Predictability Limits and Data Assimilation

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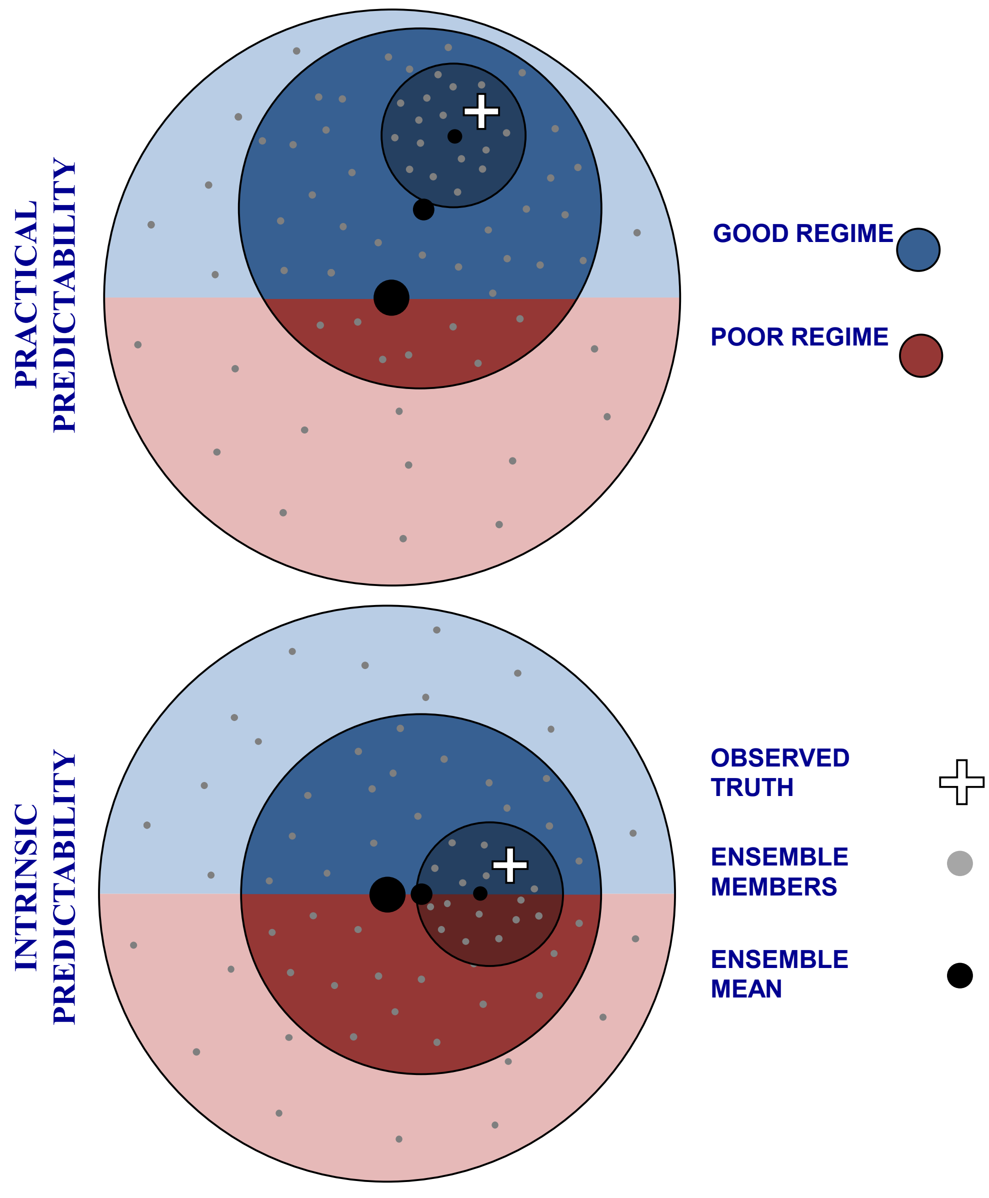
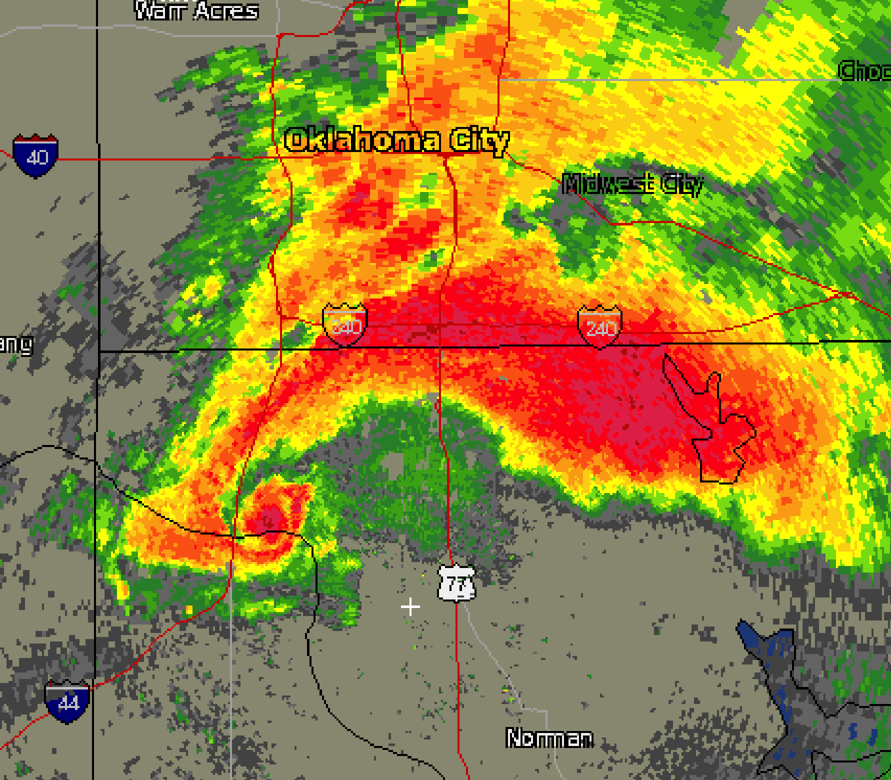
PRACTICAL vs. INTRINSIC PREDICTABILITY

(Melhauser & Zhang 2012 JAS; Lorenz 1996)

Practical predictability: the ability and uncertainty to predict given practical initial condition uncertainties and/or model errors, both of which remain significantly big in the present-day forecast systems.

Intrinsic predictability: the limit to predict given nearly perfect initial conditions and nearly perfect forecast systems, in other words when the initial condition and model errors become infinitesimally small.

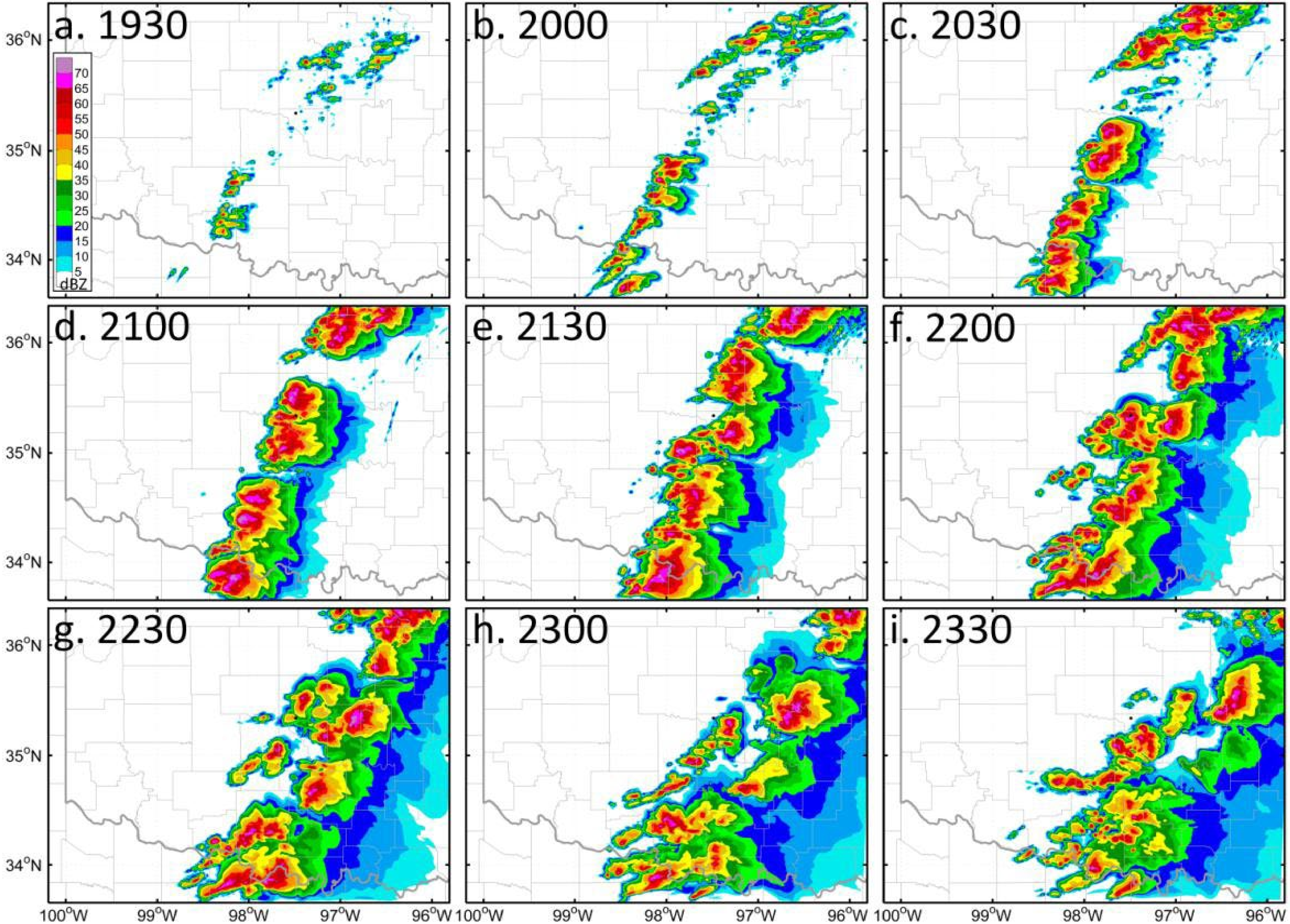




Predictability of a Tornadic Thunderstorm Event: *Moore, 20 May 2013*

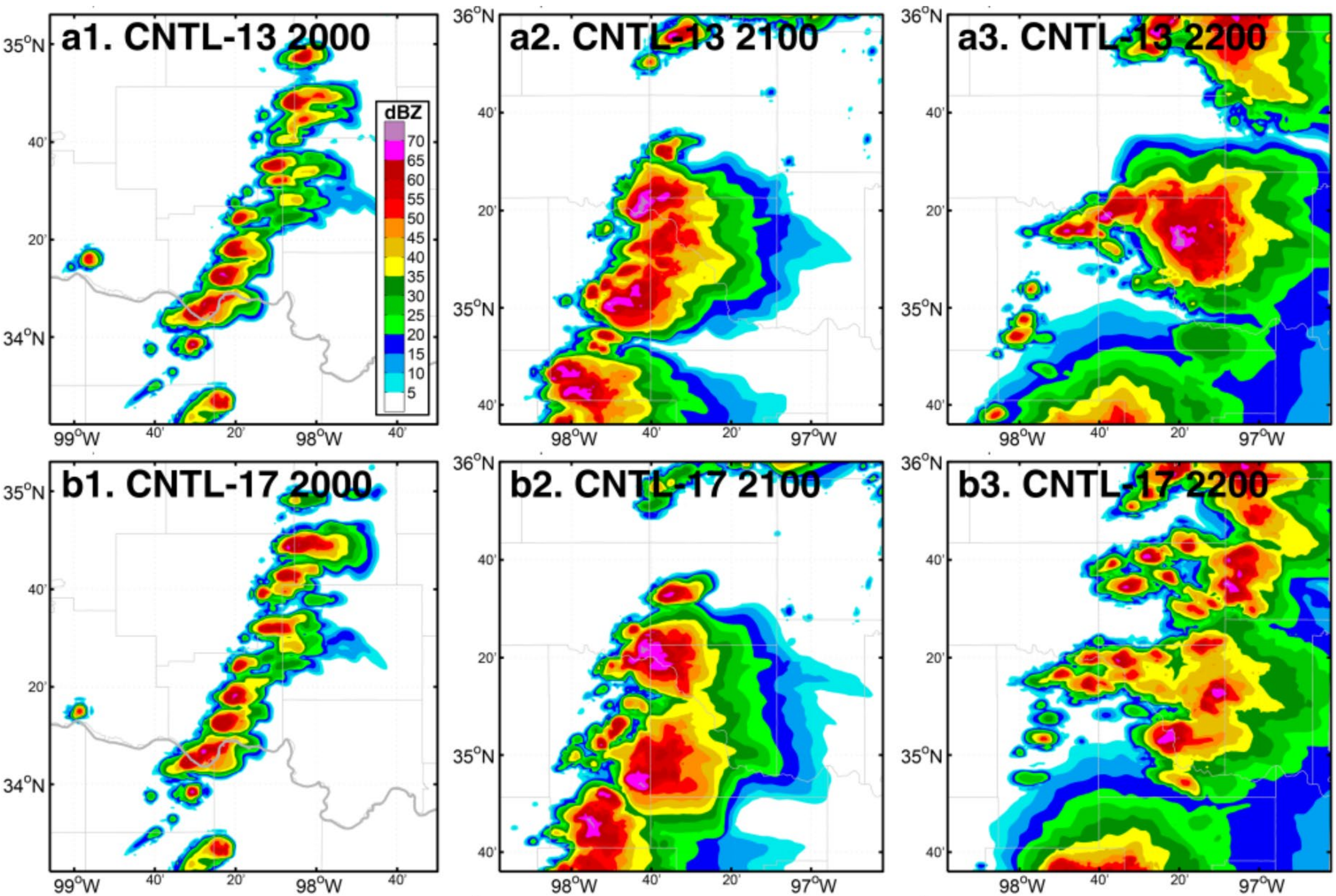
Zhang, Zhang, Meng and Stensrud (2015 2016 MWR)

