Development and Testing of Data Assimilation and Ensemble Forecasting Capabilities at CAPS for UFS

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ARPS Simulated Tornado

Outline

- Radar DA in current experimental and operational systems
- Direct assimilation of reflectivity in variational framework
- Radar DA in GSI EnKF and En3DVar and experiments with test cases
- Extended testing in a quasi-operational mode at GSL and comparison with HRRRv3 and HRRRv4
- GOES-R GLM lightning DA in GSI
- Preliminary results analyzing reflectivity in JEDI
- Testing and evaluations of FV3 in realtime for HWT and HMT with different physics

Radar DA in U.S. Operational or Experimental Realtime Forecasting Systems

- RAP has been assimilating reflectivity Z data using a cloud analysis/digital filter diabatic initiation procedure for over a decade. Insertion of latent heating derived from Z is the main benefit. HRRR uses a similar procedure.
- CAPS has been using 3DVar/cloud analysis procedure for HWT forecasts since 2008, and has been working with EnKF and EnVar more in recent years.
- HRRRv4 will combine mean and perturbations of EnKF-based HRRRDAS and assimilate conventional data using GSI En3DVar, but still assimilate Z data via cloud analysis procedure.
- WoFS has been using EnKF, together with some hybrid EnVar effort.
- Hybrid EnVar coupled with EnKF is the preferred DA method for UFS at both global and regional scales. We want to be able to directly assimilate radar data within hybrid EnVar.
- Supported by NOAA JTTI and WoF funding, CAPS has developed EnKF and En3DVar capabilities for direct radar DA within GSI framework and tested them with both WRF and FV3, with retrospective cases and in realtime (at GSL).
- We have also done initial testing with JEDI for reflectivity assimilation.

Technical Background

- Direct assimilation of reflectivity Z data within a Var framework requires Z obs operator and adjoint in cost function.
- The non-linearity of Z operator creates convergence problems and infinity values in certain situations.
- When using mixing ratios as control variables, cost function gradient of Z obs term can overwhelm gradients of other obs, rendering assimilation of other data ineffective, and convergence very slow.
- Wang and Wang (2017) proposed to use Z as a control variable to avoid Z operator within En3DVar. When doing so, hybrid En3DVar has to completely rely on statistically derived static B to create hydrometeor increments.
- Our solution: Use log or power transform of hydrometeor variables to allow for efficient cost function convergence and proper assimilation of Z together with other observations.
- Additional treatments were needed to avoid spurious increments near zero Z or zero background mixing ratios.
- For multi-moment microphysics (e.g., Thompson) schemes, consistent Z operator should be used, and total number concentrations should also be analyzed which can introduce additional problems.

Reflectivity Obervation Operators for Lin-type SM Schemes

- Exponential and logarithmic functions of mixing ratios

Assuming exponential DSD $N_x(D) = N_{0x}\exp(-\lambda_x D_x)$

$$Rain: \quad Z_{e,r} = \frac{720\times10^{18}}{\pi^{7/4} N_{0r}^{3/4} \rho_r^{7/4}} (\rho \underline{q_r})^{7/4}$$

$$Dry\ Snow: \quad Z_{e,s} = \frac{720\times10^{18} |K|_{ice}^2 \rho_s^{1/4}}{\pi^{7/4} |K|_w^2 N_{0s}^{3/4} \rho_i^2} (\rho \underline{q_s})^{7/4} \quad \underline{T} < 0\,C$$

$$Wet\ Snow: \quad Z_{e,s} = \frac{720\times10^{18}}{\pi^{7/4} N_{0s}^{3/4} \rho_s^{7/4}} (\rho \underline{q_s})^{7/4} \quad T > 0\,C$$

$$Hail: \quad Z_{e,h} = \left(\frac{720\times10^{18}}{\pi^{7/4} N_{0h}^{3/4} \rho_h^{7/4}}\right)^{0.95} (\rho \underline{q_h})^{1.6625}$$

Z_e in mm^6/m^3
q_r, q_s, q_h in kg/kg

Total reflectivity in dBZ: $$\boxed{Z = 10\log_{10}\left(Z_{e,r} + Z_{e,s} + Z_{e,h}\right)}$$ Nonlinear!

Smith, Meyer and Orville (1975), Tong and Xue (2005), Dowell et al. (2011)

Z Formula for Double-Moment Scheme

- Functions of mixing ratios and total number concentrations

$$N_x(D) = N_{Tx} \frac{\nu_x}{\Gamma(1+\alpha_x)} \lambda_x^{\nu_x(1+\alpha_x)} D^{\nu_x(1+\alpha_x)-1} \exp[-(\lambda_x D)^{\nu_x}], \quad (1)$$

$$M_x(p) \equiv \int_0^\infty D^p N_x(D)\, dD = \frac{N_{Tx}}{\lambda_x^p} \frac{\Gamma(1+\alpha_x+p/\nu_x)}{\Gamma(1+\alpha_x)}. \quad (2)$$

By setting $\nu_x = 1$, (1) reduces to a three-parameter function involving N_{Tx}, α_x, and λ_x as

$$N_x(D) = N_{0x} D^{\alpha_x} e^{-\lambda_x D}, \quad (3)$$

where

$$N_{0x} = N_{Tx} \frac{1}{\Gamma(1+\alpha_x)} \lambda_x^{1+\alpha_x}. \quad (4)$$

$$\lambda_x = \left[\frac{\Gamma(1+d_x+\alpha_x)}{\Gamma(1+\alpha_x)} \frac{c_x N_{Tx}}{\rho q_x} \right]^{1/d_x}. \quad (5)$$

$$Z_x = M_x(6) = \frac{G(\alpha_x)}{c_x^2} \frac{(\rho q_x)^2}{N_{Tx}}, \quad (6)$$

q_x and N_{Tx} are prognostic variables

α_x is either specified or diagnosed

$$G(\alpha_x) = \frac{(6+\alpha_x)(5+\alpha_x)(4+\alpha_x)}{(3+\alpha_x)(2+\alpha_x)(1+\alpha_x)}.$$

Using Raleigh theory, Z_x can also be converted to the equivalent radar reflectivity Z_{ex} using

$$Z_{ex} = \frac{|K|_i^2}{|K|_w^2} \left(\frac{c_x}{c_r}\right)^2 Z_x, \quad (7)$$

with the ratio of the dielectric constants for ice and liquid water $|K|_i^2/|K|_w^2 = 0.224$ (F94), and $c_r = (\pi/6)\,\rho_w$, where ρ_w is the density of water. Equations (4)–(6), along with the microphysical source/sink terms to predict changes in N_{Tx}, q_x, and Z_x, constitute a three-moment bulk scheme to predict the size spectra for hydrometeor category x.

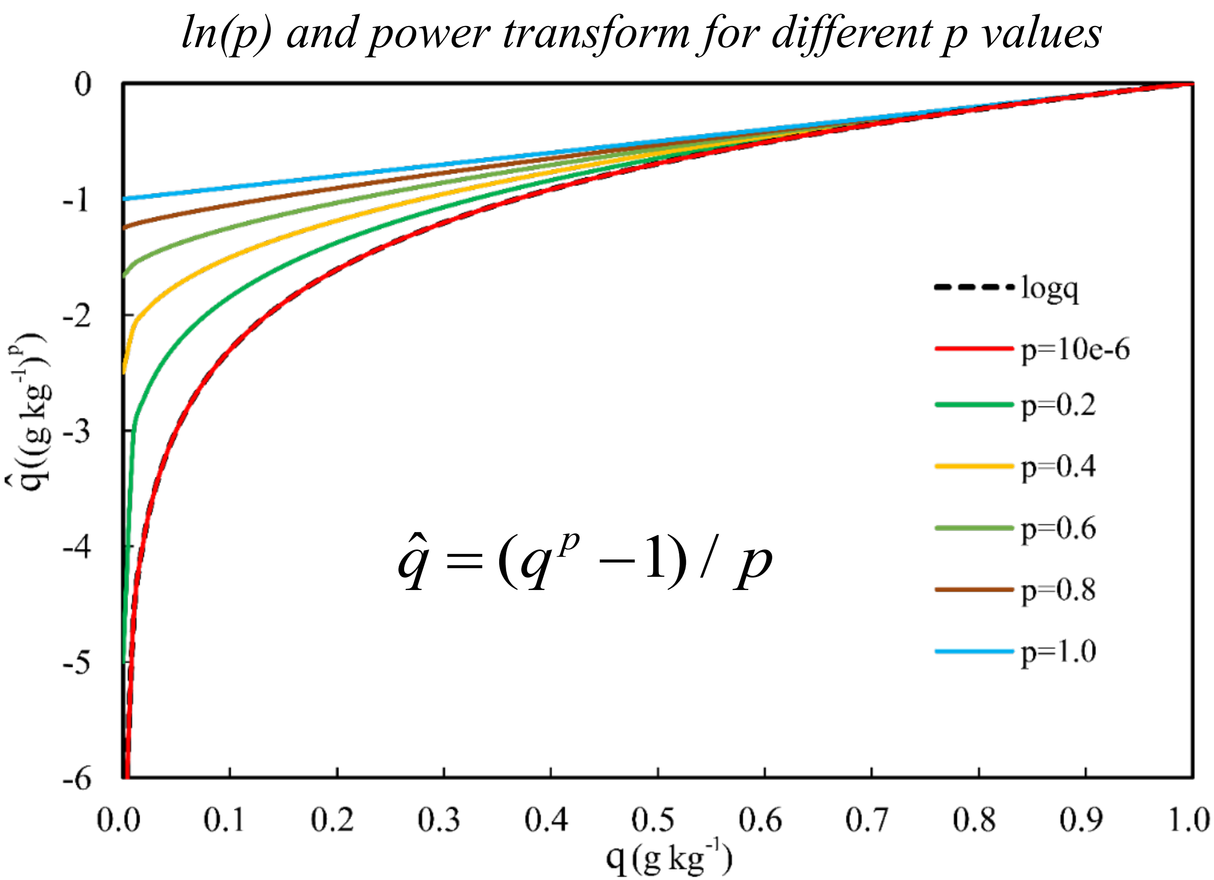
Direct Variational Assimilation of Radar Z and Vr Data: Issues with Nonlinear Reflectivity Operator

- When using q_x as the control variables (CV_q), the extremely large gradients in regions with weak background precipitation cause the assimilation of Z in storm regions and of Vr ineffective.
  - Impose lower limits on background q and Ze
  - Have to analyze Z separately from Vr, etc.
- Use $\log(q_x)$ as control variables (CV_logq), the mixing ratio analysis increments may show strange spatial structures due to the nonlinear relationship.
  - Special treatment to avoid spurious analysis increments when converting back to q
- Use power transform of mixing ratios and number concentrations as control variables (CVpnr)
  - Most flexibility

$$\hat{q} = (q^p - 1)/p \quad \hat{N}_T = (N_T^p - 1)/p \quad (0 < p \le 1)$$

Liu, C., M. Xue, and R. Kong, 2020: Direct variational assimilation of radar reflectivity and radial velocity data: Issues with nonlinear reflectivity operator and solutions. *Mon. Wea Rev.*, **148,** 1483–1502.

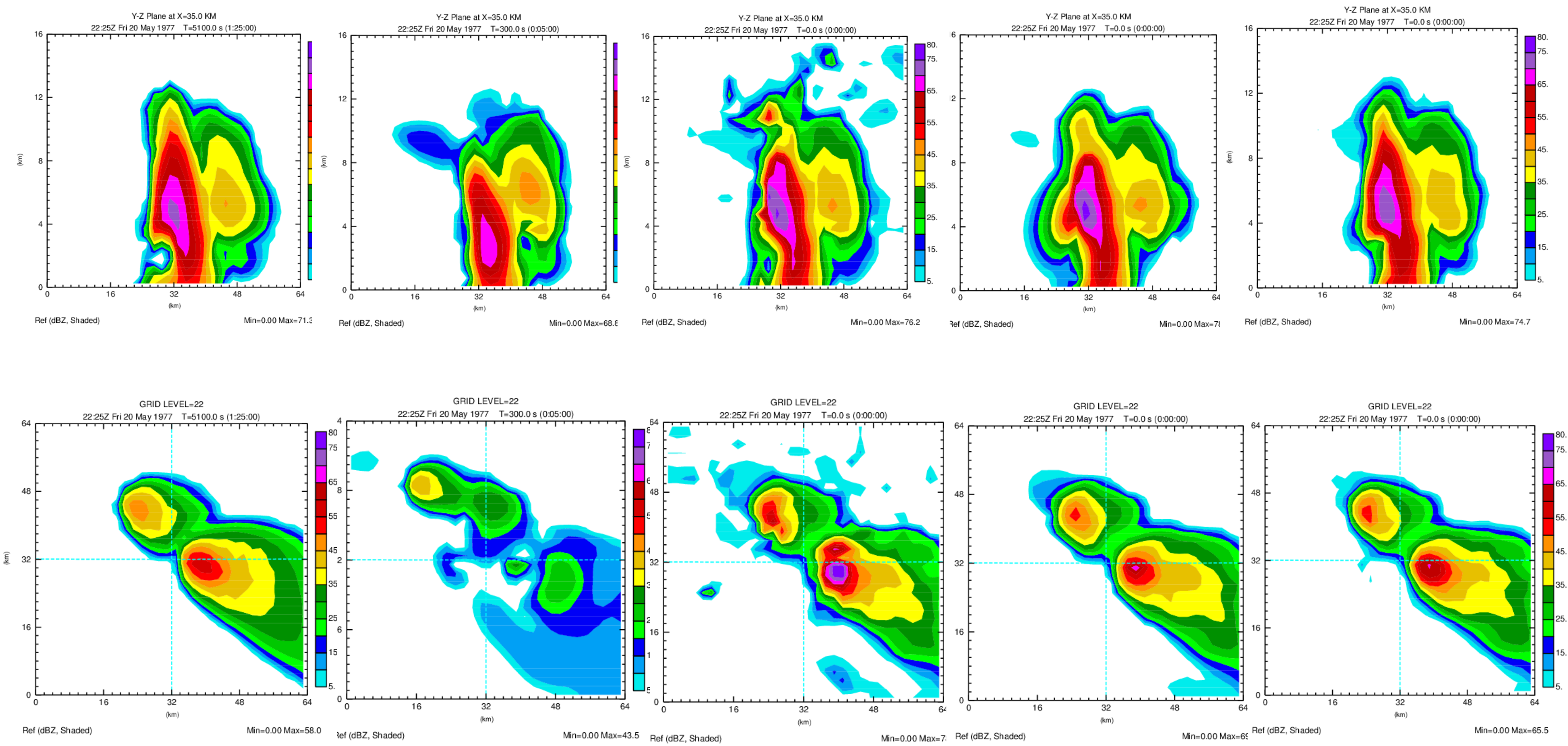
Chen, L., C. Liu, M. Xue, R. Kong, and Y. Jung, 2020: Use of power transform mixing ratios as hydrometeor control variables for direct assimilation of radar reflectivity in GSI En3DVar and tests with five convective storm cases. Mon. Wea. Rev., Conditionally accepted.



p=1 → q, p=0 → log(q)

Yang, R., R. J. Purser, J. R. Carley, M. Pondeca, Y. Zhu, S. Levine and W. Wu, 2019: Applying a general nonlinear transformation to the analysis of surface visibility and cloud ceiling height. *WGNE Bluebook*.

OSSE Results with CV_logq and Special Treatments

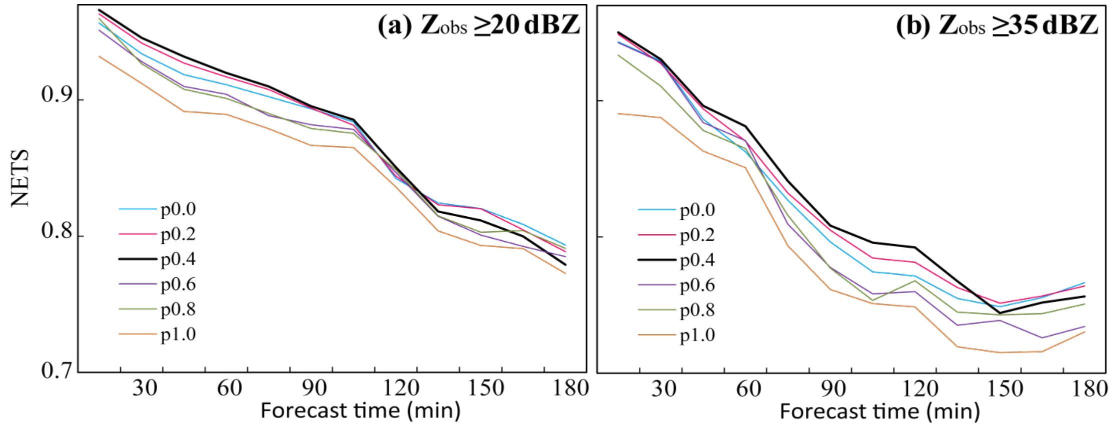


obs | background | CV_logq without treatment | CV_logq with X_b_Lim | CV_logq with X_b_Lim & smooth

Liu, C., M. Xue, and R. Kong, 2020: Direct variational assimilation of radar reflectivity and radial velocity data: Issues with nonlinear reflectivity operator and solutions. *Mon. Wea Rev.*, **148,** 1483–1502.

