Reflectivity Assimilation using Cloud Analysis and Ensemble Kalman Filter

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Outline of Talk

- Radar Reflectivity Observations
- Complex Cloud Analysis within the ARPS System
- Case studies and realtime forecasts using ARPS 3DVAR/Cloud analysis
- Radar Reflectivity (and Vr) DA using EnKF
- Concluding Remarks

Radar Reflectivity Measurement

- Radar reflectivity factor represents total amount of scattering of hydrometeors integrated over the drop size distributions (DSD).

- Equivalent reflectivity factors for rain, rain-snow/hail mixtures, and dry snow/hail ($x = r, s, h$) are given by :

$$Z_{e,x} = \int_0^\infty N(D) D^6 dD$$

- Total reflectivity in dBZ:

$$Z = 10 \log_{10} \left(Z_{e,r} + Z_{e,s} + Z_{e,h} \right)$$

Reflectivity Formulae for Precipitating Hydrometeors

Assuming exponential DSD,

$$n_x(D) = n_{0x}\exp(-\lambda_x D_x) \qquad \text{where} \quad \lambda_x = \left(\frac{\pi\rho_x N_{0x}}{\rho q_x}\right)^{0.25} \text{ is DSD slope}$$

The resulting (equivalent) reflectivity formulae are:

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

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

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

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

Z_e in mm^6/m^3

q_r, q_s, q_h in kg/kg

Precipitating Hydrometeors (cont.)

$$Z_e = Z_e(q_r, q_s, q_h, N_{0r}, N_{0s}, N_{0h}, etc.)$$

Hydrometeor mixing ratios are assigned based on inverse of the reflectivity formulae.

$$Z = 10\log(Z_e)$$

$$Z_e = 10^{(Z/10)}$$

Measured Z_e is partitioned into Z_r, Z_s & Z_h based on cloud type identification scheme and temperature.

Problem is under-determined! Need help! From physical constraints, e.g., numerical model.

Solutions

- 4DVAR uses model equations as a strong constraint (but has difficulties with nonlinear ice physics), and multi-time level data
- EnKF uses model constraints in a statistical representation, and accumulate info in time.
- Complex cloud analysis schemes employ physical models (e.g., parcel theory) and semi-empirical rules, and observations, and update state variables that they can.

ARPS Complex Cloud Analysis

- Construct 3D cloud fields using radar reflectivity data, surface cloud observations, satellite data, and the background from previous forecast by semi-empirical rules.
- Retrieve hydrometeors and adjusts in-cloud temperature and moisture.

ARPS Cloud Analysis

- GOES Satellite Data
  - Vis: Cloud fraction
  - IR: Cloud top temperature
- Radar Data
  - Reflectivity to precipitation hydrometeors
- Surface Observations
  - Cloudbase height
- Originated from the LAPS cloud analysis, with adaptation and updates by Jian Zhang and Keith Brewster, et al.

(also Xue et al. 2003 MAP, Hu et al. 2006 MWR)

Estimating the Cloud Water

- Use parcel theory to find saturation dq_{vsat}/dz and increment cloud water
- Water is carried with parcel - less a mixing/dilution factor (Warner curve)
- Ice created when colder than –10 C
- Cloud water/ice reduced in later step if precipitating hydrometeors are prescribed (presumed converted by coalescence or aggregation)

In-cloud temperature adjustment (Diabatic Heating)

- Original:

$$\Delta\theta' = \beta_\theta L_v (\Delta q_c + \Delta q_i) / (c_p \pi)$$

- Updated:
  - Moist-adiabatic temperature profile
  - Warner entrainment curve
  - Heating applied only in updraft regions

Moisture adjustment

- Adjusted to saturation within cloudy regions.
- May be optionally applied to the first analysis cycle only.
- Analysis increments may be applied incrementally via Incremental Analysis Update (IAU) to reduce shock.
- Cloud analysis is typically combined with ADAS or 3DVAR (including Vr data)

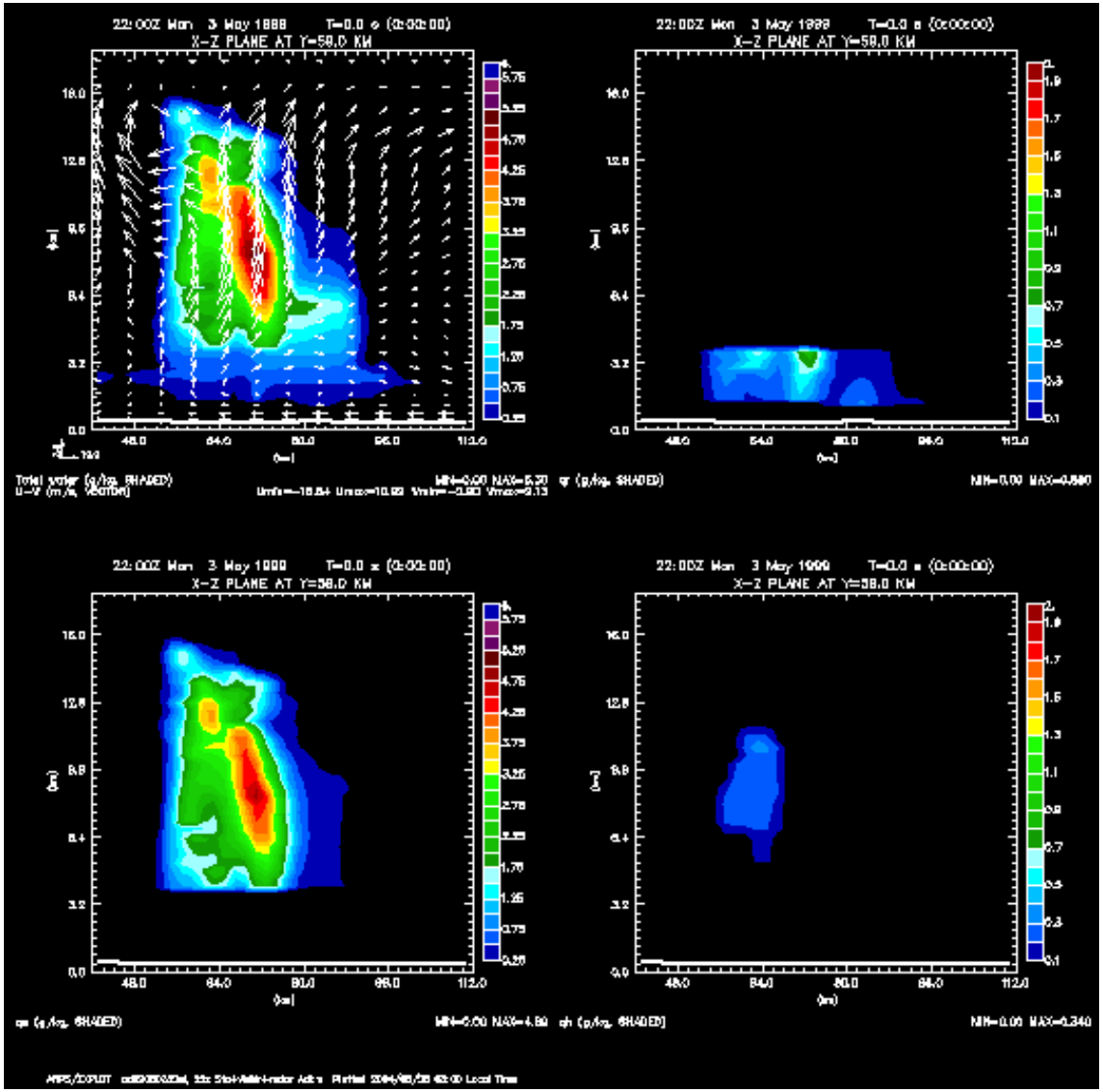
Sample Hydrometeor Vertical Cross Sections