Practical Predictability: Control 1-km WRF Run



Zhang, Zhang, Meng and Stensrud (2015 WR)

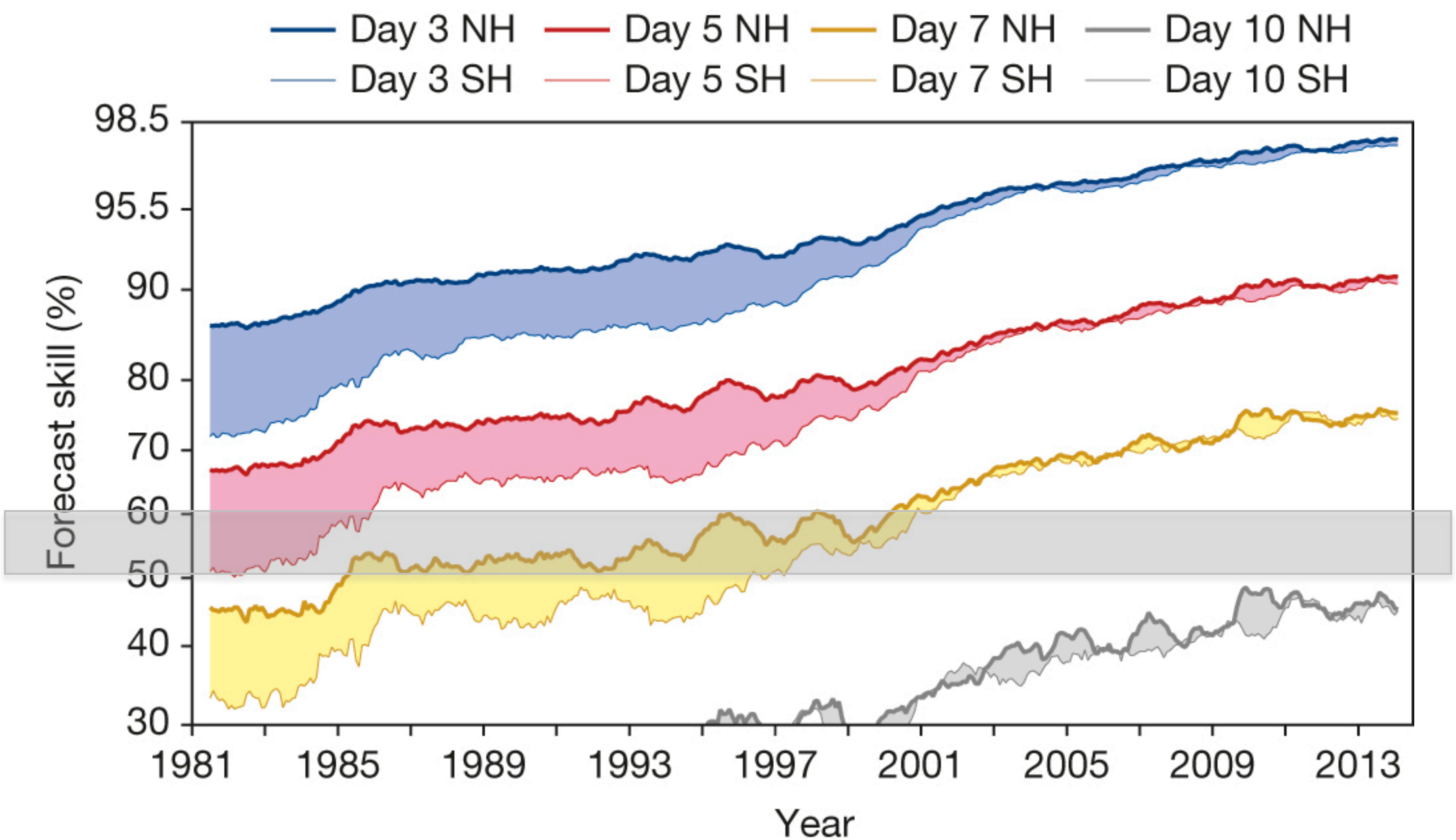
Intrinsic Predictability: ensemble w/ subgrid noises



Zhang, Zhang, Meng and Stensrud (2016 WR)

What is the Ultimate Limit of Day-to-Day Mid-latitude Weather Predictability?

Quiet Revolution of Numerical Weather Prediction



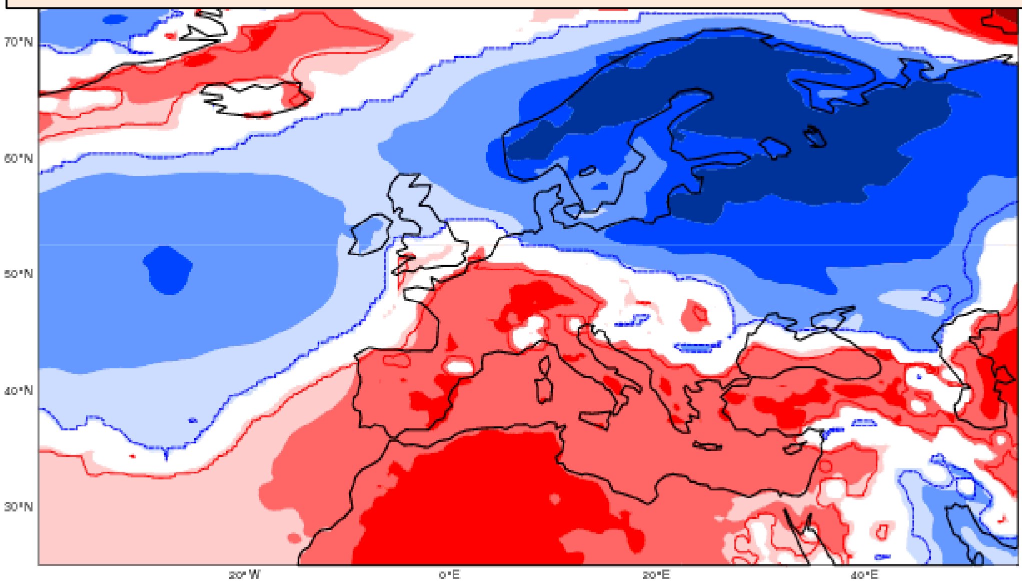
Forecast skill in terms of 500-hPa anomaly correlations in the range from 3 to 10 days ahead has been increasing by about one day per decade.

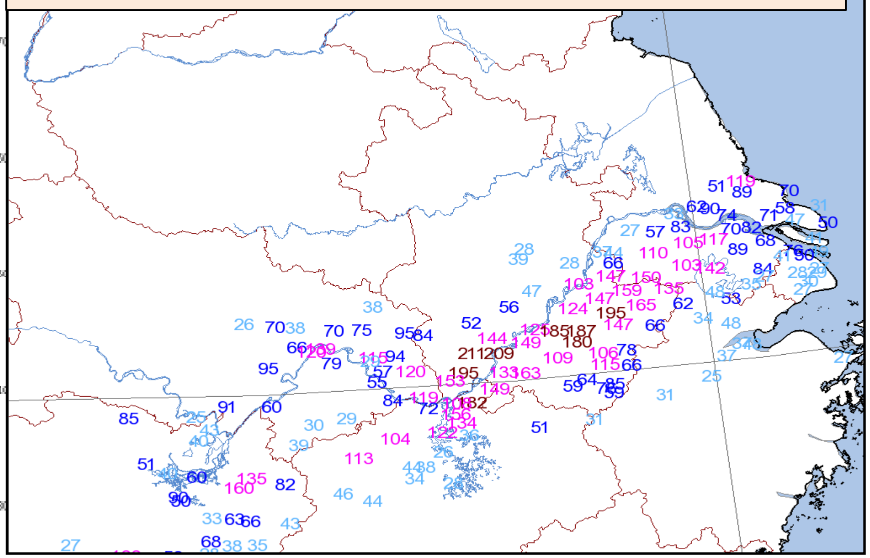
Bauer *et al.* 2015

What are the Ultimate Limits of Multi-scale Mid-latitude Weather Predictability?

Cases in Study

Europe	***China***
5-11-d fcst T anomaly early Jan 2016	24-h rainfall OBS 3 Jul 2016





Week 2 EC forecast failure on transition to cold conditions over Northern Europe

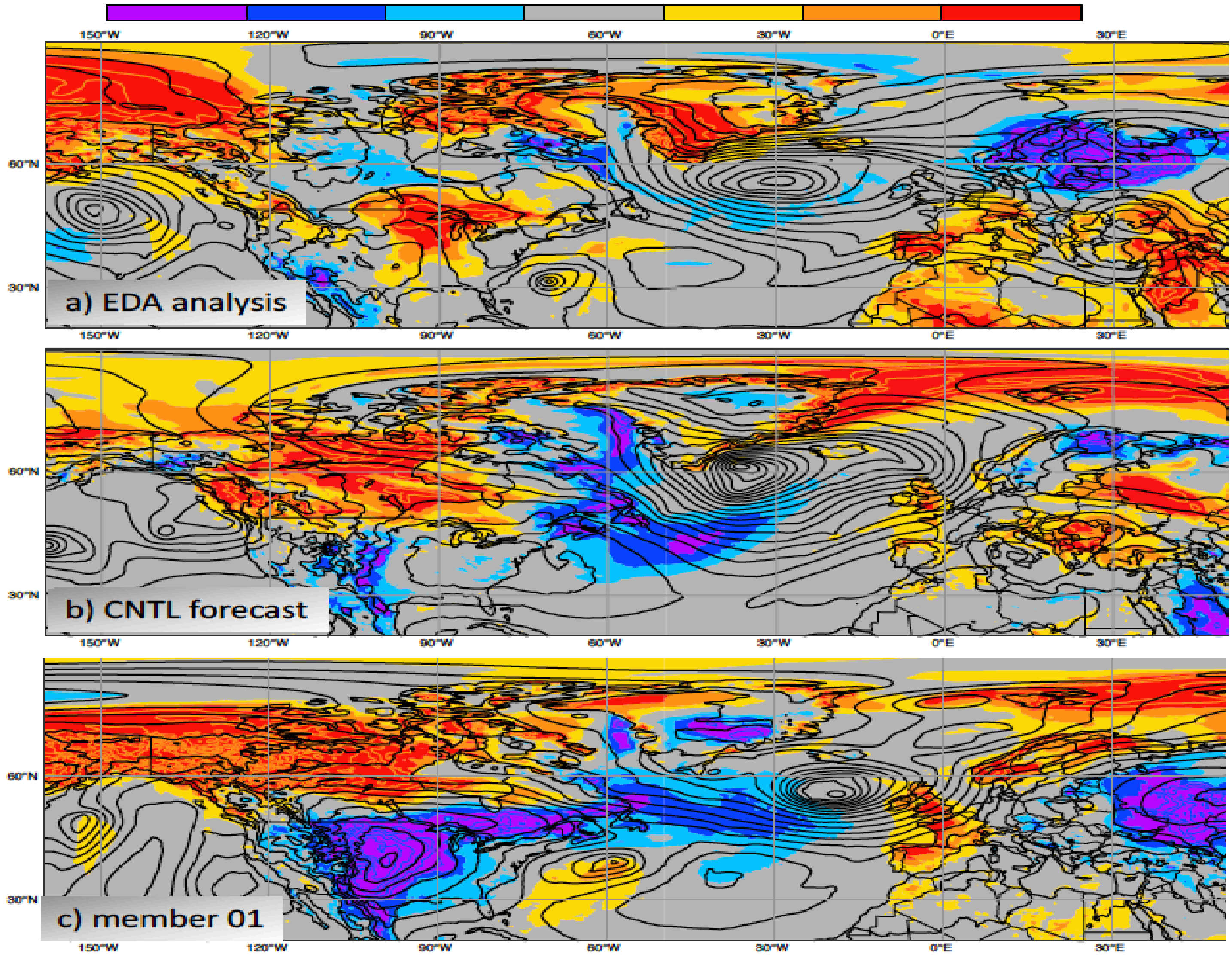
Day 3-4 Meiyu front north bias during historic China flood

- **Approach: use operational 9-km global model but 10-member 20-day ensembles, 6 different times**
- **Initial perturbations from each EDA analysis (1.0 x EDA) vs. 10% of EDA (EDA0.1 center on the CNTL)**

What are the Ultimate Limits of our Daily Weather Predictability?

