Multiscale Data Assimilation for Numerical Weather Prediction

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Acknowledgement
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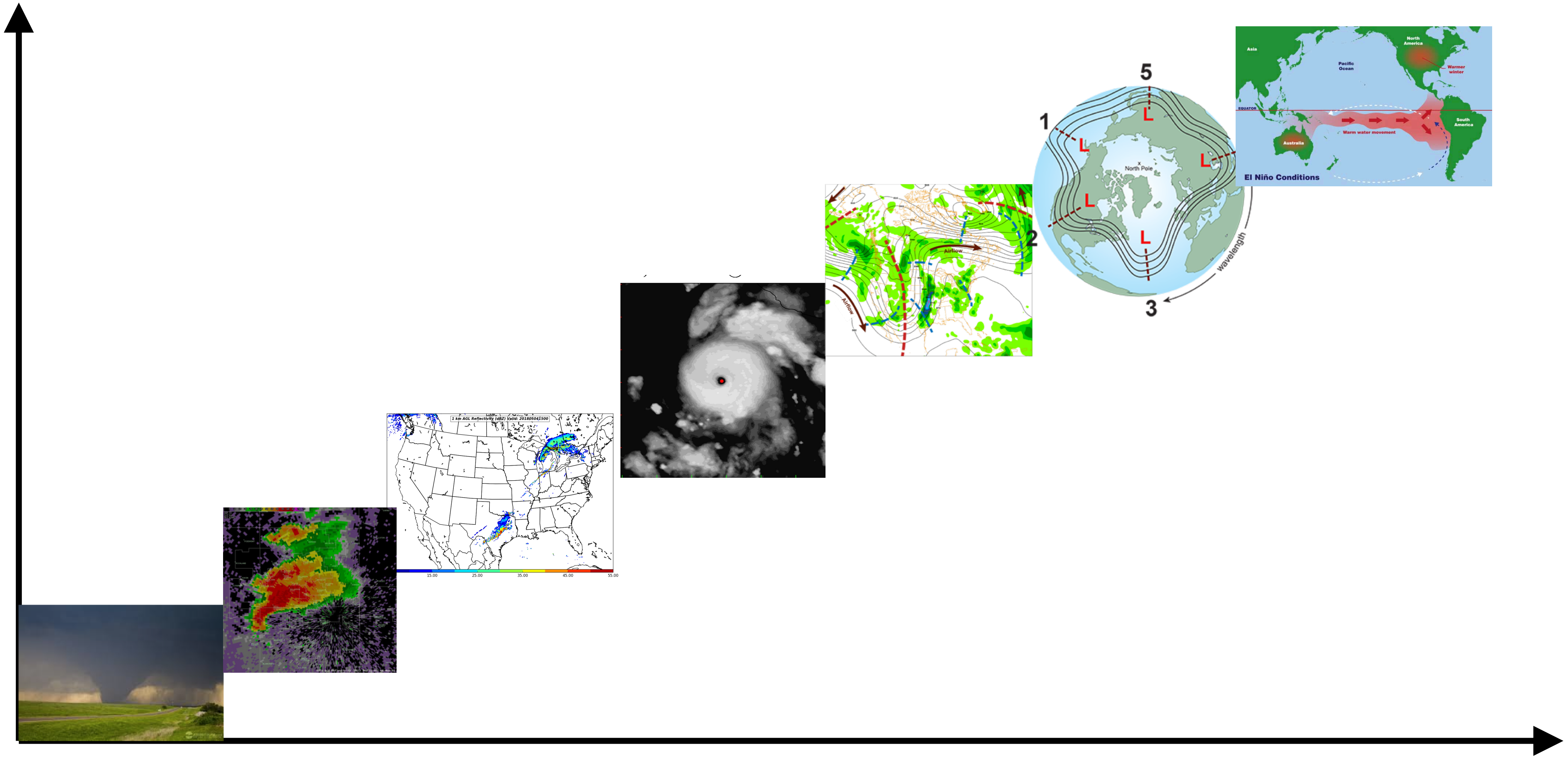
Why Multiscale DA?

Temporal Scale



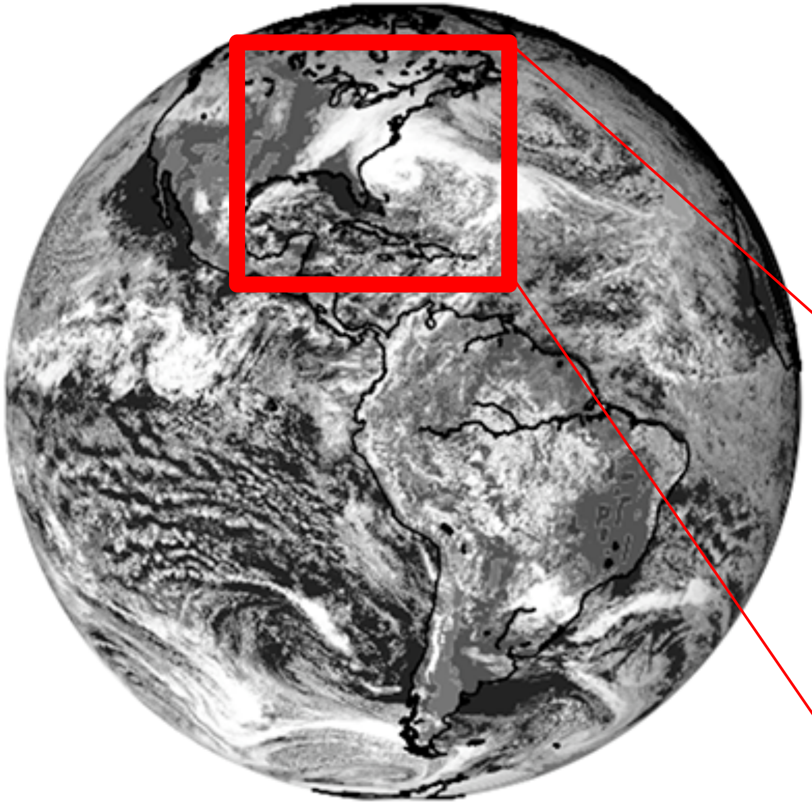
Micro-scale

Meso-scale

Synoptic-scale

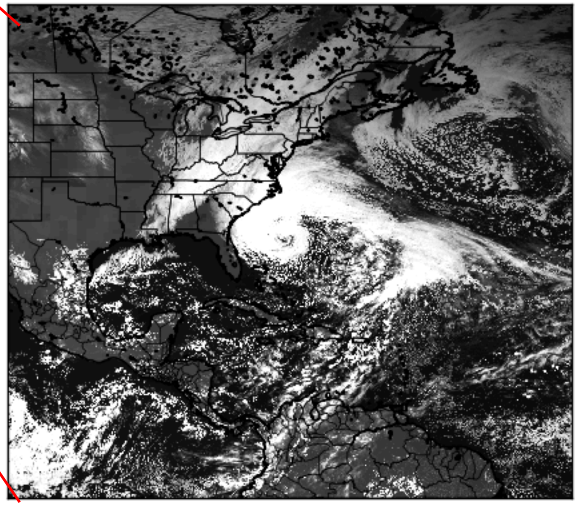
Planetary-scale

Why Multiscale DA?

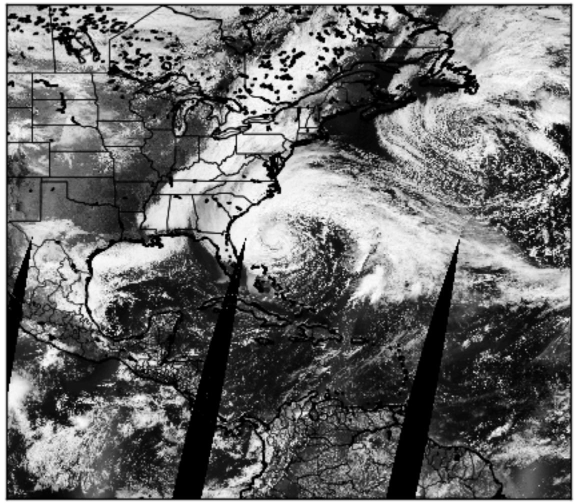


FV3 convection permitting forecast of GOES visible imagery during Hurricane Sandy 2012

- ❑ New computing resources and technologies allow for
- a significant increase of NWP model resolution



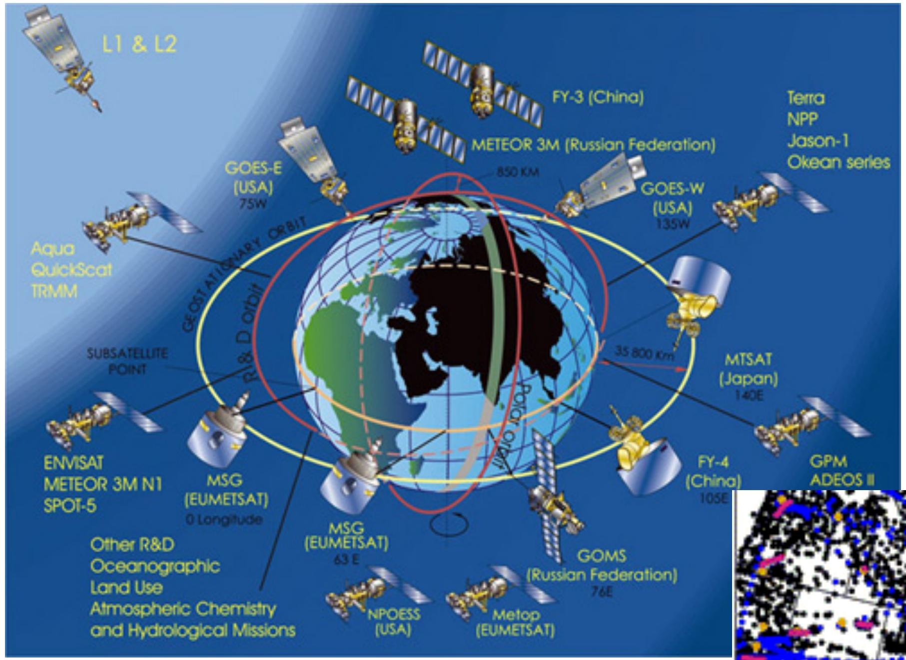
FV3 model



MODIS visible imagery

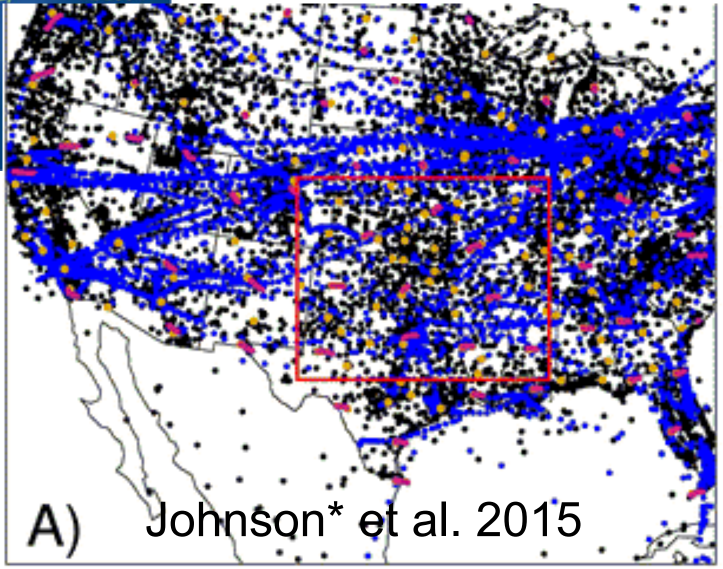
Source: https://www.gfdl.noaa.gov/fv3/fv3-applications/fv3-full-physics-cloud-permitting-simulation/

Why Multiscale DA?

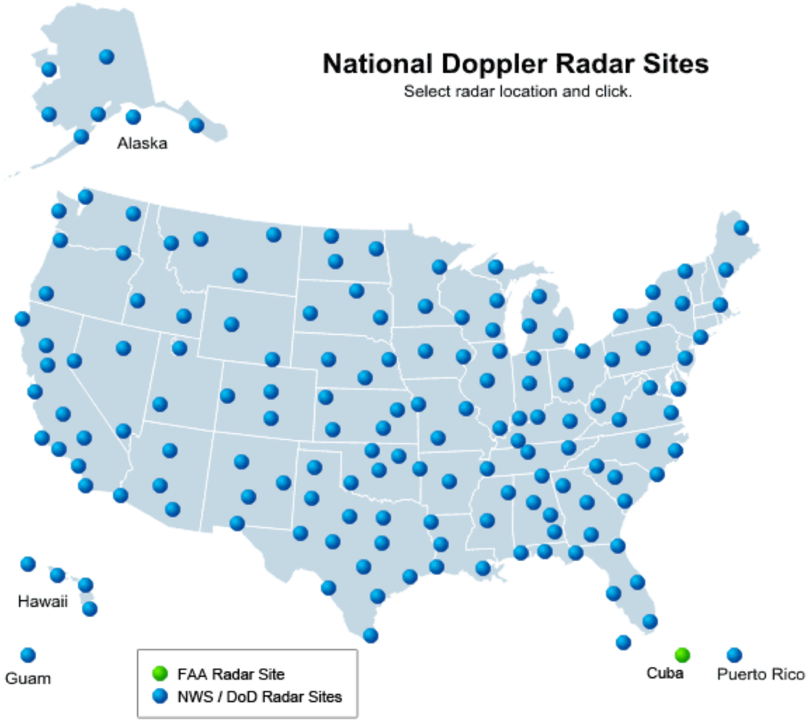


http://www.eohandbook.com/eohb05/ceos/part2_6.html

- ❑ New computing resources and technologies allow for
- ingesting a myriad of existing and new observations that sample a variety of scales to the NWP models