Use of Power Transform Mixing Ratios as Control Variables for Assimilation of Radar Reflectivity in GSI En3DVar and Tests with Five Cases (WRF Model)

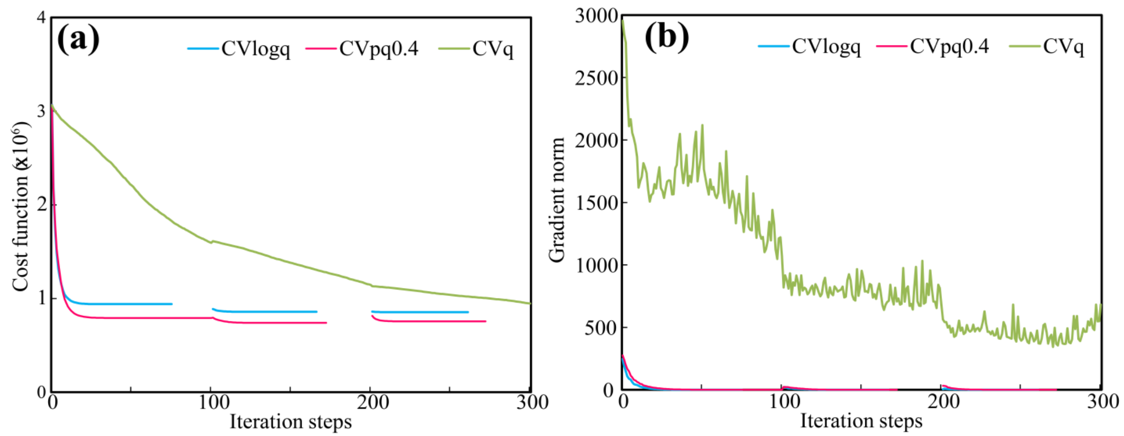
May 16, 2017 Tornadic Storm Case



P=1
→ q

5-case mean of 3h Z NETSs for different *p*

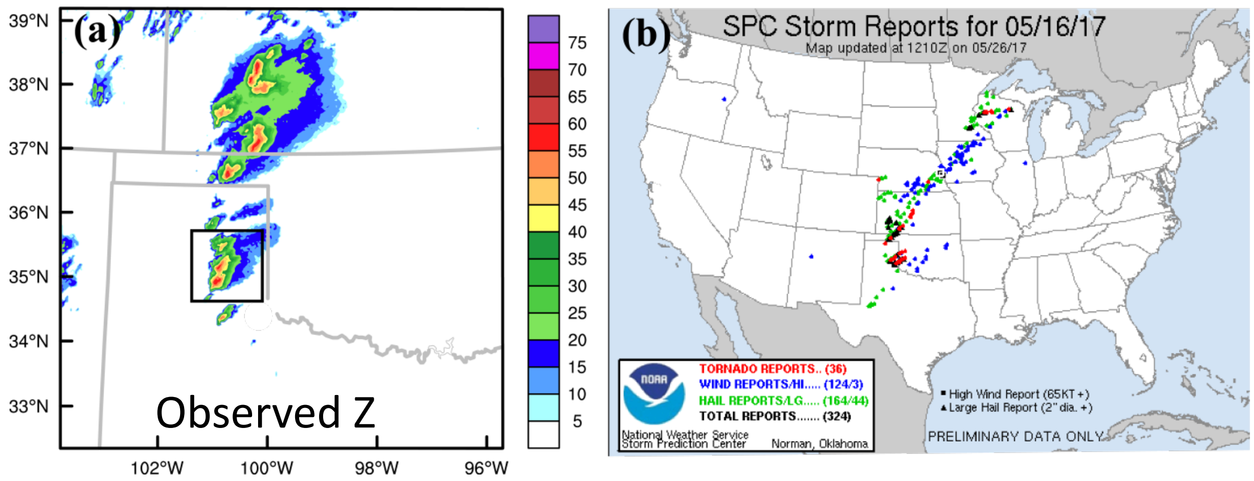
P=0
→log(q)

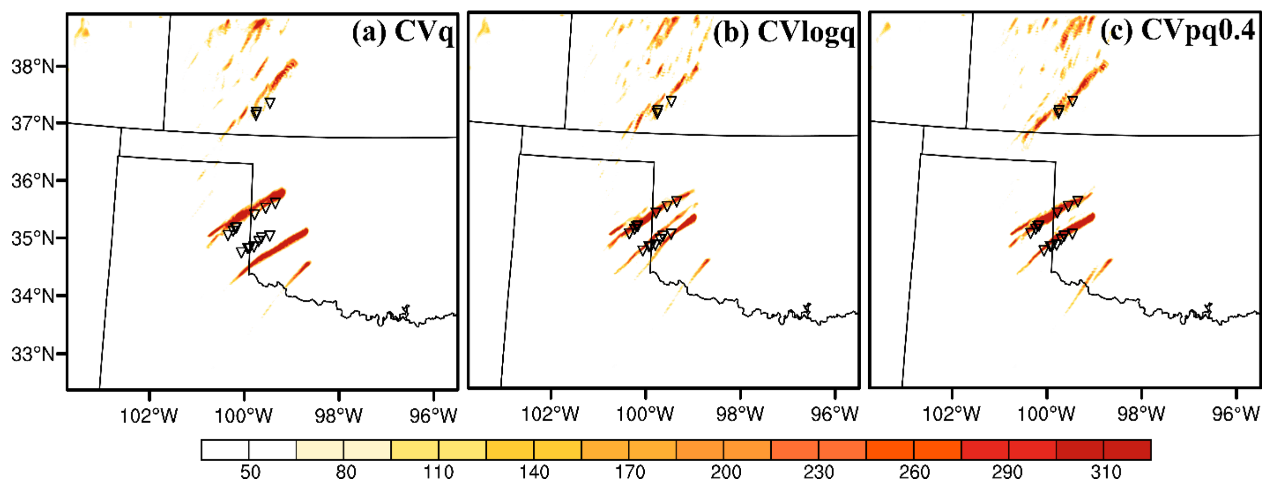


The cost function value (a) and normalized gradient (b) during the inner-loop iterations of the three outer loops for CVq, CVlogq and CVpq0.4 .

Chen, L., C. Liu, M. Xue, R. Kong, and Y. Jung, 2020: Use of power transform mixing ratios as hydrometeor control variables for direct assimilation of radar reflectivity in GSI En3DVar and tests with five convective storm cases. Mon. Wea. Rev., Conditionally accepted.

Results of May 16, 2017 Tornadic Storm Case with GSI EnVar



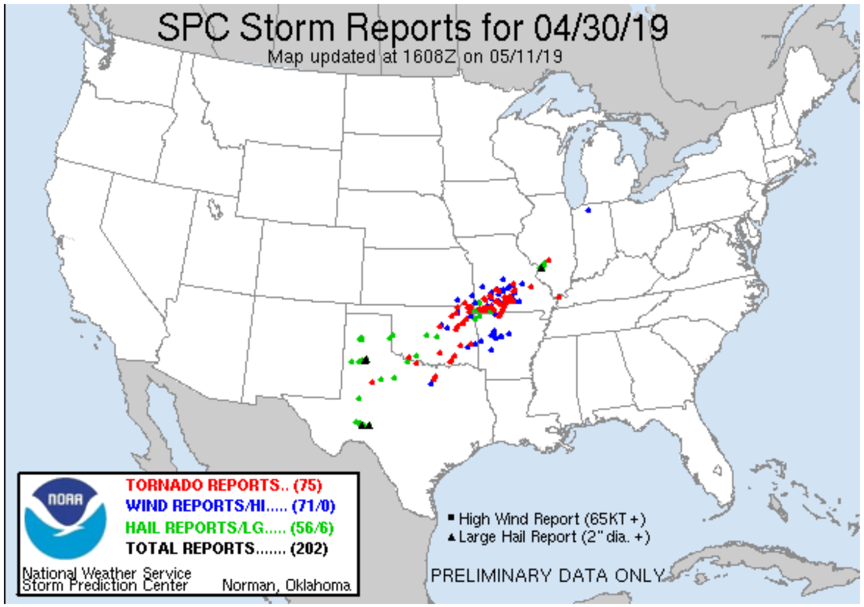


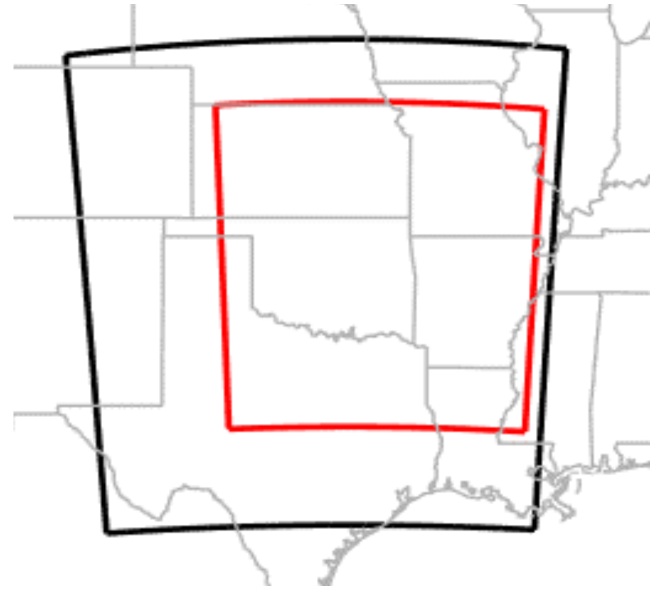
The 2-5 km UH tracks for 0-3 h forecasts using CVq, CVlogq and CVpq0.4 at 2100 UTC 16 May 2017. The triangles represent tornado reports.

Chen, L., C. Liu, M. Xue, R. Kong, and Y. Jung, 2020: Use of power transform mixing ratios as hydrometeor control variables for direct assimilation of radar reflectivity in GSI En3DVar and tests with five convective storm cases. Mon. Wea. Rev., Conditionally accepted.

Tests with SAR FV3 for 30 April 2019 Case

First paper assimilating radar data with GSI and FV3



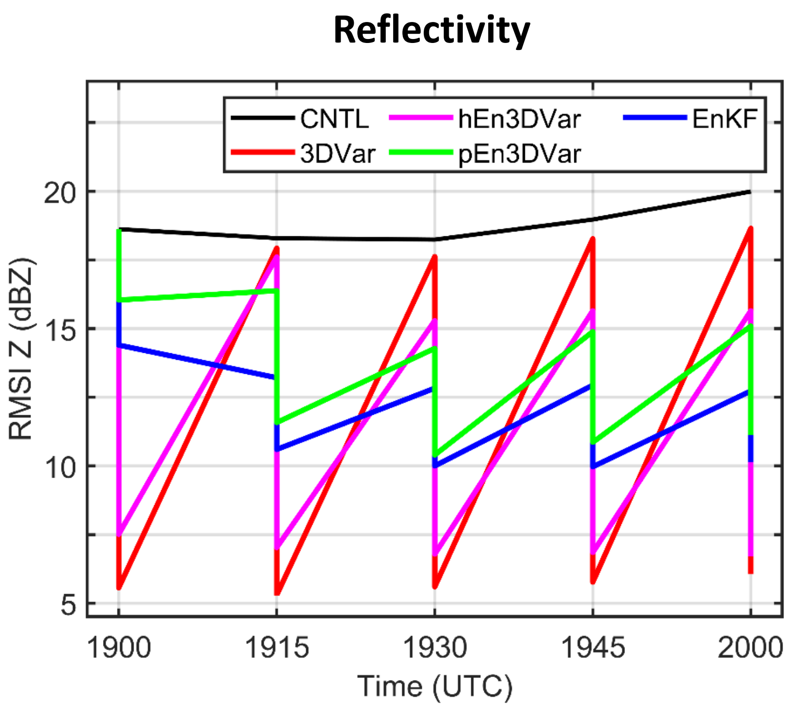


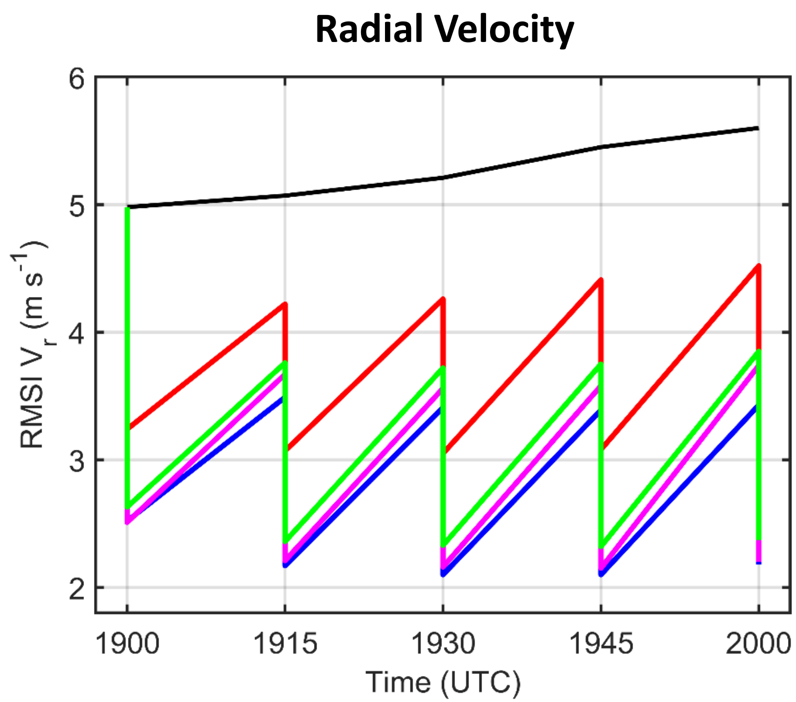
3 km SAR FV3 Grid

- **Experiments**
  - 1-h ensemble forecasts from GFS EnKF 18 Z analyses
  - **Z and Vr DA** every 15 min for 1 h, conventional data every hour
  - **3DVar**, **EnKF**, and **pure En3DVar** and **hybrid En3DVar (**75% ensemble).

Tong, C.-C., Y. Jung, M. Xue, and C. Liu, 2020: Direct assimilation of radar data within the National Weather Service operational GSI EnKF and hybrid En3DVar systems for the stand-alone regional FV3 model at a convection-allowing resolution. *Geophy. Res. Lett.*, https://doi-org/10.1029/2020GL090179.