ECMWF operational analysis, CNTL forecast, and #1 of the 0.1EDA ensemble valid at 15-day lead time

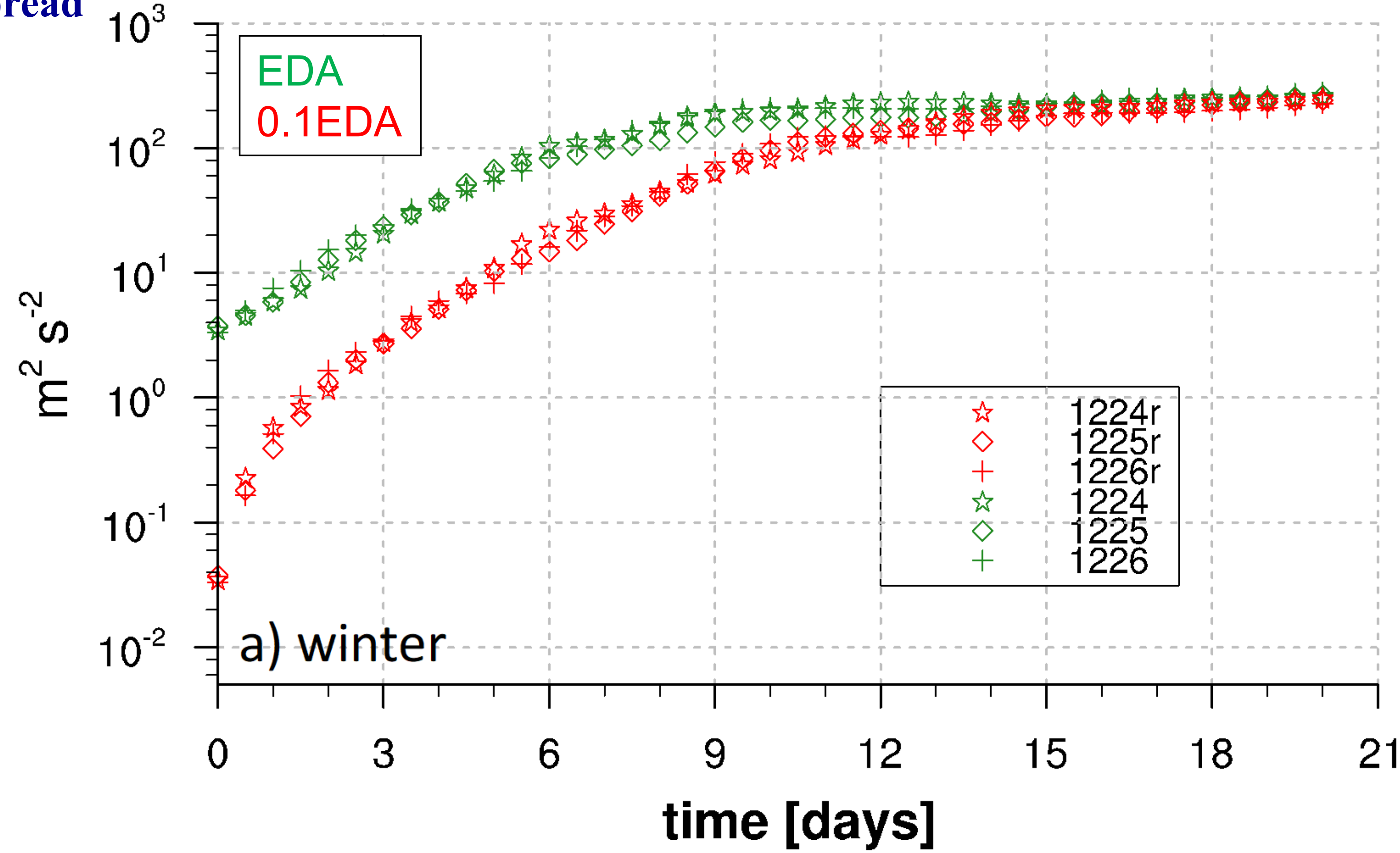
Member #1 of the 0.1EDA ensemble 10% of IC uncertainty of current EC analysis



Ongoing collaborations with ECMWF, GFDL and MIT (Zhang et al. JAS, in review)

What are the Ultimate Limits of our Daily Weather Predictability?

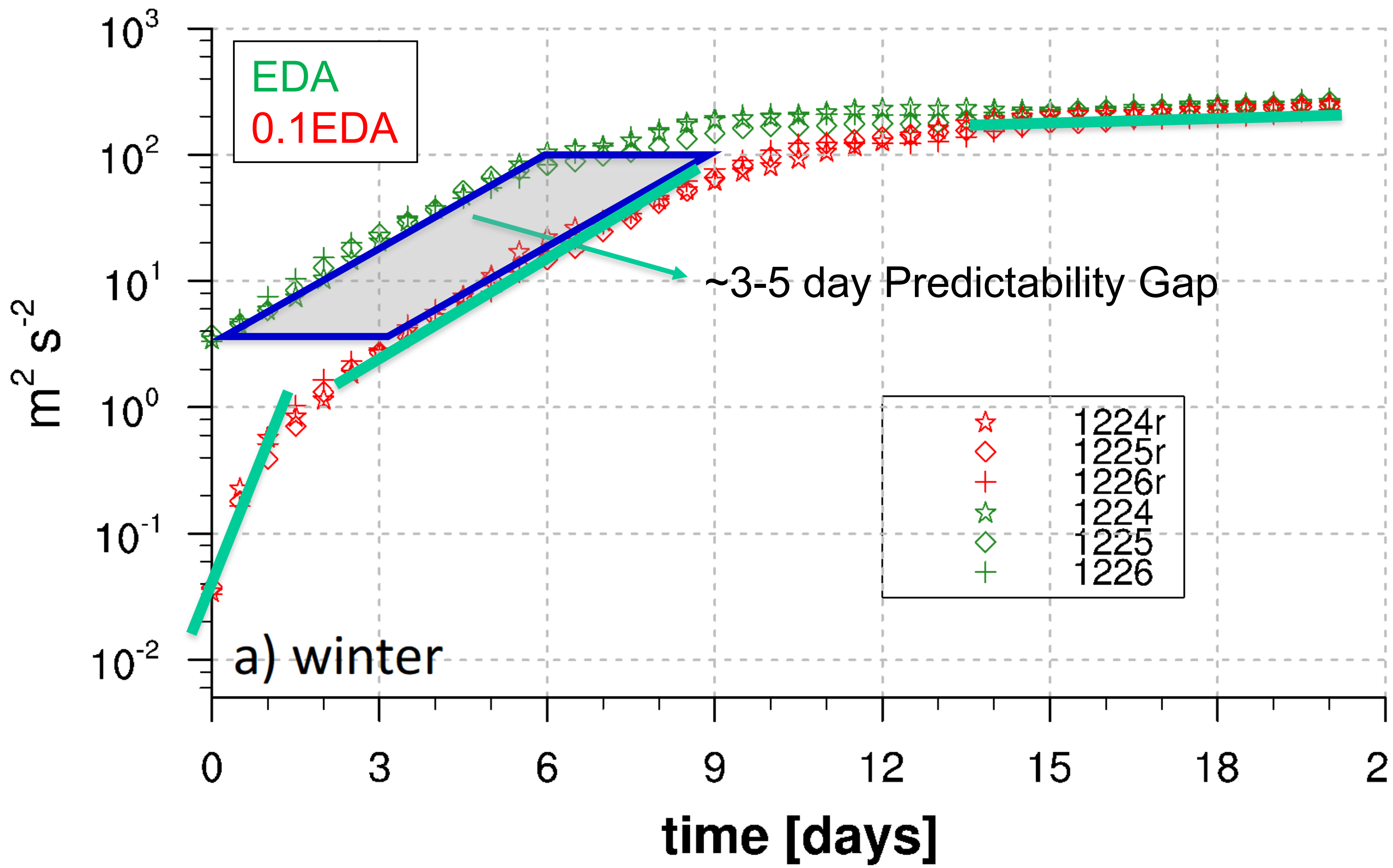
Time evolution of midlatitude (40-60N) averaged ensemble error kinetic energy spread



Ongoing collaborations with ECMWF, GFDL and MIT (Zhang et al. JAS, in review)

What are the Ultimate Limits of our Daily Weather Predictability?

Likely 3-to-5 more days can be gained through better ICs!



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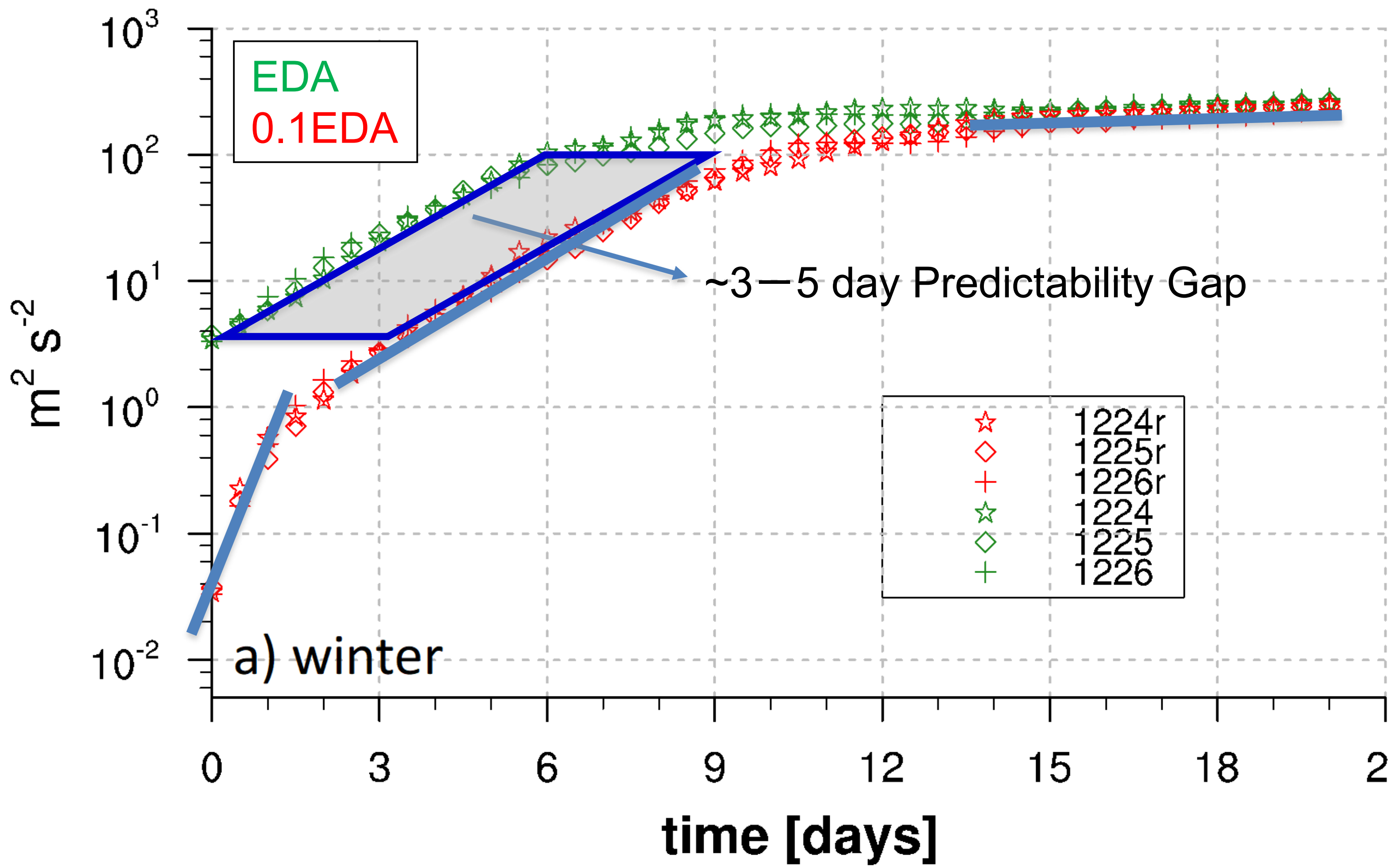
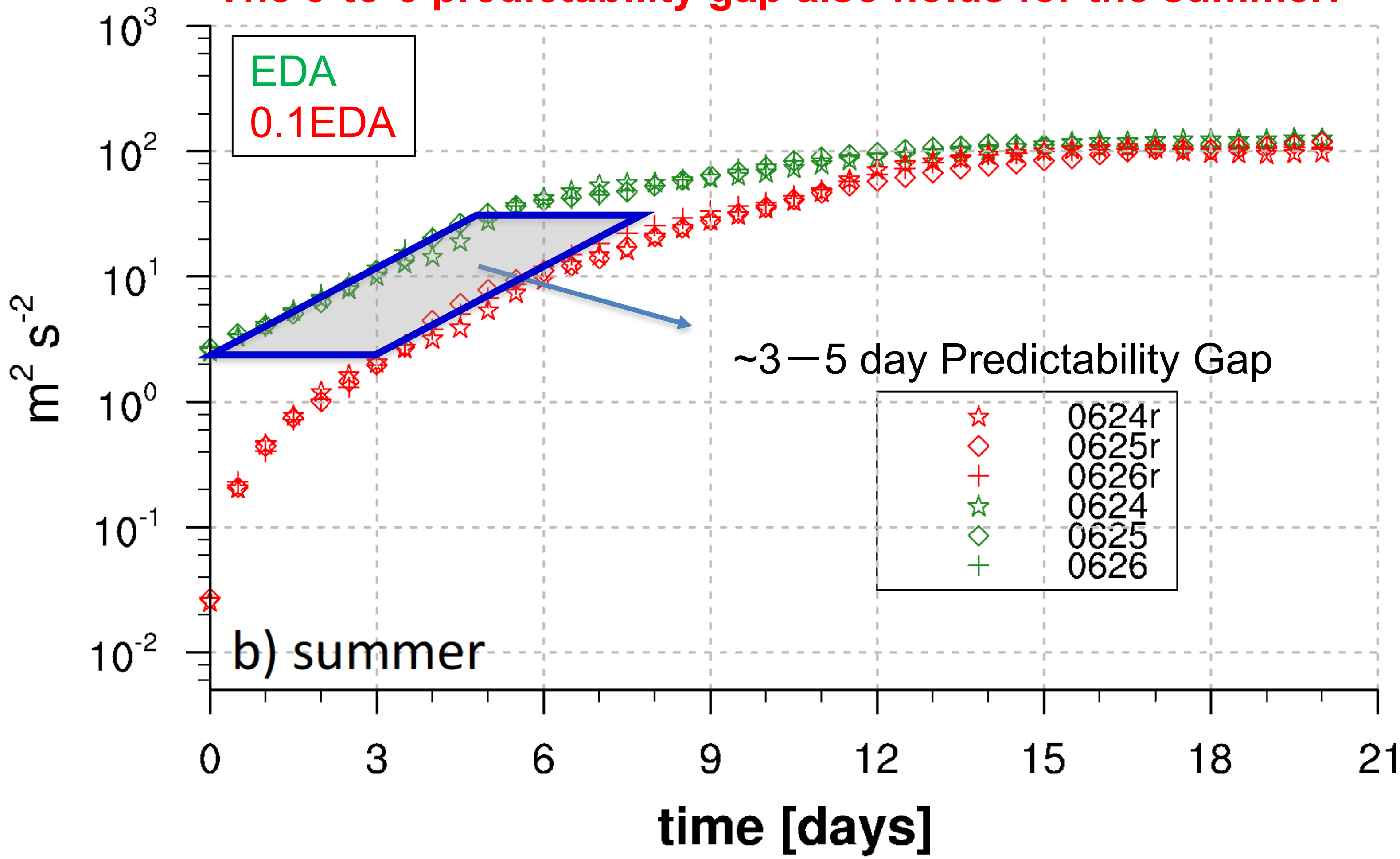