Total Water

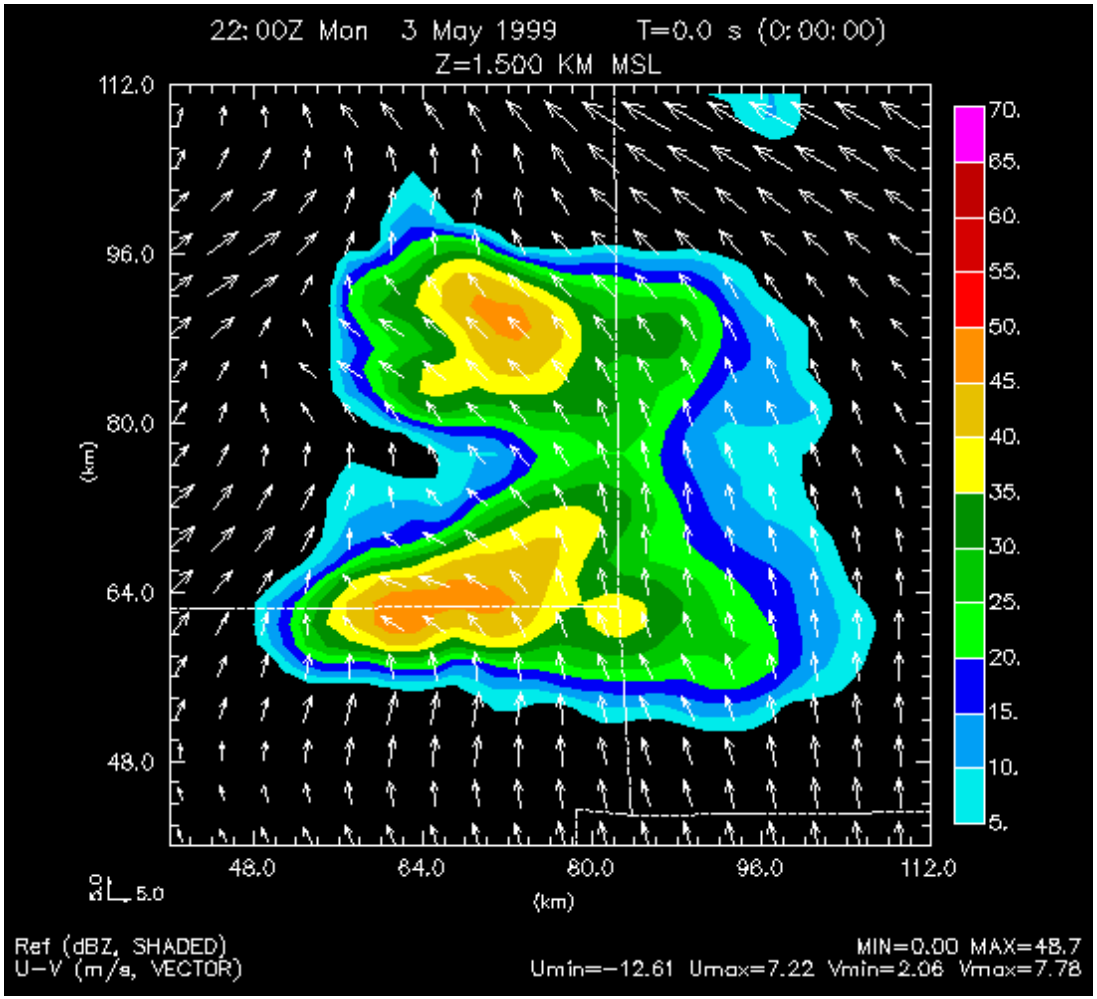
Rain

Snow

Hail



Initial Model Reflectivity and Wind for May 3rd, 1999 Tornado Case



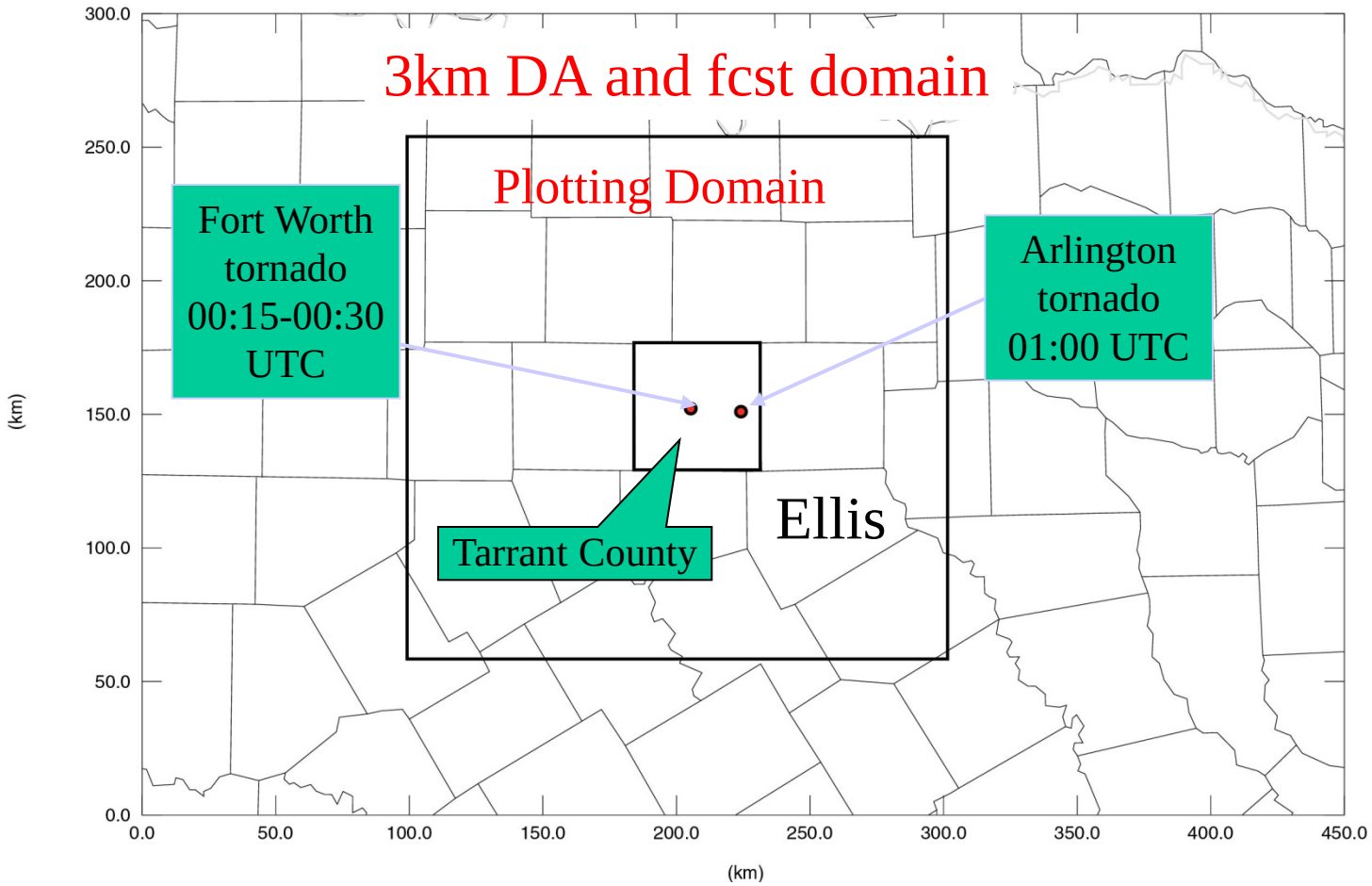
Case Studies and Systematic Realtime Forecast Evaluations

Fort Worth Tornado Case

- Fort Worth area tornadoes of 28 Mar 2000
- ADAS/3DVAR with Cloud Analysis
- 9-km ARPS Forecast 18 UTC-06 UTC
- 3-km ARPS Nested Forecast 23 UTC-06 UTC
- 10-min analysis cycle for 1 hour using NEXRAD Level-II Winds 22 UTC-23 UTC.
- Experiments
  - Vr and Z
  - Vr Alone
  - Z Alone

Fort Worth Tornado Case

Analysis domain and period



- Analysis focus on 00:15-01:00 UTC

List of Experiments

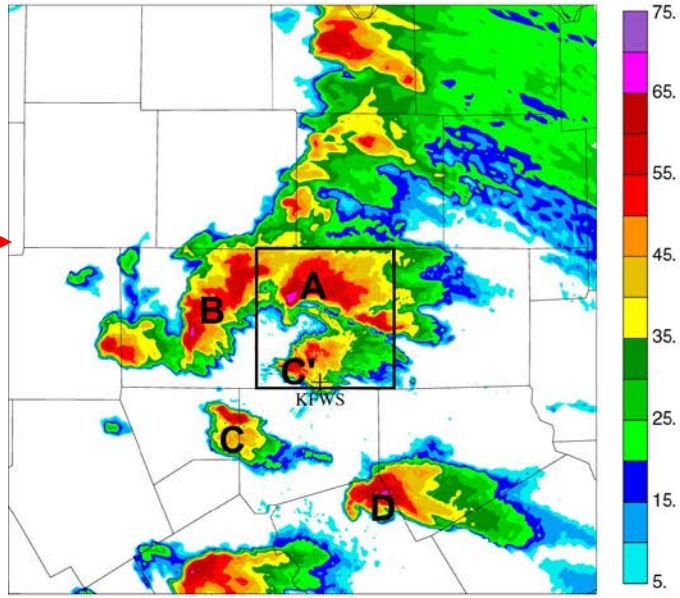
Experiment Name	Use of Reflectivity	Use of radial velocity	Mass continuity constraint
CNTL	Yes	Yes	$J_c = \frac{1}{2}(1000)^2 \left(\frac{\partial \bar{\rho} u}{\partial x} + \frac{\partial \bar{\rho} v}{\partial y} \right)^2$
CLD	Yes	No	N.A.
Vr	No	Yes	$J_c = \frac{1}{2}(1000)^2 \left(\frac{\partial \bar{\rho} u}{\partial x} + \frac{\partial \bar{\rho} v}{\partial y} \right)^2$

- Data from single Fort-Worth radar are used

Hu et al. (2006a,b)

Radar observation

Radar Observation

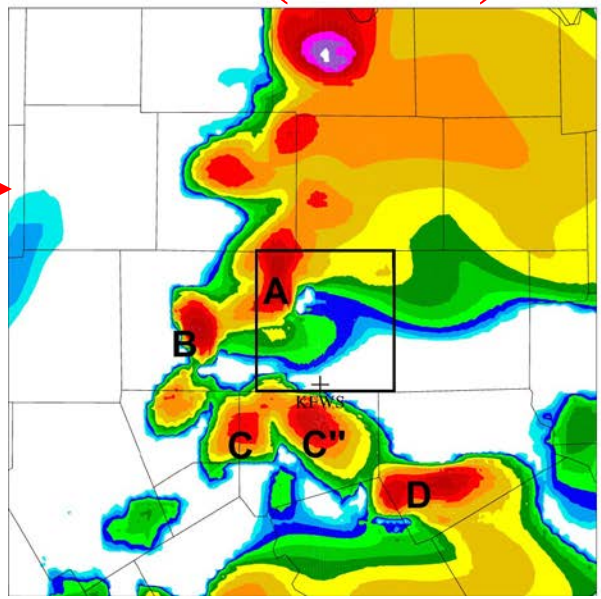


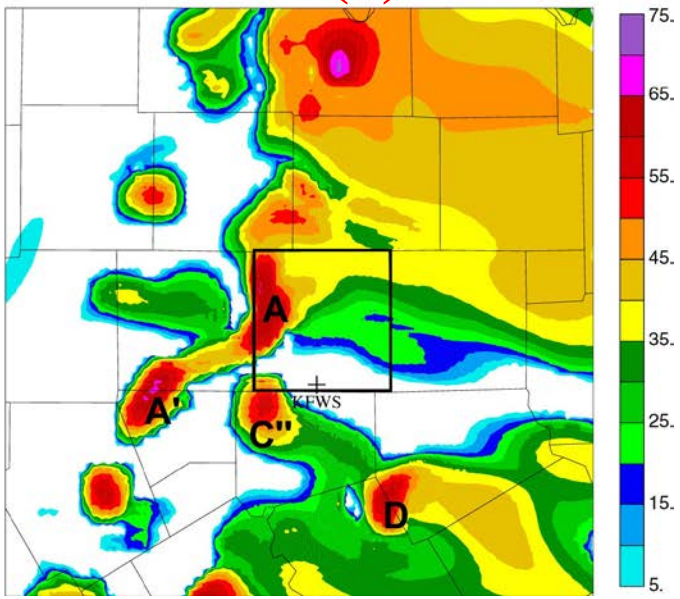
Reflectivity at 1.45° radar elevation at 00:15 UTC, 3/29/2000

CNTL (Vr and Z)

CLD (Z)