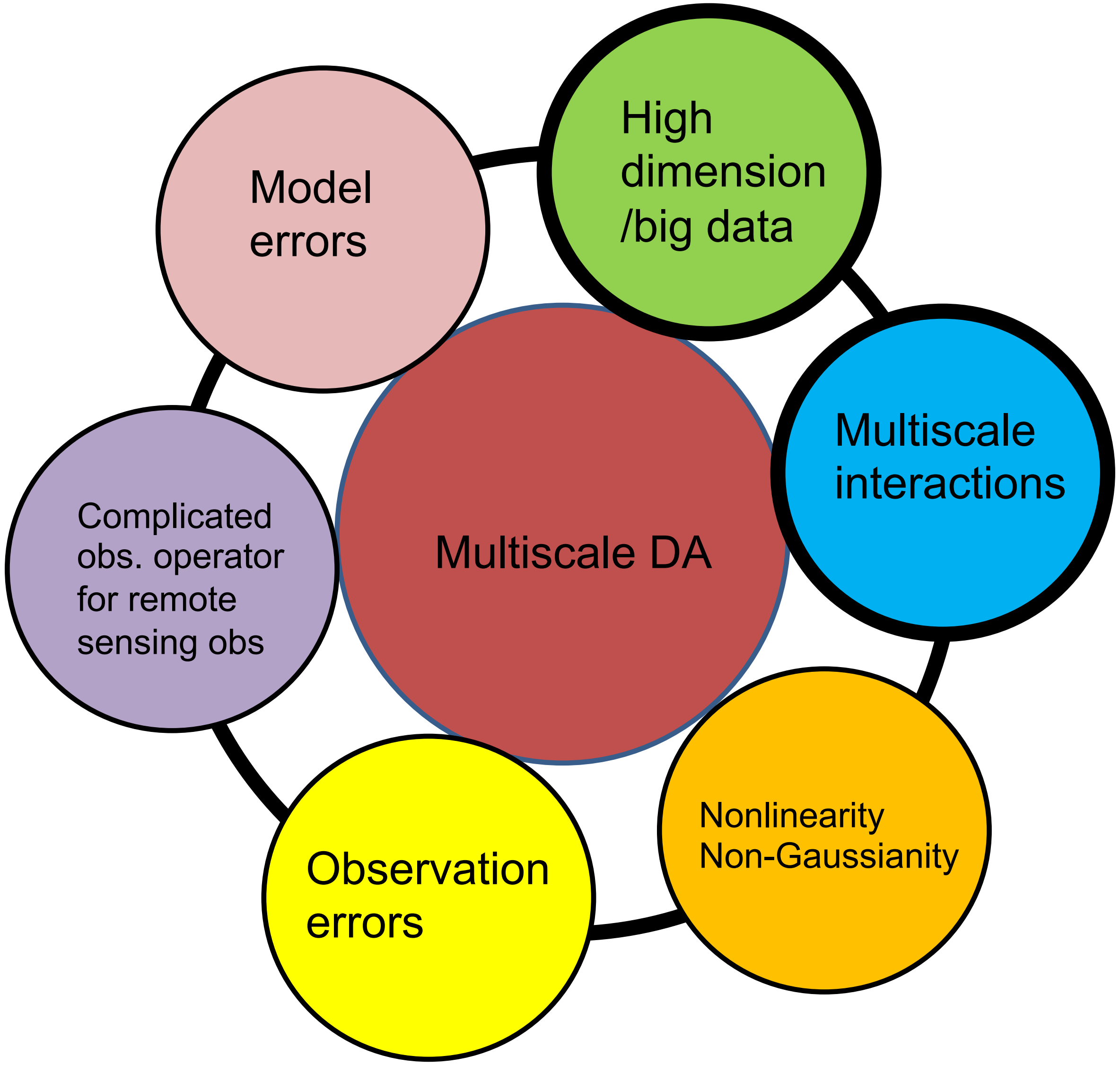


Johnson* et al. 2015



www.weather.gov

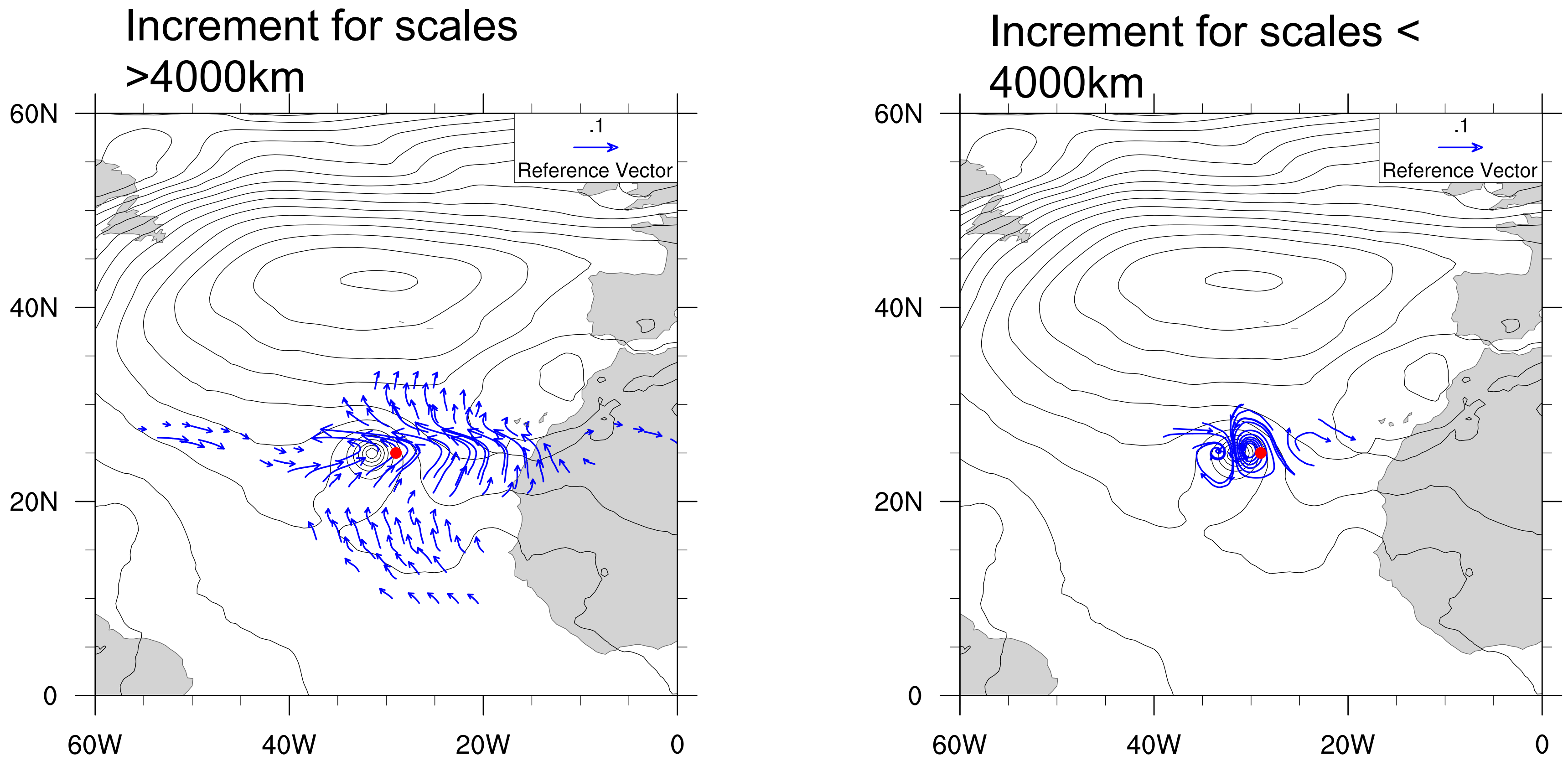
Challenges of MDA



- A next generation data assimilation system is therefore required to **effectively analyze the state and quantify its uncertainty across multiple scales**, termed as “multiscale data assimilation (MDA)”.

Simultaneous Multiscale DA

- A simultaneous multiscale DA approach, as opposed to a sequential approach, allows all observations to correct all resolved scales at once (Wang X., 2021).



- A single obs. can correct multiple scales in simultaneous MDA
- Simultaneous multiscale DA also defines cross scale band error correlation

Huang*, Wang et al. 2021

OU MAP Lab current MDA efforts

❑ Fundamental research:

- **Develop a new simultaneous MDA algorithm/solver**: MLGETKF (Wang, X. et al. 2021)
- **Advance simultaneous MDA method in EnVar**: Kay* and Wang 2020, Wang* and Wang 2022, Jones* and Wang 2022)

❑ Implementation of MDA for UFS applications and for R2O

- Global Medium Range Weather (FV3 based **GFS)** (Kay* and Wang 2020, Huang*, Wang et al. 2021, Jones* and Wang 2022)
- CONUS convective scale weather (**RRFS/HRRR, WoF)** (Wang* and Wang 2022ab)
- Convective allowing Hurricane (**HAFS)** (Lu* and Wang 2022)

Part I: A Multi-Resolution Ensemble 4DEnVar for FV3GFS

Kay* and Wang, 2020; Jones* and Wang, 2022

- Hybrid 4DEnVar (Wang and Lei* 2014)

Single-scale localization

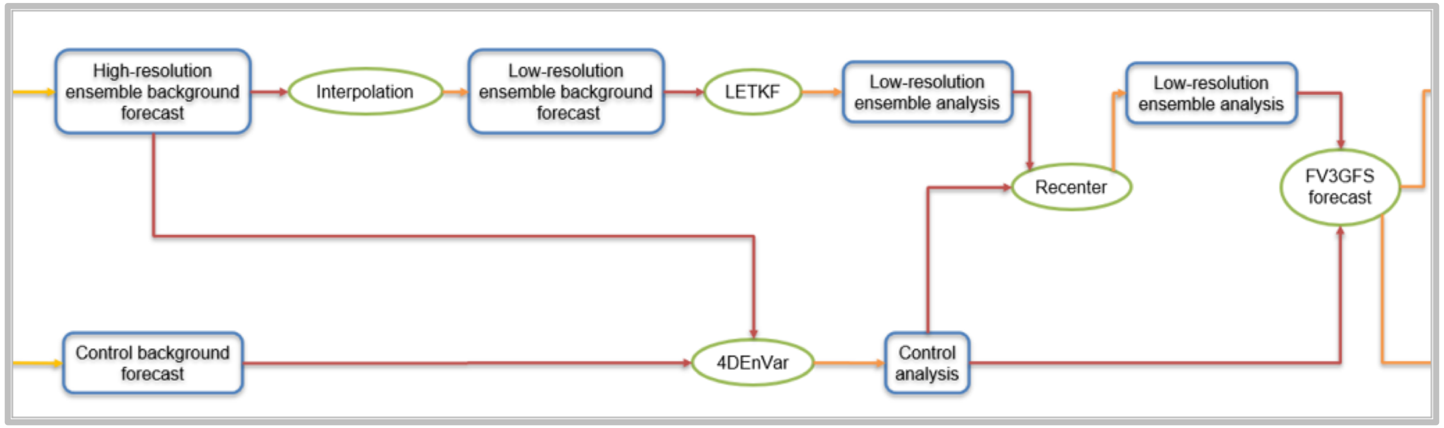
$$J[(\mathbf{x}_1')_t, \boldsymbol{\alpha}] = \frac{1}{2}\beta_1(\mathbf{x}_1')_t^{\mathrm{T}}\mathbf{B}_1^{-1}(\mathbf{x}_1')_t + \underbrace{\frac{1}{2}\beta_e(\boldsymbol{\alpha})^{\mathrm{T}}\boxed{\mathbf{A}^{-1}}(\boldsymbol{\alpha})}_{\text{single-res ensemble}} + \frac{1}{2}\sum_{t=1}^{L}(\mathbf{H}\mathbf{x}_t' - \mathbf{y}_t^o)^{\mathrm{T}}\,\mathbf{R}^{-1}(\mathbf{H}\mathbf{x}_t' - \mathbf{y}_t^o)$$

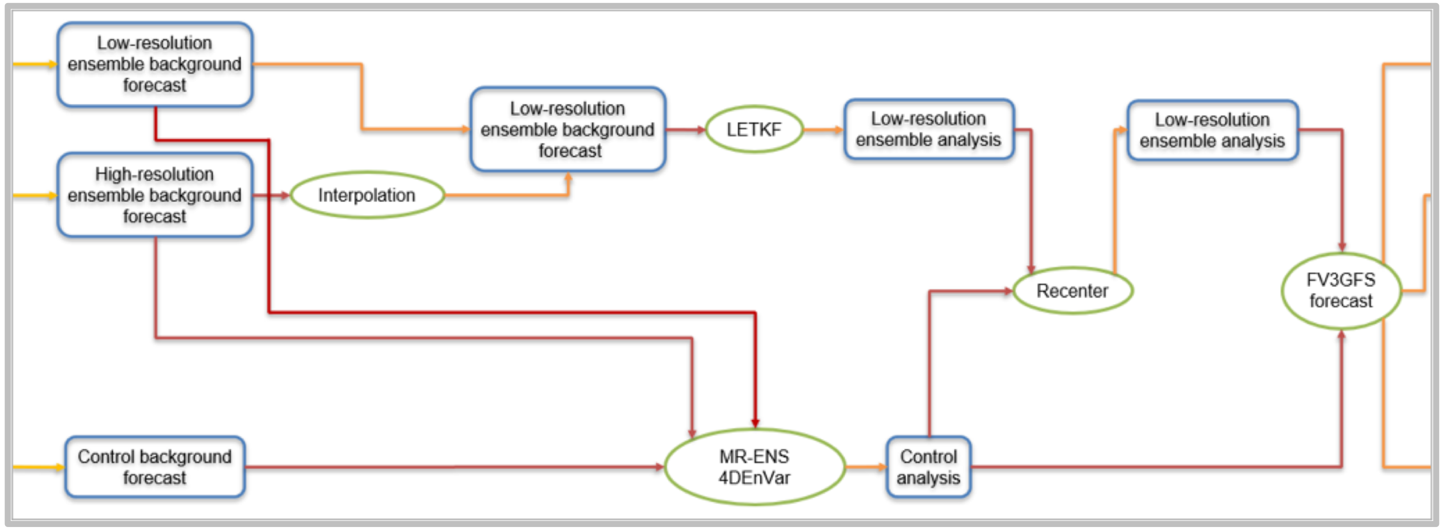
- Multi-resolution ensemble (Kay* and Wang 2020) hybrid 4DEnVar

Large localization radius applied for low-res ensemble

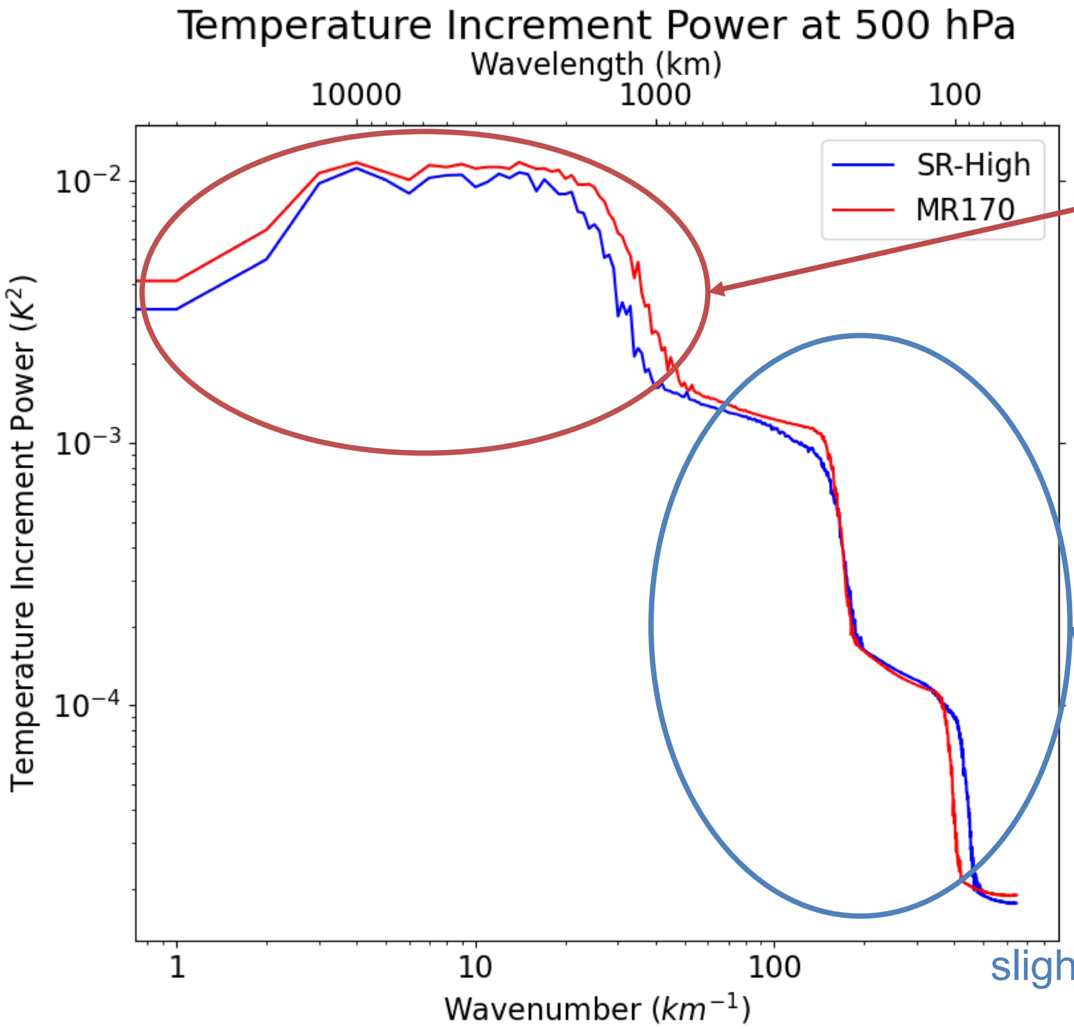
$$J[(\mathbf{x}_1')_t, \boldsymbol{\alpha}^L, \boldsymbol{\alpha}^H] = \frac{1}{2}\beta_1(\mathbf{x}_1')_t^{\mathrm{T}}\mathbf{B}_1^{-1}(\mathbf{x}_1')_t + \underbrace{\frac{1}{2}\beta_L(\boldsymbol{\alpha}^L)^{\mathrm{T}}\boxed{\mathbf{A}_L^{-1}}(\boldsymbol{\alpha}^L)}_{\text{low-res ensemble}} + \underbrace{\frac{1}{2}\beta_H(\boldsymbol{\alpha}^H)^{\mathrm{T}}\boxed{\mathbf{A}_H^{-1}}(\boldsymbol{\alpha}^H)}_{\text{high-res ensemble}} + \frac{1}{2}\sum_{t=1}^{L}(\mathbf{H}\mathbf{x}_t' - \mathbf{y}_t^o)^{\mathrm{T}}\,\mathbf{R}^{-1}(\mathbf{H}\mathbf{x}_t' - \mathbf{y}_t^o)$$