RMS Innovation Statistics through DA Cycles

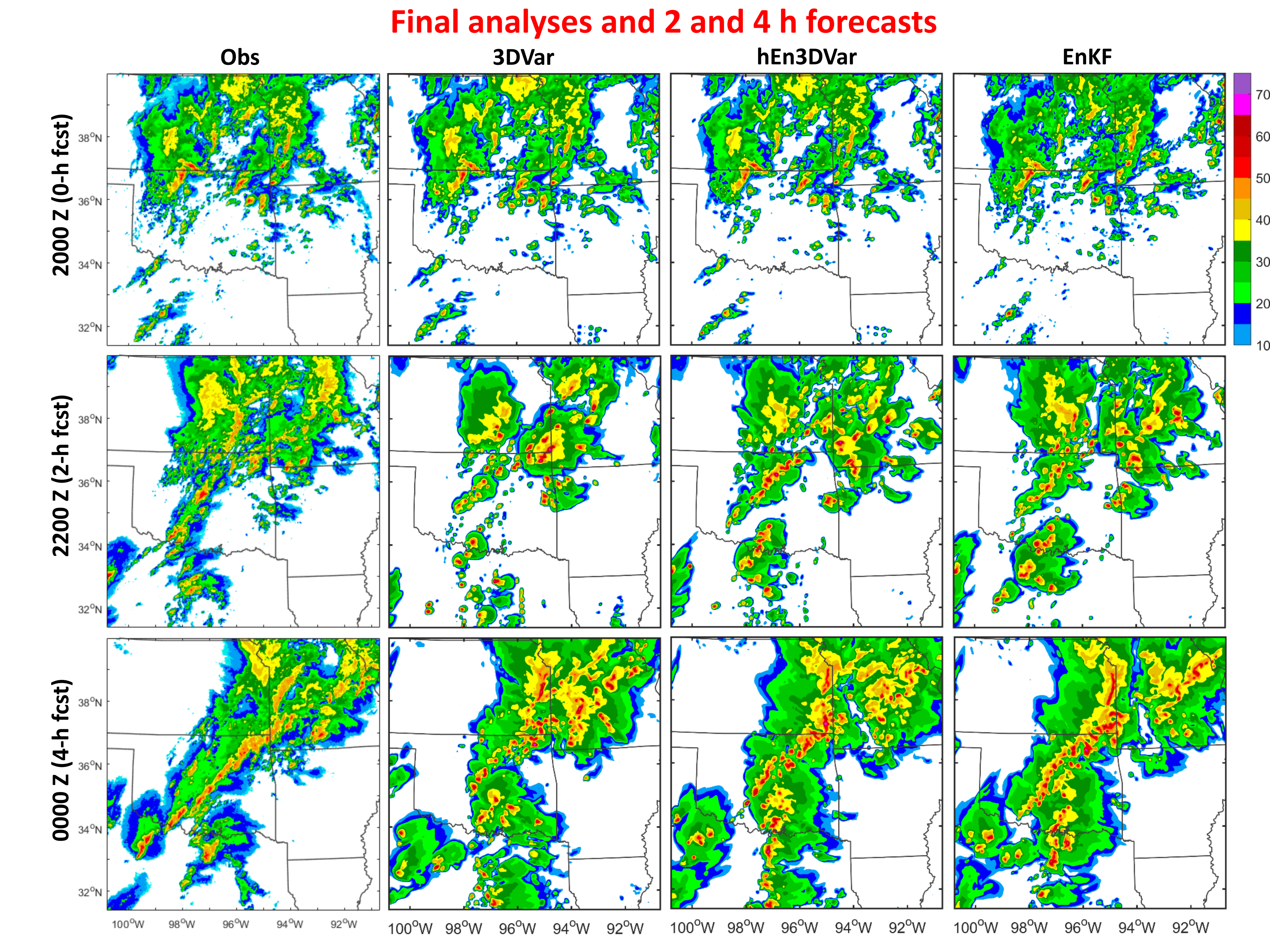




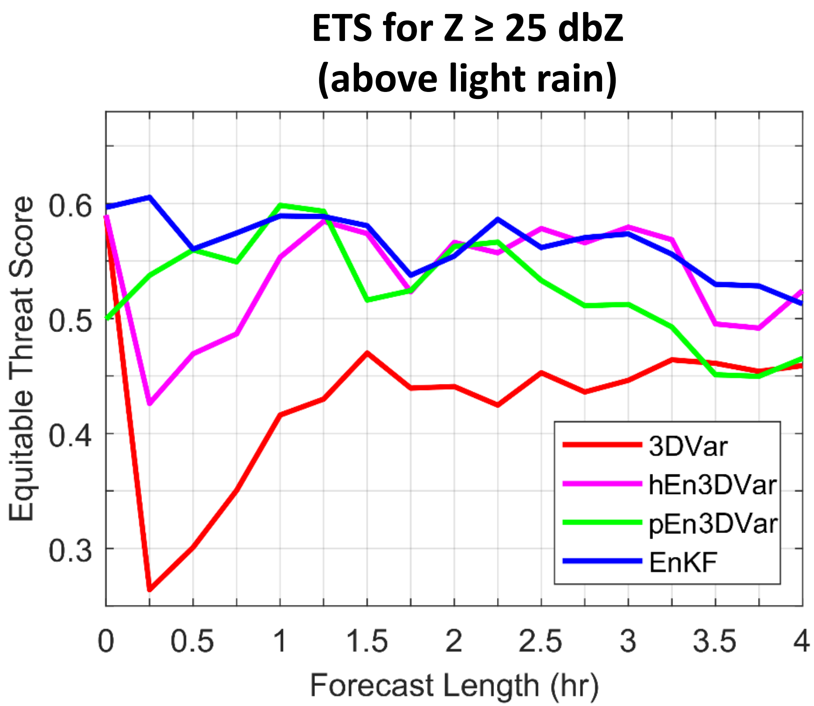
For Z, 3DVar and hEn3DVar fit obs better, EnKF and pure En3DVar show slower forecast error growth.

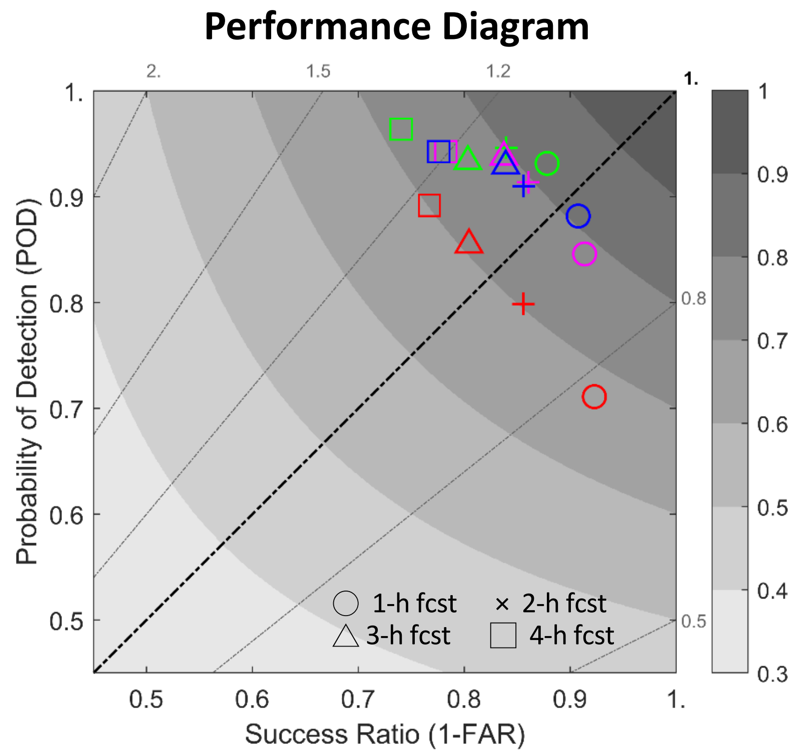
For Vr, 3DVar is clearly worse

Note: Lin Z operator was used in variational methods but Thompson Z operator was used in EnKF.


Final analyses and 2 and 4 h forecasts
Obs
3DVar
hEn3DVar
EnKF
2000 Z (0-h fcst)
2200 Z (2-h fcst)
0000 Z (4-h fcst)
38°N
36°N
34°N
32°N
100°W
98°W
96°W
94°W
92°W
70
60
50
40
30
20
10

Neighborhood (42-km) Verification of Composite Z

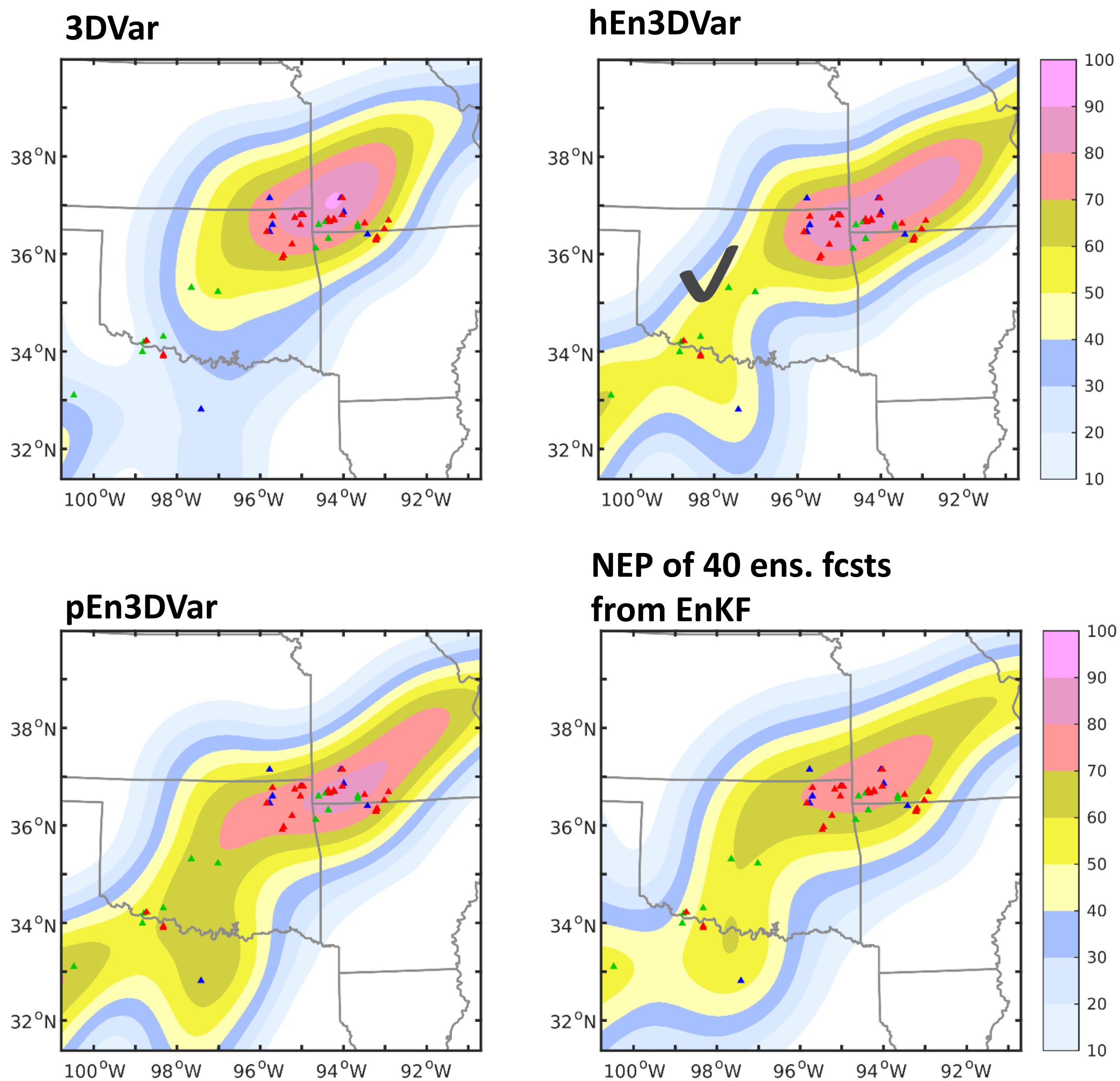




- Application of full ensemble-based BEC mitigates the score drop within the first 15-min forecast.
- EnKF produces highest ETS while 3DVar scores the lowest.
- Highest POD by pEn3DVar, followed by EnKF and hEn3DVar. 3DVar lowest CSI.

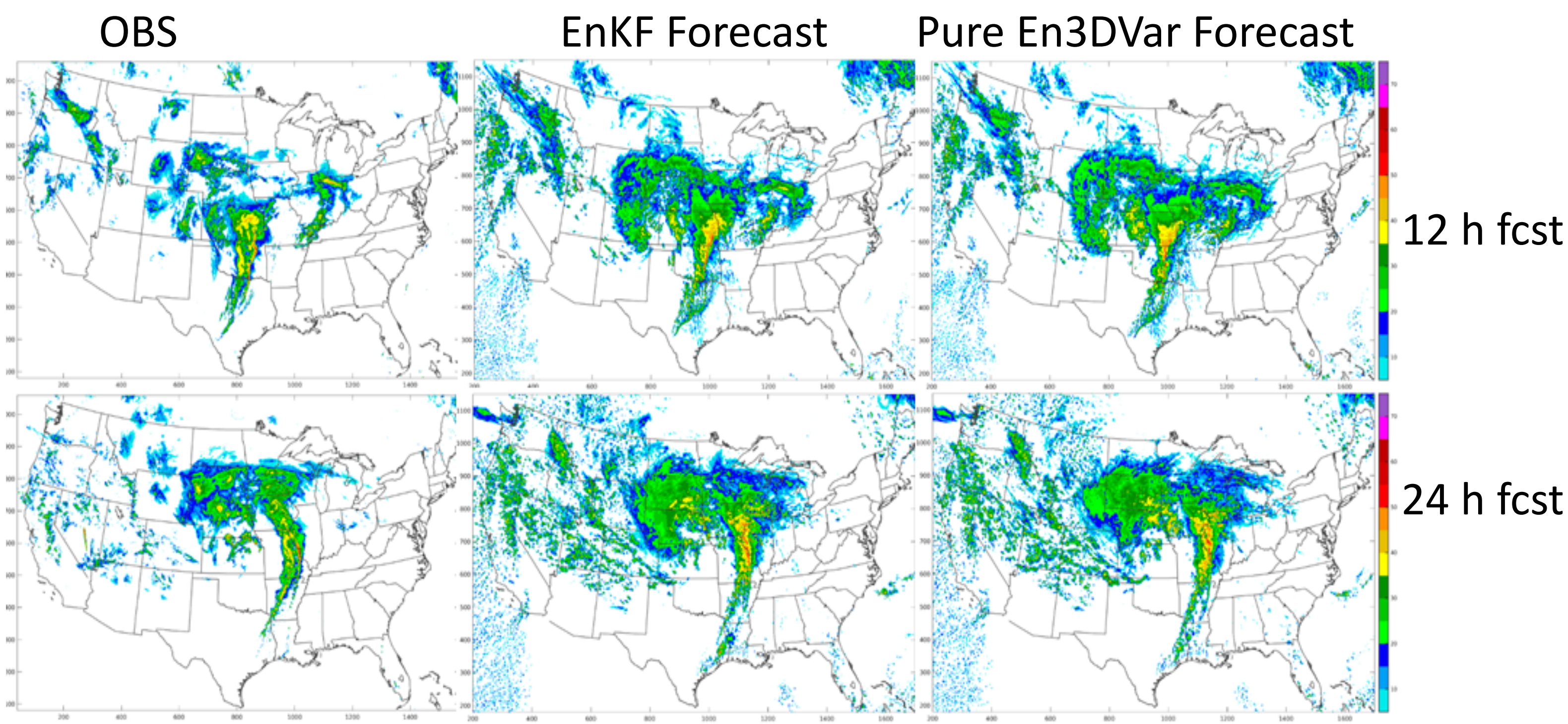
Neighborhood Probability (NP) of 4-h forecast max UH ≥ 75 m^2/s^2

- 3DVar missed most of the SW tornado reports
- hEn3DVar shows highest confidence on tornadoes around four state corners with largest NP ≥80%.
- The most extensive ≥30% NP of pEn3DVar can be linked to its greatest over-forecast tendency.



Tested with FV3-LAM on CONUS-Sized 3-km Grid

- In the En3DVar experiment, Thompson Z operator is now used
- Power transform of both mixing ratio (q) and total number concentration (N_t) used as control variables.

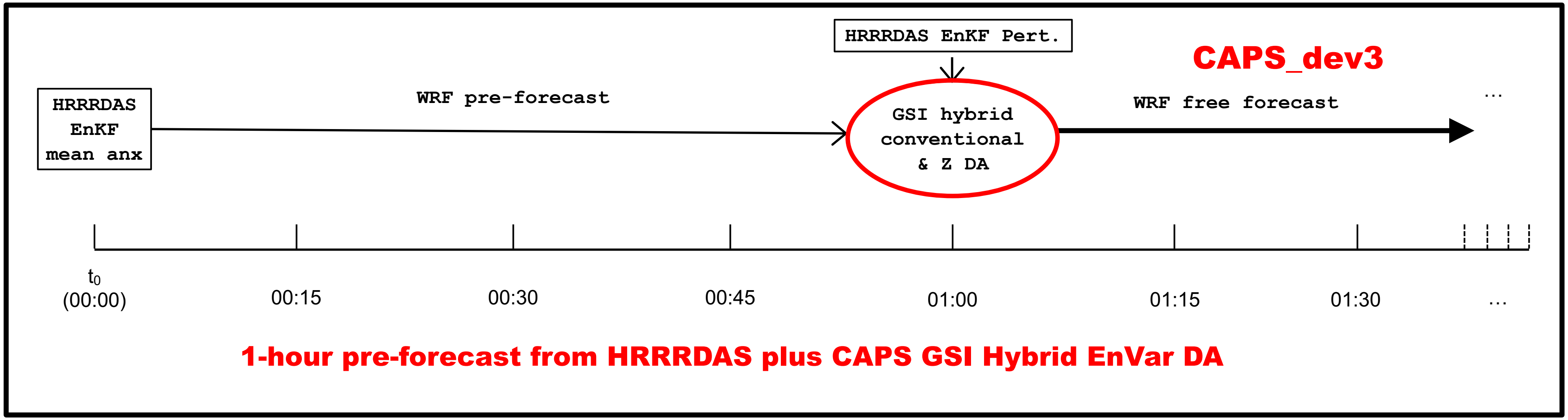


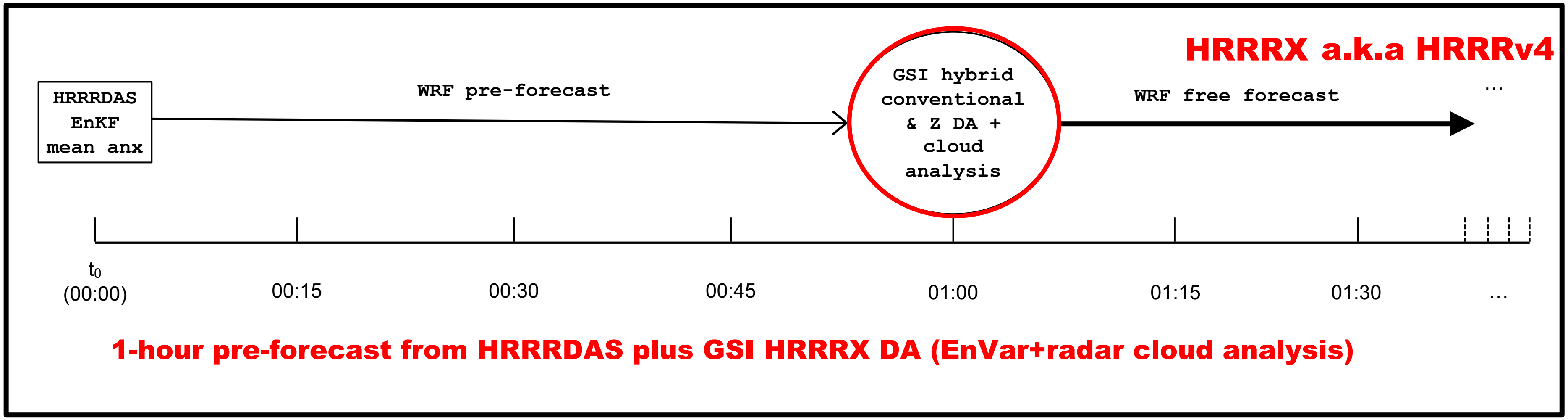
Good forecasts with both EnKF and En3DVar