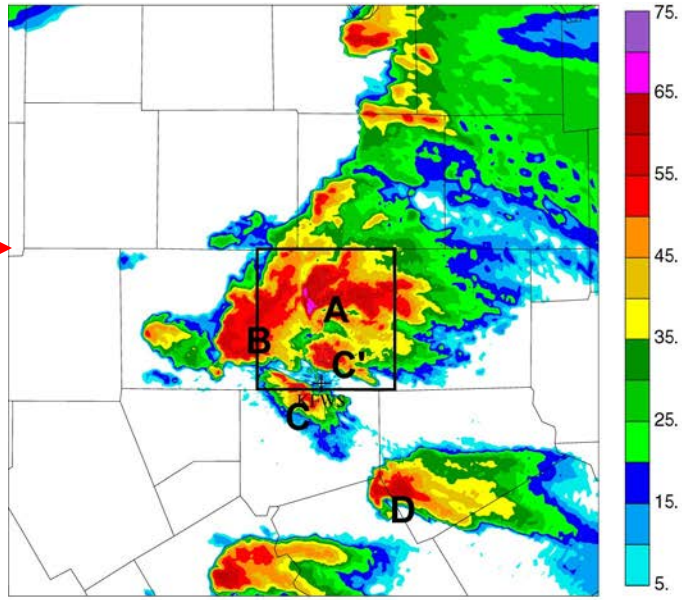
1h 15m Prediction





Radar observation

Radar Observation

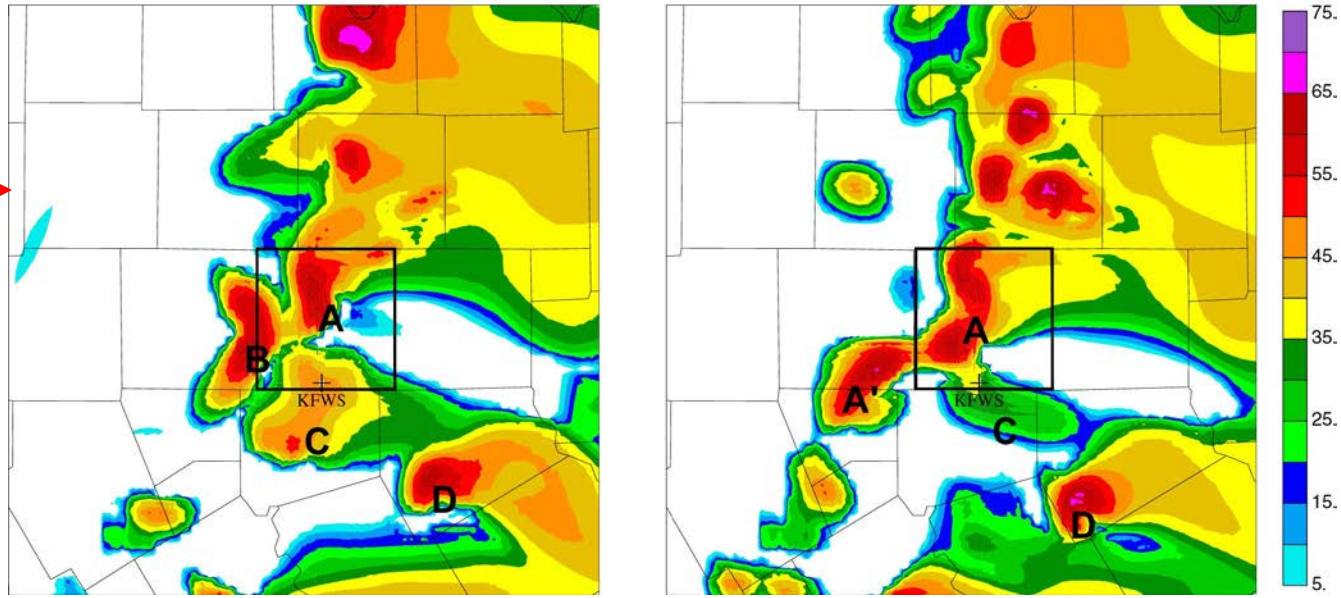


Reflectivity at 1.45° radar elevation at 00:30 UTC, 3/29/2000

CNTL (Vr and Z)

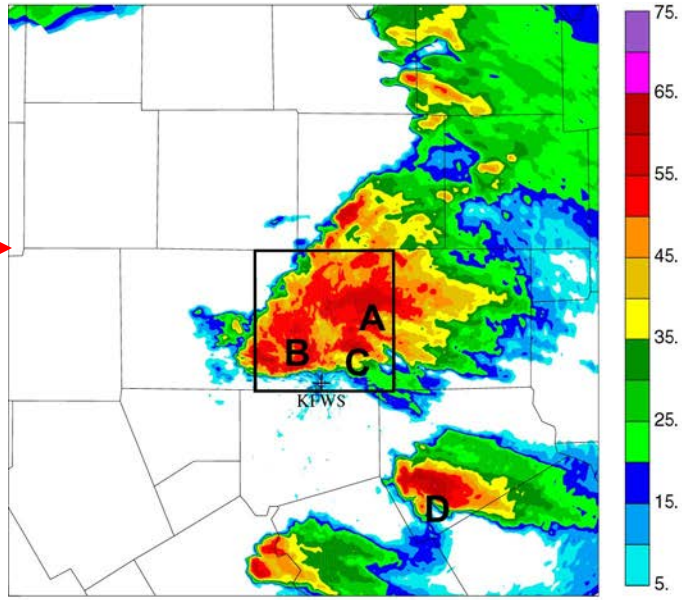
CLD (Z)

1h 30m Prediction



Radar observation

Radar Observation

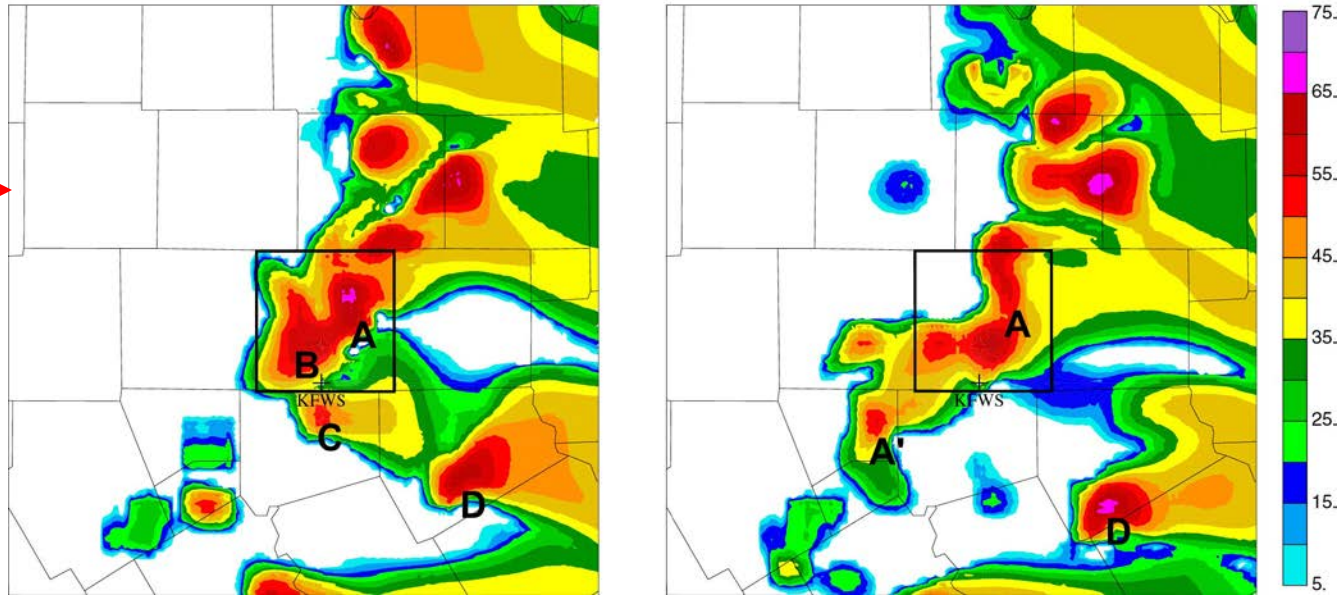


Reflectivity at 1.45° radar elevation at 00:45 UTC, 3/29/2000

CNTL (Vr and Z)

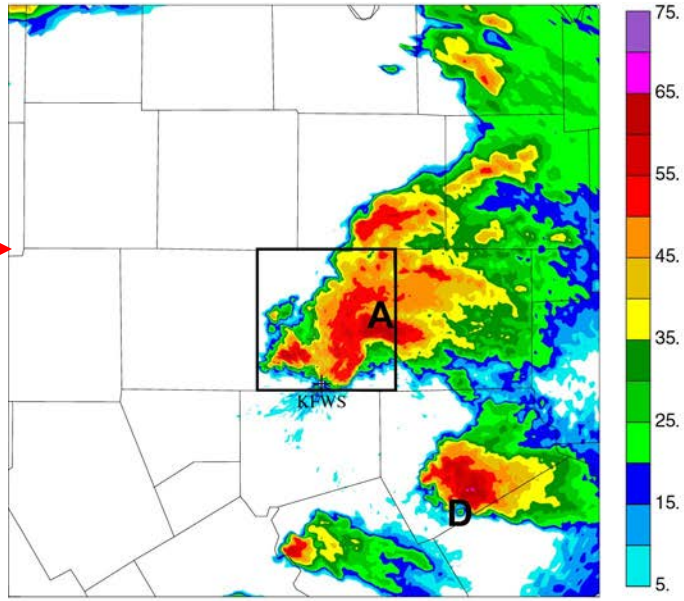
CLD (Z)

1h 45m Prediction



Radar observation

Radar Observation

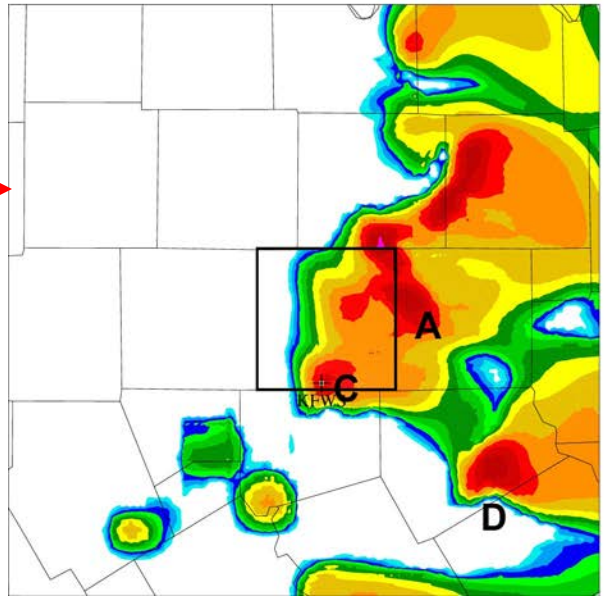


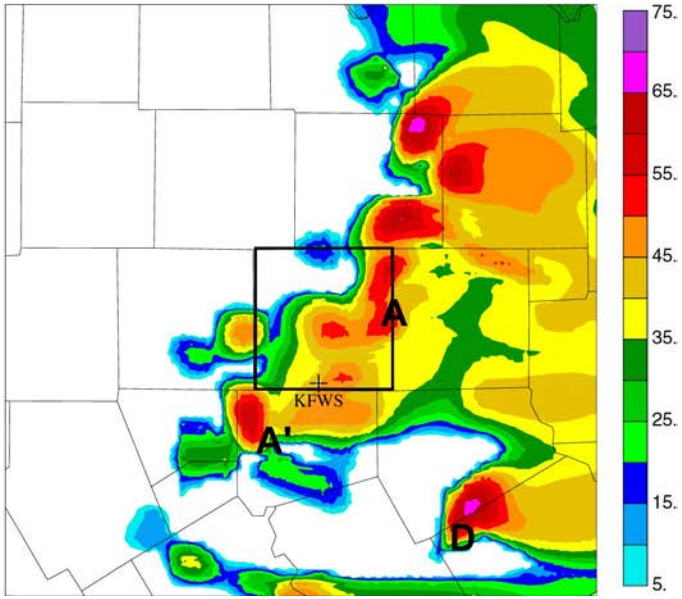
Reflectivity at 1.45° radar elevation at 01:00 UTC, 3/29/2000

CNTL (Vr and Z)

CLD (Z)