Small localization radius applied for high-res ensemble

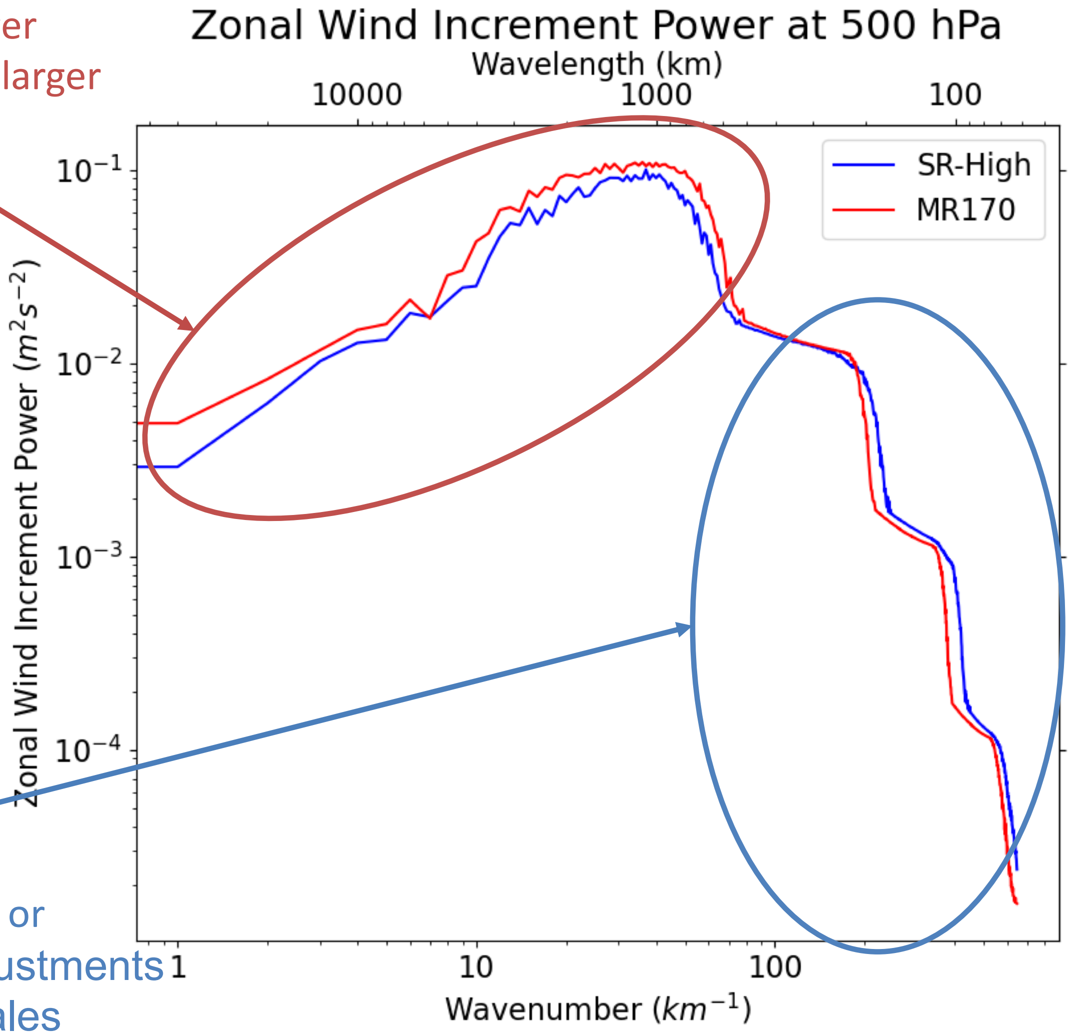




Analysis Increment Power Spectrum



MR170
makes larger
adjustment in larger
scales

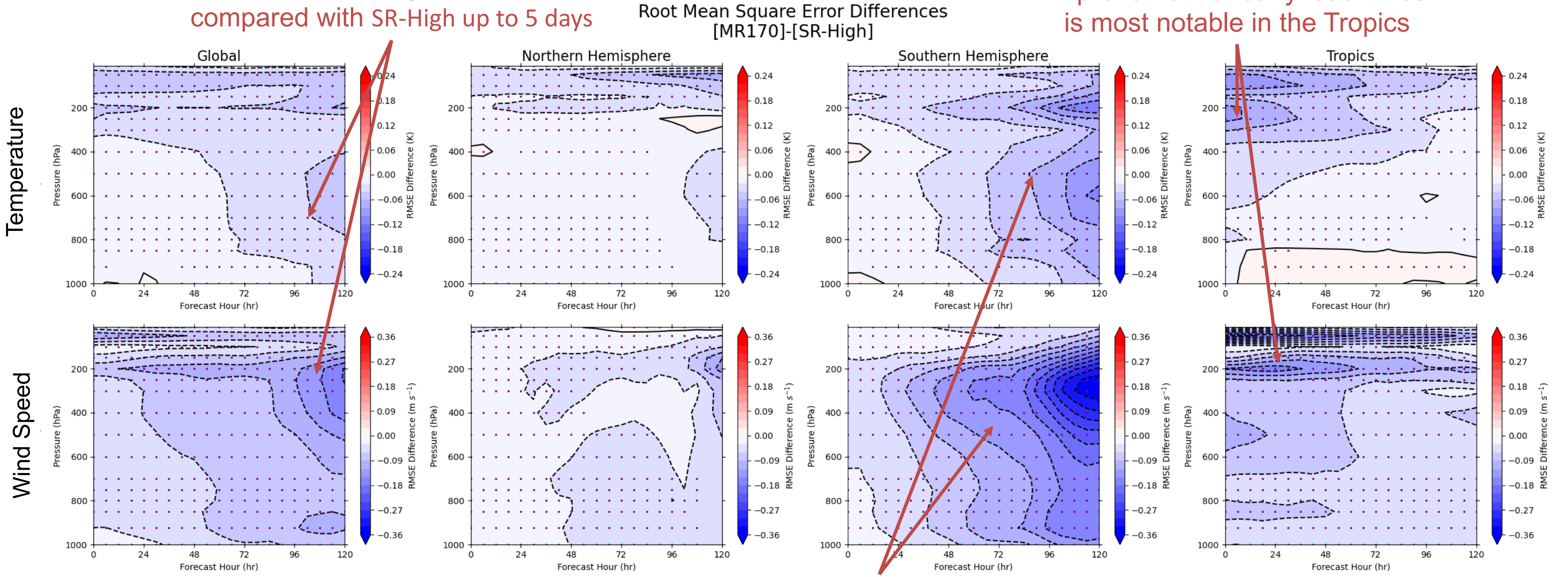


MR170
makes similar or
slightly smaller adjustments
in smaller scales

Impact on global forecast RMSE from cycled month long experiment

MR170 improves global forecast compared with SR-High up to 5 days

Improvement at early lead times is most notable in the Tropics

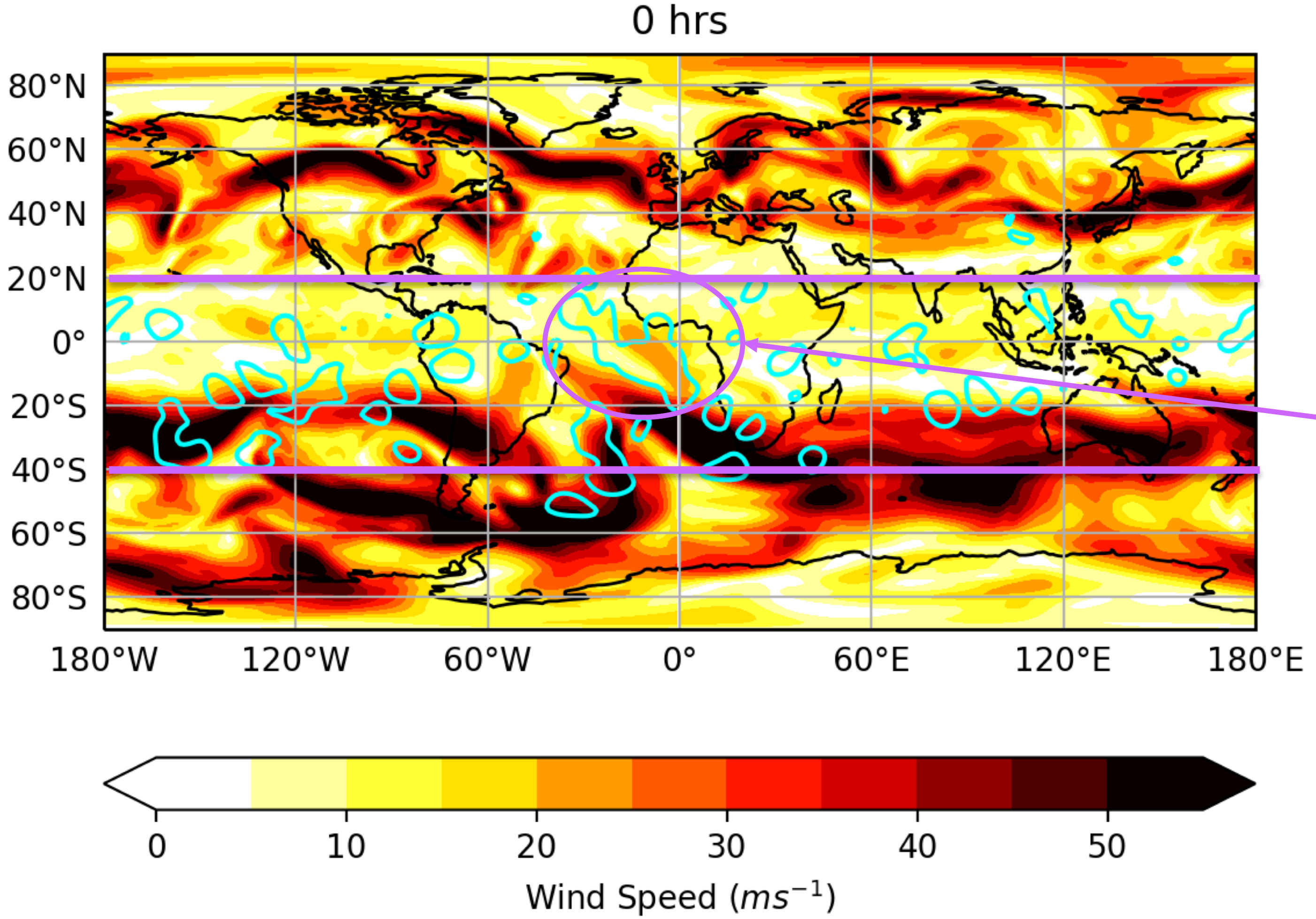


Improvement at longer lead times is most notable in the Southern Hemisphere

Error calculated using ERA-Interim as verification. Purple asterisks indicate 95% confidence using a paired *t*-test.

Why Multi-Resolution Ensemble 4DEnVar helps?

250 hPa Wind Speed and Difference in Total Energy Error



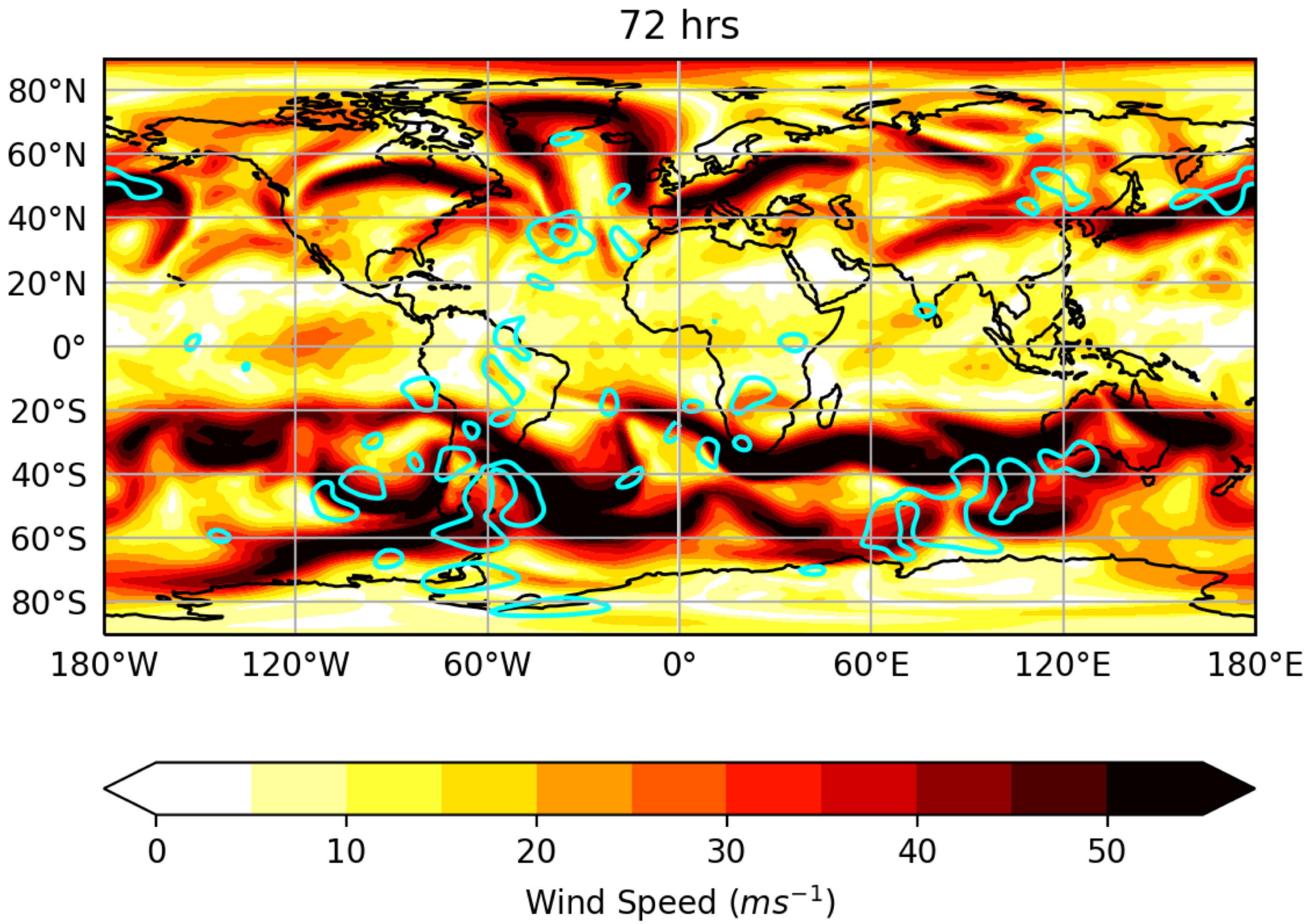
At analysis time, largest MR170 improvement in the tropics and SH subtropics

Largest area of improvement in region typically associated with Tropical Easterly Jet

Analysis time: 0000 UTC on 12 September 2017. Cyan contours indicate the 5% maximum improvement of total energy error filtered to include wavenumbers 5 to 25 for MR170 compared with SR-High

Why Multi-Resolution 4DEnVar helps?