Extended Testing at GDL in Quais-Operational Environment, Building off HRRRv4 Testing Infrastructure (Work of Jeff Dudda, GSL Collaborator of JTTI Project)

- Latest GSI codes from CAPS
- Only EnVar portion used (not EnKF), and non-cycled results to be shown
- EnKF perturbations borrowed from hourly HRRRDAS cycles
- About 140 forecasts were run in late July – early Sept. 2020
- Results compared with experimental HRRRv4 (HRRRX) and operational HRRRv3

Setup of CAPS_dev3 and HRRRX_Control (a.k.a. HRRRv4) Experiments

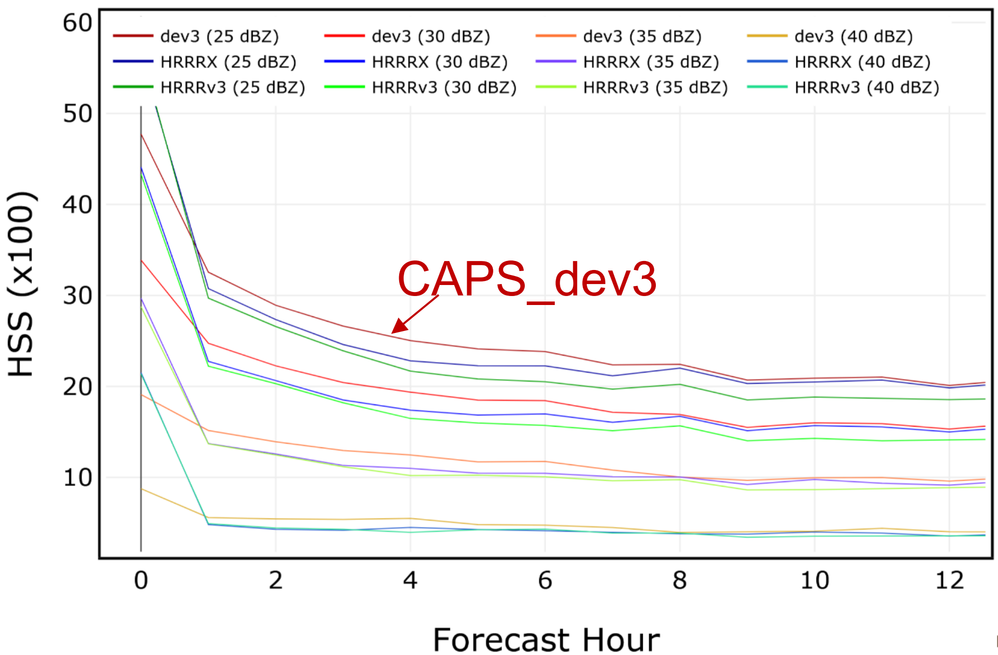


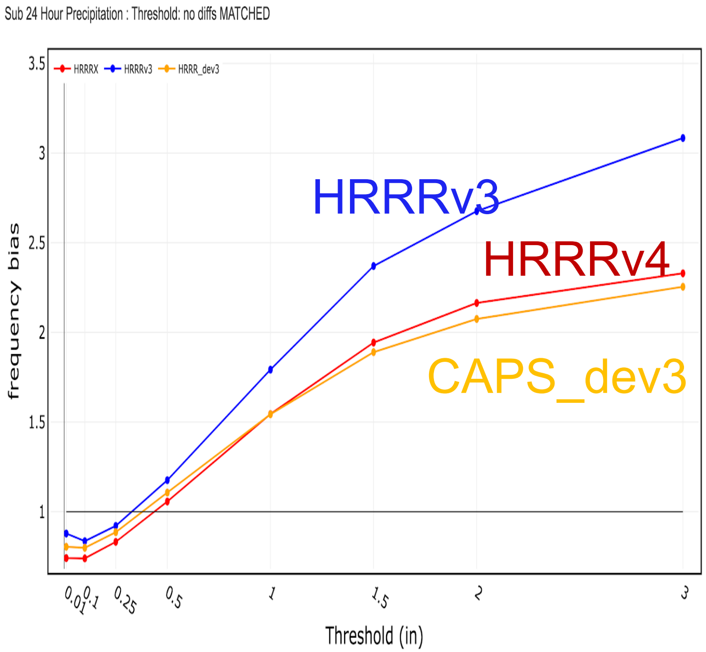


CAPS radar DA includes Thompson Z operator, variable power transform and other special treatments
Perturbations from HRRRDAS EnKF are used

Scores for Extended Runs at GSL
Hourly reflectivity Heidke Skill Scores and 6 h Precip Biases

Dev3 = CAPS, HRRRX=HRRRv4, HRRRv3



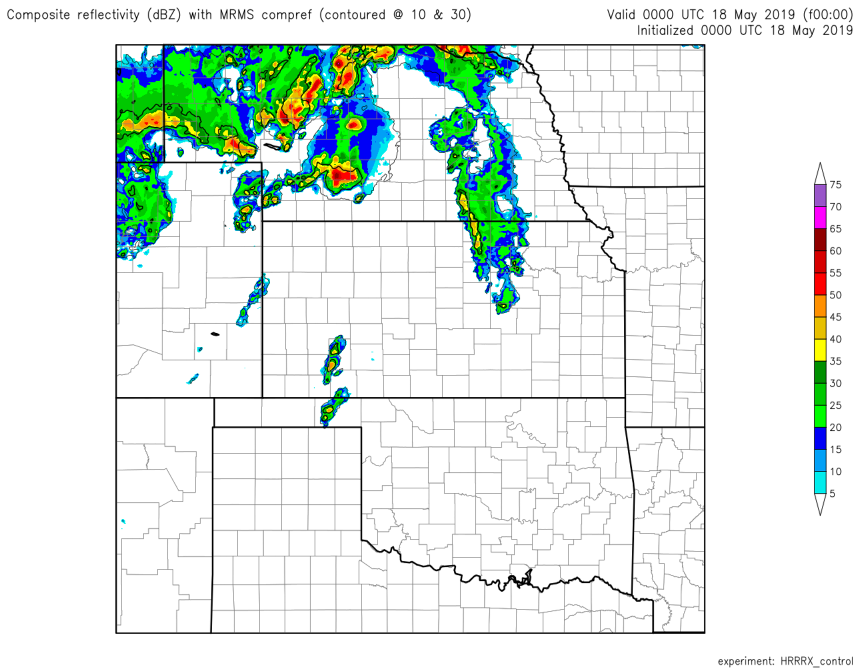


Bias for 6 h precip

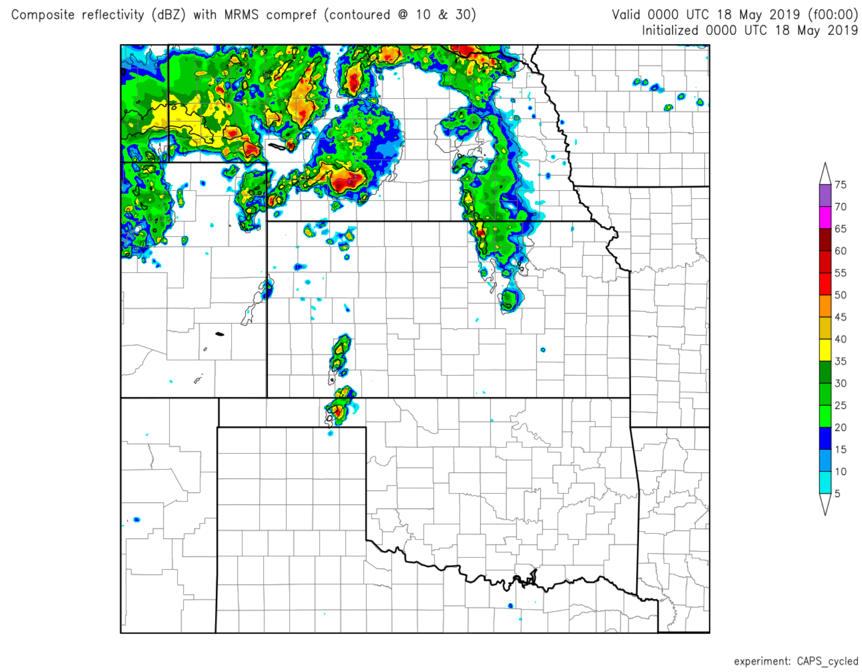
Composite reflectivity – 0 h analysis

(for 18 May 2019 Test Case)

HRRRX



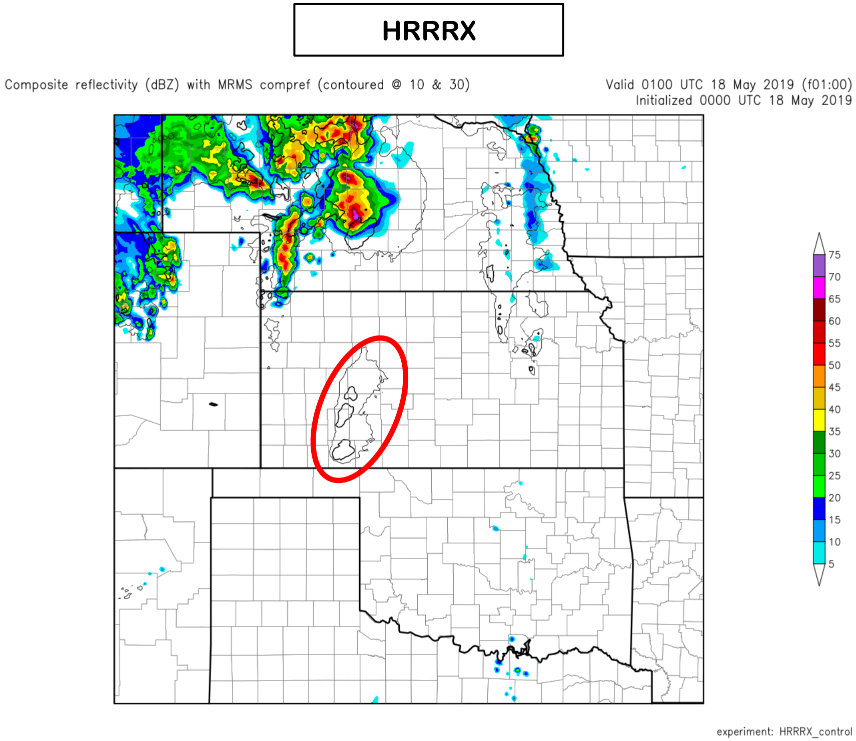
CAPS_dev3

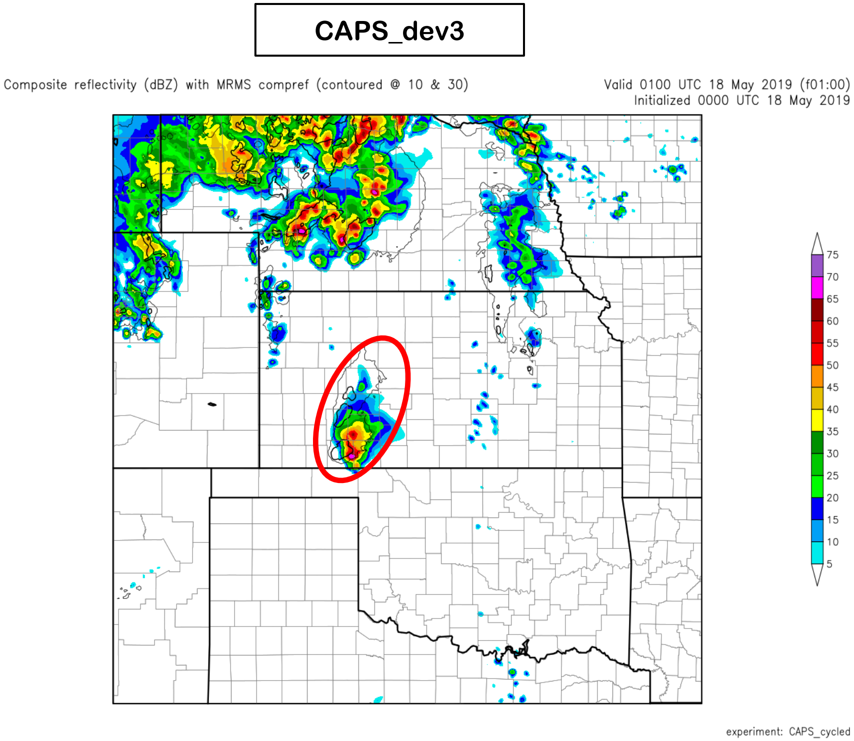


Both analyses match Z observation (contours) pretty well.

Composite reflectivity – 1 h forecast

(for 18 May 2019 Test Case)



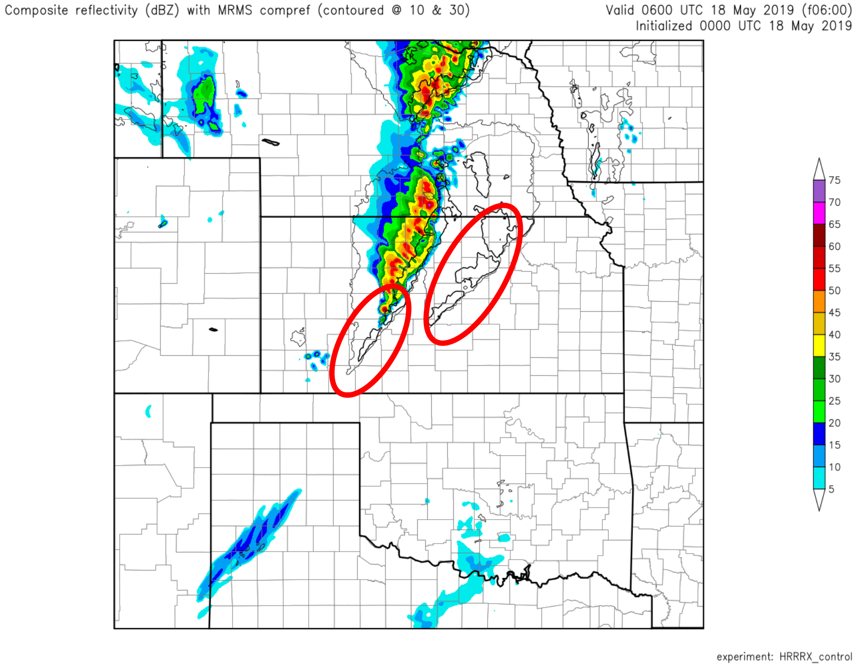


CAPS_dev3 sustained storms in SW KS but HRRRX_control missed it.