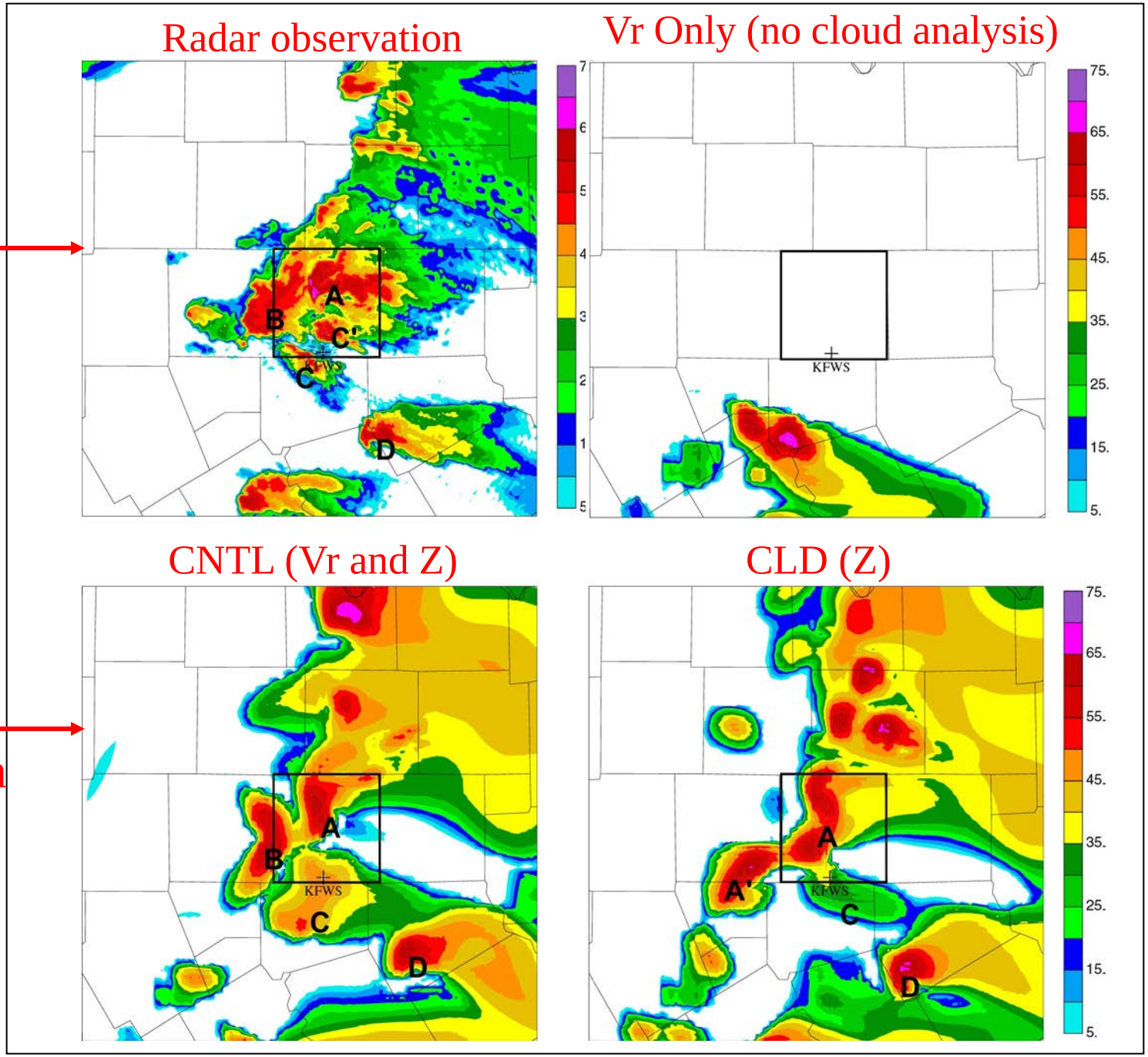
2h Prediction





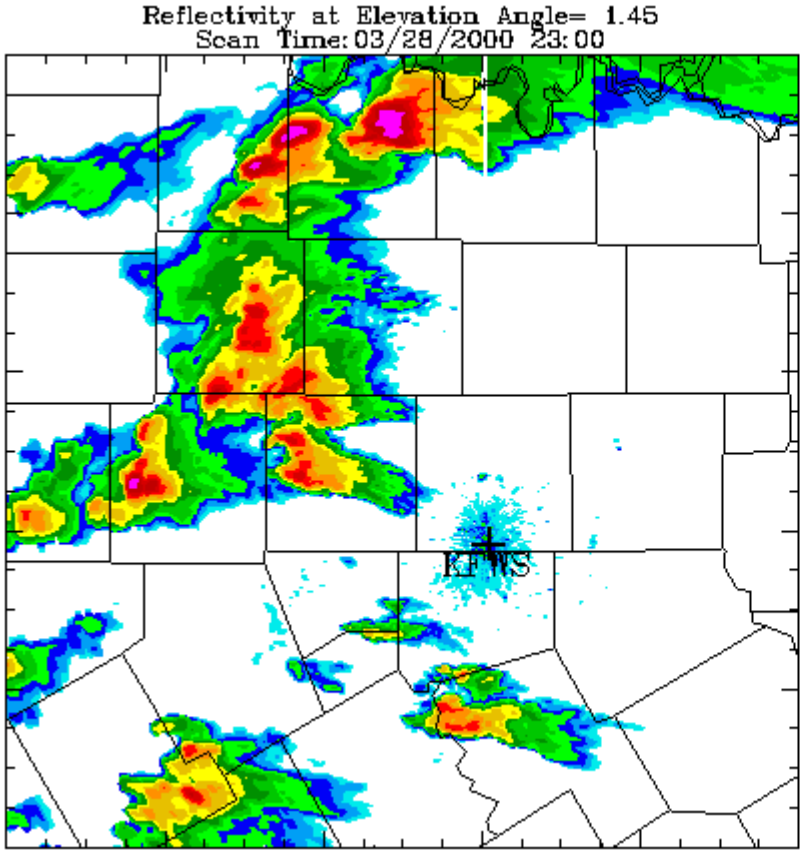
Radar Observation

1h 30m Prediction

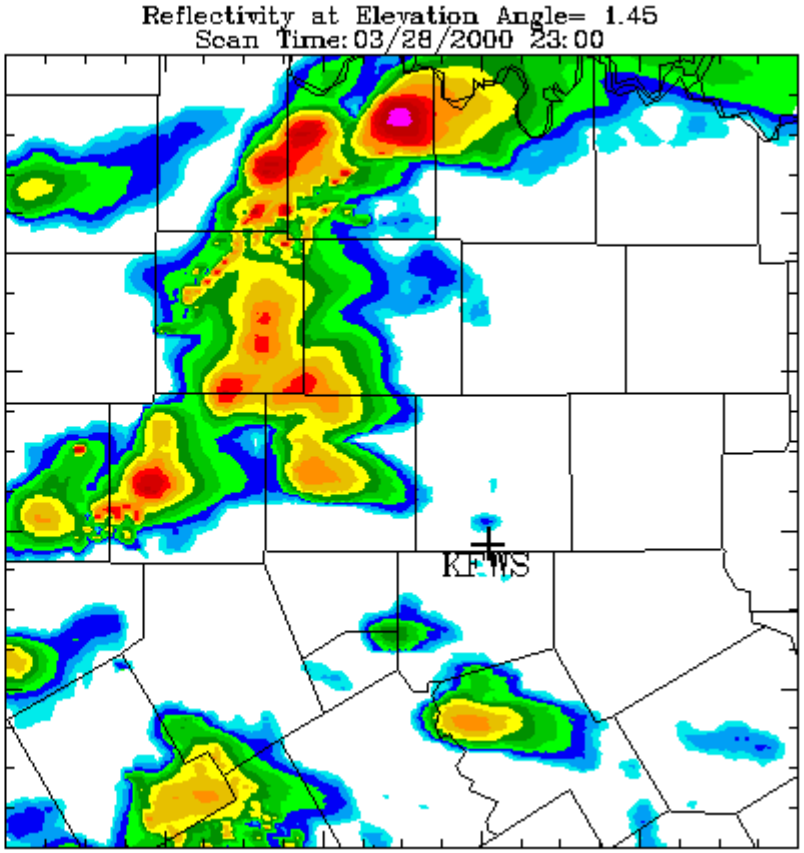


Forecast of experiment CNTL

Radar observation



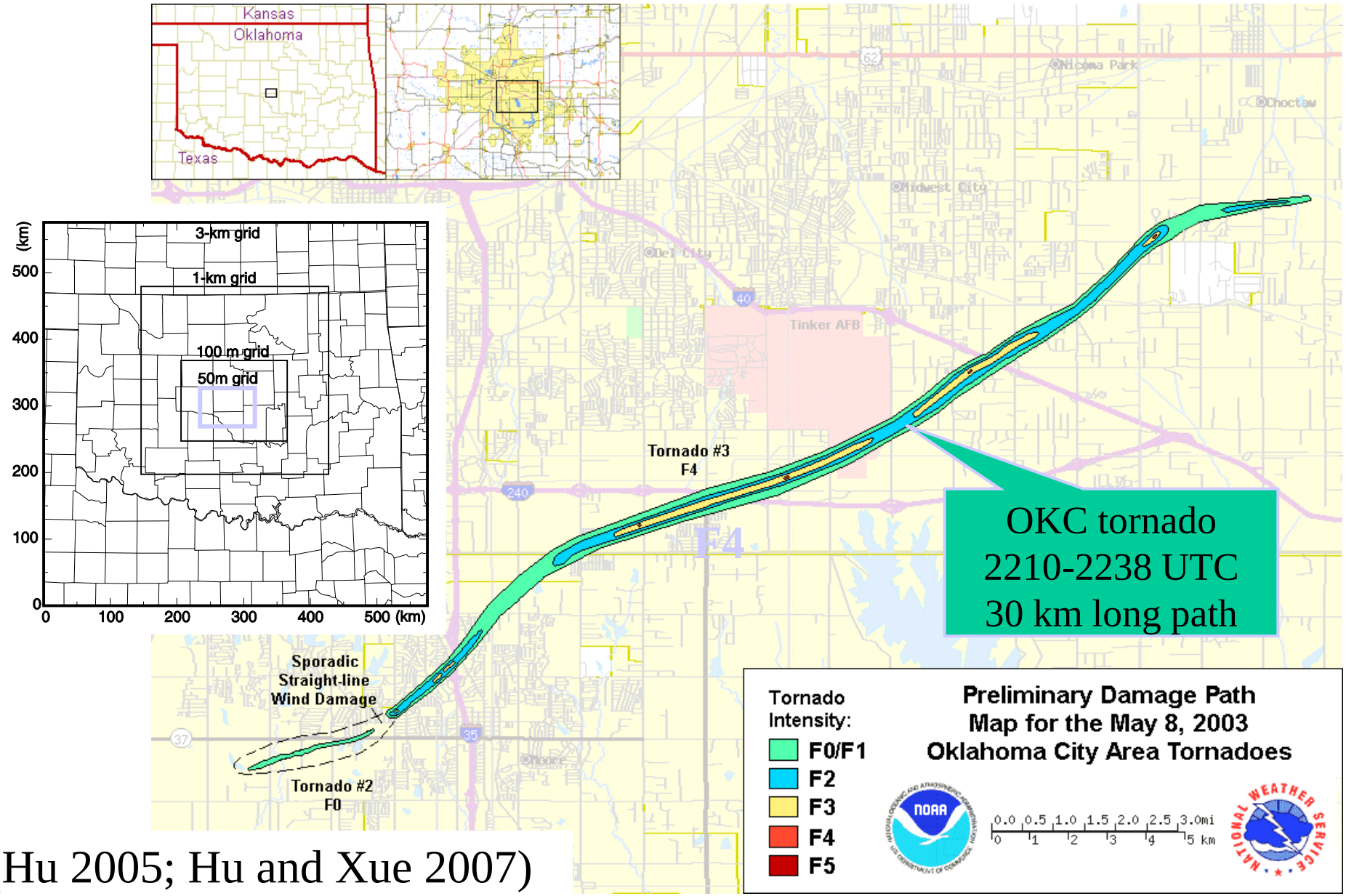
Forecast of CNTL



Ft Worth Case Conclusions

- Accurate short-term predictions of individuals cells at 3-km grid spacing including development of significant surface rotation associated with two rotating supercells
- Reflectivity data via cloud analysis most important.
- Better forecast with both Z and Vr data
- Wind data alone not sufficient to develop correct storms