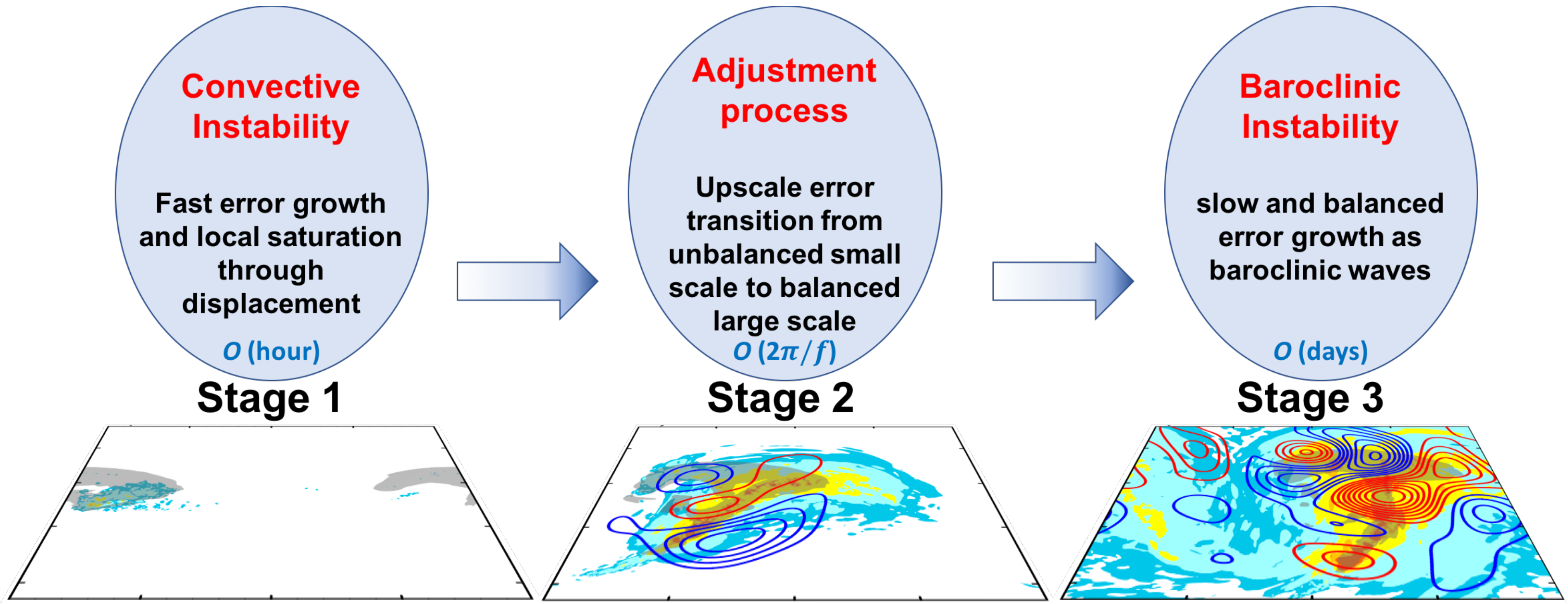
Ongoing collaborations with ECMWF, GFDL and MIT (Zhang et al. JAS, in review)

The 3-to-5 predictability gap also holds for the summer!



Ongoing collaborations with ECMWF, GFDL and MIT (Zhang et al. JAS, in review)

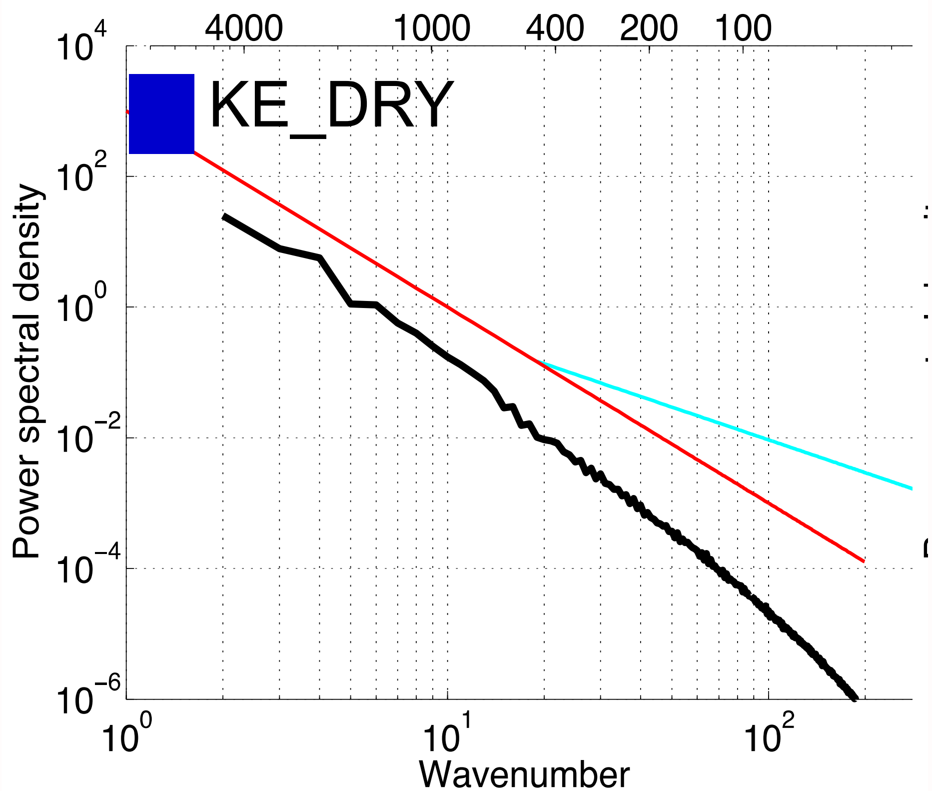
A Multistage Error Growth Model for Multiscale Predictability

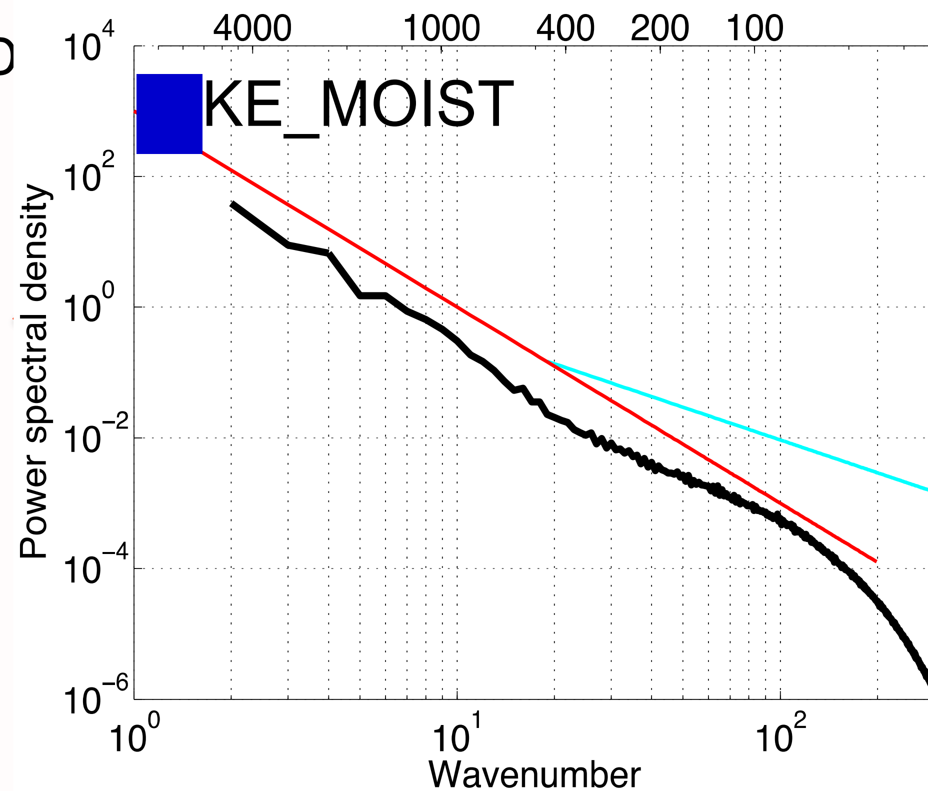


(Zhang et al. 2007, JAS)

Kinetic Energy Spectra with and without Moisture

(Sun and Zhang 2016 JAS)