Largest MR170 improvement shifts to extratropics, especially in SH



Largest areas of improvement tend to occur in regions influenced by jet interactions

Analysis time: 0000 UTC on 12 September 2017. Cyan contours indicate the 5% maximum improvement of total energy error filtered to include wavenumbers 5 to 25 for MR170 compared with SR-High

Part II: Simultaneous MDA with scale dependent localization (SDL) in FV3GFS 4DEnVar

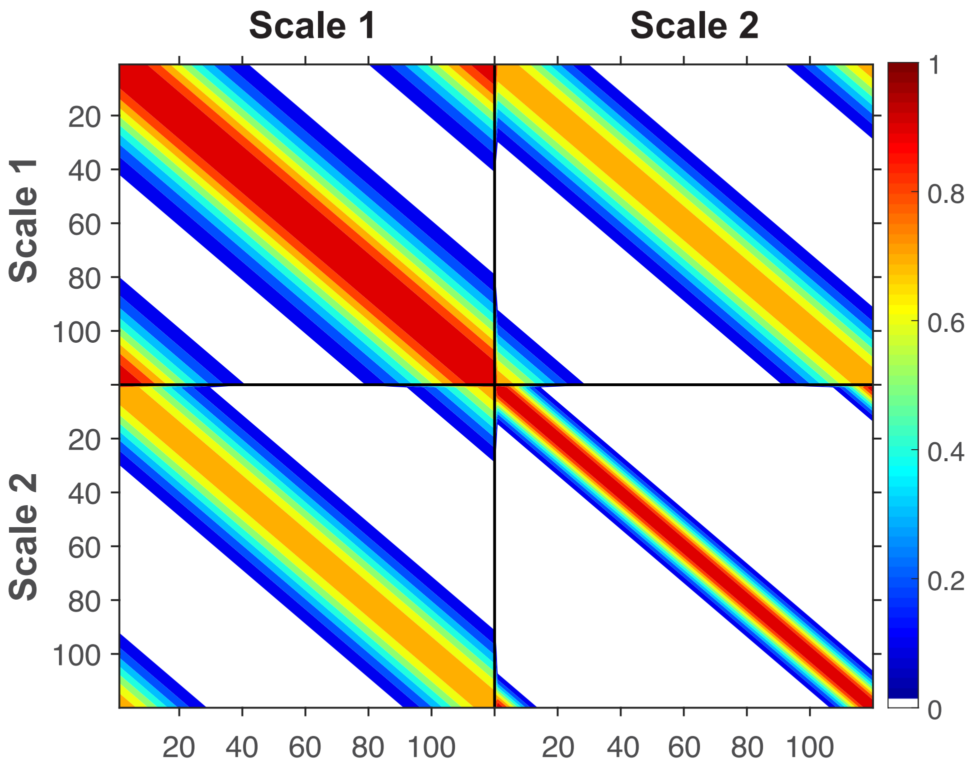
Huang*, Wang et al. 2021

- In the operational 4DEnVar, horizontal localization functions are scale-invariant at each level

- A simultaneous multiscale DA using scale dependent localization (SDL) in 4DEnVar for NCEP FV3-based GFS is implemented

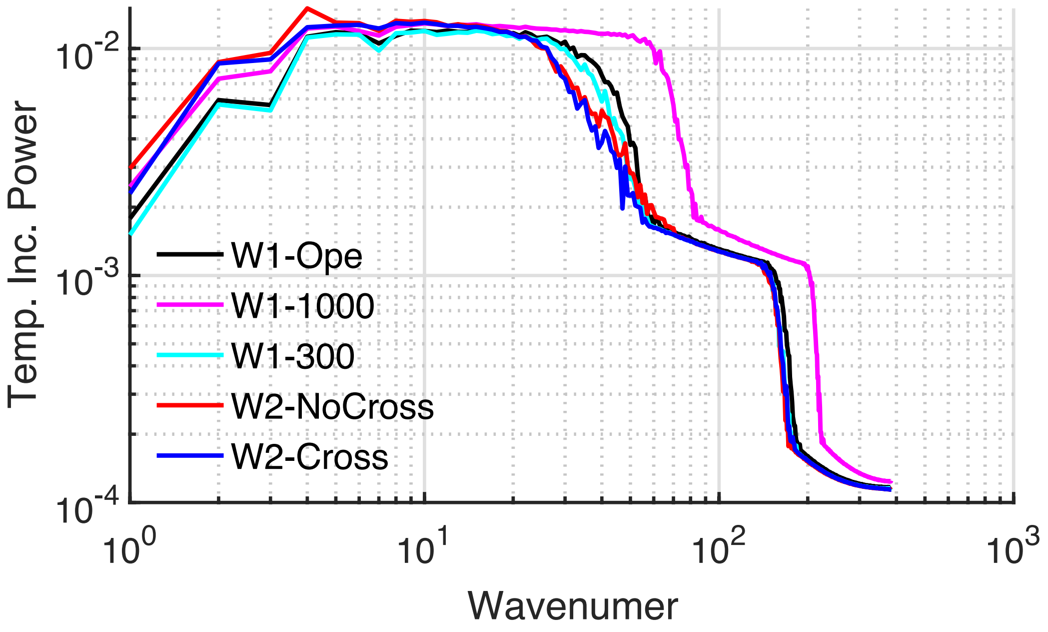
Ensemble perturbation scale decomposition and scale dependent localization

$$J(\mathbf{x}_1', \hat{\mathbf{a}}) = \frac{1}{2}\beta_1(\mathbf{x}_1')^{\mathrm{T}}\mathbf{B}_1^{-1}(\mathbf{x}_1') + \frac{1}{2}\beta_2(\hat{\mathbf{a}})^{\mathrm{T}}\boxed{\hat{\mathbf{A}}}^{-1}(\hat{\mathbf{a}}) + \frac{1}{2}\sum_{t=1}^{L}(\mathbf{y}_t^{o\prime} - \mathbf{H}_t\mathbf{x}_t')^{\mathrm{T}}\mathbf{R}_t^{-1}(\mathbf{y}_t^{o\prime} - \mathbf{H}_t\mathbf{x}_t'),$$

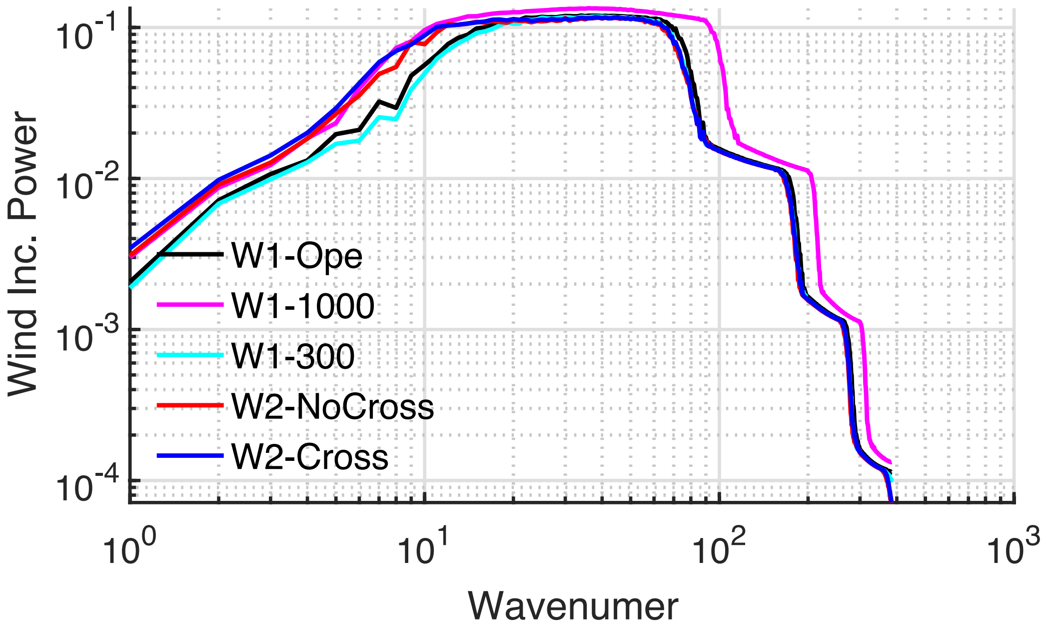


Analysis Increment Power

Temp at 500 hPa



Wind at 500 hPa

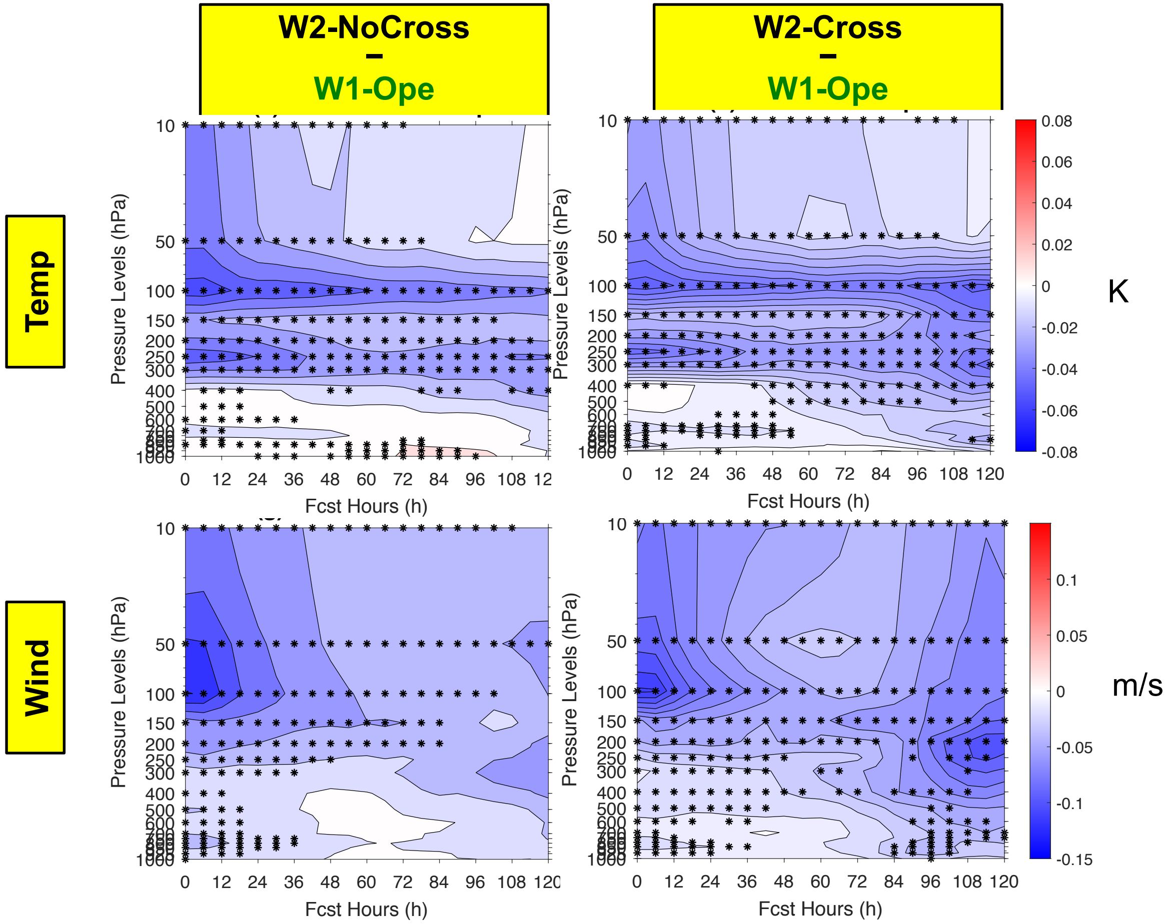


- ❑ By comparing W1 experiments, wider localization length results in larger analysis increment power.
- ❑ As expected, analysis increment power in W2-NoCross and W2-Cross is closer to W1-1000 (W1-300) at small (large) total wavenumbers **-> MDA can simultaneously update large and small scales**

Month long cycled global forecast verification against EC analysis

RMSE difference (blue/red→ improvement/degradation relative to W1-Ope)

- MDA improves global forecasts almost at all pressure levels over applying the fixed uniform localization once at all scales in W1.



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Part III: Simultaneous MDA with scale dependent localization (SDL) for HAFS

Lu* and Wang 2022

- The simultaneous MDA with SDL is recently implemented for the next general Hurricane Analysis and Forecast System (HAFS)
- DA cycling experiments were conducted for basin scale HAFS for Hurricane Laura (2020)

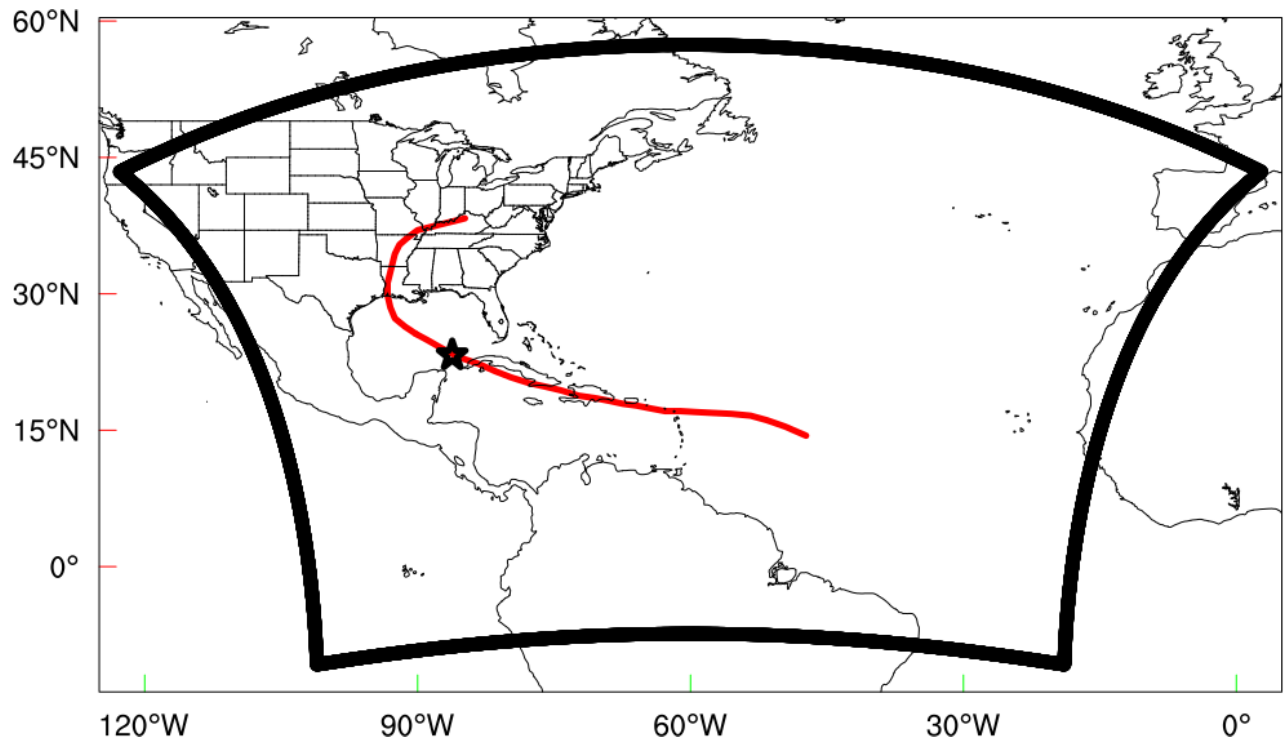
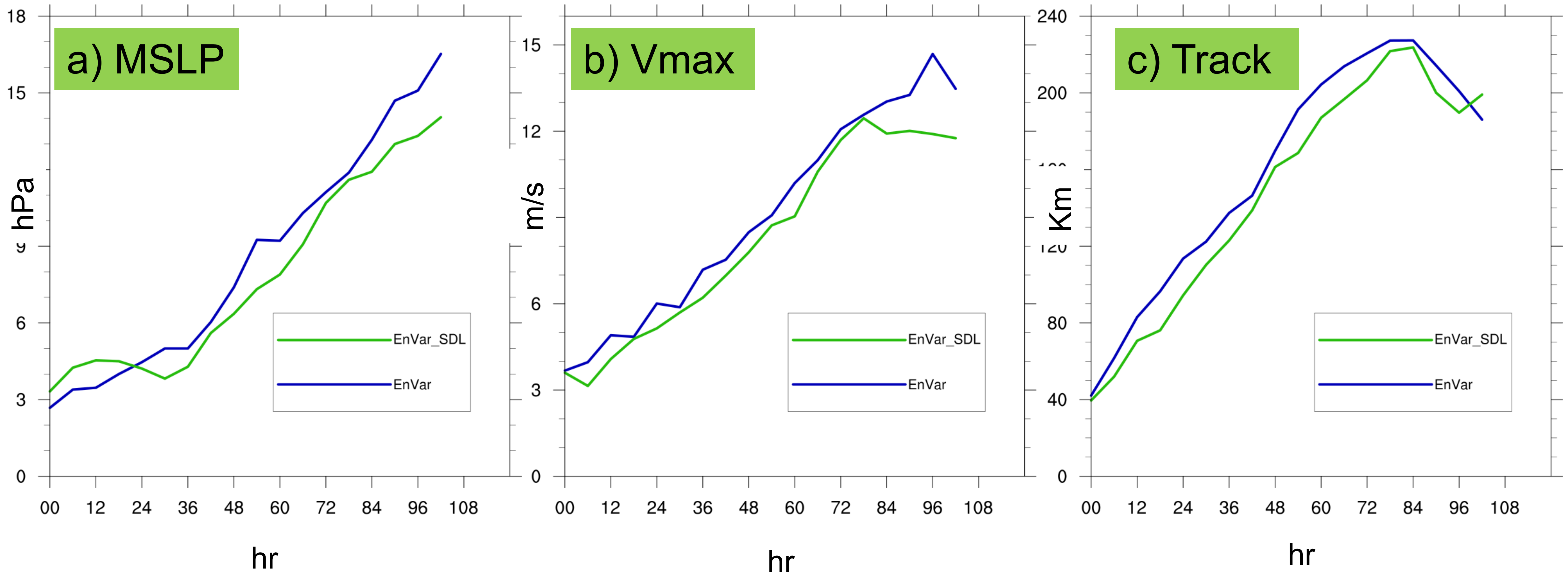


Figure. DA and forecast domain of HAFS. Best track for Laura (2020) is shown in red. Star shows 202008251200 UTC.