May 8th, 2003 OKC Tornado Case

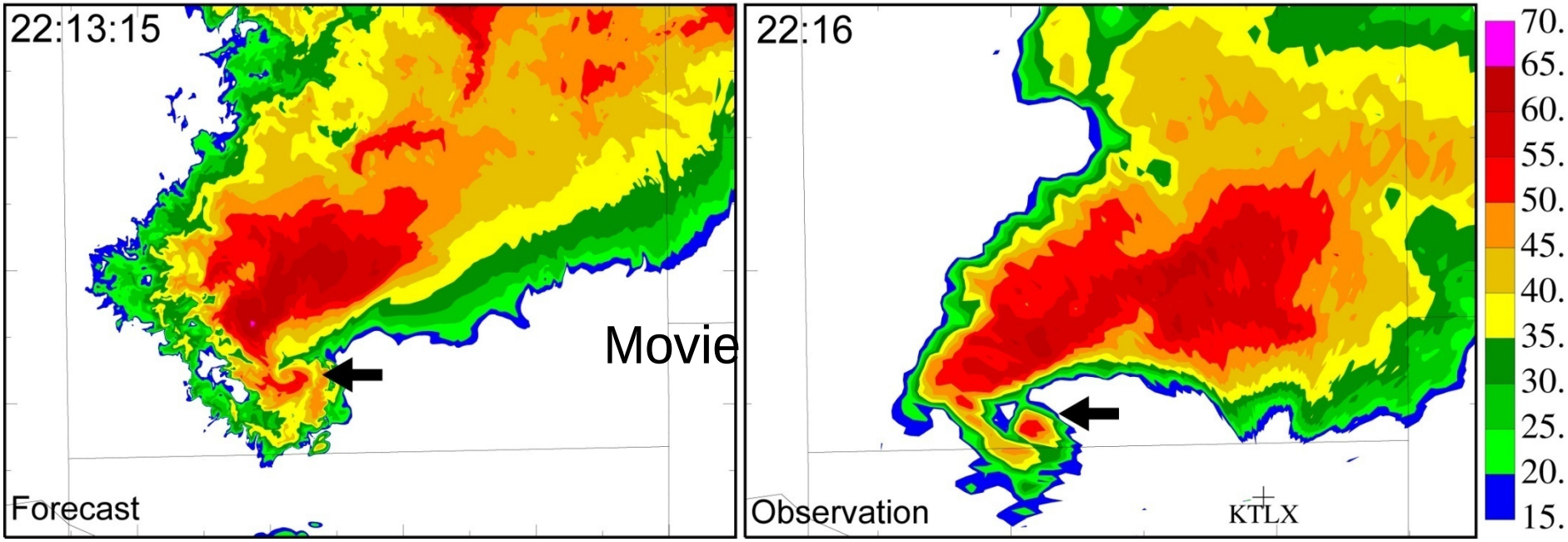


(Hu 2005; Hu and Xue 2007)

50 m grid forecast initialized with 3DVAR/Cloud analysis of radar data on 1 km grid

(May 8, 2003 OK Tornadic Thunderstorm)

50-m Grid Forecast v.s. Observation (Movie)



Forecast Low-level Reflectivity

Observed Low-level Reflectivity

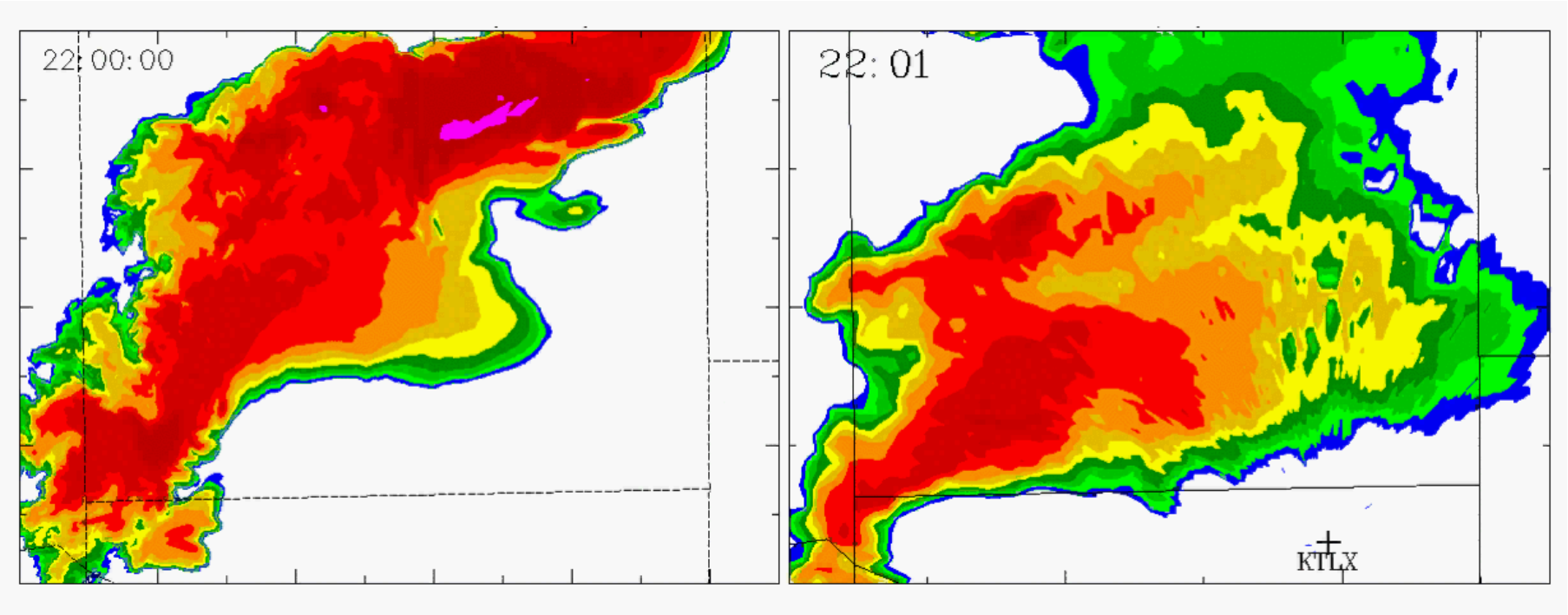
43 minute forecast

(Hu and Xue 2007 MWR, Xue et al. 2007)

Prediction using the ARPS Model with radar data assimilation for the May 8, 2003 OKC Tornado