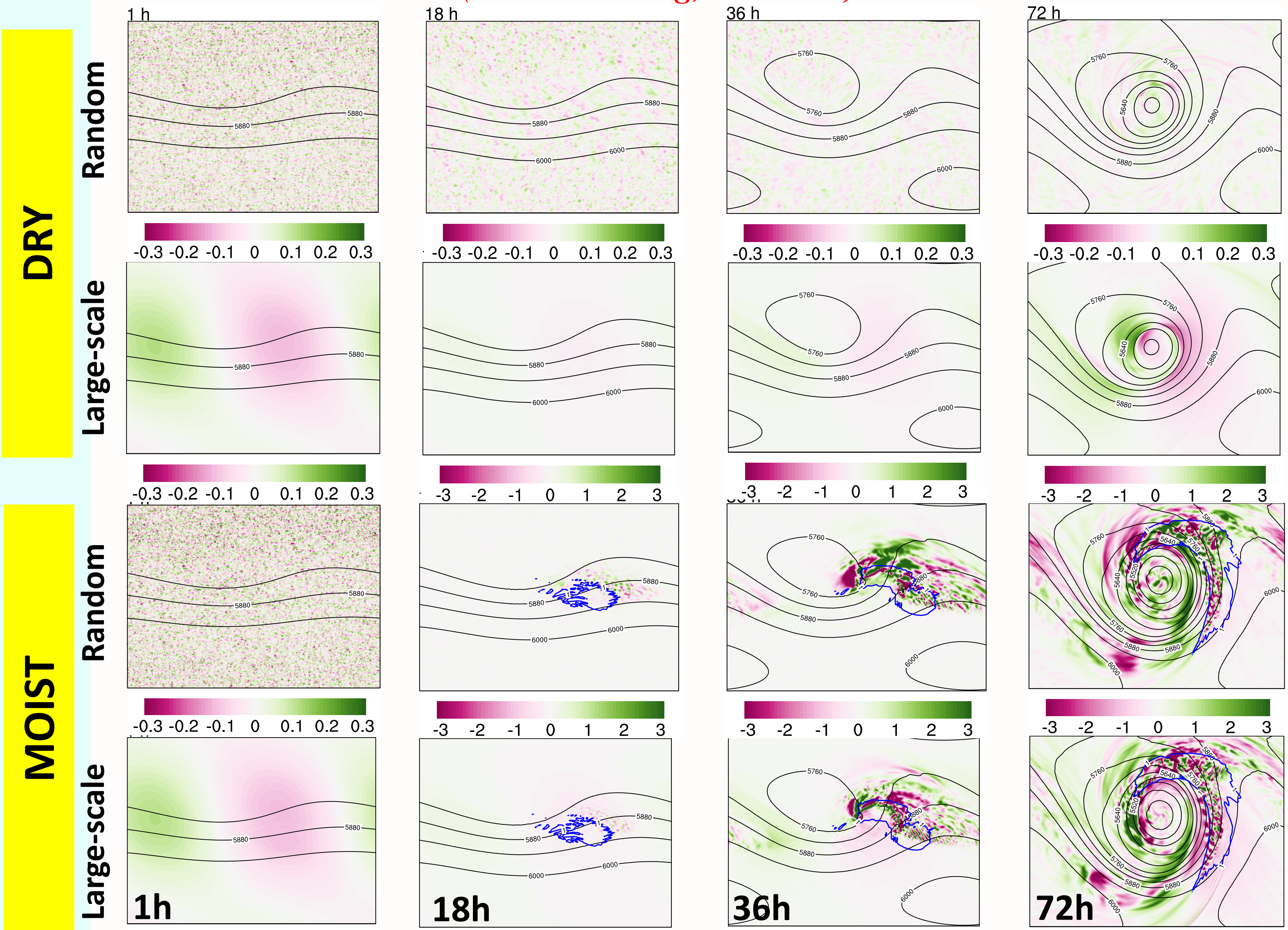




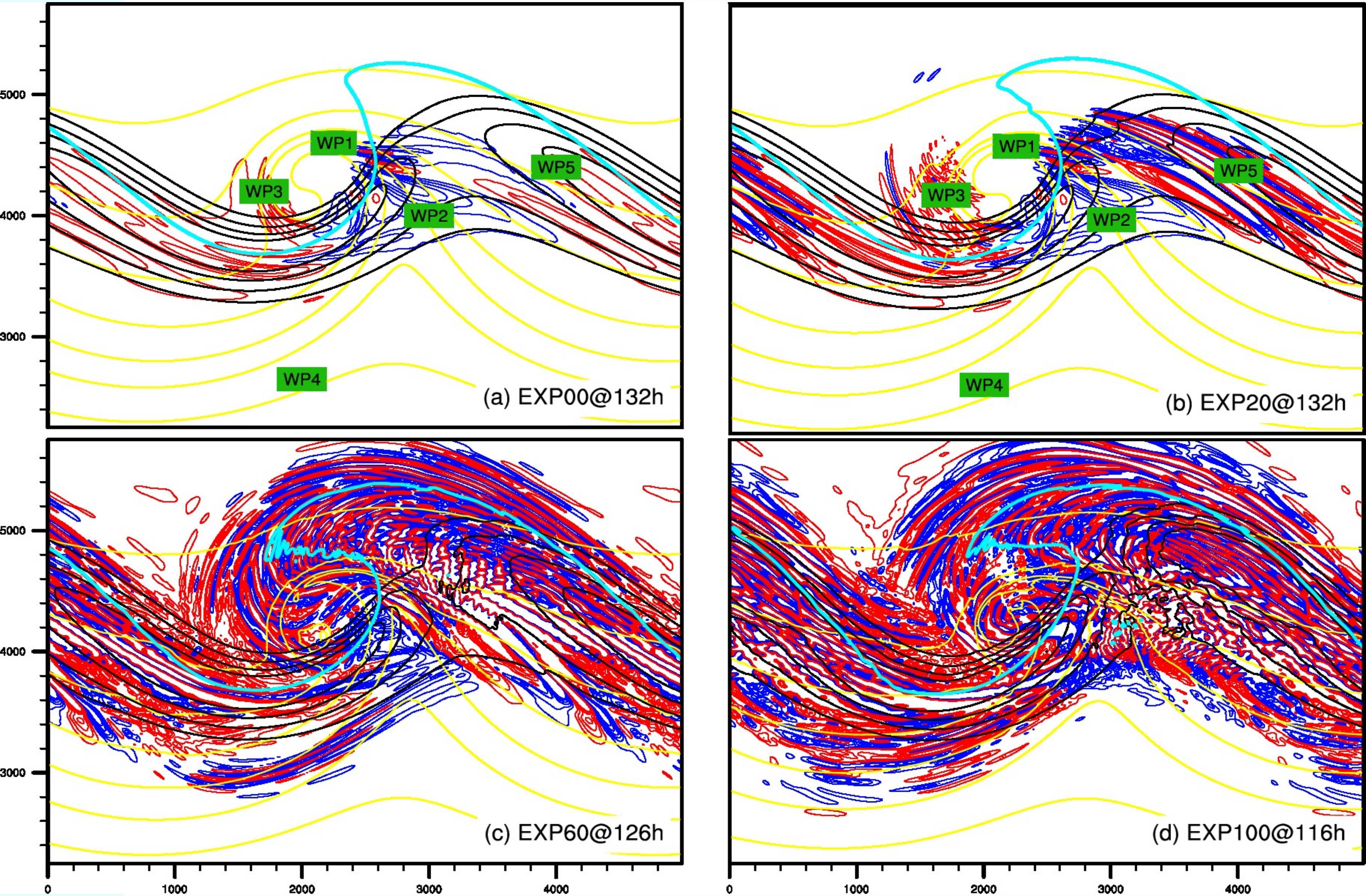
- Moist convection is the key to mesoscale predictability; dry and “fakedry” have -3 spectral slope, moist run has -5/3 at L<400km.
- Implication of spectral slopes on intrinisc predictability consistent with the recent study of Rotunno and Snyder (2008 JAS).
- Convection and gravity waves are key processes that lead to the flattened meso/small-scale spectral slope close to -5/3.

Predictability: Random vs. large-scale IC error, dry vs. moist BWs

(Sun and Zhang, 2016 JAS)

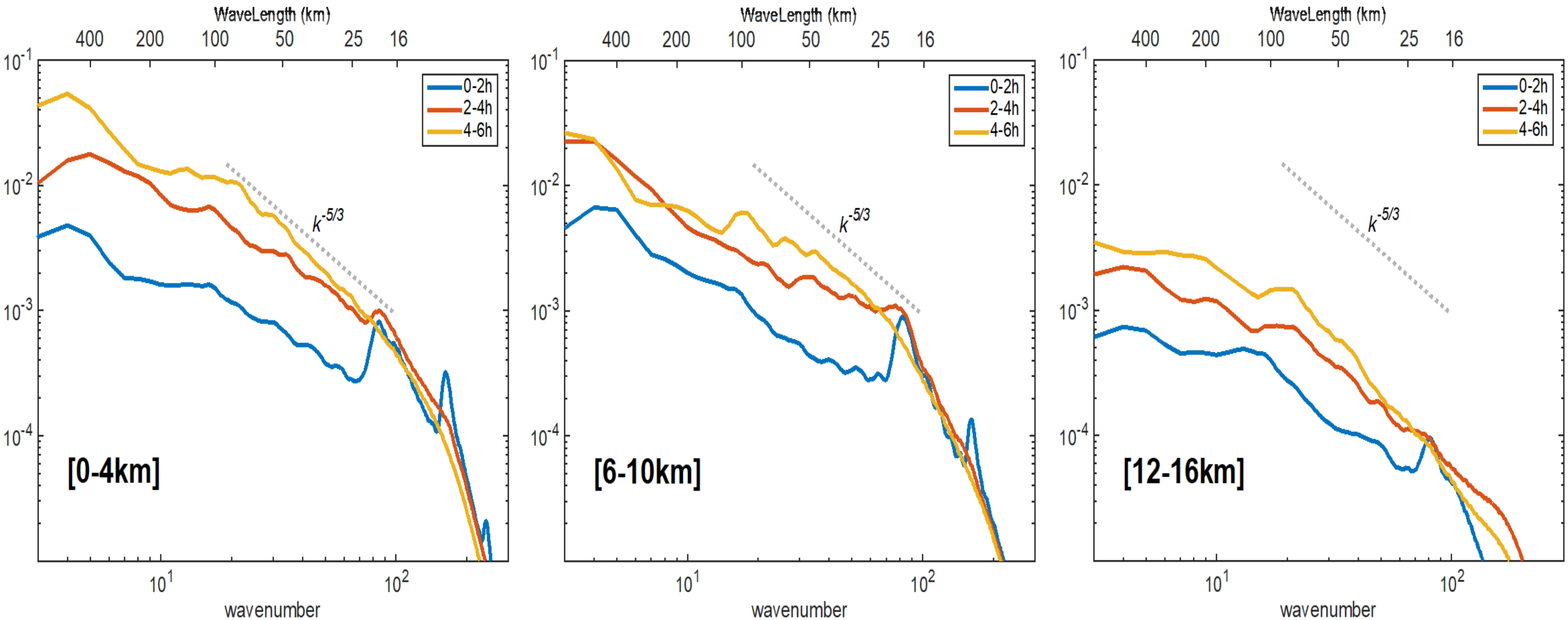


Gravity Waves in Baroclinic Jets: Dry vs. Moist



(Zhang 2004 JAS; Wei and Zhang 2014 JAS; 2015 JAMES; Wei. Zhang Richter 2016 JAS)

Power spectra buildup for convective storms with f=0
Kinetic Energy Spectra at different altitude



lower troposphere

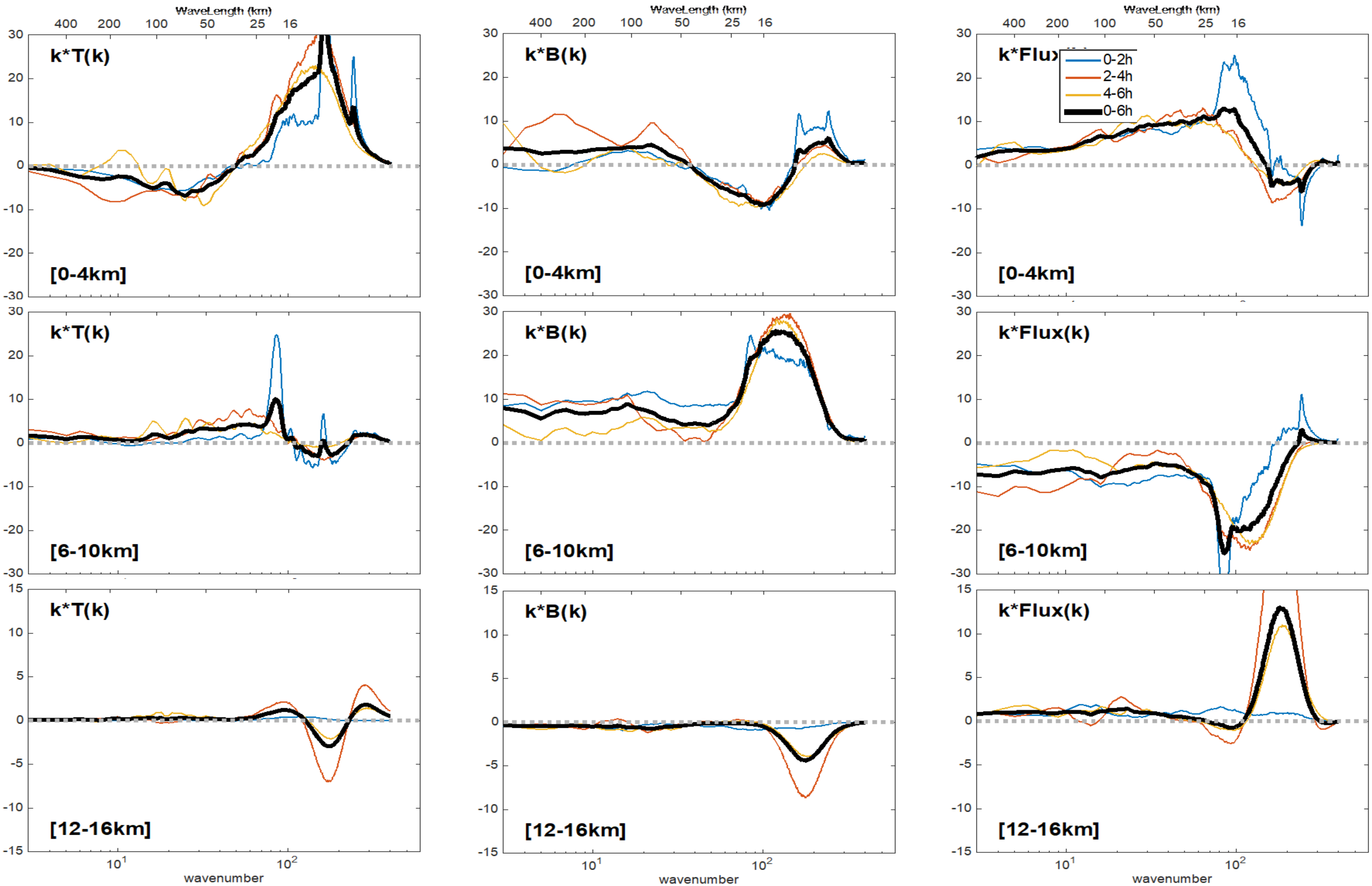
upper troposphere

lower stratosphere

(Sun, Rotunno and Zhang 2017 JAS)