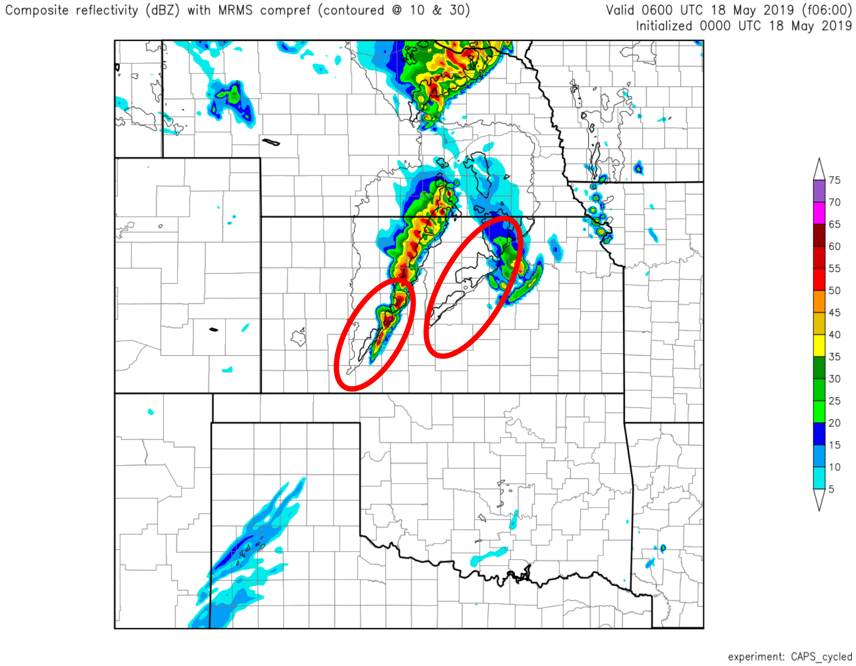
Composite reflectivity – 6 h forecast

(for 18 May 2019 Test Case)

HRRRX

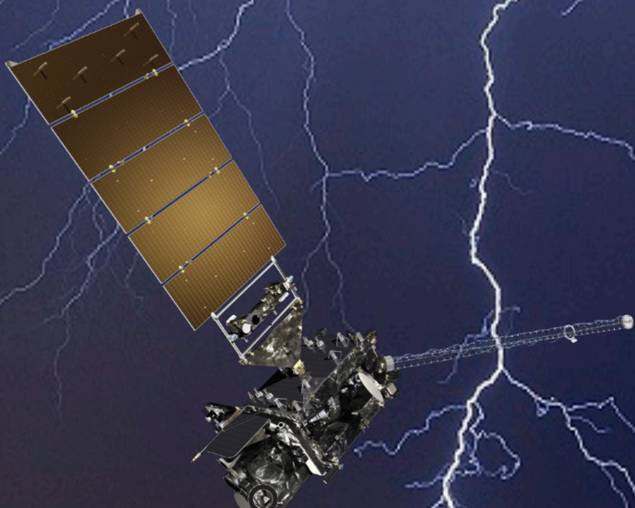


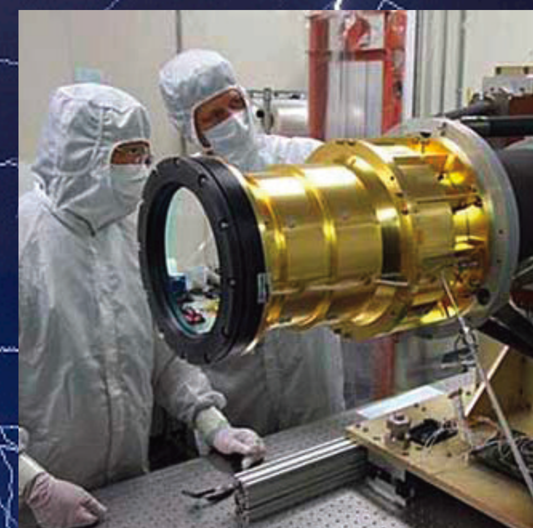
CAPS_dev3



CAPS_dev3 better matches the length of the squall line at southern end.
HRRRX missed pre-squall line reflectivity entirely.

Assimilation of GOES-R Global Lightning Mapper (GLM) Total Flash Rate Data in GSI EnKF and Hybrid En3DVar

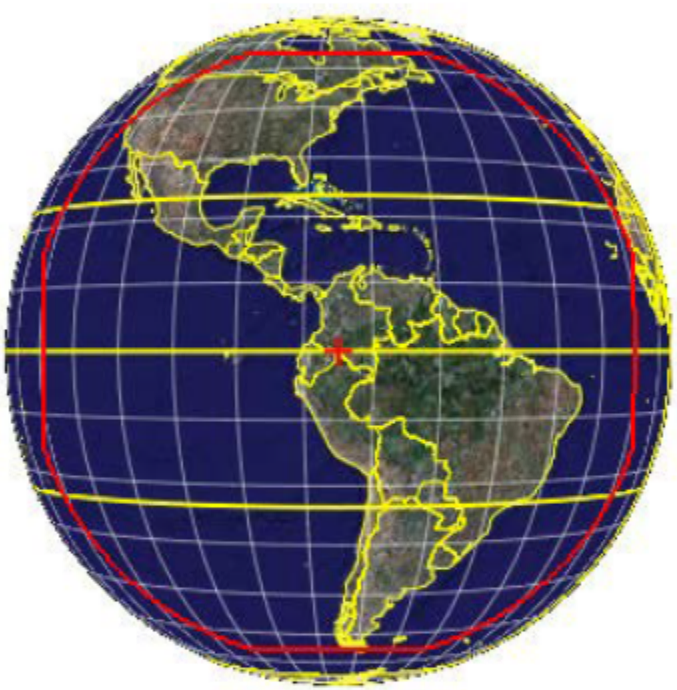




Supported by GOES-R Risk Reduction Program
Collaboration between CAPS and NSSL

Credit: Rowland Beardsell

GOES-16/17 Global Lightning Mapper (GLM) Data and Experiments



GLM field of view.

- The GLM total lightning flash measurements are collected at 20 s intervals and with 8-12 km pixel resolution.
- Existing methods for lightning data assimilation mostly use indirect methods, that assimilates pseudo-moisture, proxy-reflectivity data or via latent heat adjustment.
- Ground-based lightning data can go into RAP, HRRR and NAM after being converted to proxy-reflectivity.
- Direct methods using obs operator and ensemble covariance can better extract information and produce multi-variate convective-scale analyses.
- Developed EnKF (Kong et al. 2020a) and En3DVar (Kong et al. 2020b) capabilities within GSI to assimilate GLM flash extent density (FED) data (total flashes through ~10 km pixel per min)
- Tested with MCS and supercell cases
- Assimilating FED every 5 min for 1 hour, using 3DVar, EnKF or En3DVar
- Assimilating FED only, radar only, or both and compare with no DA base line.
- 3 km for MCS and 1 km grid spacing for supercell case.

Kong, R., M. Xue, A. O. Fierro, Y. Jung, C. Liu, E. R. Mansell, and D. R. MacGorman , 2020a: Assimilation of GOES-16 Geostationary Lightning Mapper Flash Extent Density Data in GSI EnKF for the Analysis and Short Term Forecast of a Mesoscale Convective System. Mon. Wea. Rev., 48, 2111-2133.

Baseline Lightning Observation Operators

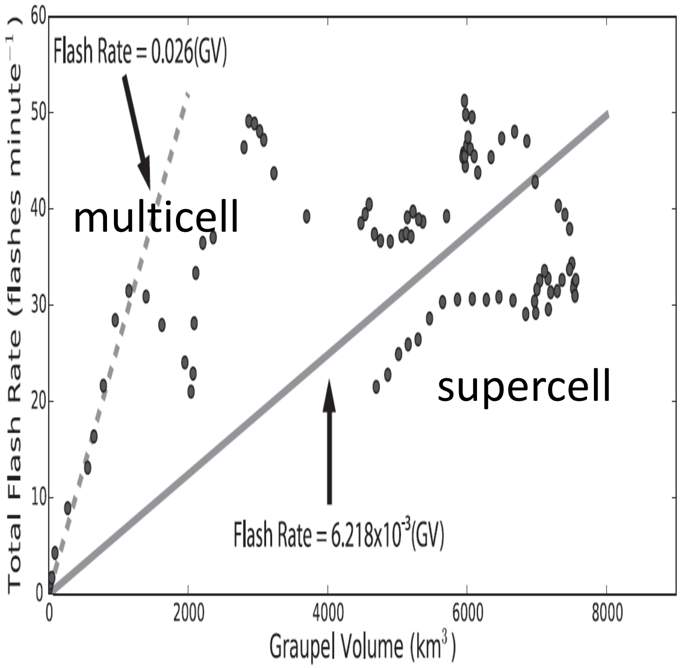


FIG. 7. Scatterplot of flash rate and graupel volume data from the supercell case, with the best-fit lines from this case (solid line) and the the multicell case (dashed line) overlaid.

- The lightning observation operators based on graupel mass (FEDM) and graupel volume (FEDV) from Allen *et al*. (2016) are given by:

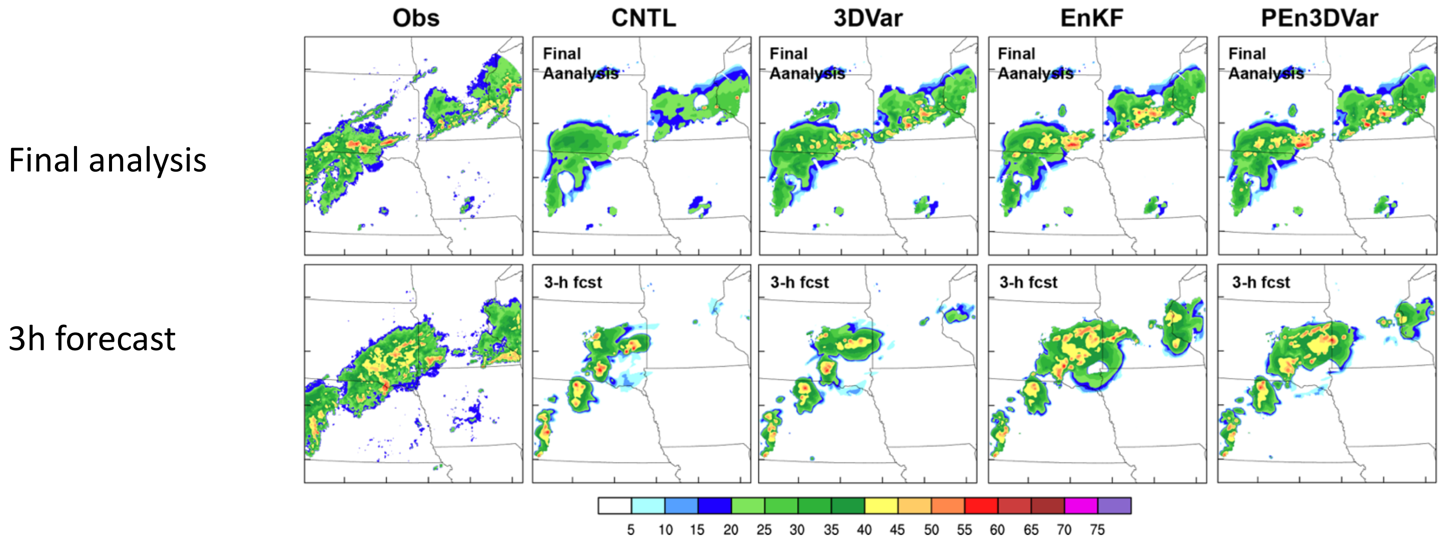
$$\mathrm{FEDM} = 2.088 \times 10^{-8} (\mathrm{GM})$$

$$\mathrm{FEDV} = 1.5 \times 0.017 (\mathrm{GV})$$

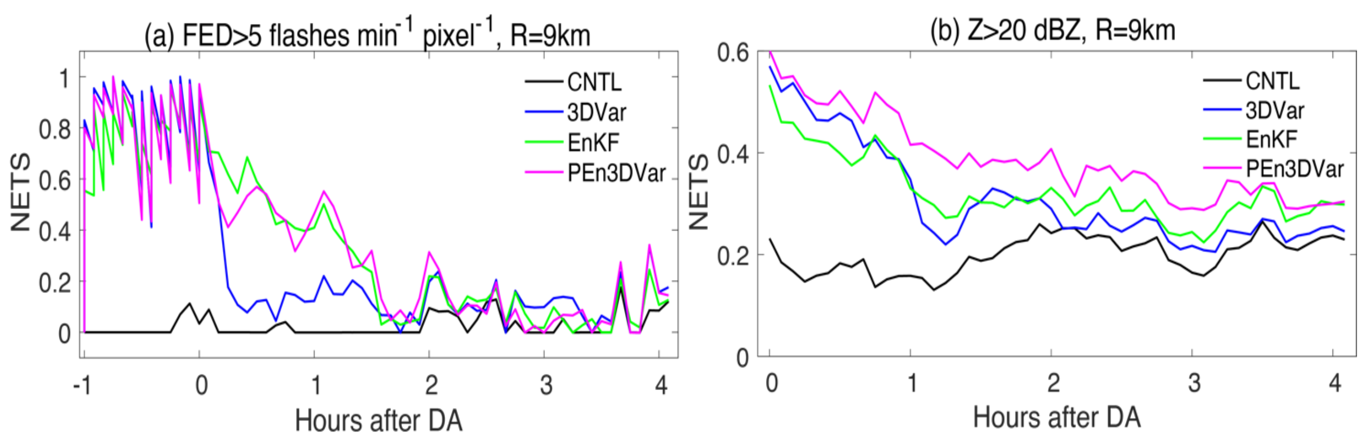
GM: graupel mass within a 10 x 10 km column in kg

GV: volume of graupel $q_g > 0.5$ g kg^{-1} in m^3 in the column

Forecasts of a MCS case with FED DA using GSI 3DVar, EnKF and En3DVar



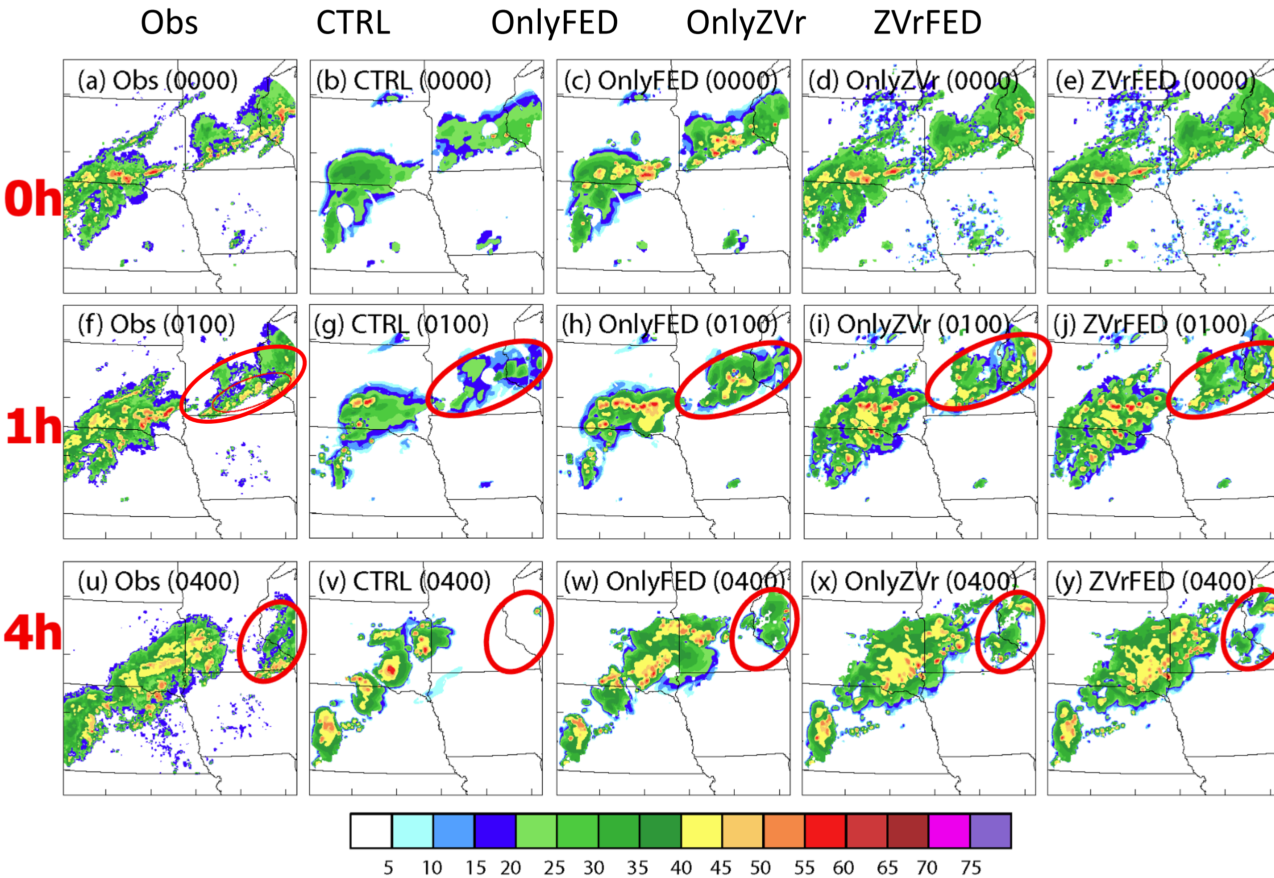
Analysis and forecast composite reflectivity for a MCS case



Neighborhood ETS scores of (a) FED and (b) composite Z forecasts for an MCS case, for no-DA CTRL, analyses and forecasts in the 1-hr DA window and 0~4h free forecasts of FED DA experiments using GSI 3DVar, EnKF and pure En3DVar methods.

Kong, R., M. Xue, C. Liu, A. O. Fierro, E. R. Mansell, and D. R. MacGorman, 2020: Assimilation of GOES-16 geostationary lightning mapper flash extent density data in GSI 3DVar, EnKF and hybrid En3DVar for the analysis and short term forecast of two convective storm cases. *Mon. Wea. Rev.*, Submitted.