Using 3DVAR/Cloud Analysis DA

50-m Grid Forecast v.s. Observation



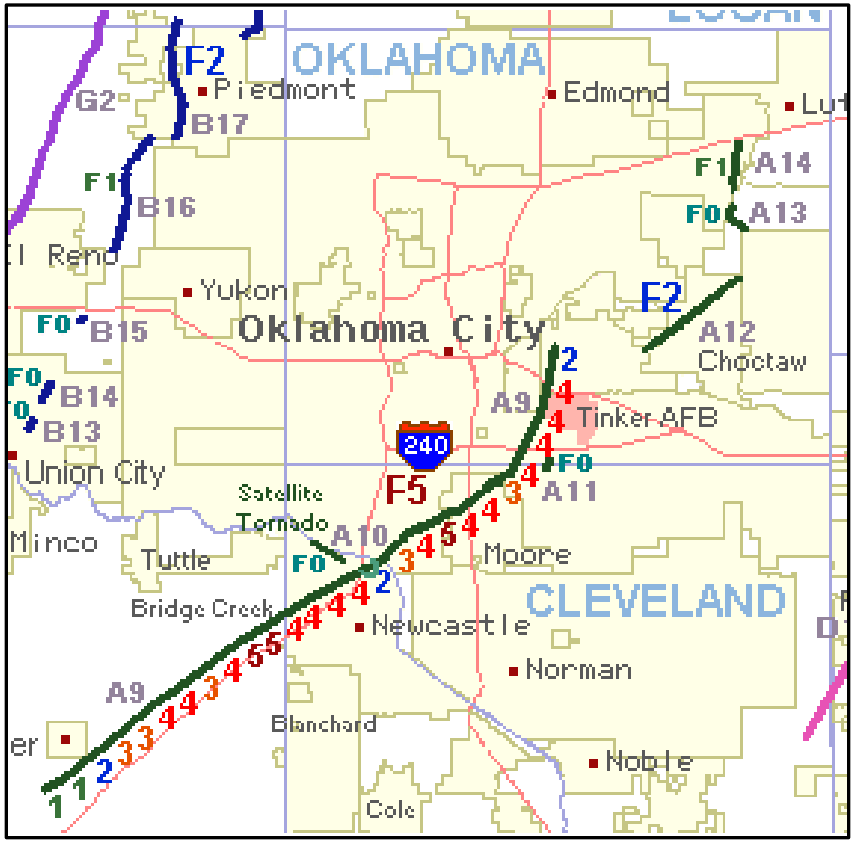
Forecast Low-level Reflectivity

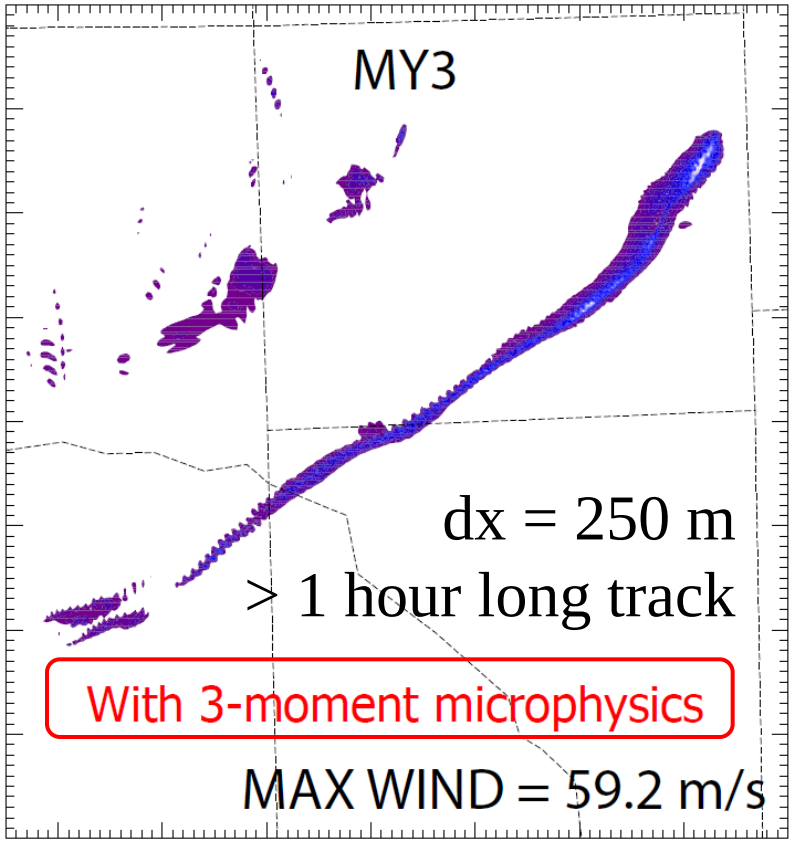
Observed Low-level Reflectivity

43 minute forecast

Used ARPS 3DVAR/Cloud analysis DA

3 May 1999 F5-Tornado Outbreak in Central Oklahoma



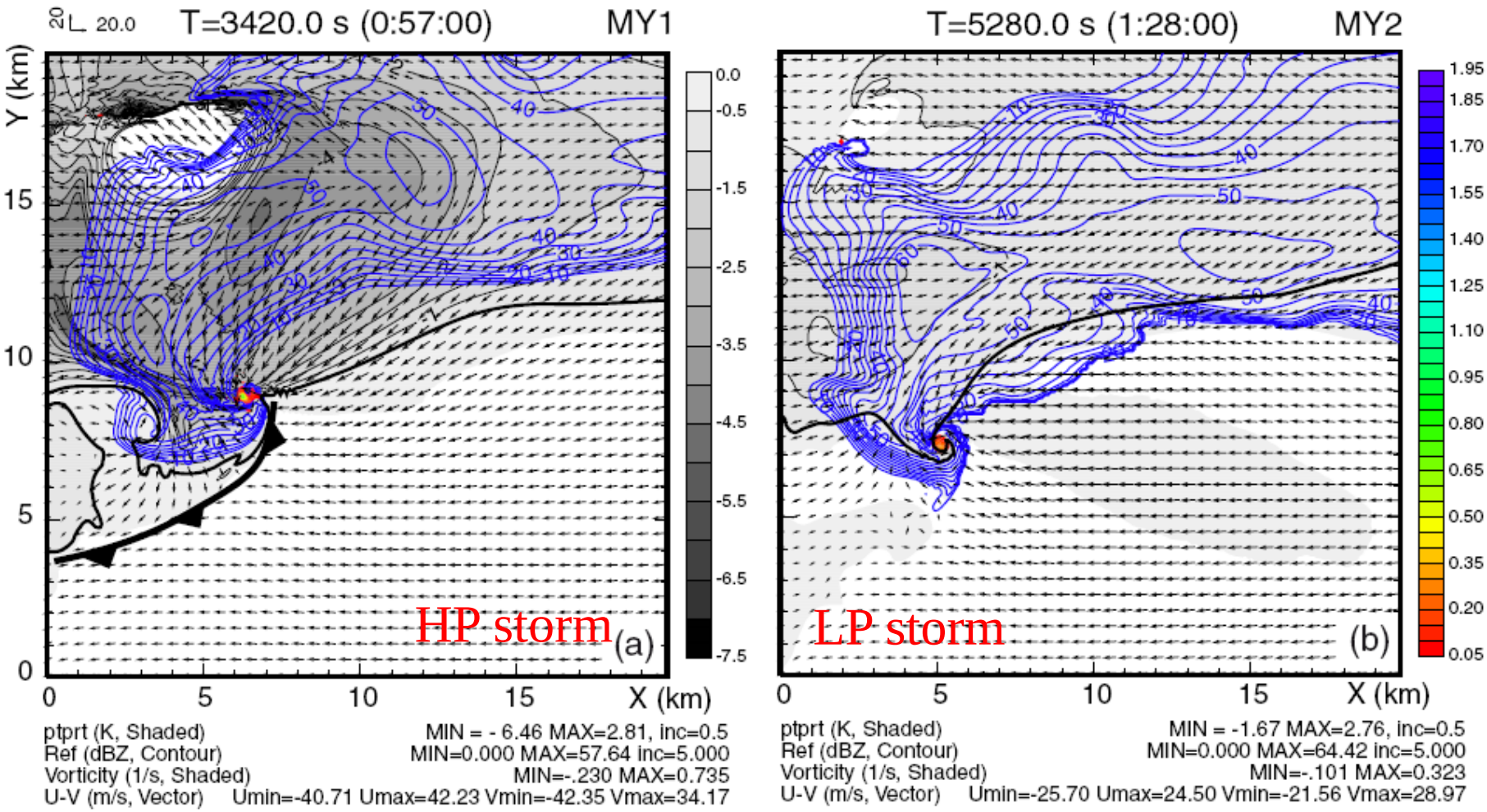


cs

Observed Damage Track v.s Predicted Surface Wind Swaths

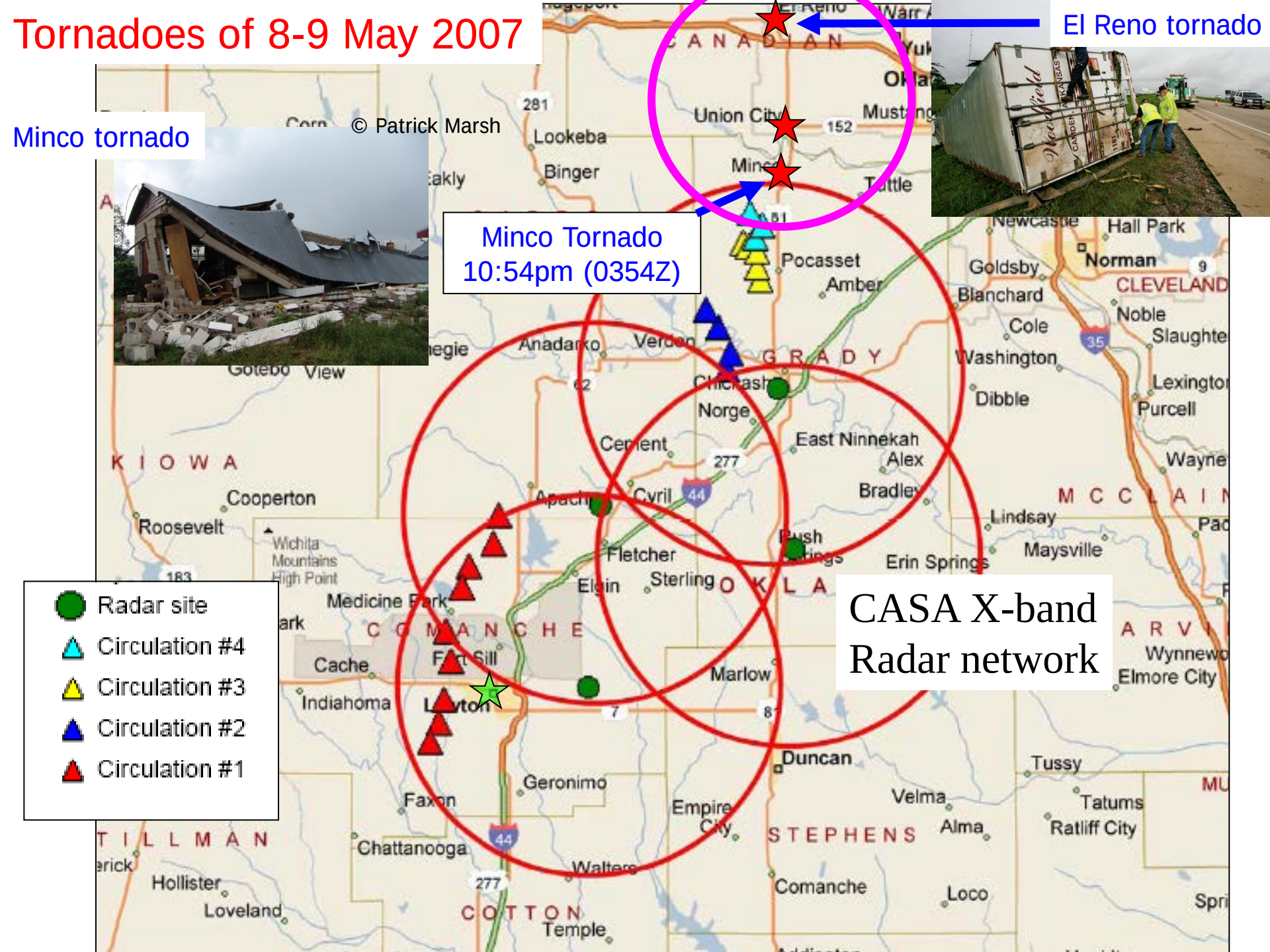
Dawson et al. (2009; 2012)

100 m simulations with MY1 and MY2 schemes

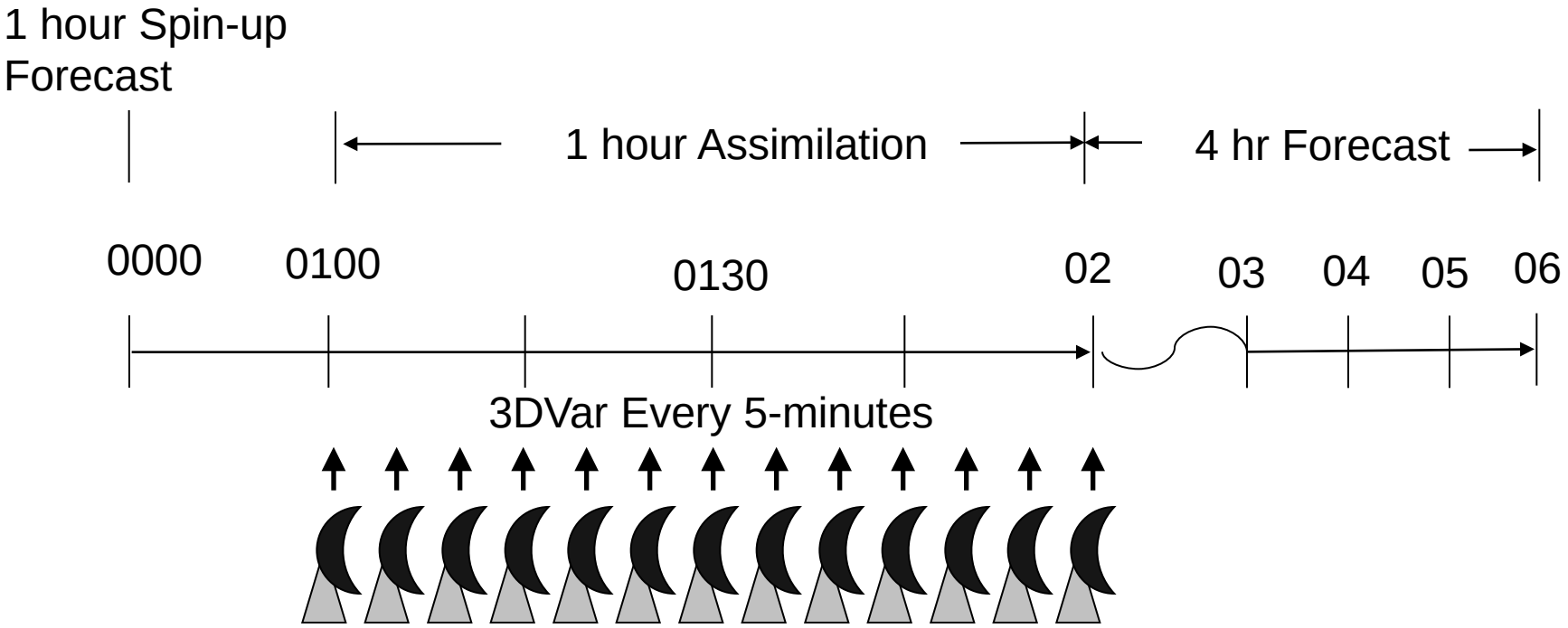


Surface θ ’ (gray shading), Z (blue contours), vertical vorticity (color shading), and wind vectors at the time of largest vertical vorticity using 100 m resolution and with MY1 (a) and MY2 (b) schemes.

