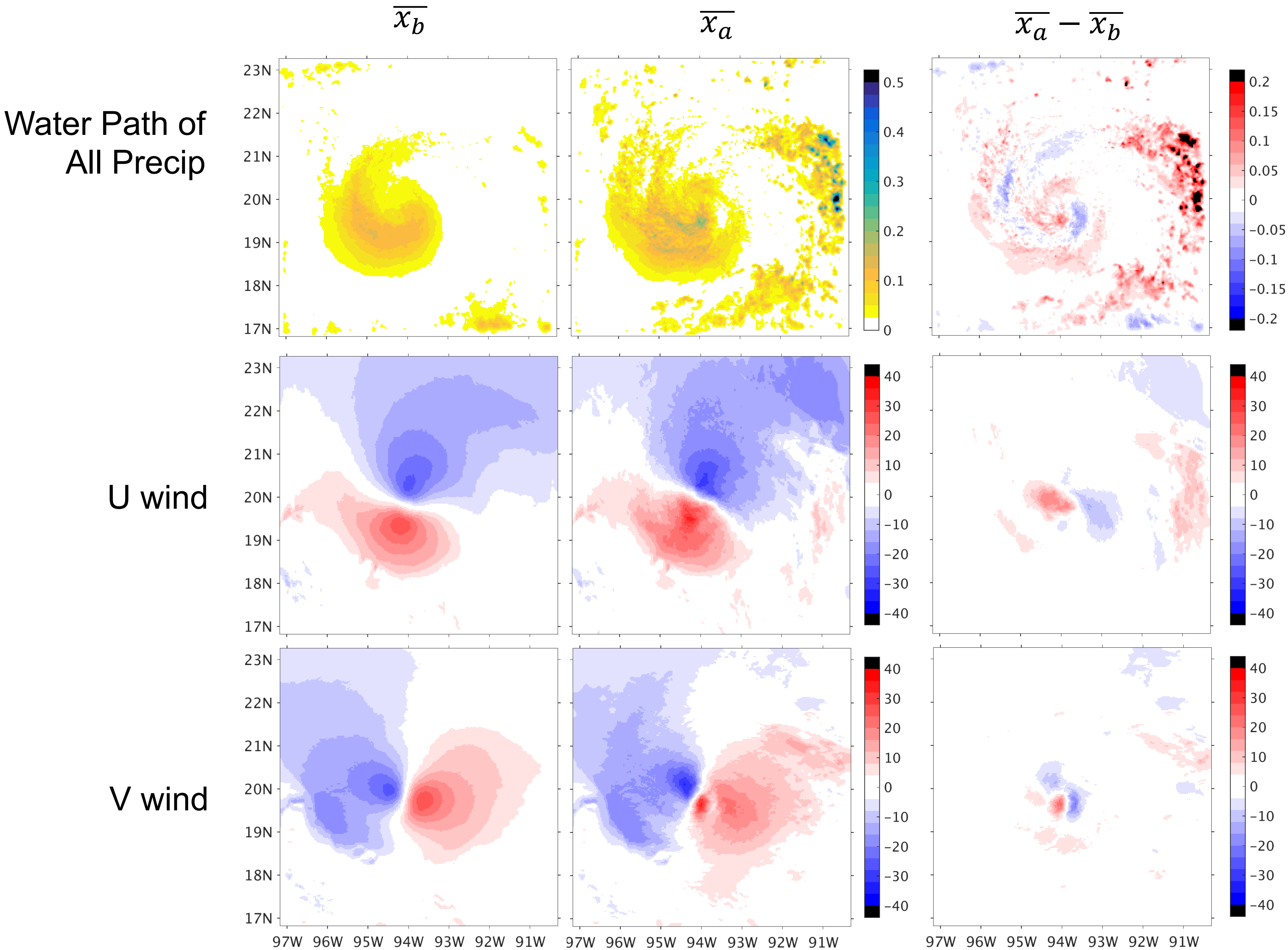
First Convection-permitting EnKF Experiment Assimilating Real-data SSMIS BTs for Karl (2010)

Prior: at 00Z/17 3-h ensemble forecast from 21Z/16 SEP 2010
WRF-EnKF, 27, 9 & 3 km (D1-D3), 60-member, AOEI, SCL, RTPP

First only assimilate the 19.35-GHZ channel which is very rain sensitive



The EnKF posterior updates of the observed channel is quite promising!