RMS intensity and track errors for all cycles of Laura (2020)

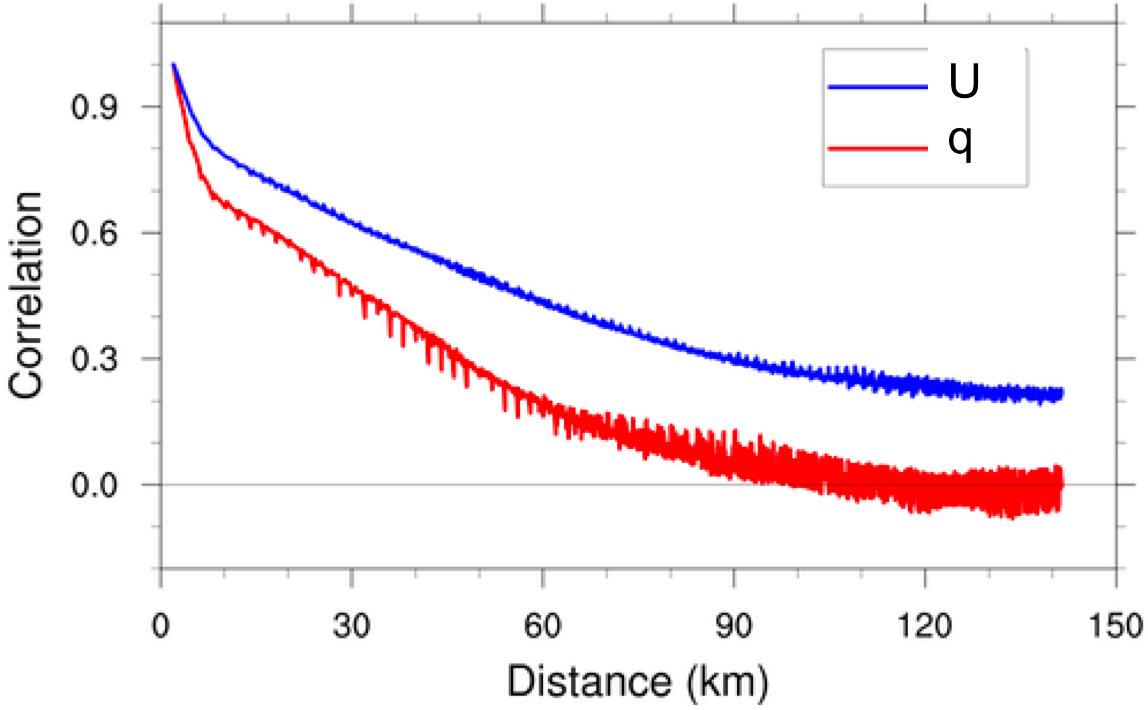


- Simultaneous MDA in EnVar improves Laura's intensity and track forecasts

Part IV: The need to further develop simultaneous multiscale DA for convective scale weather prediction (WoF, RRFS/HRRR)

Wang* and Wang 2022ab

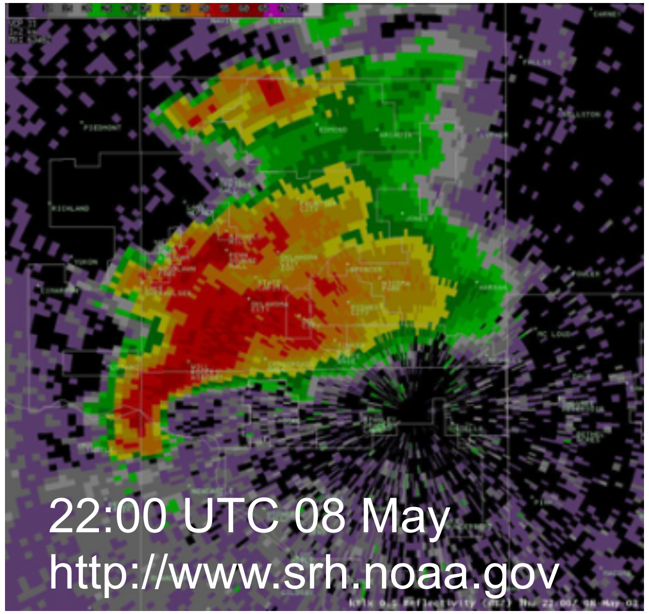
correlation functions of u and q



Wang, Y* and X. Wang
2022a

- In most convective scale radar data assimilation, a fixed uniform localization length (5-20km) is commonly applied, which restricts the data to update storms only.
- An effective MDA radar data can update not only the storm but also the storm environment properly
- For a given spatial scale, moisture, hydrometeor mixing ratio and vertical velocity show distinct smaller scales than other variables
- Therefore, this study further develops simultaneous MDA algorithm in EnVar by including intrinsic scale differences in both space and variable

Experiments on the 8 May 2003 OKC Tornadic Supercell

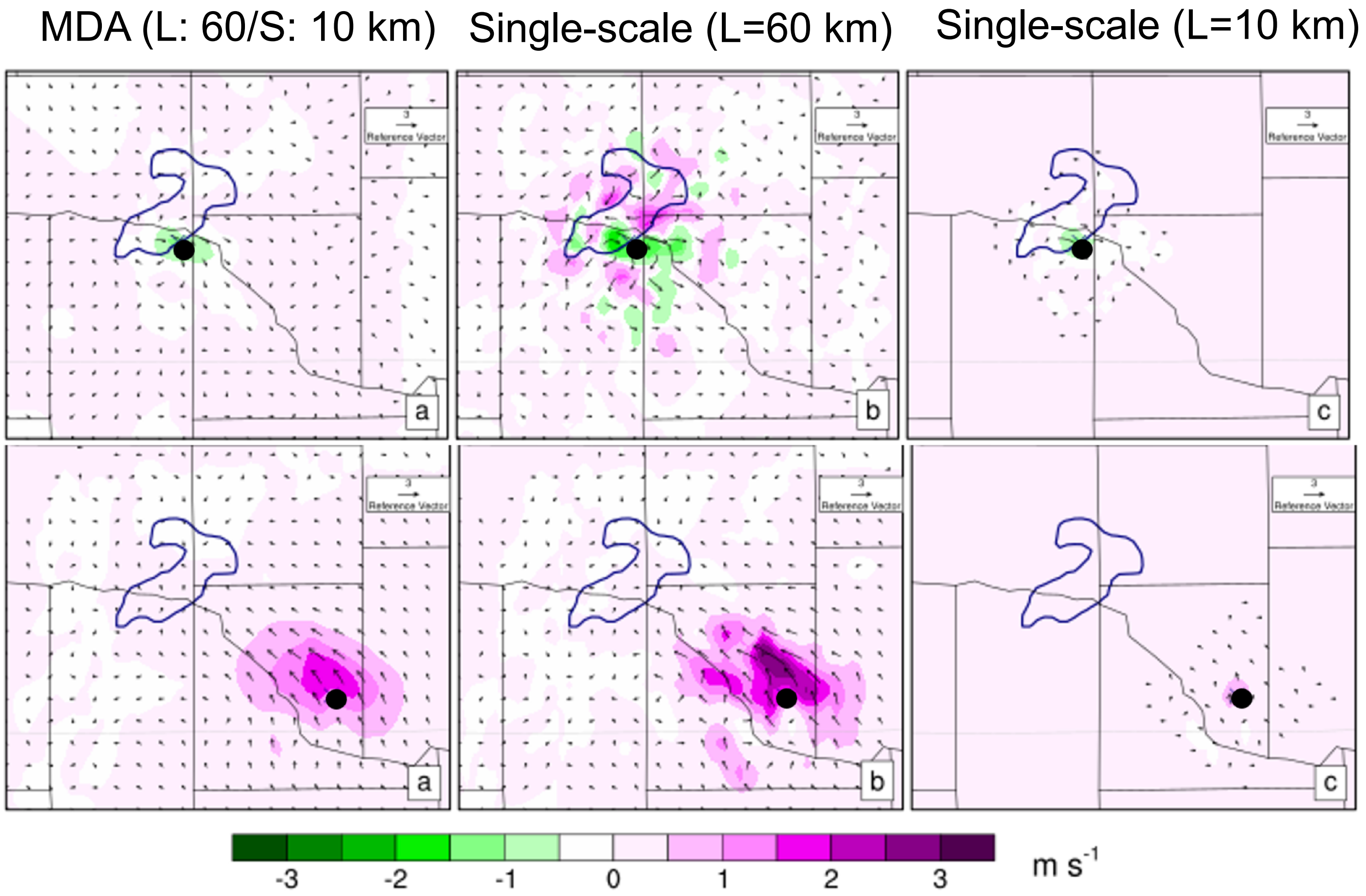


Exps	Specifications
Single-scale L	Single-scale localization length of 10 km
SDL	Localization lengths of 60 and 10 km applied to large and small scales, respectively
SDLVDL	Same as MDA, except applying variable dependent localization

- Observed supercell maintained well beyond 2300 until about 0000 UTC.
- Only radar reflectivity and radial velocity are assimilated in all experiments.

Multiscale vs single scale DA

Single observation experiment

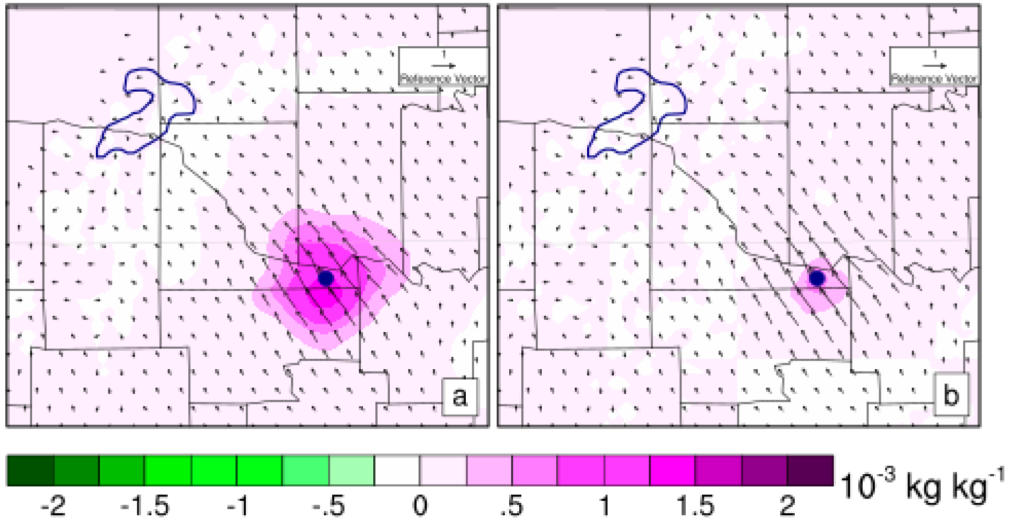


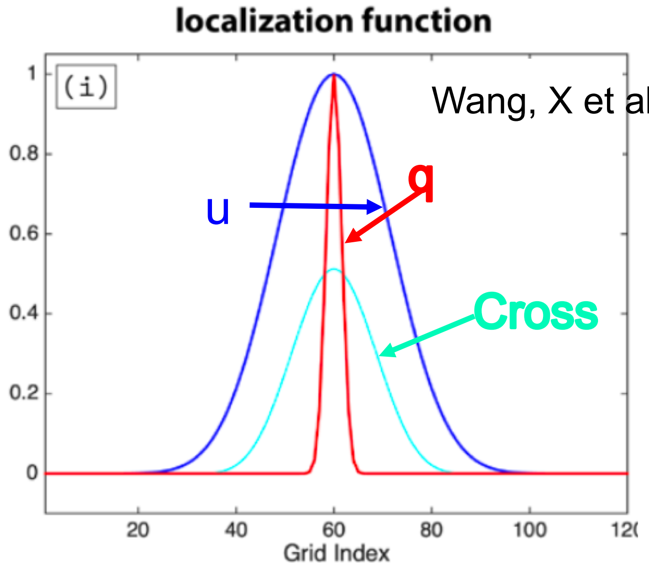
- MDA through SDL can simultaneously properly correct both the storm and its ambient environment which represent different scales

Analysis increments of wind (vector) and v-wind (shaded) through assimilating a single observation of Vr with an innovation of -30 m/s at 1 km AGL.

Impact of including intrinsic variable scale differences in MDA

SDL SDLVDL





Wang, X et al. 2021, MWR

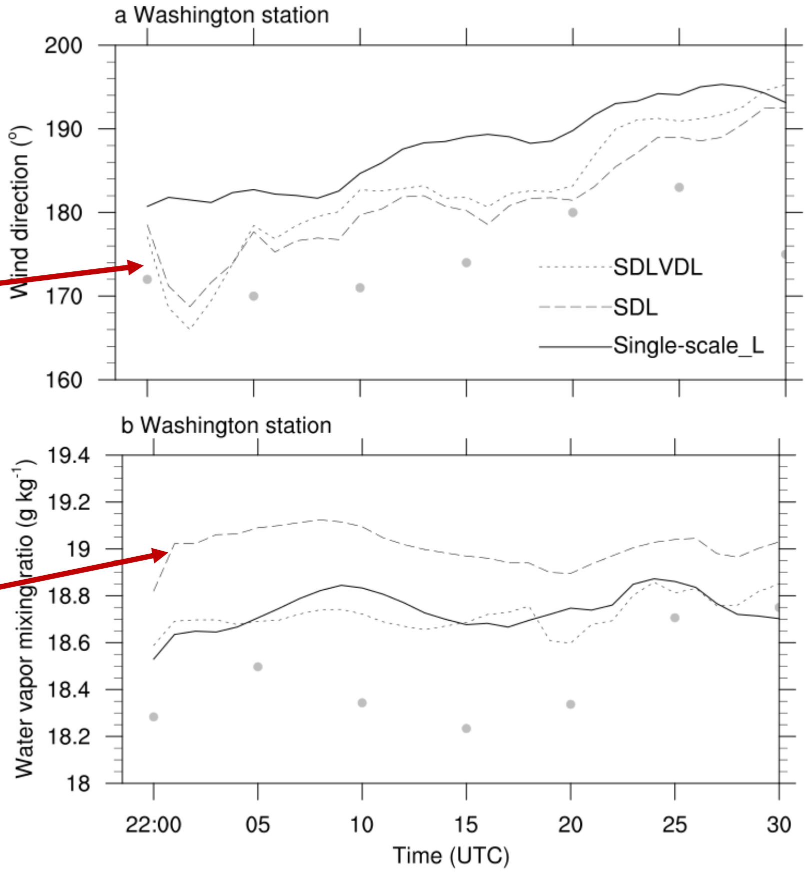
Analysis increments of wind (vector) and water vapor (shaded) through assimilating the KTLX radar observations valid at 2145 UTC

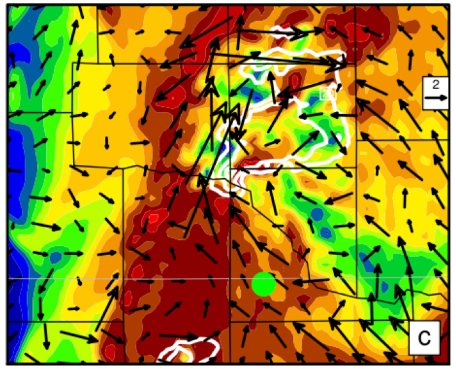
- In SDL, increments of q are produced through the cross covariances between wind and q. The spatial scale of the q increment is therefore comparable with that of wind.
- Using VDL with an appropriately smaller localization for q greatly reduces spurious intensity and coverage of moisture increments compared to using MDA.