Tornadoes of 8-9 May 2007



3DVar/Cloud Analysis Assimilation Experiments

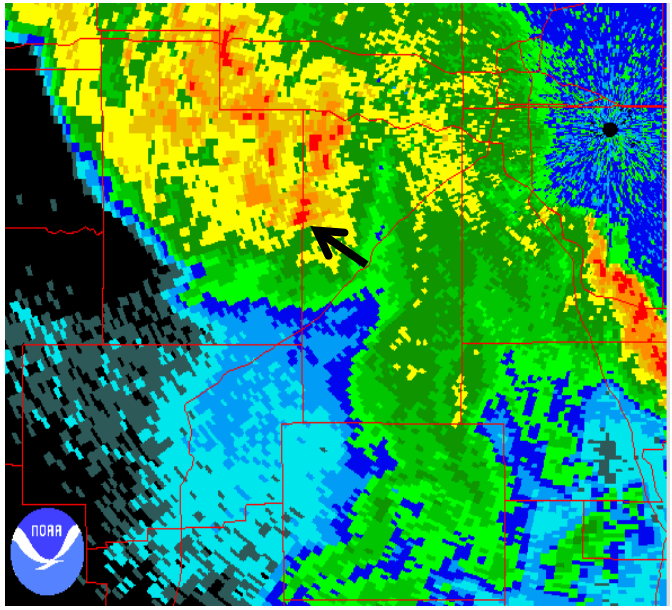


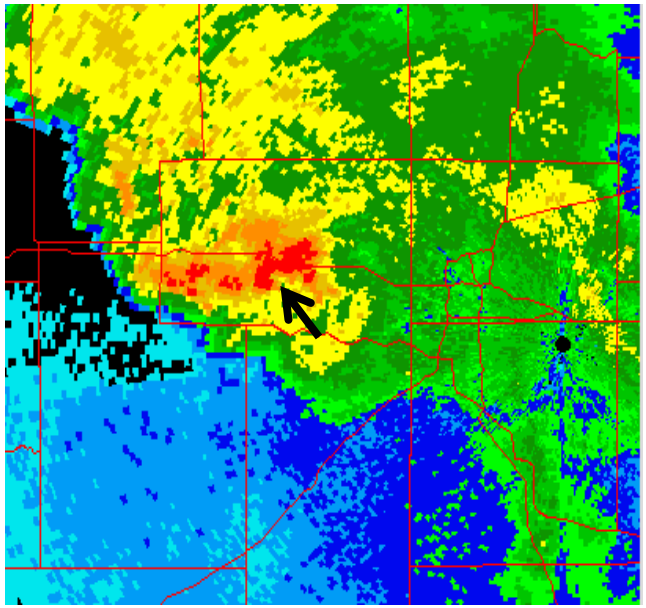
3DVar analysis run in 5-minute cycles for 1 hour
at 2 km resolution

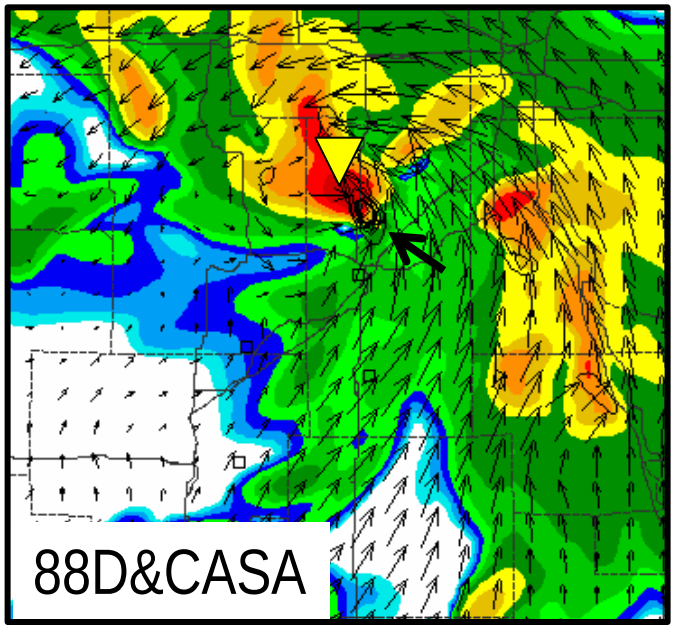
(Schenkman et al. 2011a,b)

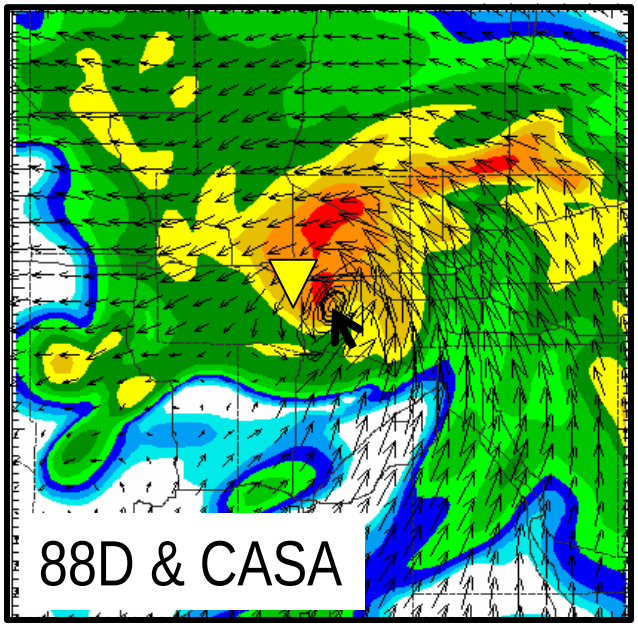
0350 UTC, 1h 30min forecast
Time of Minco Tornado

0440 UTC 2h 40m forecast
Time of El Reno Tornado



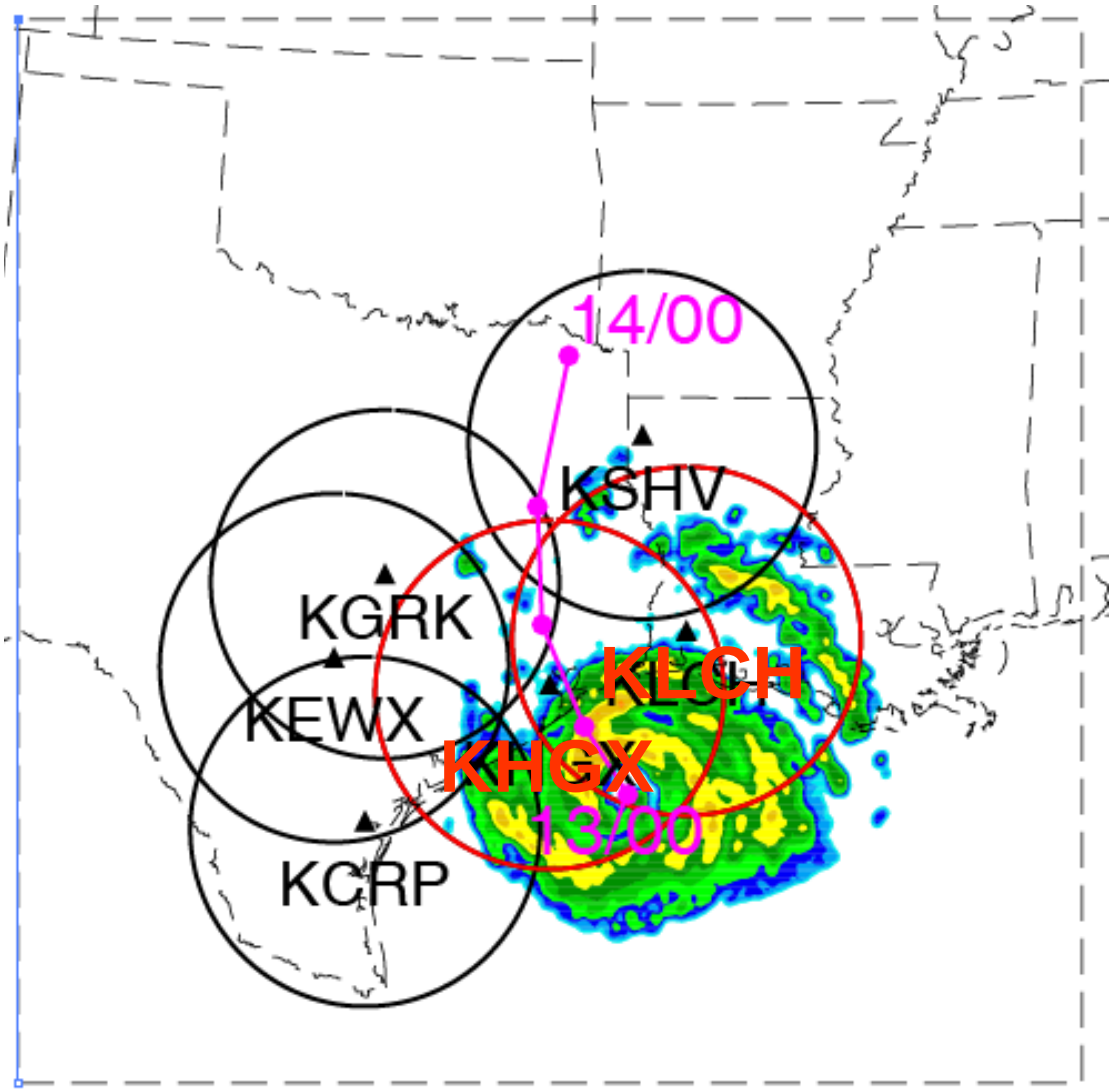




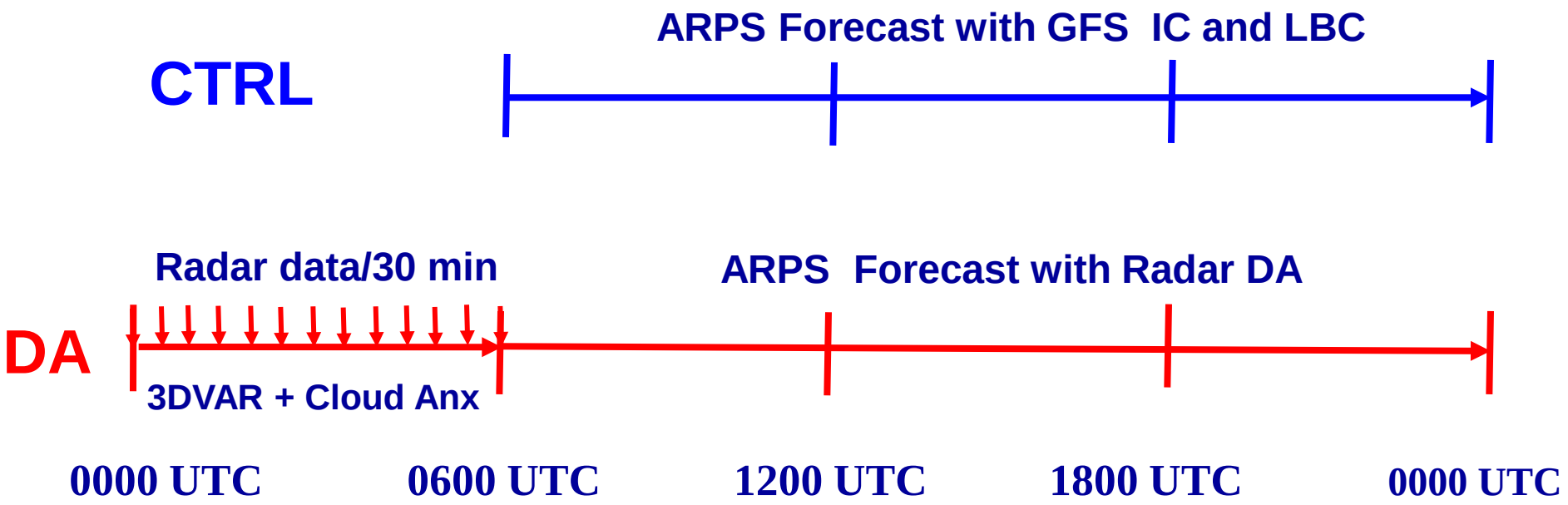


(Schenkman et al. 2011a,b)