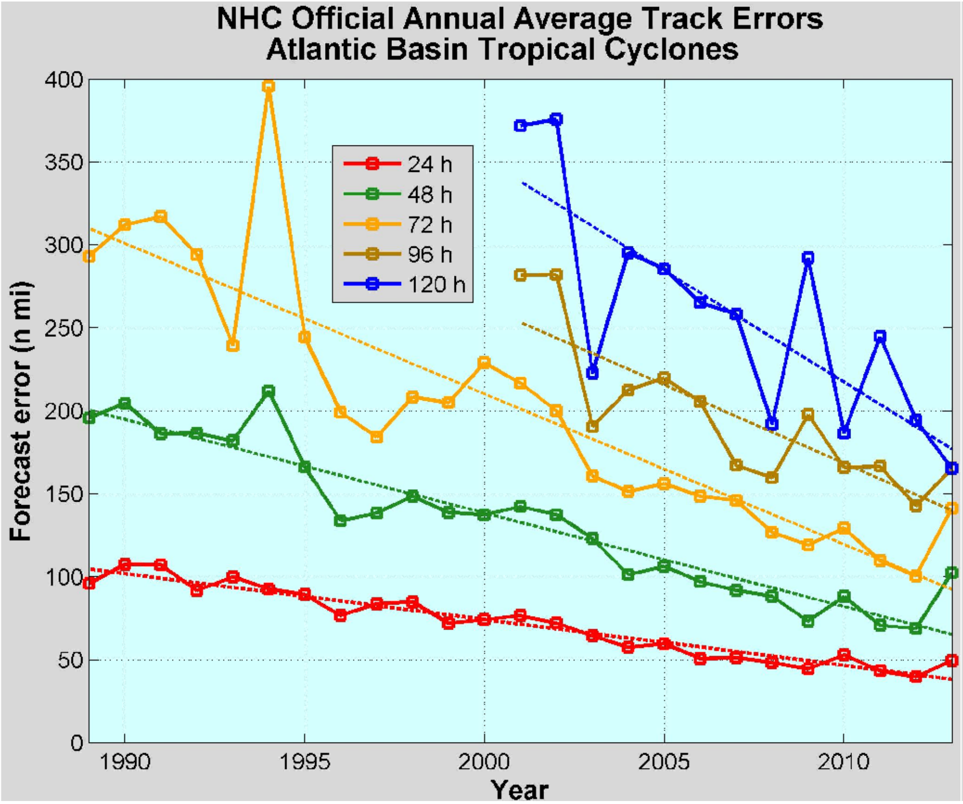
KE Spectra budget across scales at different altitudes

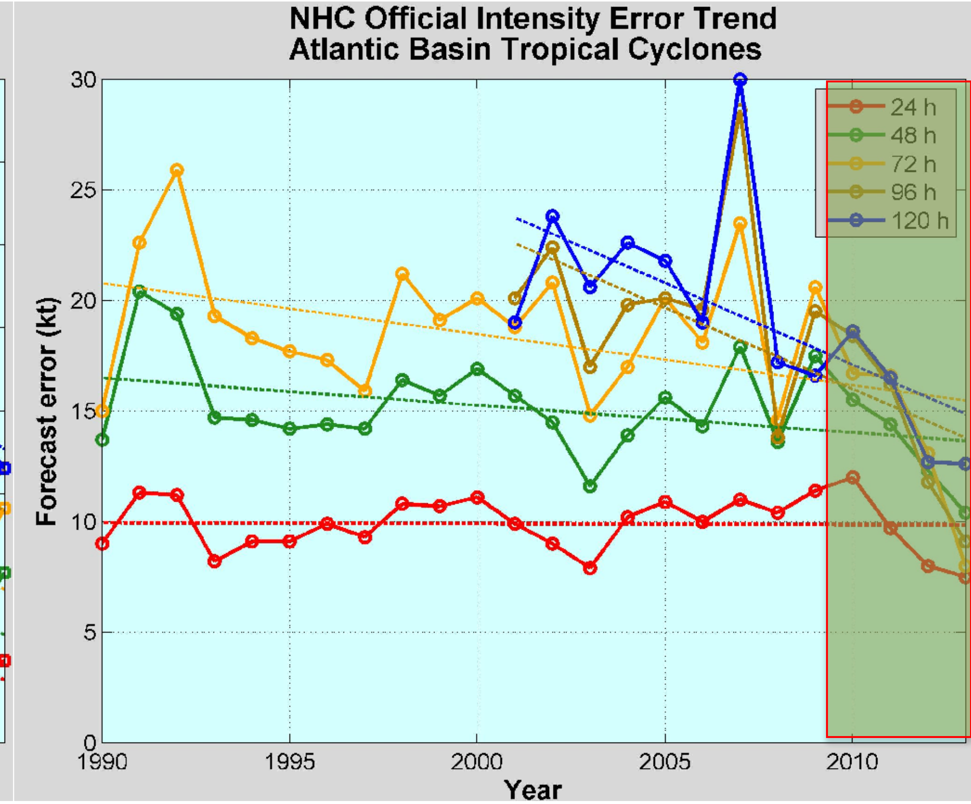
(Sun, Rotunno and Zhang 2017 JAS)



T(k): nonlinear transfer term across scales; B(k) buoyancy term; Flux(k): vertical transport

National Hurricane Center Official TC Forecast Errors



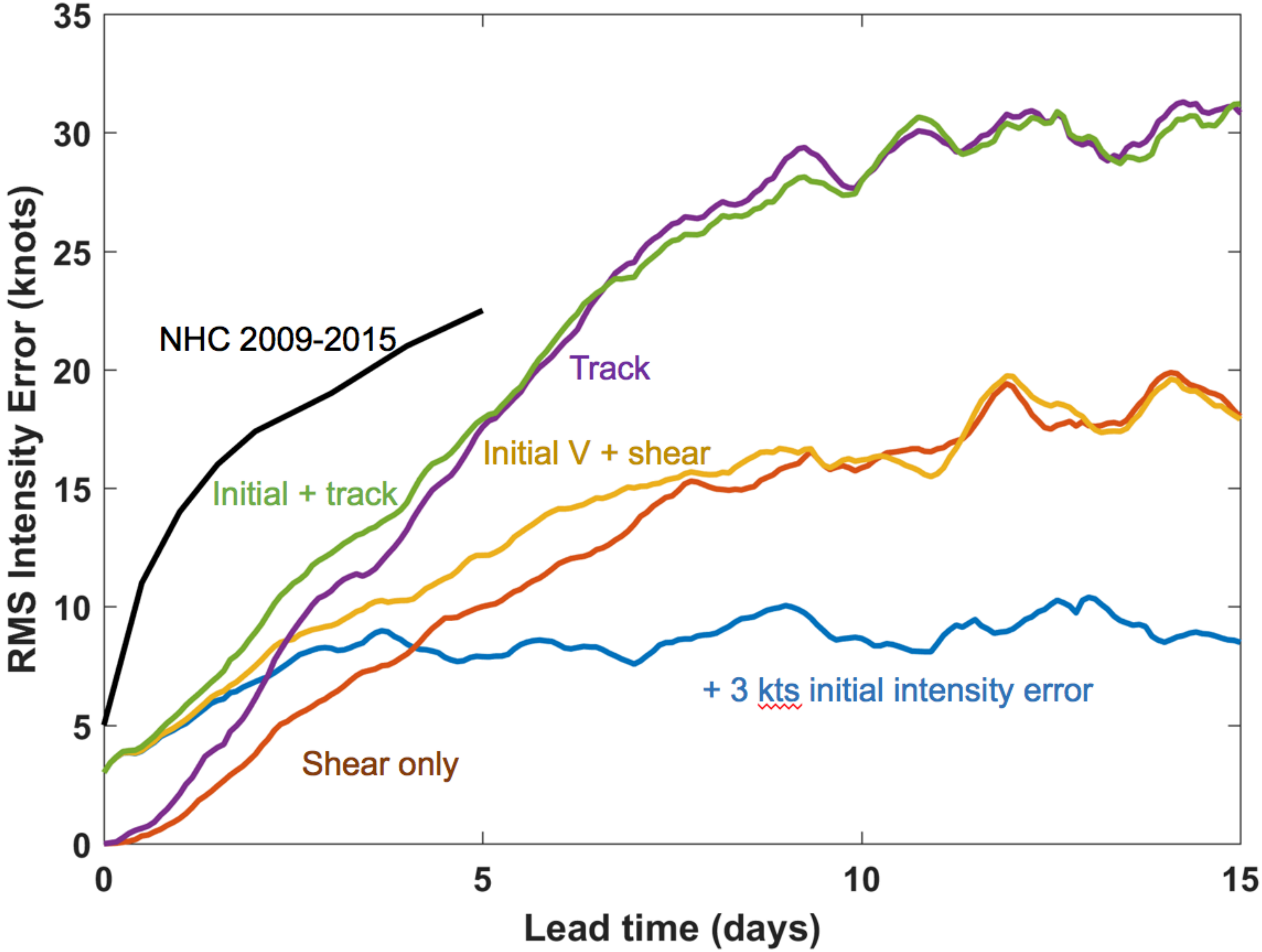


Track forecasts have improved drastically over past 25 years: a 3-day forecast today is as accurate as a 1-day forecast was in 1989.

Intensity forecast accuracy has remained generally stagnant over that same period, except for the last few years, thanks to the Hurricane Forecast Improvement Program (HFIP) led by NOAA.

Predictability and Error Sources of Tropical Cyclone Intensity Forecasts: CHIPS 2009-2015 Intensity Forecast with Different Uncertainties

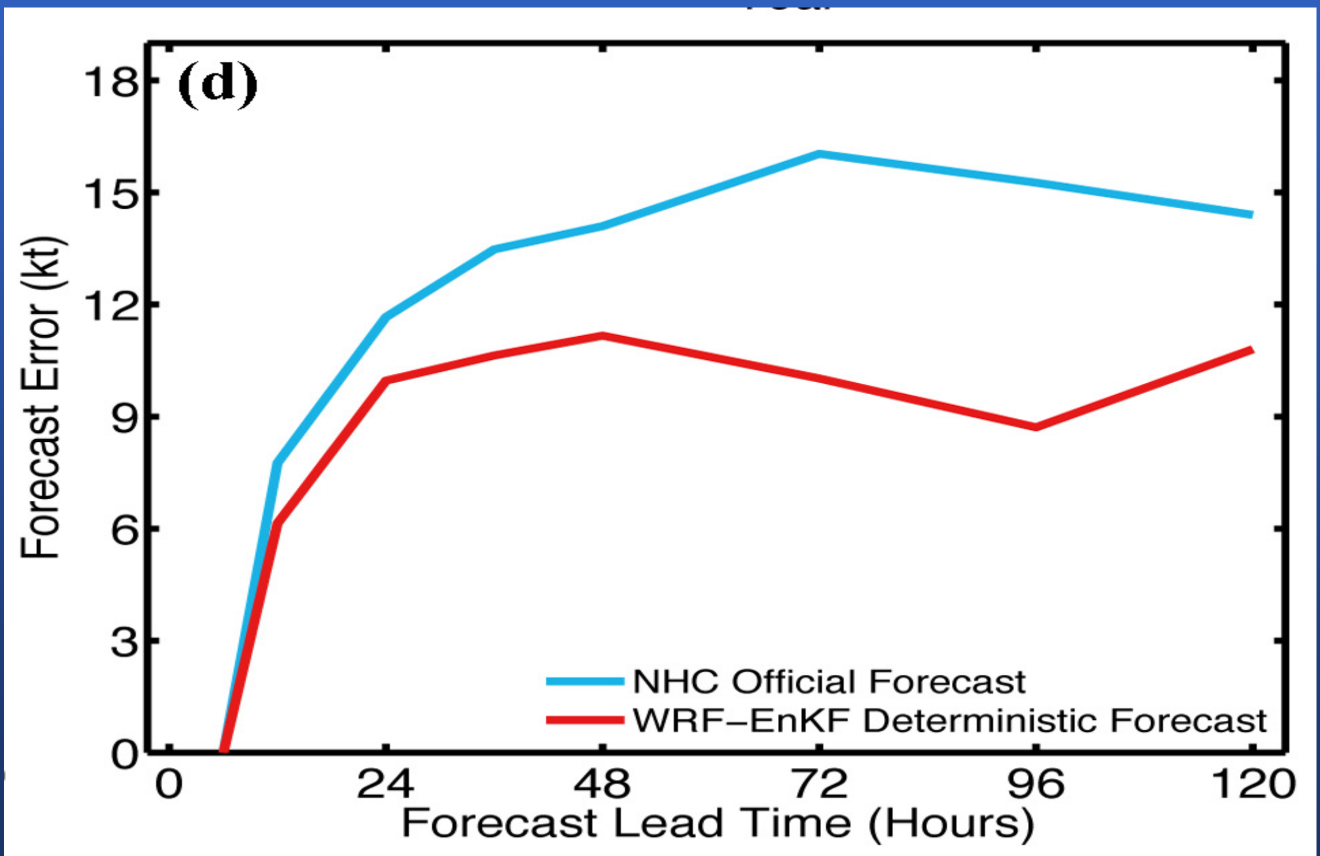
(Emanuel and Zhang 2016 JAS, 2017 JAS)