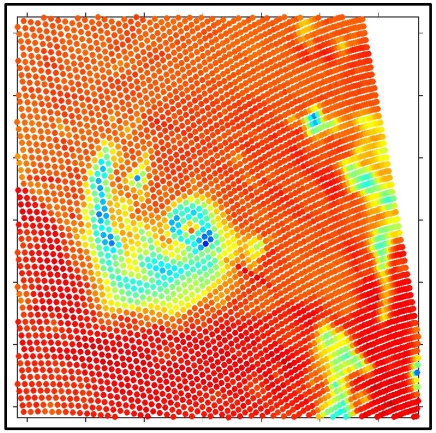
$\overline{x_b}$
$\overline{x_a}$
$\overline{x_a} - \overline{x_b}$
Water Path of All Precip
U wind
V wind
23N
22N
21N
20N
19N
18N
17N
97W 96W 95W 94W 93W 92W 91W
0.5
0.4
0.3
0.2
0.1
0
0.2
0.15
0.1
0.05
−0.05
−0.1
−0.15
−0.2
40
30
20
10
−10
−20
−30
−40

First Convection-permitting EnKF Experiment Assimilating Real-data SSMIS BTs for Karl (2010)

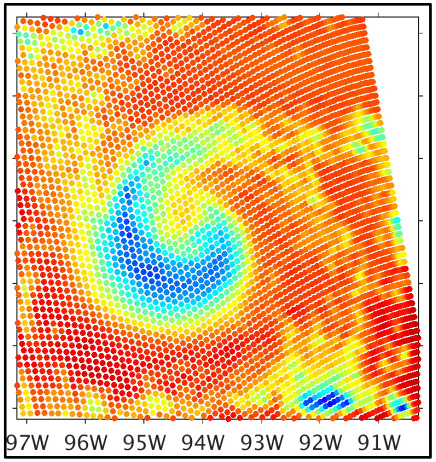
Prior: at 00Z/17 3-h ensemble forecast from 21Z/16 SEP 2010
WRF-EnKF, 27, 9 & 3 km (D1-D3), 60-member, AOEI, SCL, RTPP