Impact on forecasts
(Verification against in-situ observations)

Improved SSE wind

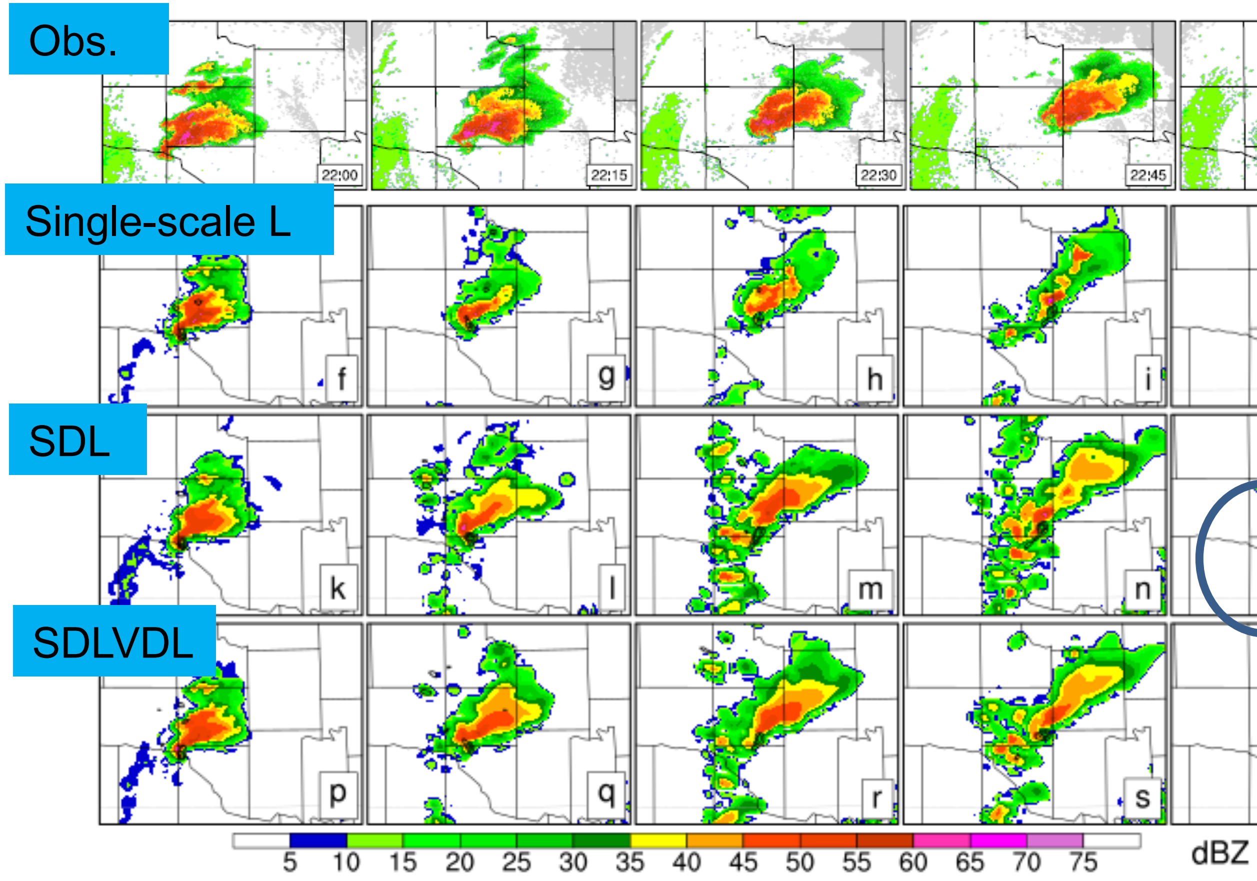
Improved q

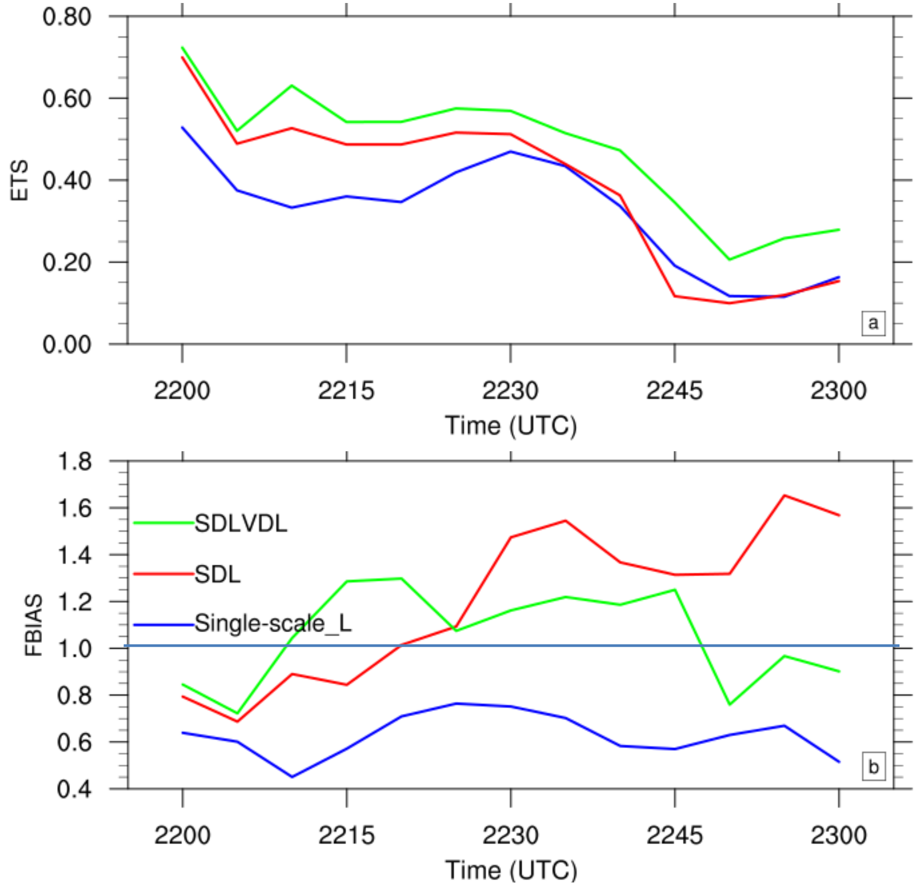




- ➢ The SSE wind produced by SDL and SDLVDL is closer to observations than Single-scale_L;
- ➢ Compared to SDL, SDLVDL with reduced *q* is more consistent with observations.

Impact on forecasts
(Reflectivity @ 1km AGL)

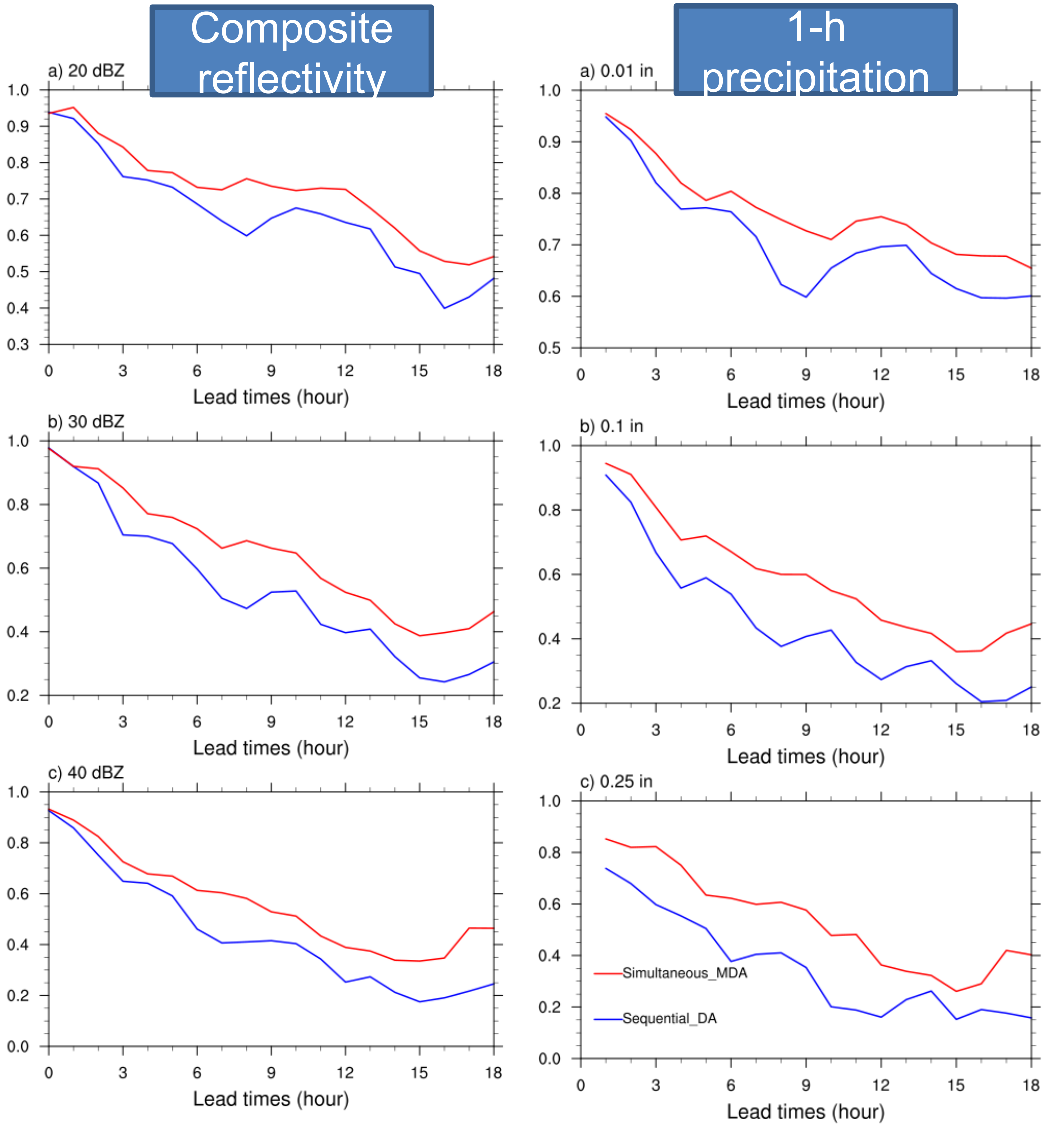




- ❑ SDLVDL performs the best, which has less spurious storms and further enhances supercell than SDL

Experiments on CONUS case assimilating both radar and conventional in-situ observations (RRFS context)

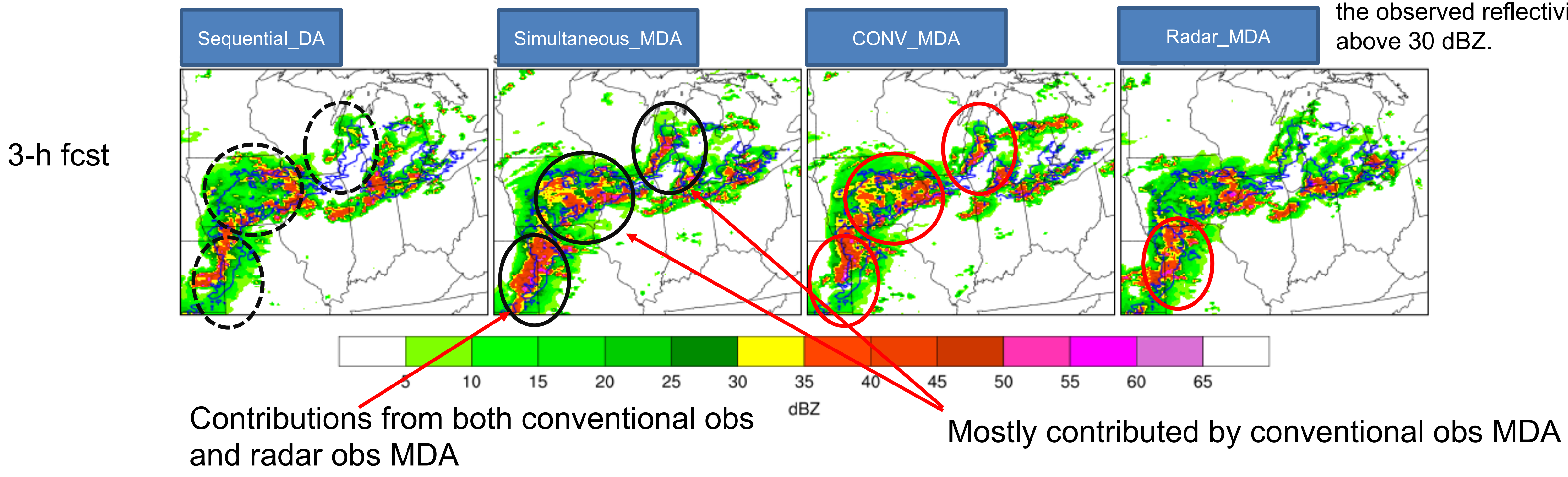
Wang Y.* and X. Wang 2022b



- Simultaneous_MDA has consistently higher FSS scores than Sequential_DA at all thresholds during the entire 18-h forecast period for both composite reflectivity and 1-h precipitation.

Experiments on the 3 May 2018 CONUS case
Impact on forecasts

The blue contours indicate the observed reflectivity above 30 dBZ.



- Compared to Sequential_DA, Simultaneous_MDA produces more organized reflectivity distributions, which are closer to the observations.
- These improvements by Simultaneous_MDA are attributed to conventional obs MDA and radar obs MDA.

Part V: A New MDA method: MLGETKF

Wang, X. et al., 2021, Mon. Wea. Rev.

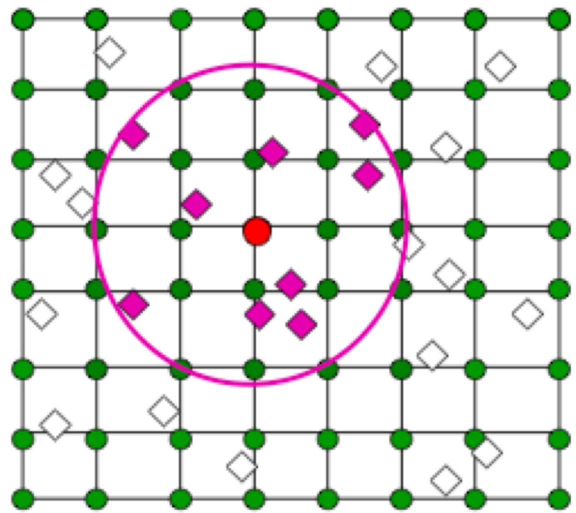
- A new ensemble-based, multiscale data assimilation (MDA) method, MLGETKF (Multiscale Local Gain Form Ensemble Transform Kalman Filter), is developed, embracing the following:

- MLGETKF **simultaneously corrects all resolved scales by assimilating all observations at once**, allowing more effective use of information of all observations.