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)

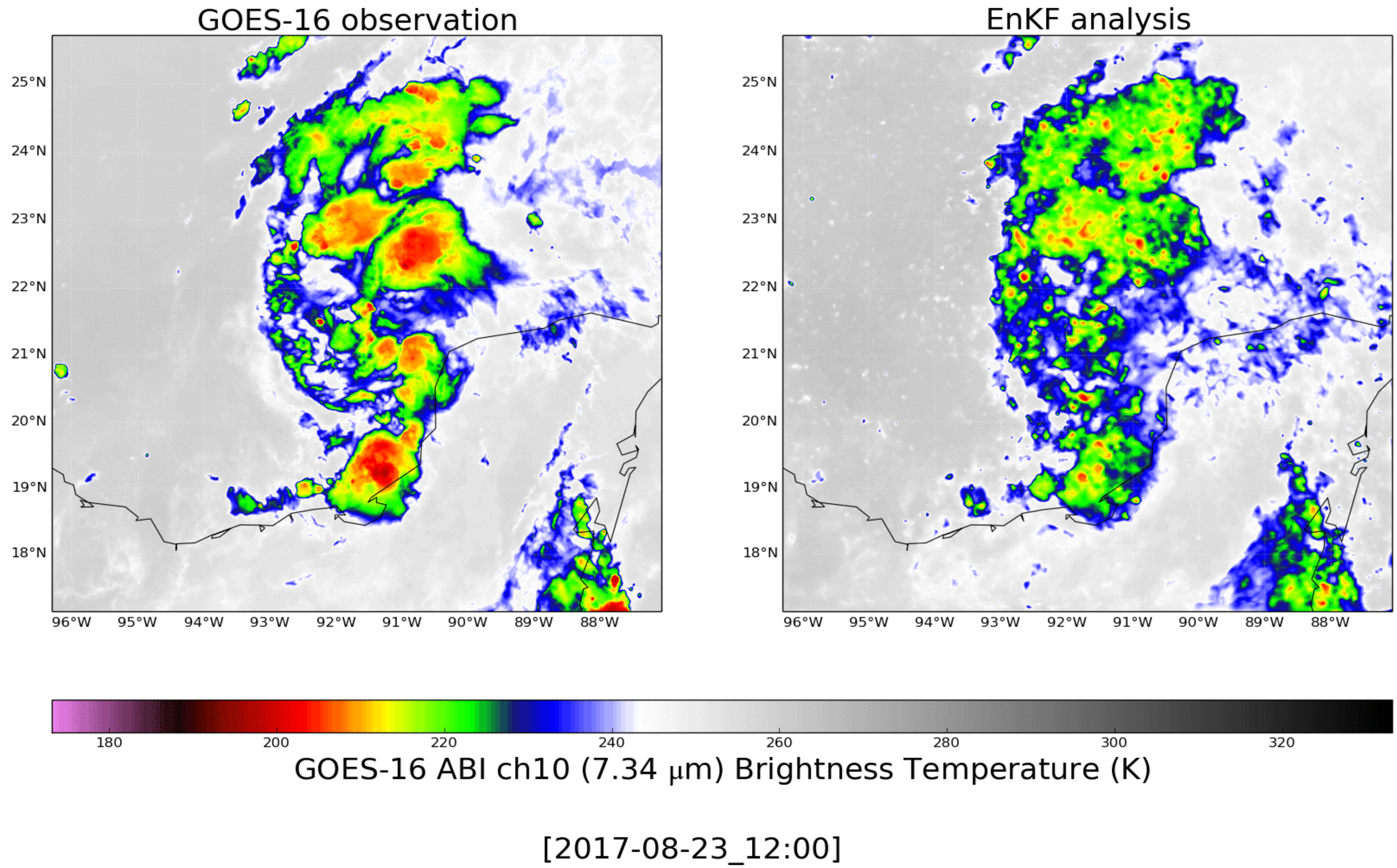


(F. Zhang and Y. Weng 2015, Bulletin of the American Meteorological Society)

Assimilating All-sky GOES-R Radiances: Harvey 2017

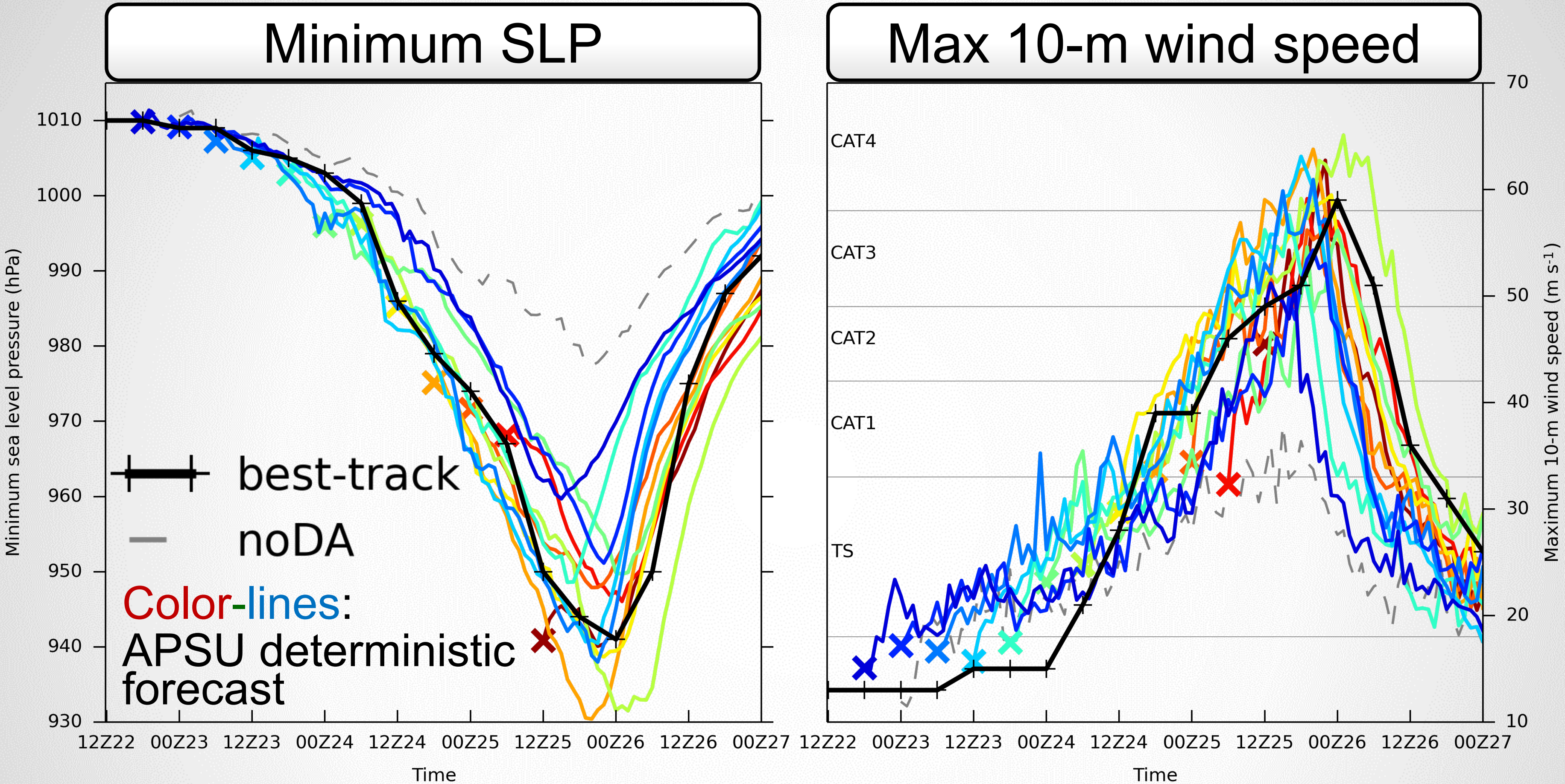
PSU WRF-EnKF assimilates channel 8 radiances every 1 hour

Independent observations vs. EnKF analysis of channel 10



(Zhang et al. 2016 GRL; 2018 BAMS in review; Minamide&Zhang, 2017, 2018 MWR)

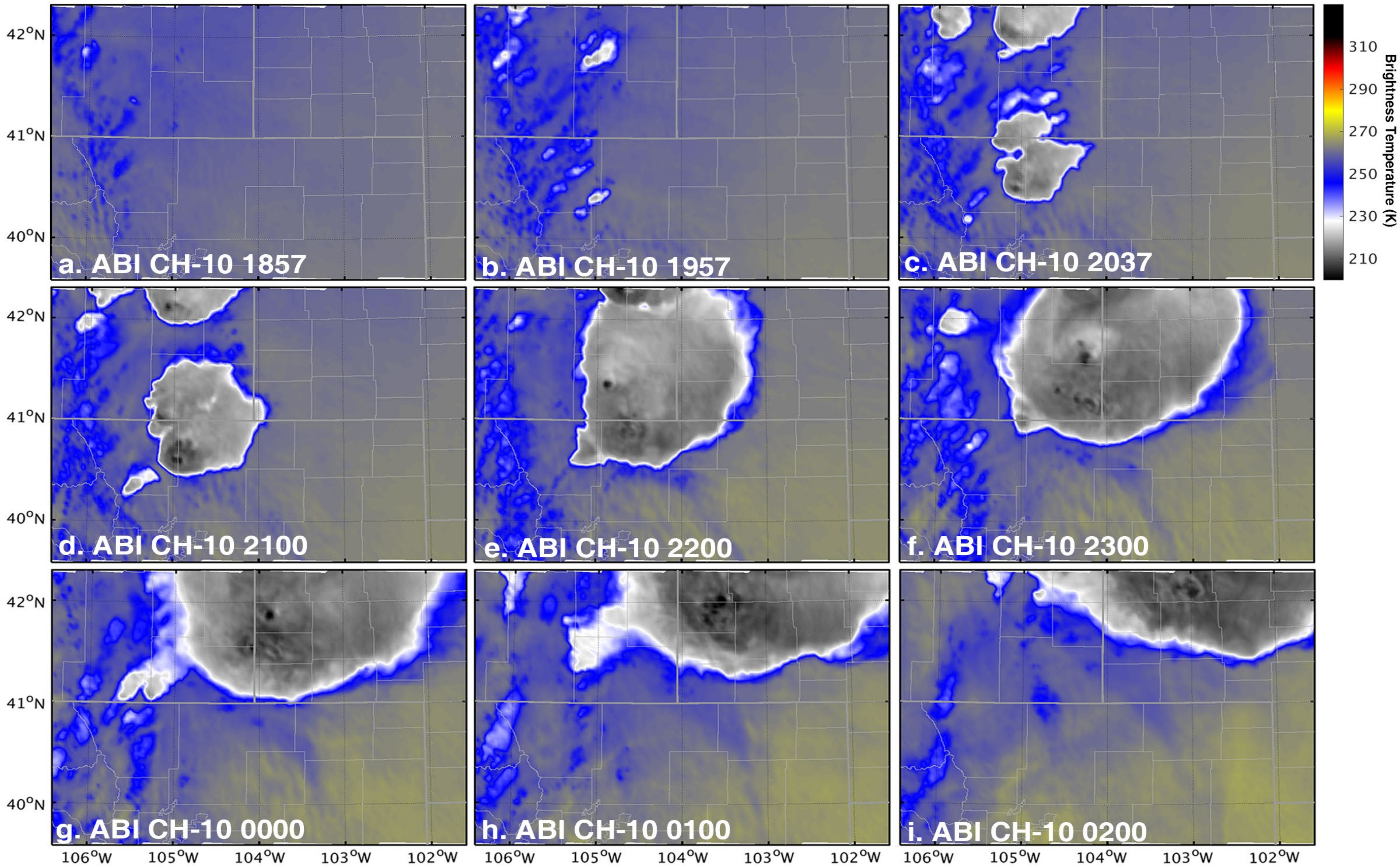
EnKF Performance on deterministic forecast