Forecasts of a MCS case assimilating FED, radar, or both data

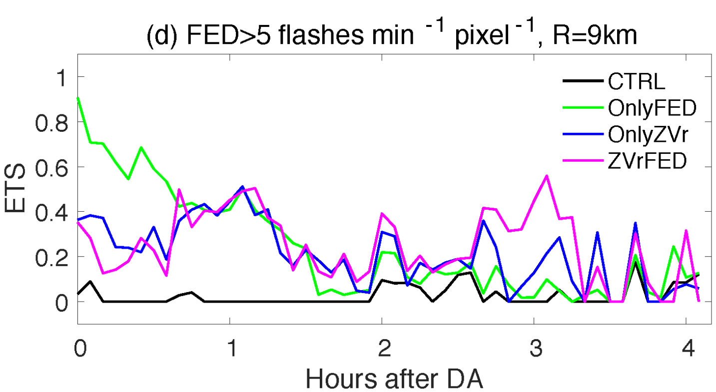


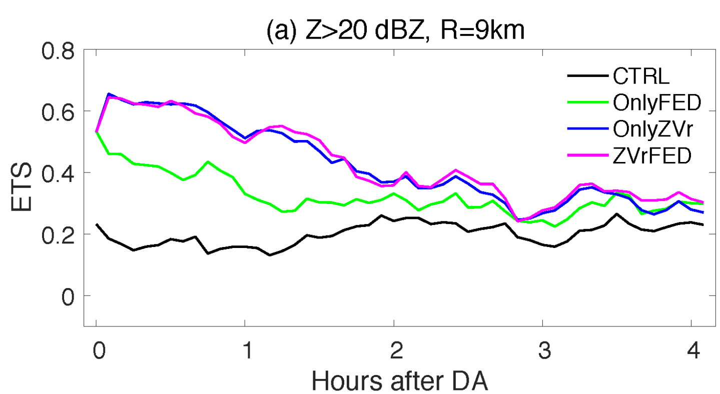
OnlyFED produces comparable results as OnlyZVr

Results encouraging given that FED data are only 2D

More valuable over ocean where no radar data is available

Summited a JTTI proposal together with GSL to implement and test FED DA inside JEDI

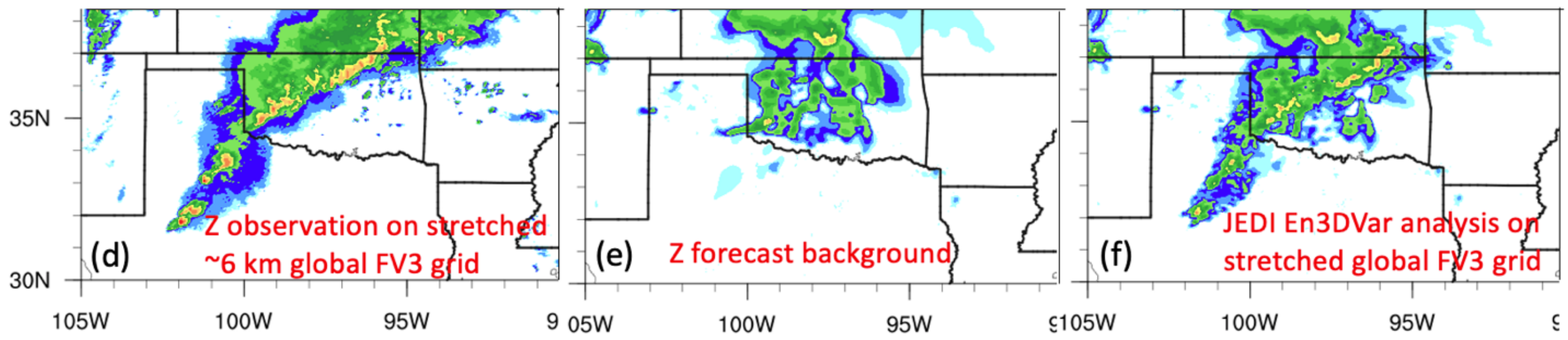




Kong, R., M. Xue, C. Liu, A. O. Fierro, and E. R. Mansell, 2020: Assimilation of GOES-16 geostationary lightning mapper flash extent density and radar data in GSI EnKF for a mesoscale convective system. *Mon. Wea. Rev.*, Under preparation.

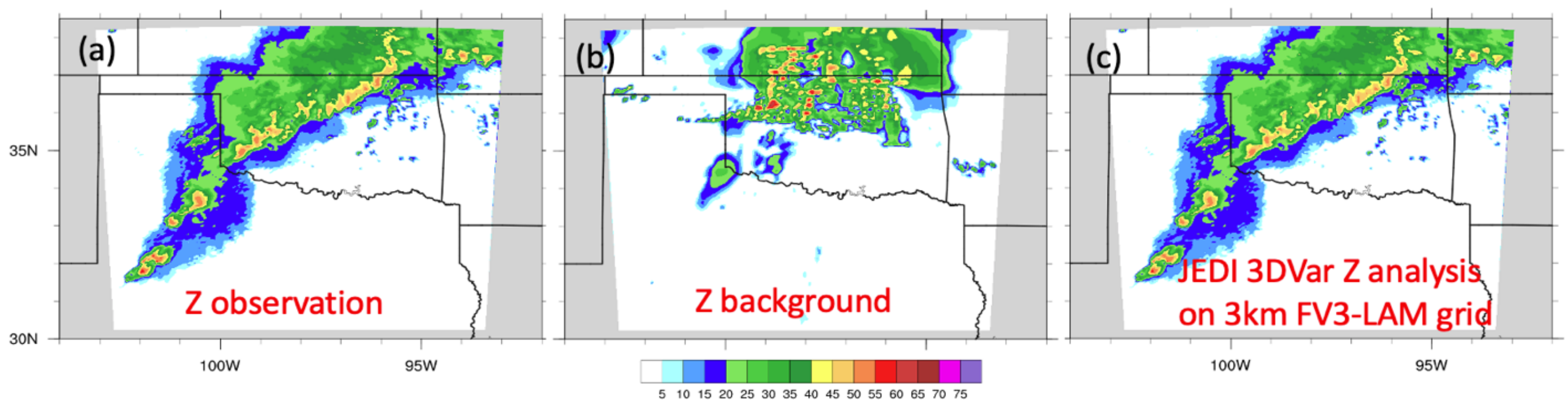
Analysis of Reflectivity Data with JEDI – Preliminary Implementation and Tests

Based on pre-release JEDI on stretched global FV3 Grid



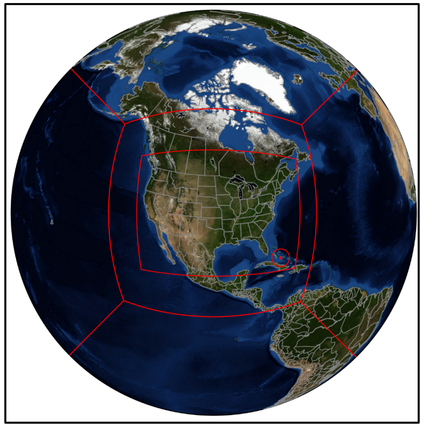
(d) Observation, (e) forecast background, (f) analyzed Z by CAPS-enhanced JEDI En3DVar with Thompson Z operator, on a stretched global FV3 grid with ~6 km grid spacing over central U.S.

Based on 1st public release of JEDI on FV3-LAM Grid



(a) Observation, (b) background, (c) analyzed reflectivity using CAPS-enhanced JEDI 3DVar on a regional ~3 km FV3-LAM grid with Lin Z operator

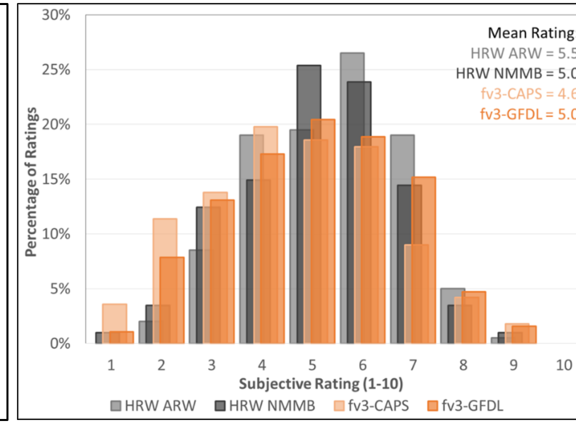
Testing and Evaluations of FV3 UFS in Realtime during HWT SFE and HMT WWE & FFaIR



In 2017, CAPS Implemented Thompson MP into FV3, ran Global FV3 with a CONUS nest for HWT SFE and HMT FFaIR (GFDF ran with Lin MP)

It was the first time FV3 was applied to realtime CAM forecast.

Results helped establish the credibility of FV3 for CAM forecasting



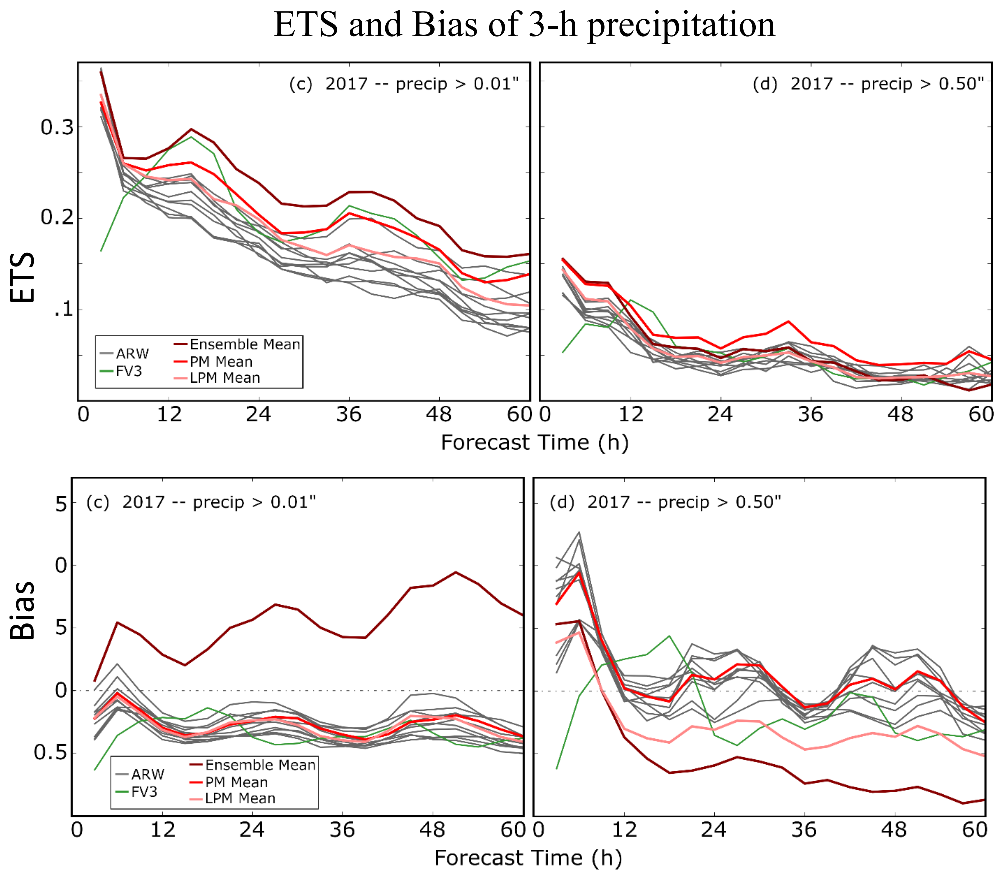
FV3 obtained more 9 ratings from HWT participants

TABLE 2. Configurations for ARW and FV3 members of the 2017 CAPS HMT FFaIR storm-scale ensemble. All members use RRTMG for parameterization of longwave and shortwave radiation. All members use no cumulus parameterization, except FV3, which uses scale-aware SAS on the global domain only.

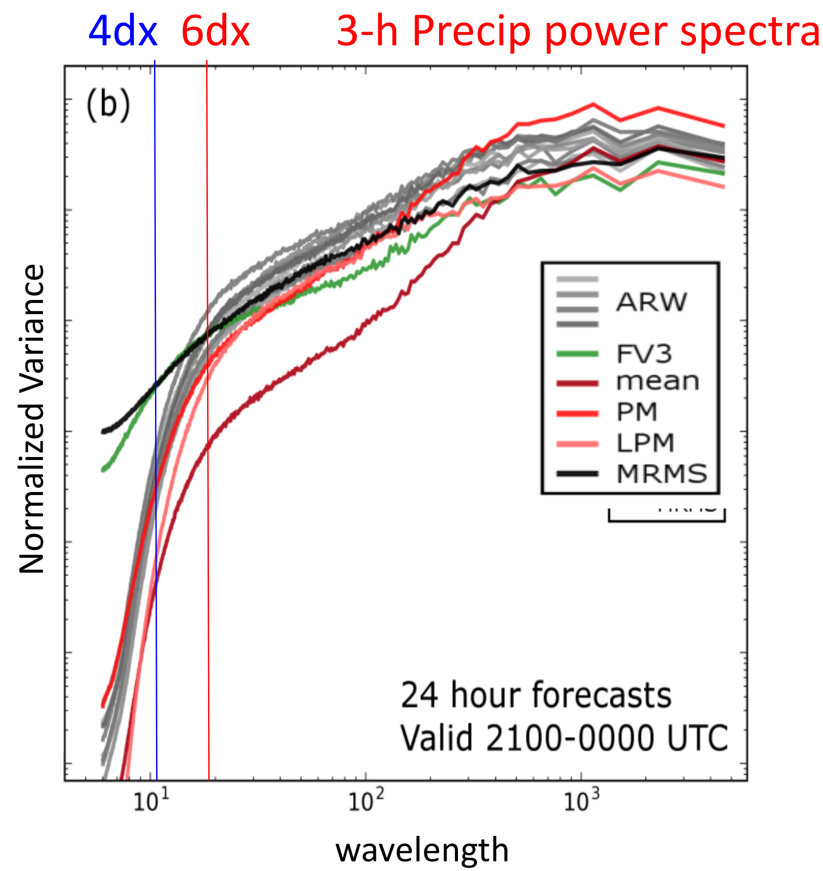
Member	Initial conditions	Boundary conditions	Radar data	Microphysics	Land surface model	PBL
arw_cn	0000 UTC ARPSa	0000 UTC NAMf	Yes	Thompson	Noah	MYJ
arw_m2	arw_cn + arw-p1_pert	2100 UTC SREF arw-p1	Yes	P3	Noah	YSU
arw_m3	arw_cn + arw-n1_pert	2100 UTC SREF arw-n1	Yes	MY	Noah	MYNN
arw_m4	arw_cn + arw-p2_pert	2100 UTC SREF arw-p2	Yes	Morrison	Noah	MYJ
arw_m5	arw_cn + arw-n2_pert	2100 UTC SREF arw-n2	Yes	P3	Noah	MYNN
arw_m6	arw_cn + nmmb-p1_pert	2100 UTC SREF nmmb-p1	Yes	MY	Noah	MYJ
arw_m7	arw_cn + nmmb-n1_pert	2100 UTC SREF nmmb-n1	Yes	Morrison	Noah	YSU
arw_m8	arw_cn + nmmb-p2_pert	2100 UTC SREF nmmb-p2	Yes	P3	Noah	MYJ
arw_m9	arw_cn + nmmb-n2_pert	2100 UTC SREF nmmb-n2	Yes	Thompson	Noah	MYNN
arw_m10	arw_cn + arw-n3_pert	2100 UTC SREF arw-n3	Yes	Thompson	Noah	MYJ
fv3	0000 UTC GFS	—	No	Thompson	Noah	MRF

Snook, N., F. Kong, K. Brewster, M. Xue, K. W. Thomas, T. A. Supinie, B. Albright, and S. Perfater, 2019: Evaluation of Convection-Permitting Precipitation Forecast Products using WRF, NMMB, and FV3 Models for the 2016-2017 NOAA Hydrometeorology Testbed Flash Flood and Intense Rainfall Experiments. Wea. Forecasting, 34, 781-804.

Normalized variance spectra of 3-hourly precipitation from CAPS WRF ensemble and FV3 forecasts for 2017 HMT FFaIR Experiment



FV3 scored higher/lower than WRF ARW for light/heavy rain
FV3 had similar biases as ARW (somewhat larger low bias for 0.5").

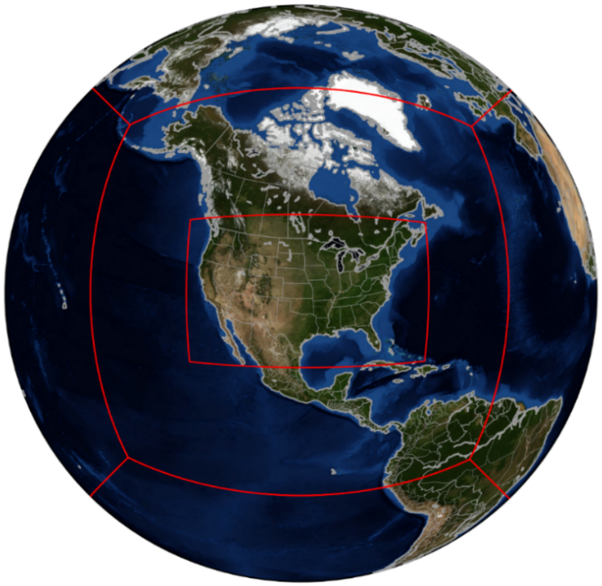


FV3 retains more energy in the sub-10 km scales than the WRF-ARW forecasts, resulting in a spectrum slope that is much closer to that of observations (black)

Snook, N., F. Kong, K. Brewster, M. Xue, K. W. Thomas, T. A. Supinie, B. Albright, and S. Perfater, 2019: Evaluation of Convection-Permitting Precipitation Forecast Products using WRF, NMMB, and FV3 Models for the 2016-2017 NOAA Hydrometeorology Testbed Flash Flood and Intense Rainfall Experiments. Wea. Forecasting, 34, 781-804.