- MLGETKF performs **multiscale localization in model space** which allows
  - proper estimate of error covariance in each individual scale-band
  - explicit cross scale-band error correlation
  - appropriate assimilation of integral observations (e.g. satellite radiance)

- MLGETKF performs **multiscale update of both ensemble mean and perturbations** and therefore automatically produces an ensemble of multiscale analyses (i.e. multiscale state + multiscale uncertainty)

- MLGETKF performs DA in **independent local volumes**, which lends the algorithm **a high degree of computational scalability** like LETKF



Key aspects of the algorithm

$$\boxed{\mathbf{Z}^{ML}} = \left(\mathbf{z}_1, \mathbf{z}_2, \cdots, \mathbf{z}_{K_{ML}}\right) = (\mathbf{I} \quad \mathbf{I} \quad \cdots \quad \mathbf{I})\left(\boxed{\mathbf{X}^{MS}} \Delta \left[\left(\boxed{\mathbf{L}^{MS}}\right)^{\frac{1}{2}}\right]\right)$$

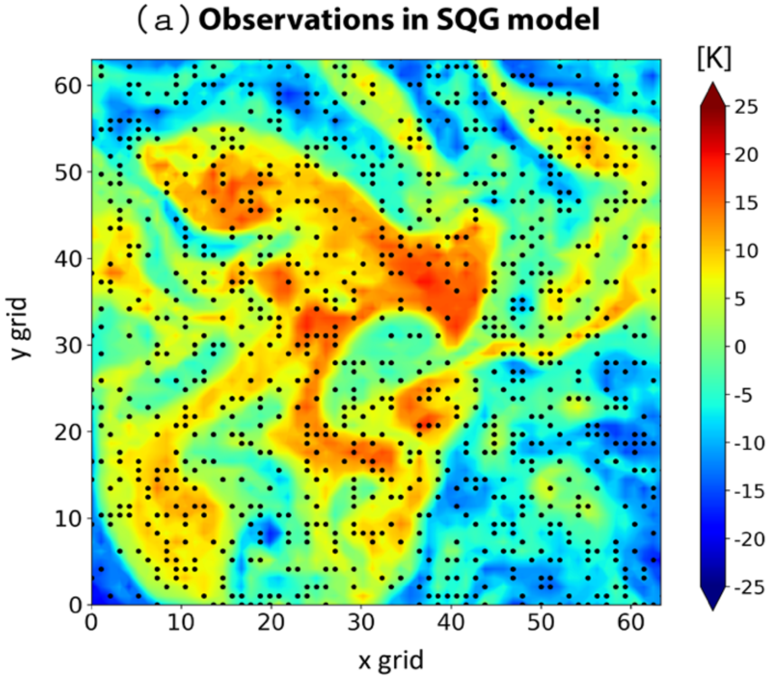
Modulated/expanded pseudo ensemble perturbations

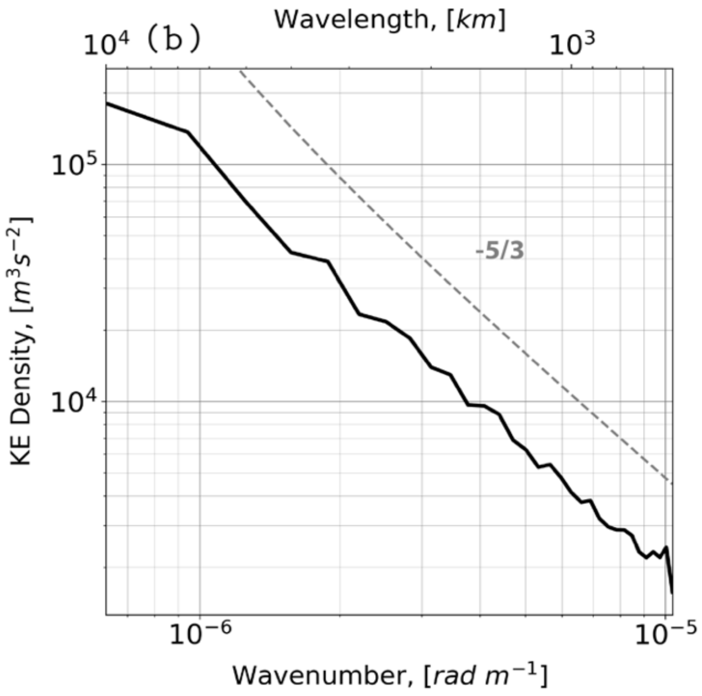
Scale decomposed raw perturbations

Multiscale model space localization

- Rapid creation of many pseudo ensemble perturbations in a local volume via a multiscale ensemble modulation procedure.
- The modulated ensemble intrinsically includes multi-scale model space localization and is used to update ensemble mean and perturbations.
- Multi-scale model space localization adopts scale-aware localization. In addition, localization of the ensemble covariances between different scales are defined.
- MLGETKF only updates and propagates the original number of ensemble members.

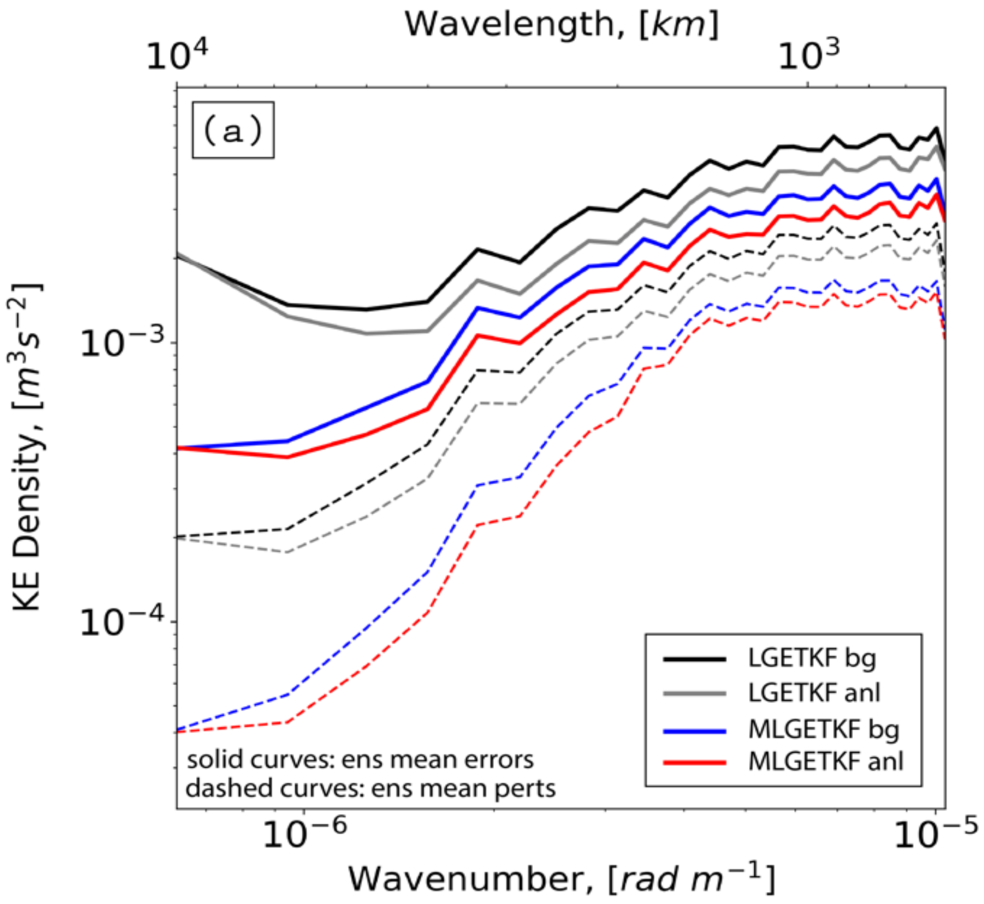
Cycled DA experiment with a Surface Quasi-Geostrophic (SQG) model





- Comparing scale aware MLGETKF vs scale unaware LGETKF
- SQG turbulence model follows Tulloch and Smith 2009
- The SQG model simulates a range of scales with its kinetic energy KE spectrum following a -5/3 slope that mimics mesoscale of the atmosphere
- Simulated obs.: potential temperature on both model surfaces with a standard deviation of 1K
- Ensemble size: 20-member
- 3-hourly data assimilation is performed for 400 cycles with the last 300 cycles used for verification.
- RTPS used for inflation

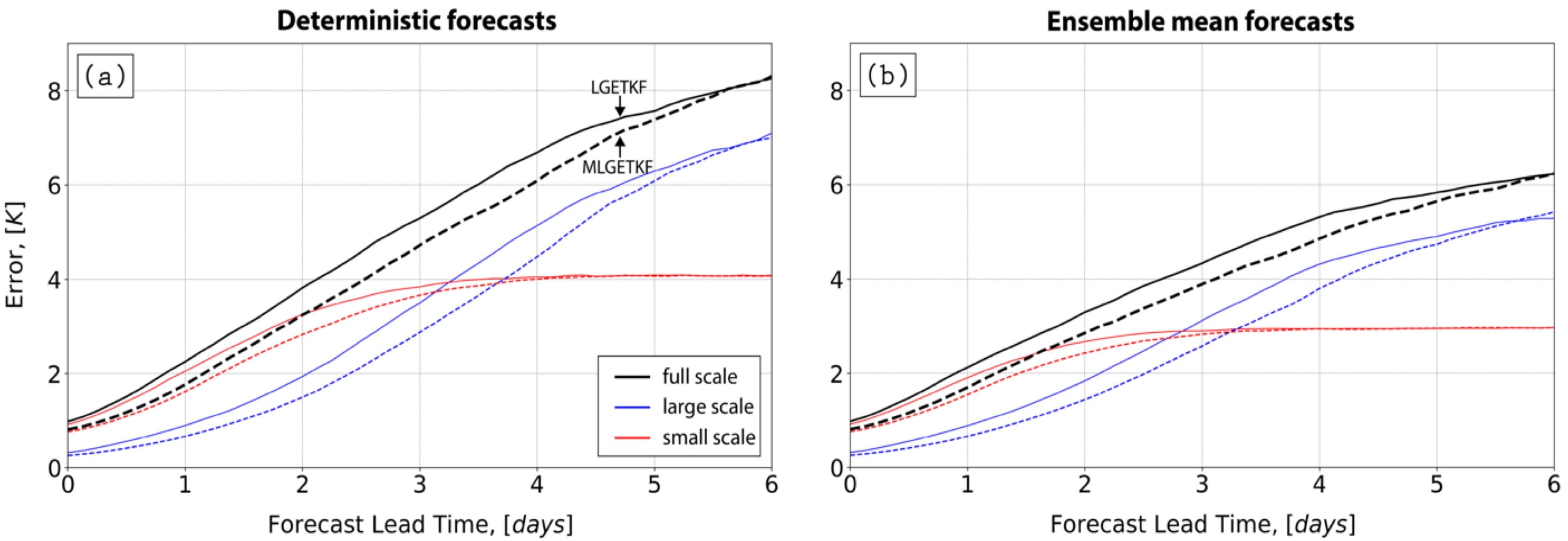
Spectrum of analysis error and spread



- ❑ Analysis and background errors/spread for both LGETKF and MLGETKF generally increase towards the smaller scales, except for LGETKF at very large scales

- ❑ MLGETKF reduces analysis and background errors relative to LGETKF for all scales, especially towards the large scales

Forecast error



- ❑ The MLGETKF deterministic/ensemble mean forecast is more accurate than LGETKF for the full and large scales up to 5-6 day lead time and more accurate for the small scale up to 3-4 day lead time
- ❑ For the full, large, and small scale forecasts, MLGETKF forecast errors saturate later than LGETKF, gaining approximately 12-hour ~ 1-day of predictability.

Summary and Remarks

- ❑ Great challenges exist to achieve effective multiscale DA for next generation NWP
- ❑ R&D on *simultaneous* MDA performed **directly using operational model and DA system**, including GFS, RRFS/HRRR, HAFS, WoF, demonstrate great potential of such approach to better utilize observations and to improve NWP
- ❑ **A new MDA method (MLGETKF)** is introduced
- ❑ **Fundamental** research is needed to address challenges associated with the **multiscale DA** for **all short range, medium range and S2S predictions**
  - MDA methodology development:
    - Include 3D space and time dimension in MDA
    - Optimize cross earth system component covariance for strongly coupled DA
    - Include treatment of nonlinearity/non-Gaussianity in MDA
  - Leveraging machine learning in MDA
  - Agile and cost effective approach
  - Objective methods to determine multiscale DA parameters (e.g. scale separation, localization, treatment of scale dependent system errors)
- ❑ **Sustained** supports of **fundamental** DA research and **workforce development** are needed

Main References

Wang, X., H. Chipilski*, C. H. Bishop, L. Satterfield, N. Baker and J. Whitaker, 2021: A Multiscale Local Gain Form Ensemble Transform Kalman Filter (MLGETKF), Mon. Wea. Rev., https://doi.org/10.1175/MWR-D-20-0290.1

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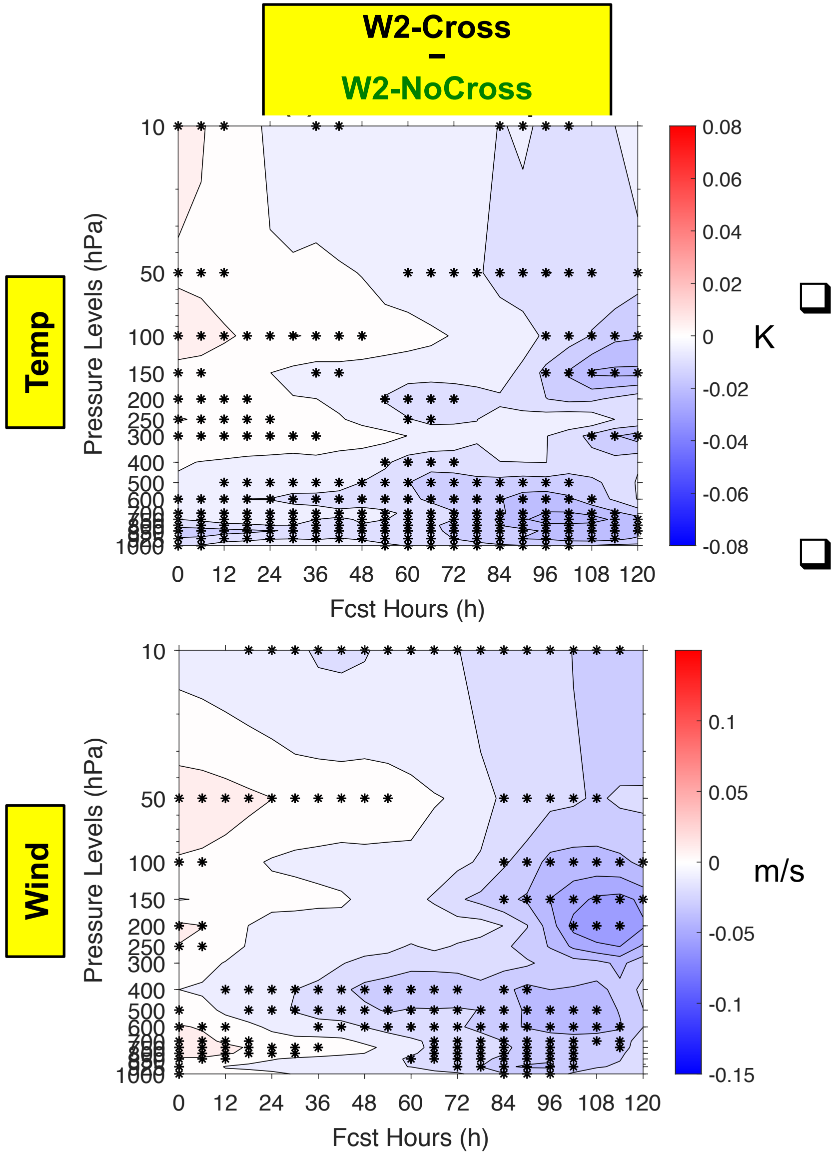
* OU MAP students and early career scientists

Impact of cross band correlation



RMSE difference between W2-Cross and W2-NoCross (blue/red→ better/worse forecasts in W2-Cross)

- W2-NoCross shows slightly better forecasts than W2-Cross within one day. This may benefit from the spatial averaging of ensemble covariances in W2-NoCross.
- Beyond one-day, W2-Cross in general shows more accurate forecasts than W2-NoCross, likely contributed by its higher degrees of retained heterogeneity of ensemble covariances and resultant analysis, and its more balanced analysis through partially including cross-waveband covariances.