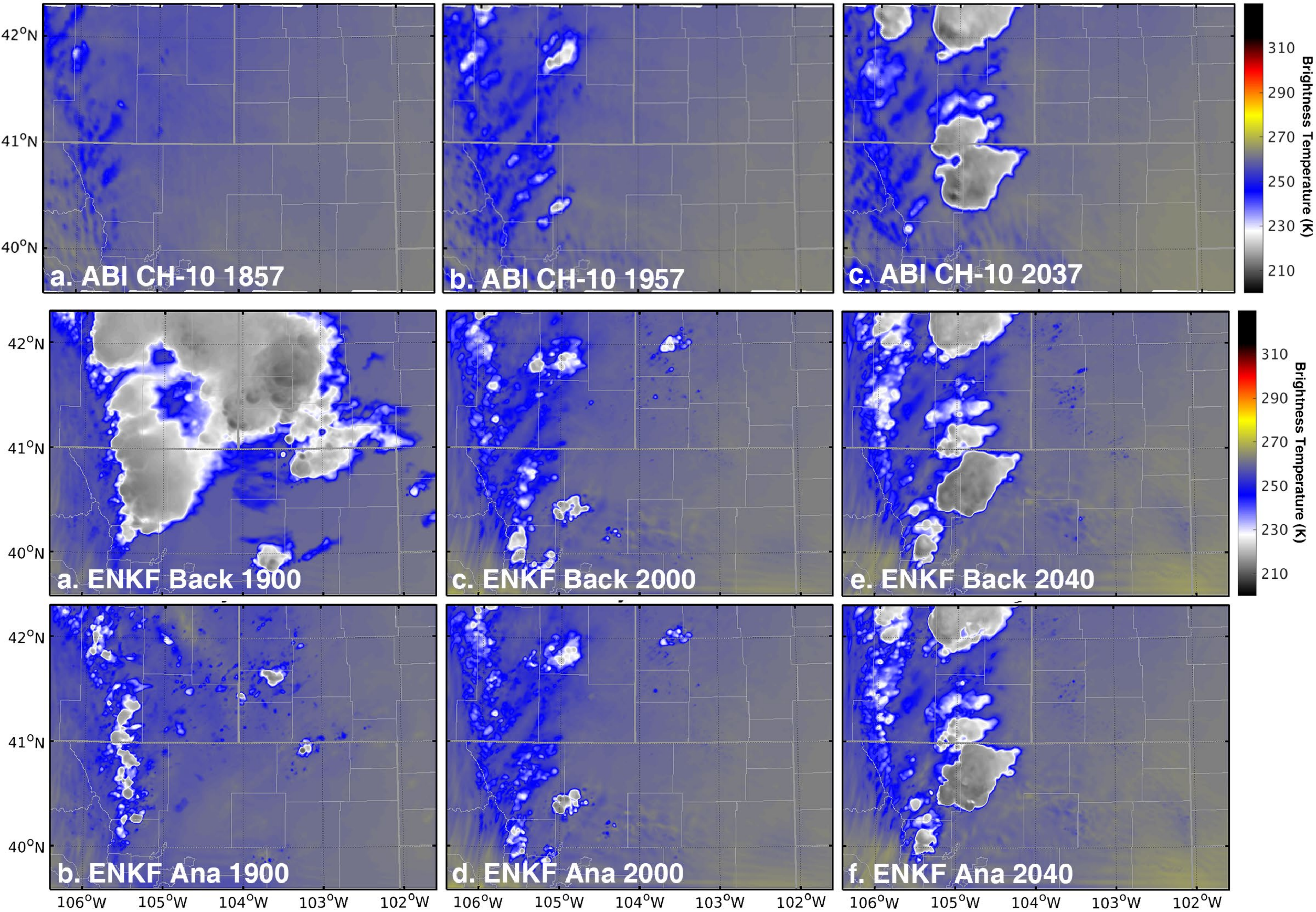
- All deterministic forecast accurately capture the RI of Harvey, which is largely improved from noDA forecast.

(Zhang et al. 2016 GRL; 2018 BAMS in review; Minamide&Zhang, 2017, 2018 MWR)

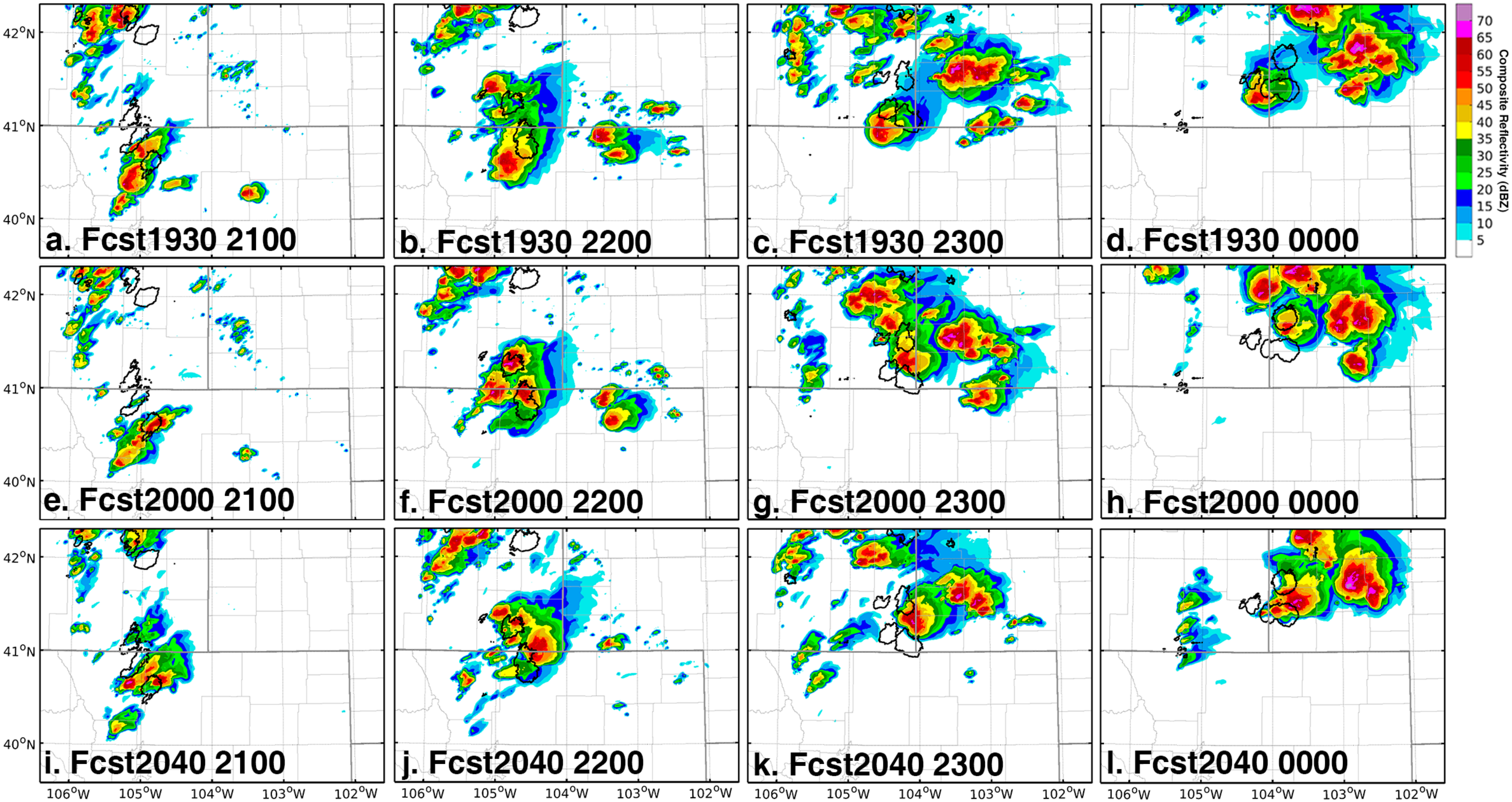
Prediction of a 2017 Tornadic Storm with GOES-R assimilation: Observations
(Zhang, Zhang, David Stensrud 2018 MWR)



Prediction of a Tornadic Storm with GOES-R assimilation: EnKF analysis vs. observations



Prediction of a Tornadic Storm with GOES-R assimilation: progressive forecasts
(Zhang, Zhang, David Stensrud 2018 MWR)



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

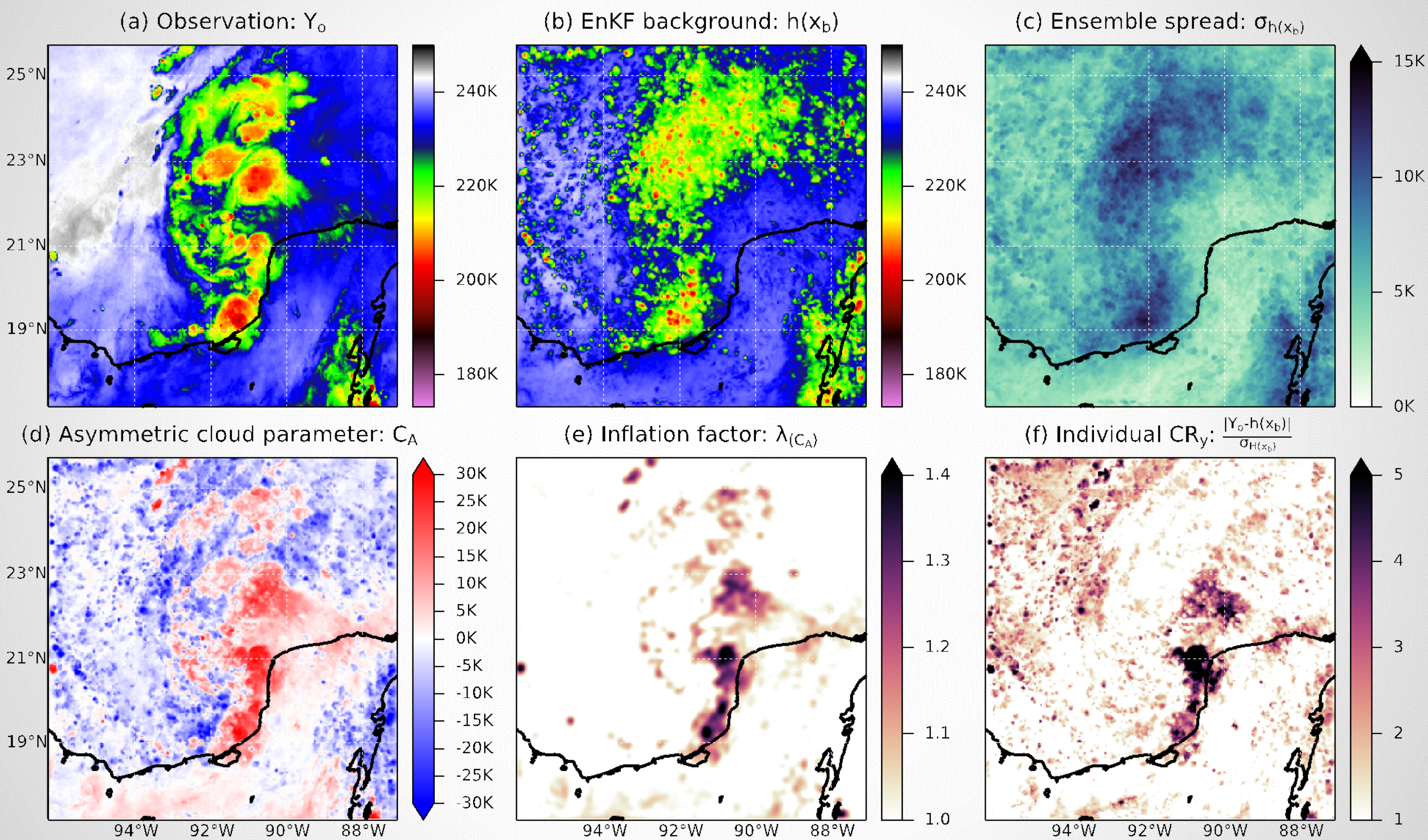
suppresses erroneous analysis increments,

relieves the issues of representativeness & sampling,

& contributes to maintaining balance.

(Minamide & Zhang, MWR, 2017)

Adaptive Background Error Inflation (ABEI)



(Minamide & Zhang, QJ, 2018 in rev.)

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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

- **Predictability of our daily weather including hurricanes and severe storms is very limited at all scales due to chaotic nature of moist convection**
- **Deterministic prediction of global midlatitude daily weather may be ultimately limited to 2 weeks; there are 3-5 days of predictable lead time to be gained**
- **Cloud-resolving weather prediction brings apparent benefits but also comes with faster error growth due to more finer-scale instability being resolved**
- **Further improvement on deterministic forecast depends on the distance between *practical* and *intrinsic* predictability limits**
- **There is a lot of room in improving practical predictability through effectively assimilating all-sky satellite radiances and radar observations**