CAPS FV3 Forecasts for HWT 2018

- To evaluate different physics for FV3 CAM forecasts



Global FV3 with a ~3 km CONUS nest
Multiple physics implemented by CAPS

The FV3 Model Configurations for 2018 HWT SFE

Forecast name	Microphysics	PBL
fv3-phys01	Thompson	SA-MYNN
fv3-phys02	Thompson	MYNN
fv3-phys03	Thompson	SA-YSU
fv3-phys04	Thompson	YSU
fv3-phys05	Thompson	EDMF
fv3-phys06	NSSL	SA-MYNN
fv3-phys07	NSSL	MYNN
fv3-phys08	NSSL	SA-YSU
fv3-phys09	NSSL	YSU
fv3-phys10	NSSL	EDMF

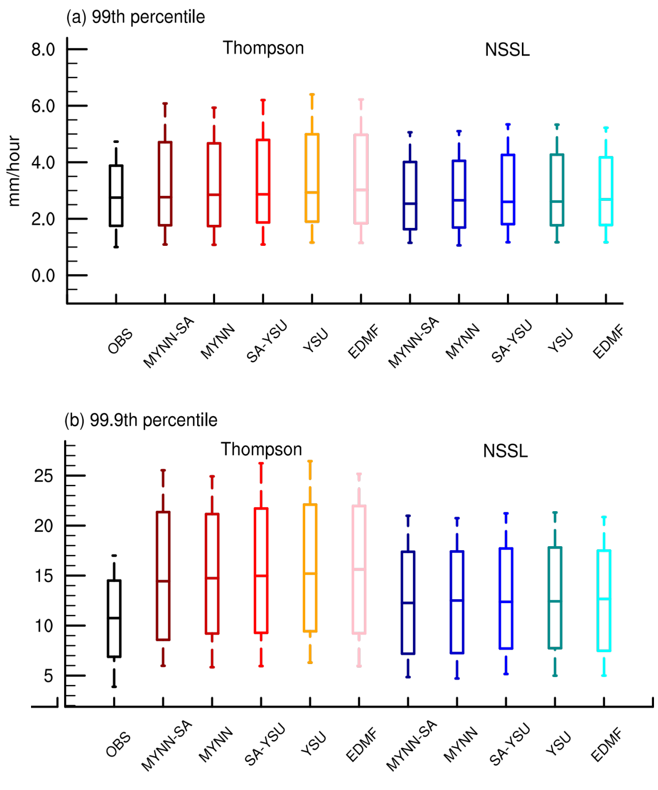
Note. All forecasts use Global Forecasting System (GFS) T1534 initial conditions, the Noah land surface model, Rapid Radiative Transfer Model for general circulation model (RRTMG) for long-wave and short-wave radiation, and the Tiedtke cumulus scheme for the global grid only. HWT, Hazardous Weather Testbed; NSSL, National Severe Storms Laboratory; PBL, planetary boundary layer; SFE, Spring Forecasting Experiment.

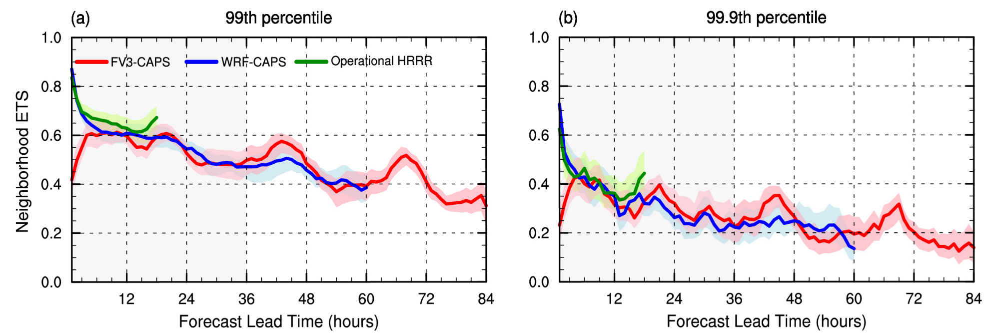
5 weeks of forecasts to 84 hours

Zhang, C., M. Xue, T. A. Supinie, F. Kong, N. Snook, K. W. Thomas, K. Brewster, Y. Jung, L. M. Harris, and S.-J. Lin, 2019: How Well Does the FV3 Model Predict Precipitation at a Convection-Allowing Resolution? Results from CAPS Forecasts for the 2018 NOAA Hazardous Weather Testbed with Different Physics Combinations. Geophys. Res. Lett., 46, 3523-3531.

CAPS FV3 Forecasts for HWT 2018

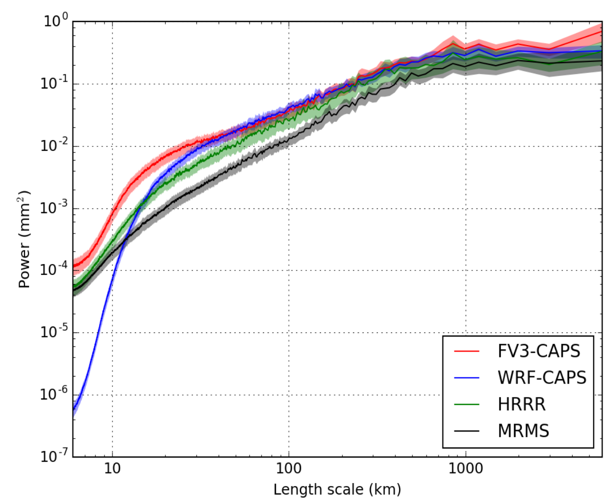
- To evaluate different physics for FV3 CAM forecasts





NETS for hourly precipitation from FV3-CAPS, WRF-CAPS and HRRR

Box-and-whisker plots of hourly precip at 99th and 99.9th percentile averaged over 12–36 h FV3 forecasts v.s. observations.



12-18h precipitation spectra MRMS, HRRR, CAPS FV3, and CAPS WRF. The lines are mean values from all 25 cases, while the shaded region indicates the 5th to 95th percentile range.

Zhang, C., M. Xue, T. A. Supinie, F. Kong, N. Snook, K. W. Thomas, K. Brewster, Y. Jung, L. M. Harris, and S.-J. Lin, 2019: How Well Does the FV3 Model Predict Precipitation at a Convection-Allowing Resolution? Results from CAPS Forecasts for the 2018 NOAA Hazardous Weather Testbed with Different Physics Combinations. Geophys. Res. Lett., 46, 3523-3531.

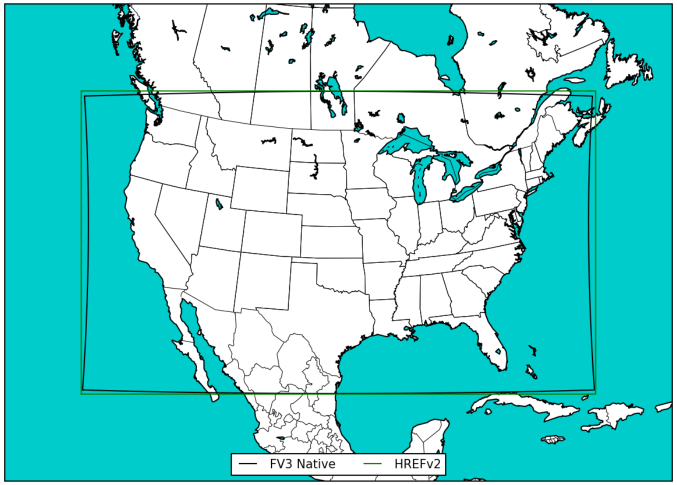
CAPS FV3-LAM Runs for 2020-21 WPC Winter Weather Experiment: Focusing on Physics Evaluation (Ongoing)

- Realtime runs initialized weekly at 00Z on Tuesdays from 3 Nov 2020 through 2 Mar 2021
  - Additional runs for two IOP weeks and other interesting cases
- 5 FV3-LAM members at 3 km grid spacing on CONUS ESG grid coordinated with EMC
- GFS IC and LBCs
- Physics configurations chosen with feedback from the CAM community (1st three close to HRRR, WoF and HAFS settings)

Physics Configurations

Experiment	Microphysics	PBL	Surface Layer	LSM
CNTL	Thompson	MYNN-EDMF	MYNN	NOAH
MP1	NSSL	MYNN-EDMF	MYNN	NOAH
MP2	Ferrier-Aligo	K-EDMF	GFS	NOAH
LSM1	Thompson	MYNN-EDMF	MYNN	RUC
LSM2	Thompson	TKE-EDMF	GFS	NOAHMP

All runs use RRMTG radiation. GFS IC and LBC

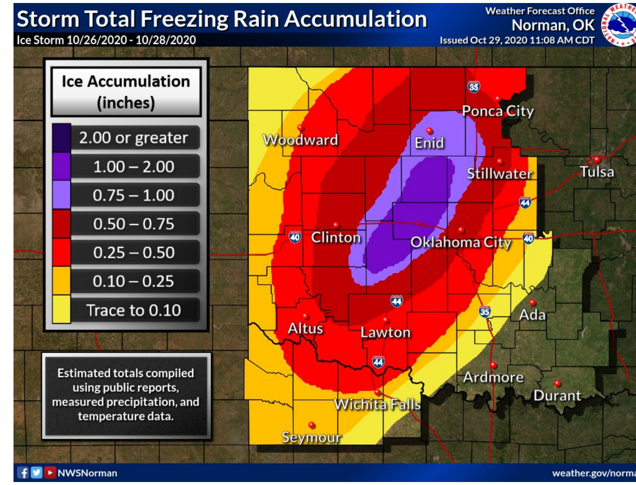


http://www.caps.ou.edu/~nsnook/HMT_winter/

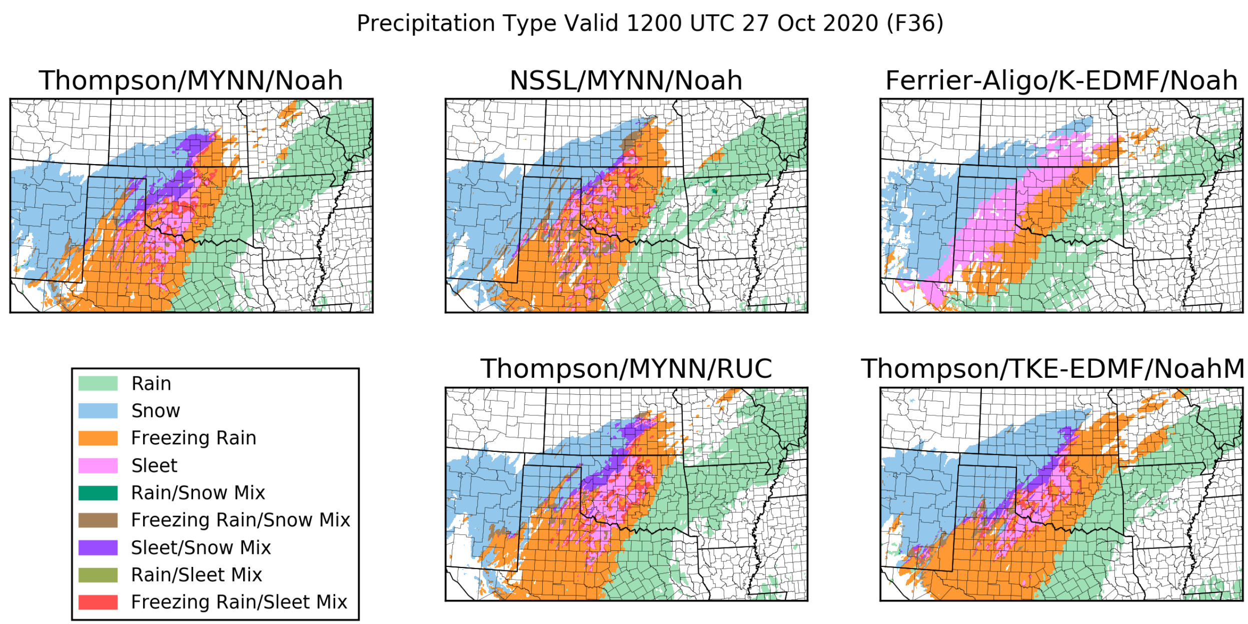
Supported by HMT Testbed Grant, UFS R2O Grant

Precipitation Type Forecast (+36h) for October 26, 2020 Oklahoma Ice Storm

- Ferrier-Aligo member uses NCEP column-based diagnostic, all others use explicit HRRR-type diagnostic
- All members have freezing rain in generally the correct band
- Column-based diagnostics appear to work better
- Thompson has more sleet (graupel) mixed with freezing rain