Now only assimilate the 91.66-GHZ channel which is very ice sensitive

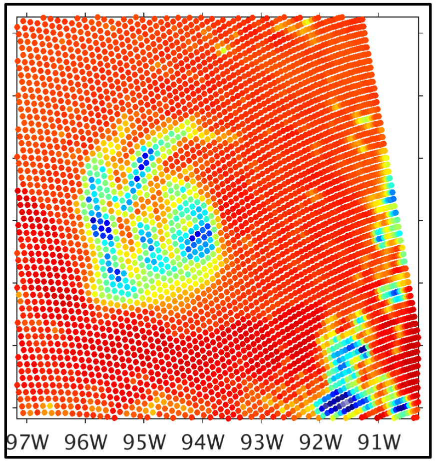
SSMIS Obs

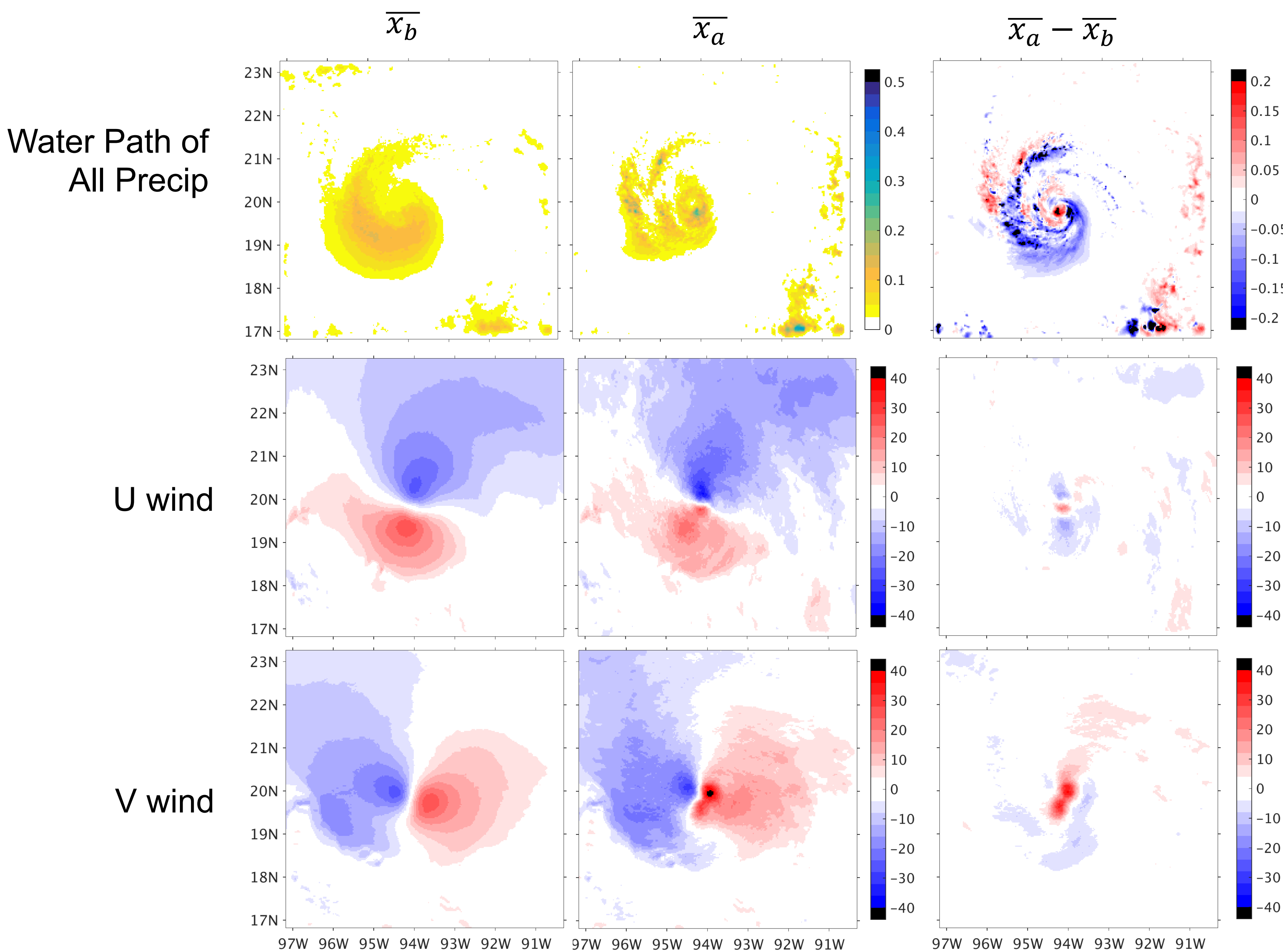


CRTM of Ensemble Mean Prior



CRTM of Ensemble Mean Posterior





$\overline{x_b}$
$\overline{x_a}$
$\overline{x_a} - \overline{x_b}$
Water Path of All Precip
U wind
V wind
23N
22N
21N
20N
19N
18N
17N
97W 96W 95W 94W 93W 92W 91W
0.5
0.4
0.3
0.2
0.1
0
0.2
0.15
0.1
0.05
−0.05
−0.1
−0.15
−0.2
40
30
20
10
−10
−20
−30
−40

Concluding Remarks

- Convection-permitting OSSEs with EnKF assimilation of GOES-R IR radiance show great success in capturing hurricane rainbands, eye, individual convective clouds as well as dry clear-sky slots.
- Forecasts of hurricane intensity initialized with the EnKF analysis of real-data GOES-13 and Himawara-8 are also promising.
- TC cloudy microwave radiances are much more challenging, …, initial test with real data is promising, in particular with building microphysics distribution-specific radiative transfer (CRTM-DS).
- Challenging issues: model error/bias (parameter estimation?), CRTM error (DS), representive observation error (AOEI), multi-scale localization (SCL), covariance inflation (RTPP), ...

Future Directions

- Refining and adding modifications, working within the CRTM repository
  - Optimize Bin Discretized computations, reduce redundant LUT queries
  - Non-spherical particle optical properties
  - Tangent linear, adjoint, K-matrix
  - Antenna pattern convolution and slant path constructions (features in satellite simulators)
  - Automatic stream number estimation

- Uses for this tool:
  - Ensemble parameter estimation
  - Observing System Experiments (testing data assimilation)
    - Simulated or real observations
  - Assimilation of both MW and IR simultaneously