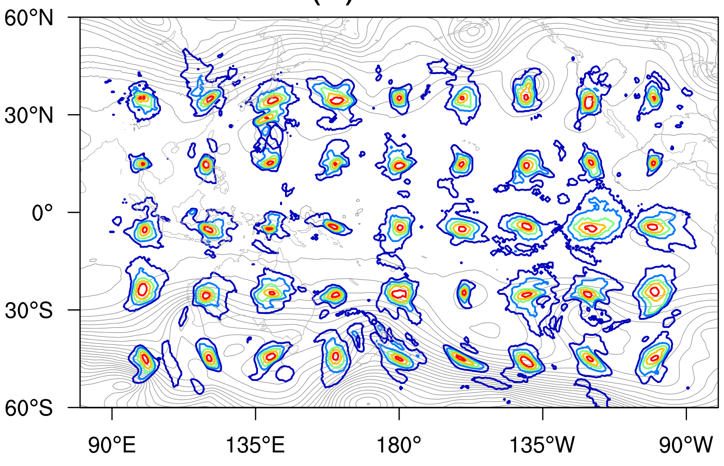
Huang*, Wang, et al. 2021

Multiscale vs Single scale ensemble based DA

Physical space visualization

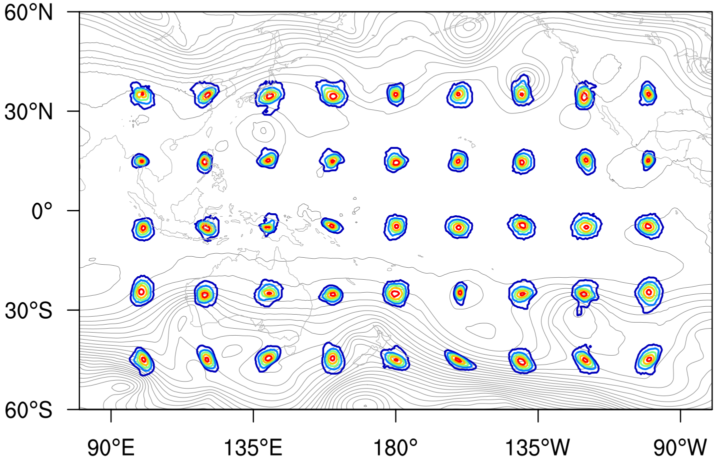
Single large

(b) W1-1000



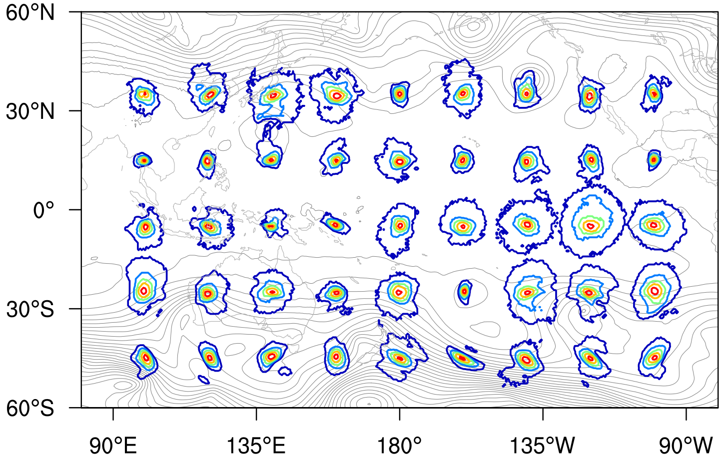
Single small

(d) W1-300



Multiscale (MDA)

(f) W2-Cross



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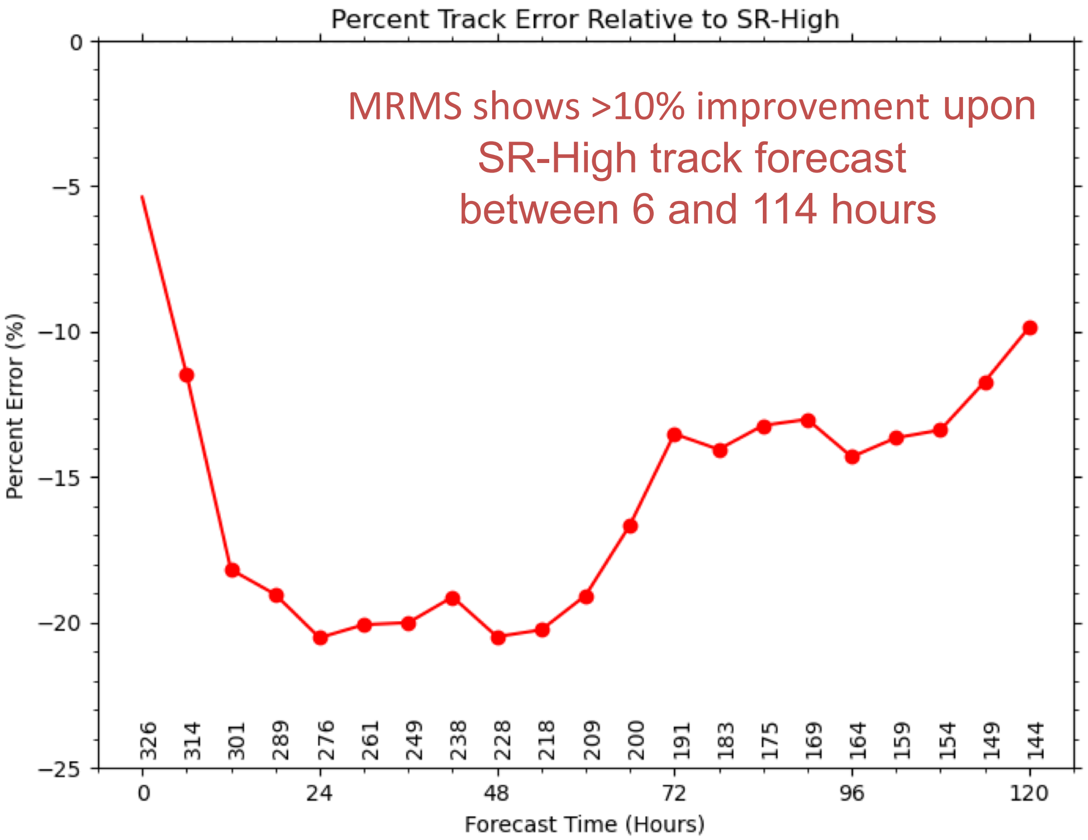
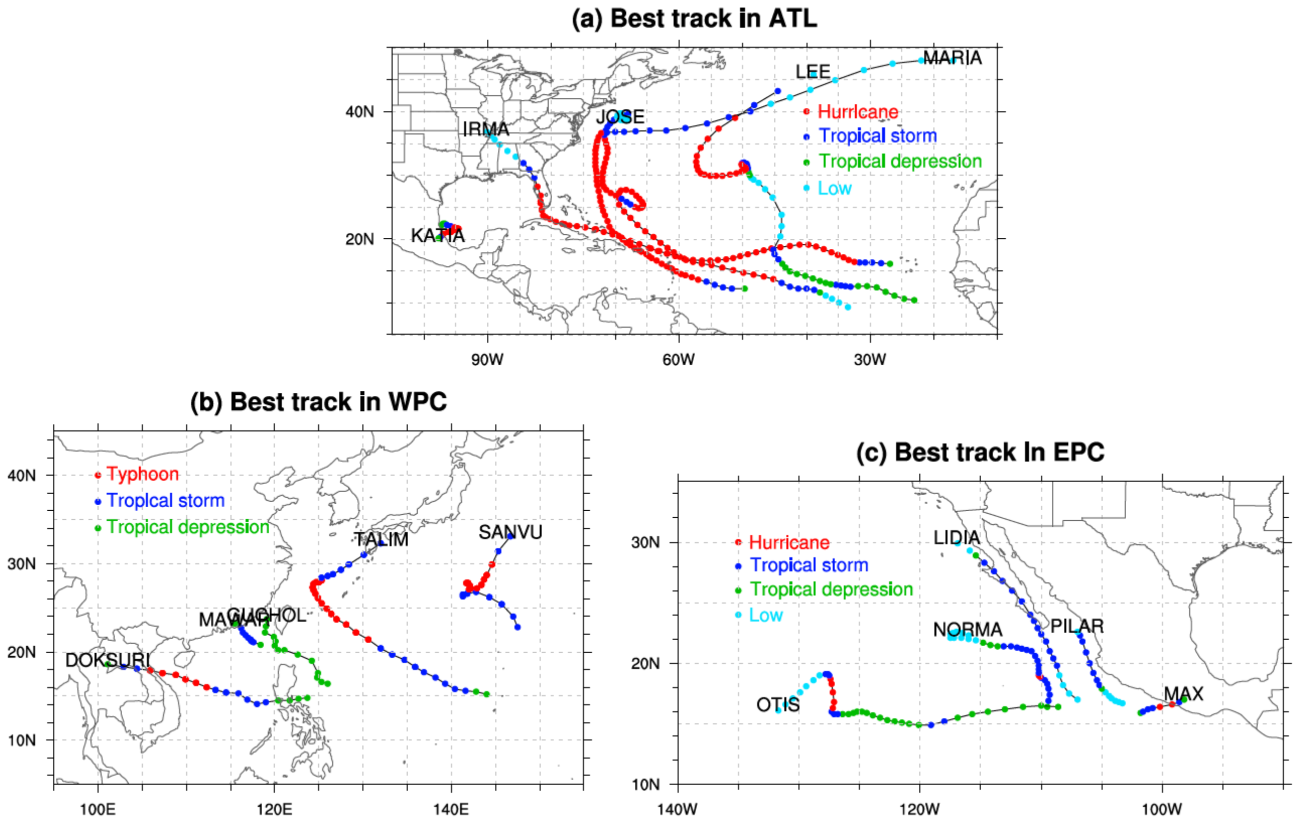
Tropical Cyclone Track Error



Tracking algorithm by Marchok (2002). Numbers above the x-axis denote how many tracks at each lead time. Filled dots indicate 95% confidence using a paired *t*-test.



Courtesy of Huang*, Wang et al. (2021). Storms used in track error calculations
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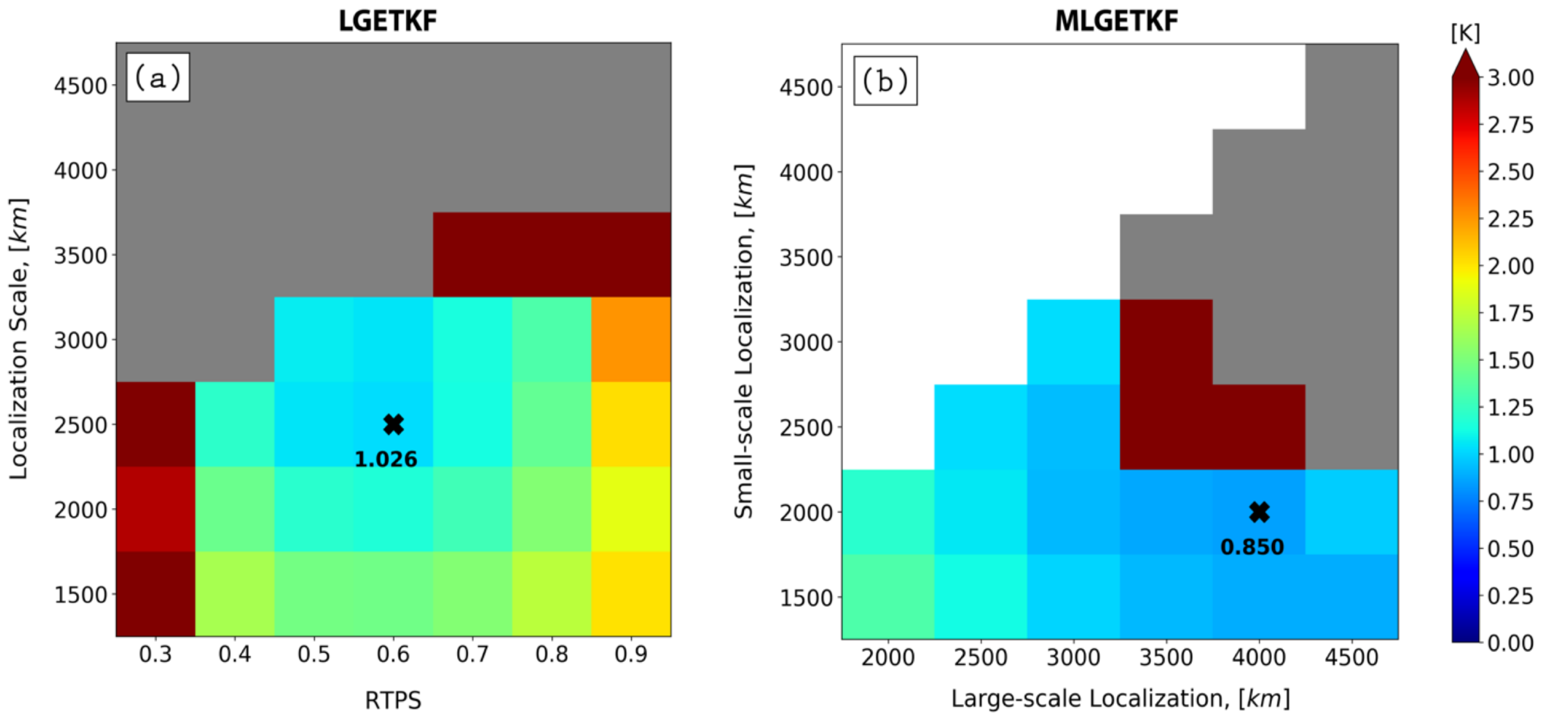
Jones* and Wang 2022

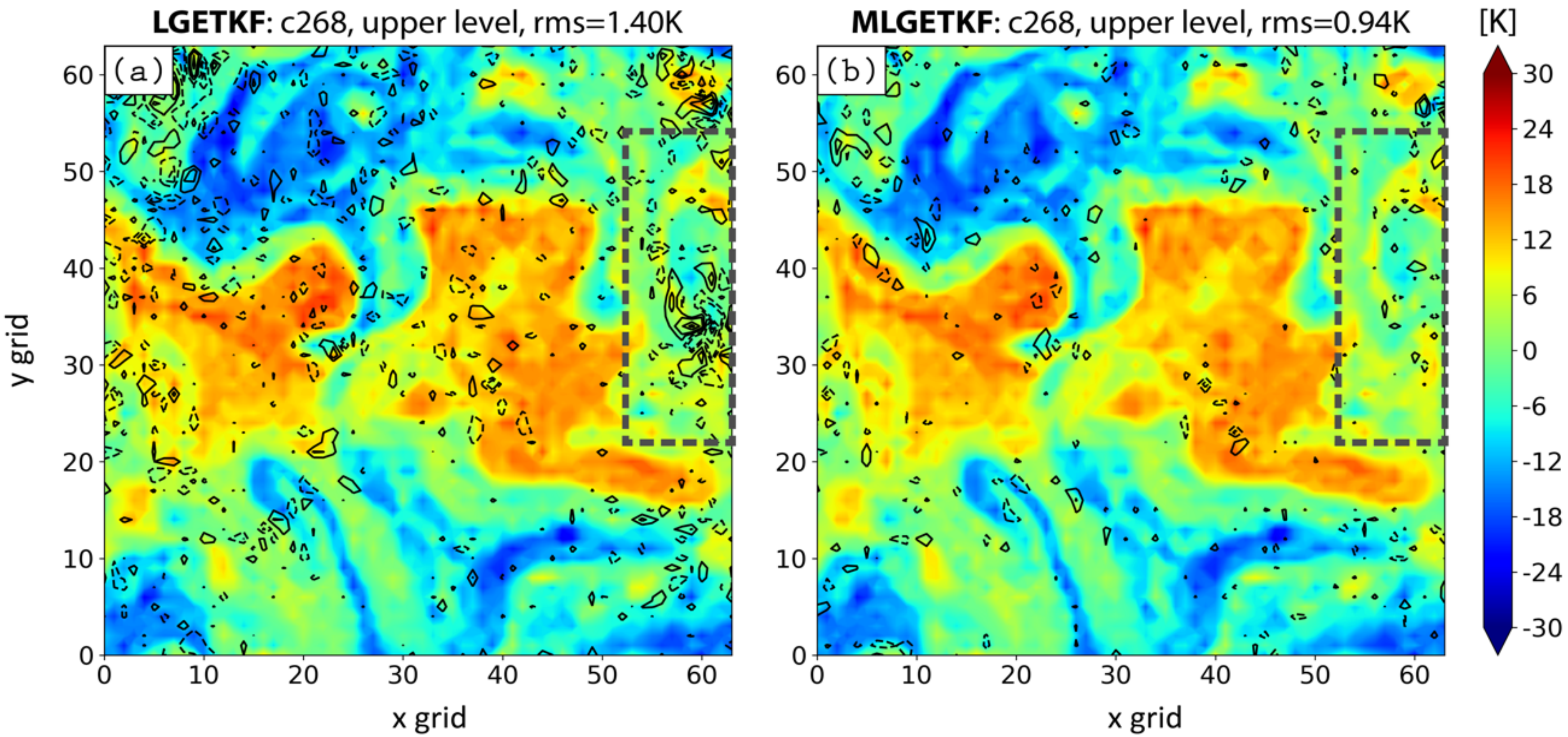
RMS analysis error



- The best performing MLGETKF(4000km, 2000km) outperforms the best performing LGETKF (2500km) by 17.2%.
- MLGETKF is less susceptible to filter divergence

Wang X. et al. 2021

Analysis error in physical space



- ❑ MLGETKF not only shows skill in decreasing the small scale component of the analysis errors, but also is effective in suppressing the development of large scale, dynamical, high-amplitude analysis errors

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