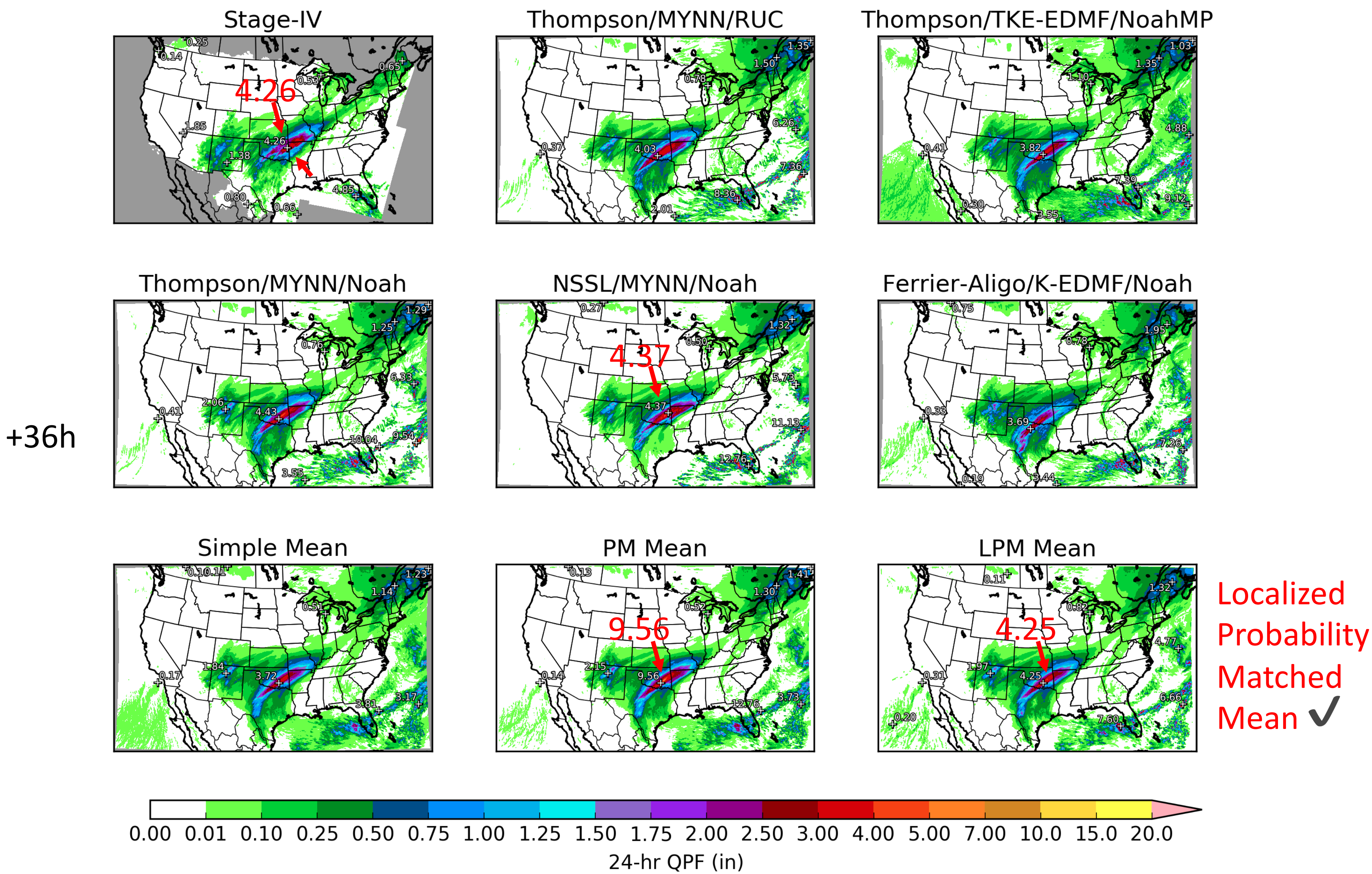


OU was closed for 2 days



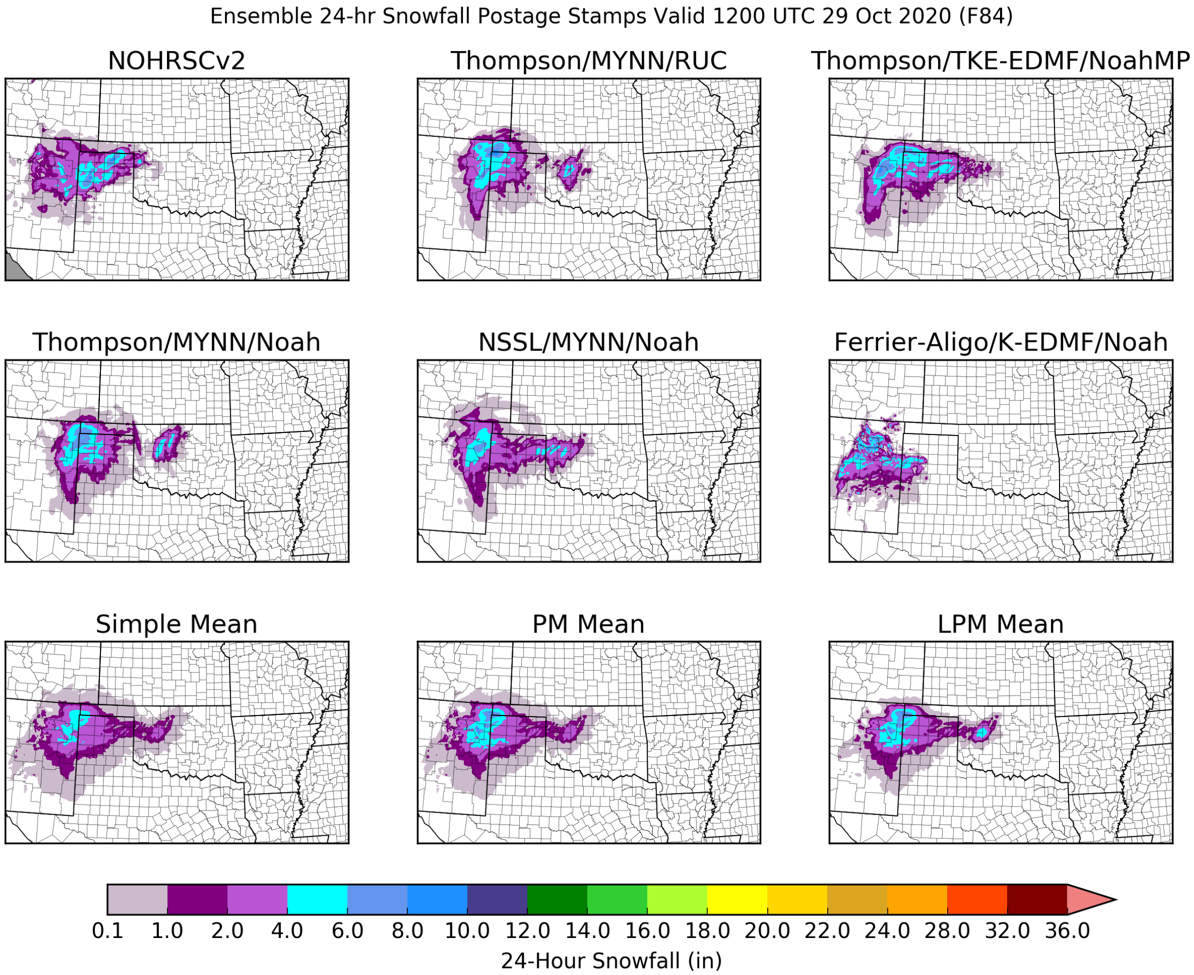
24-hr Accumulated Precip (+36h)

Ensemble 24-hr QPF Postage Stamps Valid 1200 UTC 27 Oct 2020



24-h Snow Accumulation Forecast Valid at 12 UTC 26 Oct 2020 (+84h)

- Model snow precip masked by diagnosed snow ptype
- Assumed 10:1 ratio
- NOHRSCv2 analysis used as "truth"
- All members get >2" snow in generally the right place
    - Ferrier-Aligo member displaced to the south
    - Thompson too aggressive in central OK



CAPS SAR-FV3 Runs for 2019-20 WPC Winter Weather Experiment

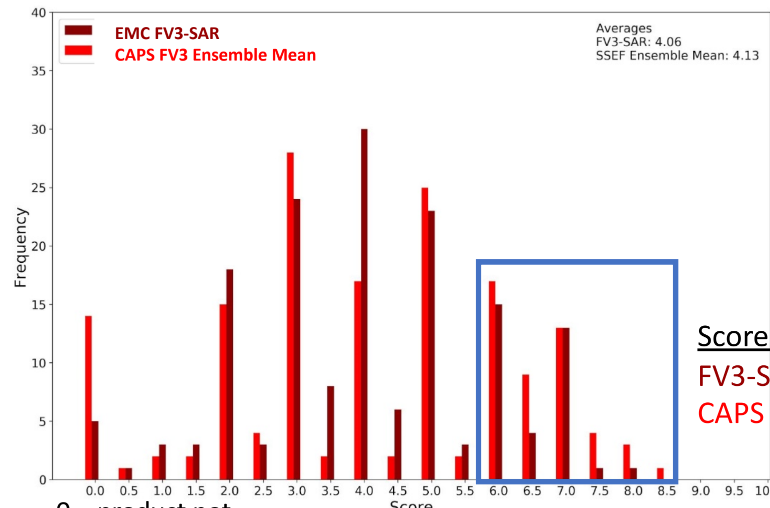
Physics Configurations

member	Microphysics	PBL	SFC layer	LSM
cntl	GFDL	K-EDMF	GFS	NOAH
mp1	Thompson	K-EDMF	GFS	NOAH
mp2	NSSL	K-EDMF	GFS	NOAH
pbl1	Thompson	MYNN	GFS	NOAH
pbl2	NSSL	MYNN	GFS	NOAH

All runs use RRMTG radiation. NAM IC and LBC

- Weekly realtime runs at 00Z on Tuesdays from 3 Nov 2020 through 2 Mar 2021
- 5 SAR FV3 runs on 3 km grid CONUS with MP and PBL physics
- NAM IC and LBCs
- HMT mainly evaluated CAPS ensemble mean forecasts

Subjective Scores from HMT WWE Final Report

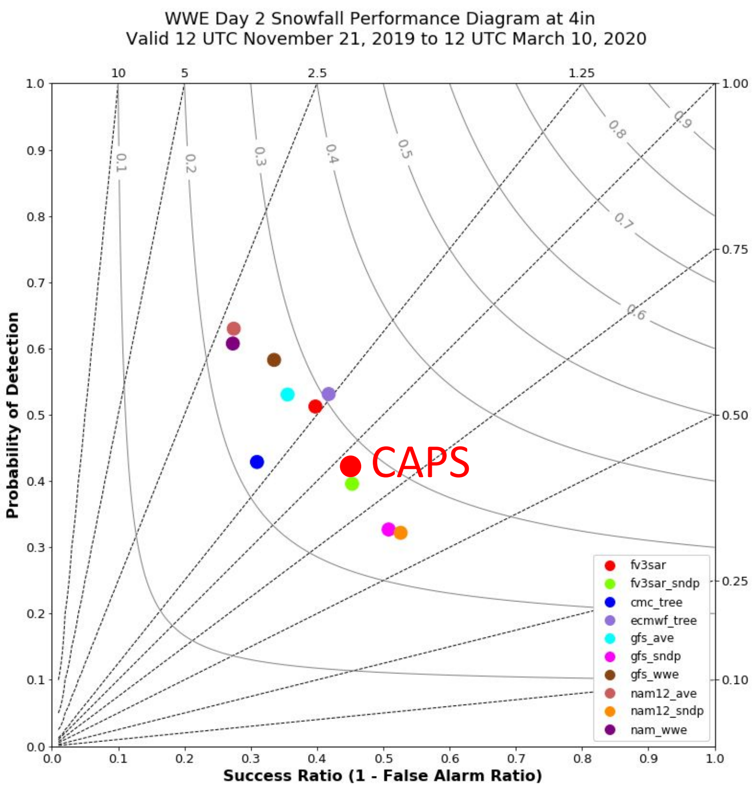


0 = product not available

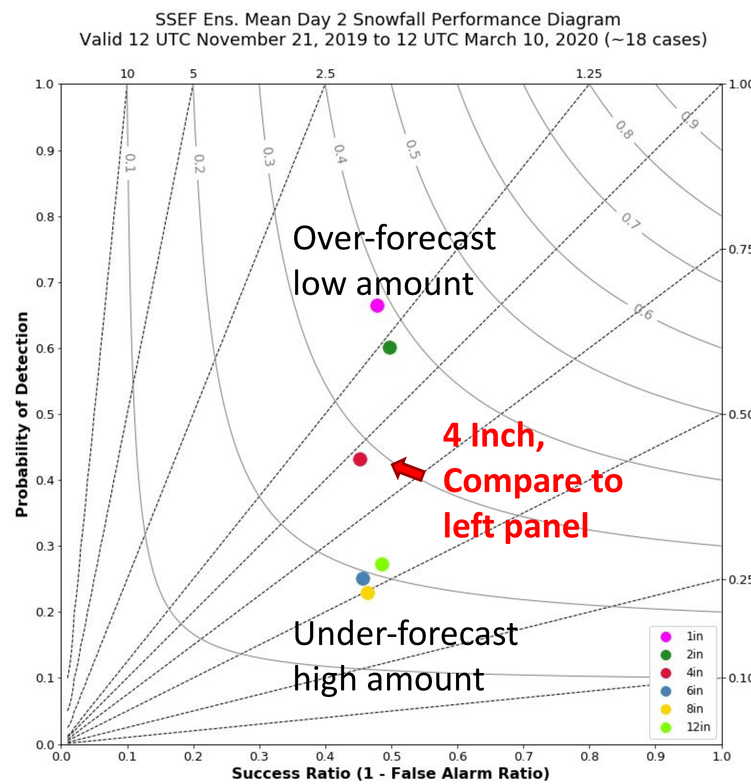
Scored 6+:
FV3-SAR: 19.
CAPS SSEF: 30

Supported by HMT Testbed Grant

Performance Diagrams for Day 2 Snowfall – From HMT Winter Final Report



CAPS Ensemble Mean (tends to be smoothed)



2020 CAPS SAR-FV3 forecasts for FFaIR

1-h Rainfall 45-km Neighborhood ETS

All runs use RRMTG radiation.

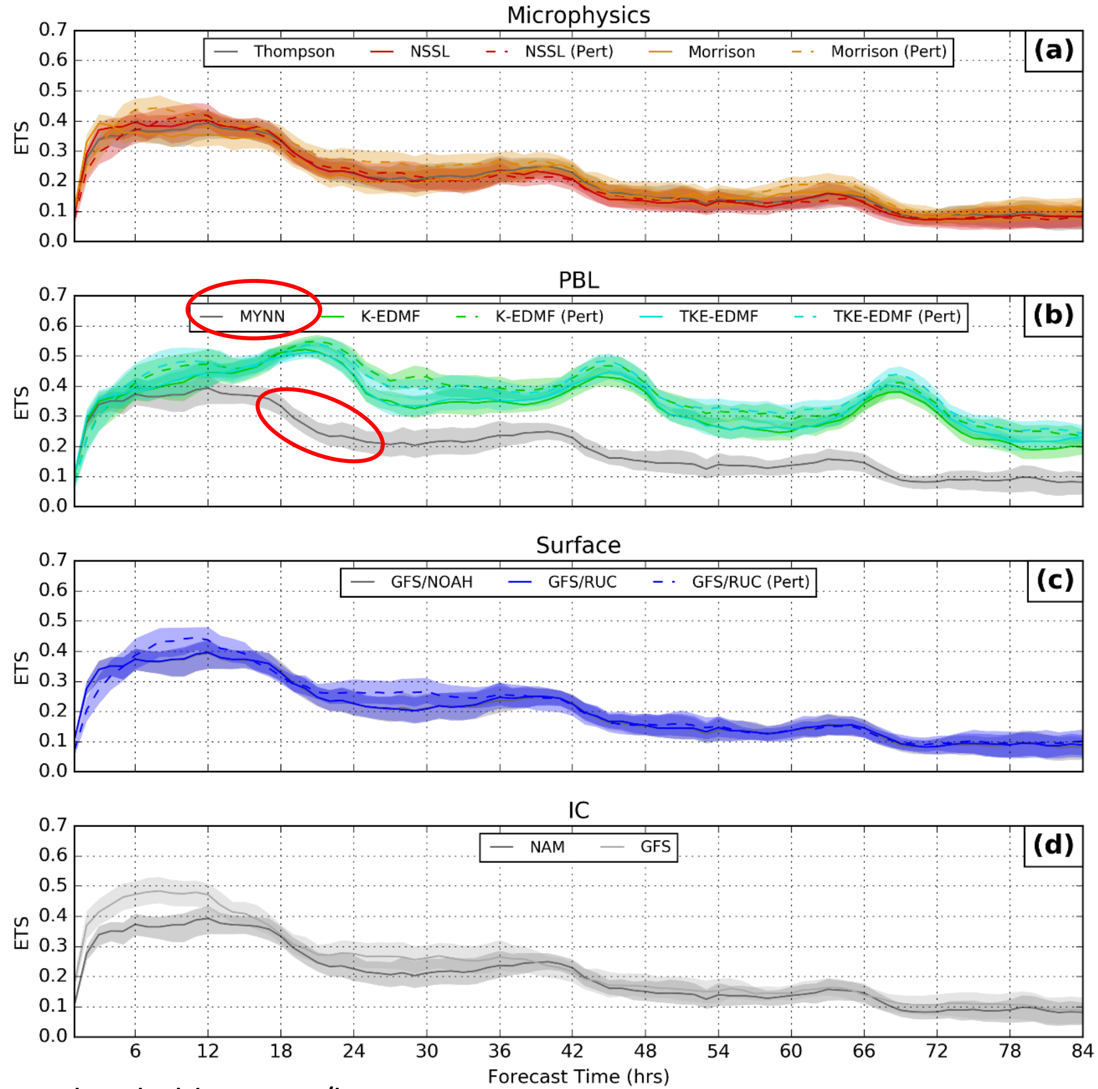
Physics Configurations

Name	MP	PBL	LSM	IC
cntl	Thompson	MYNN	Noah	NAM
mp1	NSSL	MYNN	Noah	NAM
mp2	Morrison-G	MYNN	Noah	NAM
lsm	Thompson	MYNN	RUC	NAM
pbl1	Thompson	K-EDMF	Noah	NAM
pbl2	Thompson	TKE-MF	Noah	NAM

With IC Perturbations

Name	MP	PBL	LSM	IC
cntl	Thompson	MYNN	Noah	GEFS
mp1	NSSL	MYNN	Noah	GEFS
mp2	Morrison-G	MYNN	Noah	GEFS
lsm	Thompson	MYNN	RUC	GEFS
pbl1	Thompson	K-EDMF	Noah	GEFS
pbl2	Thompson	TKE-MF	Noah	GEFS

Unfortunately, MYNN in the version used had bug → Poor scores. Rerunning the bad members



Threshold=0.01 in/h

Concluding Remarks

- Capabilities to directly assimilate radar Z and Vr data and GLM FED data, with EnKF and EnVar have been developed within GSI framework.
- Various treatments evaluated systematically with retrospective cases with WRF and FV3-LAM, on smaller and CONUS 3 km grids, mostly with HRRR physics suite. EnVar sometimes outperforms EnKF, not always.
- The EnVar radar DA capabilities compared systematically with HRRRv3 and HRRRv4. The direct DA method outperformed both, even though the ensemble perturbations used were sub-optimal (off in timing).
- The use of 15-min perturbations from HRRRDAS with current timing improved results in one case tested so far. Self-consistent ensemble DA should be coupled with EnVar. 15 min radar DA seems to be reasonably adequate.
- FV3-LAM with different physics suites were run for HWT SFE and HMT FFaIR and WWE. Some combinations do show problems, and a few schemes tested show clear interior performance, while other 'good' schemes are hard to separate in performance.
- Both Z and FED operators in DA should be consistent with MP scheme used.
- The radar and lightning DA capabilities in GSI are ready to be moved into JEDI, and beg to be used in future RRFS (and WoFS and HAFS).

Ack: Chengsi Liu, Youngsun Jun, Jeff Dudda, Rong Kong, Keith Brewster, Nathan Snook, Tim Supinie, Chong-chi Tong, Lianglv Cheng, Chunxi Zhang, Huiqi Li, Jun Park, Fanyou Kong, Jacob Carley, Curtis Alexander, Alex Fierro, Ted Mansell, Luo Wicker, Pam Heinselman, Adam Clark, Jim Nelson, et al. et al…