Assimilation of coastal radar data for hurricane Ike (2008)

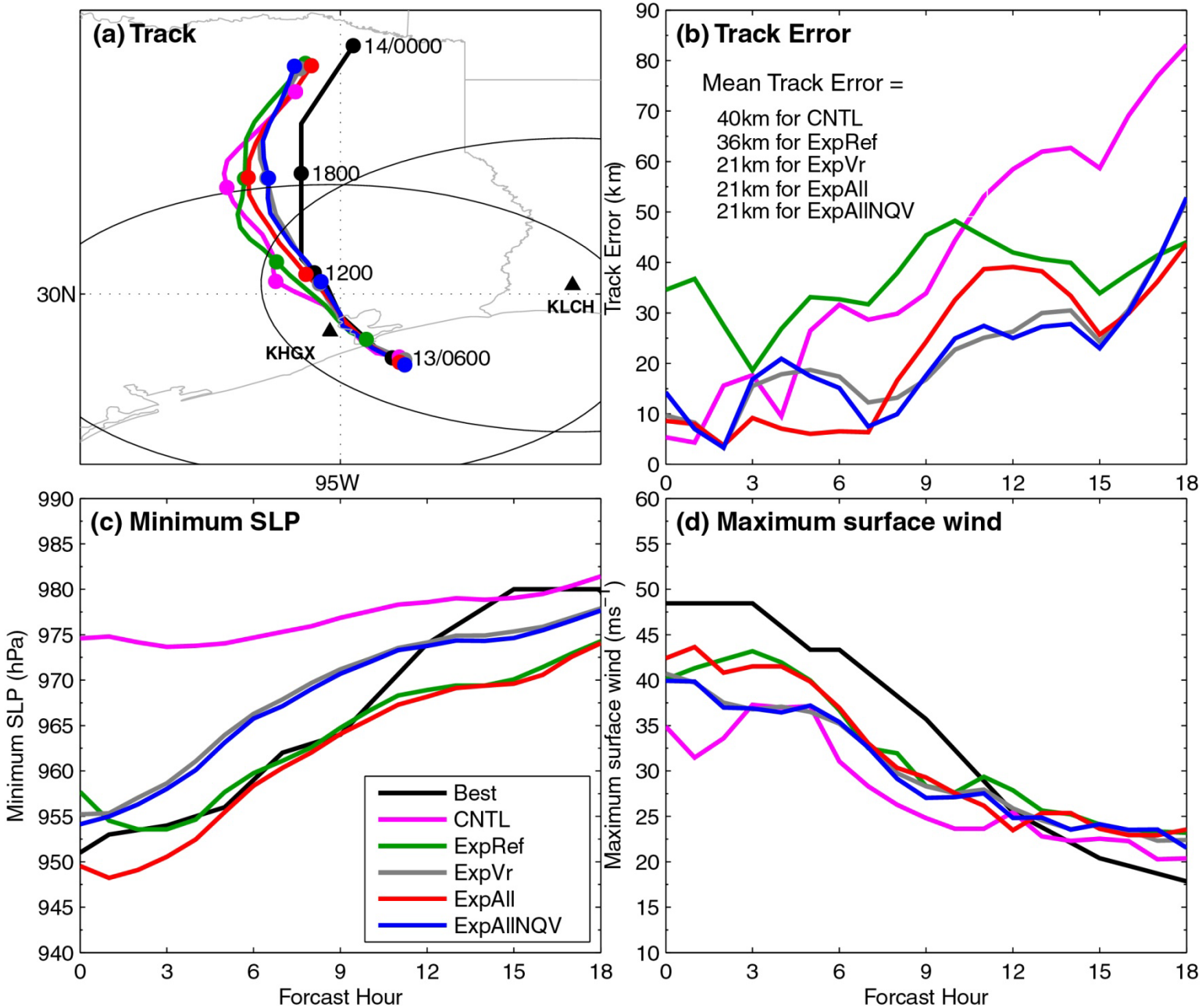


Data Assimilation Configuration



(Zhao and Xue 2009 GRL)

Intensity and Track Forecasts



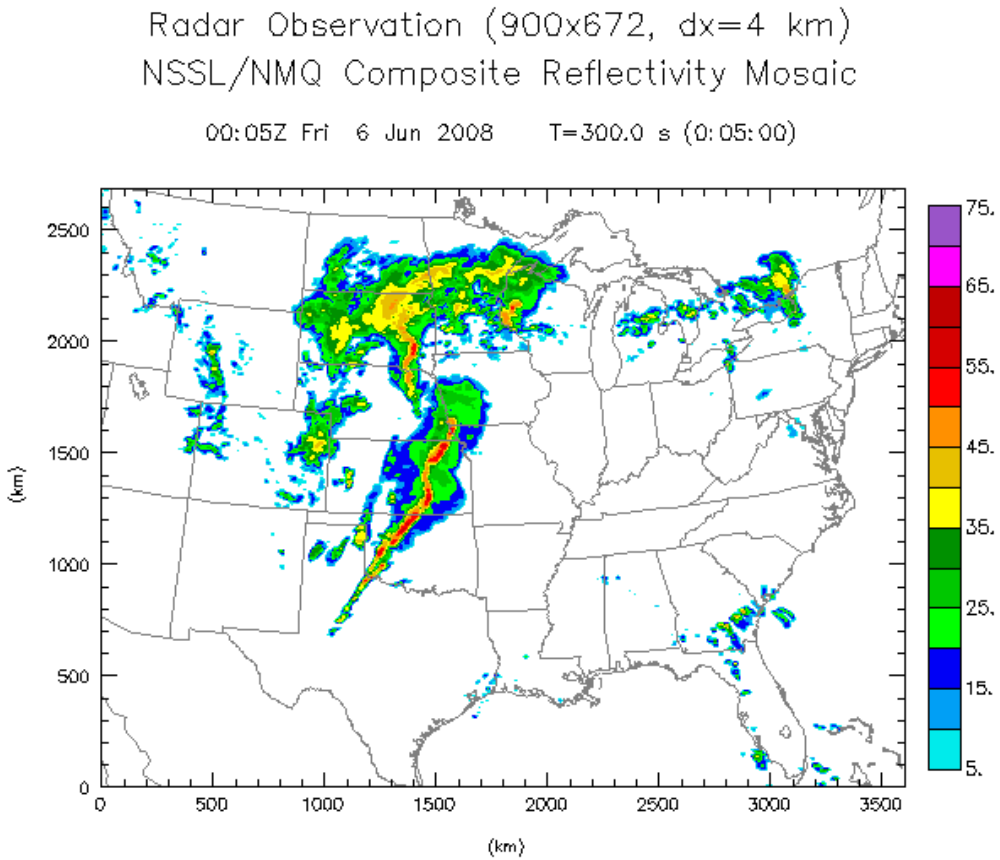
Applications of 3DVAR/Cloud Analysis to Realtime Storm-Scale Forecasting

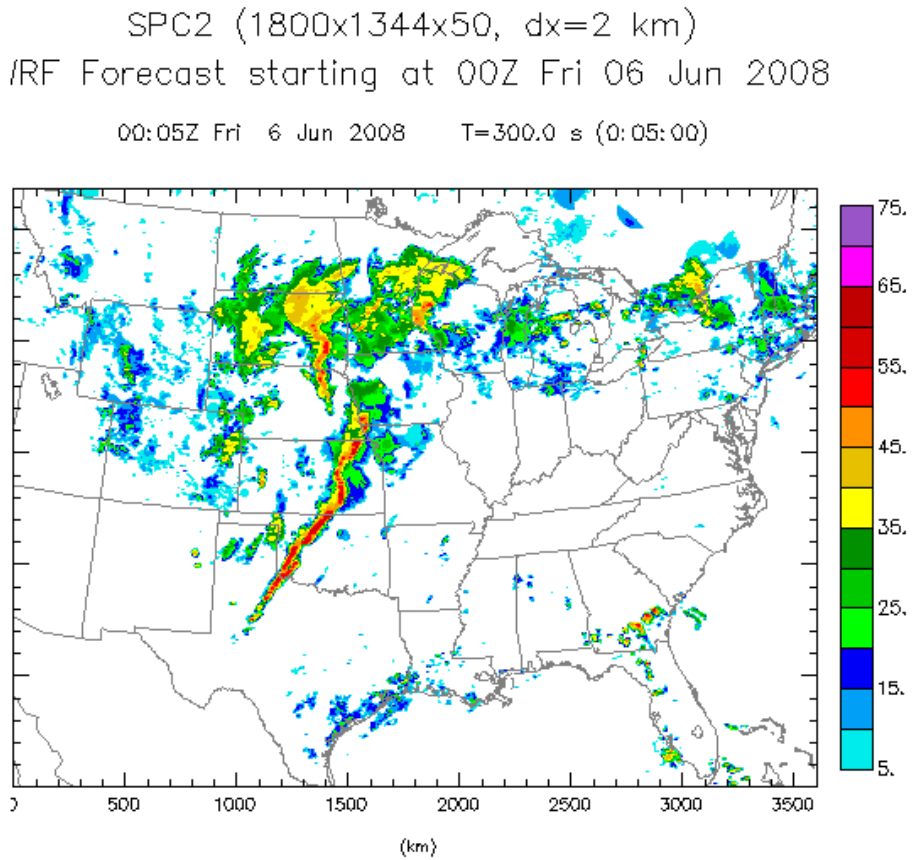
CAPS Storm-Scale Ensemble Forecasting for Hazardous Weather Test

- CAPS/OU has been producing realtime storm-scale ensemble forecasts during springs since 2007.
- Assimilation of Level-2 Vr and Z data from all WSR-88D radars, and sfc obs using ARPS 3DVAR/Cloud analysis at 4 and 2 or 1 km resolutions over CONUS since 2008.

CAPS 2 km WRF-ARW forecast v.s. observations

5 minute time intervals



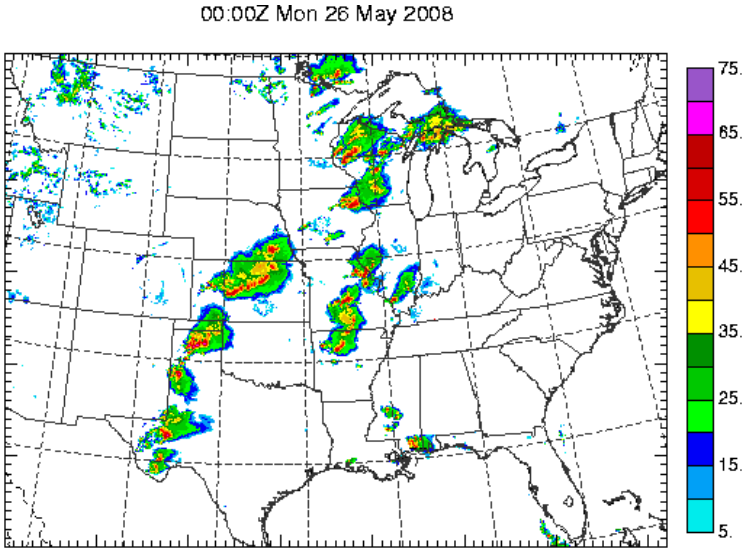


Initial condition with radar data

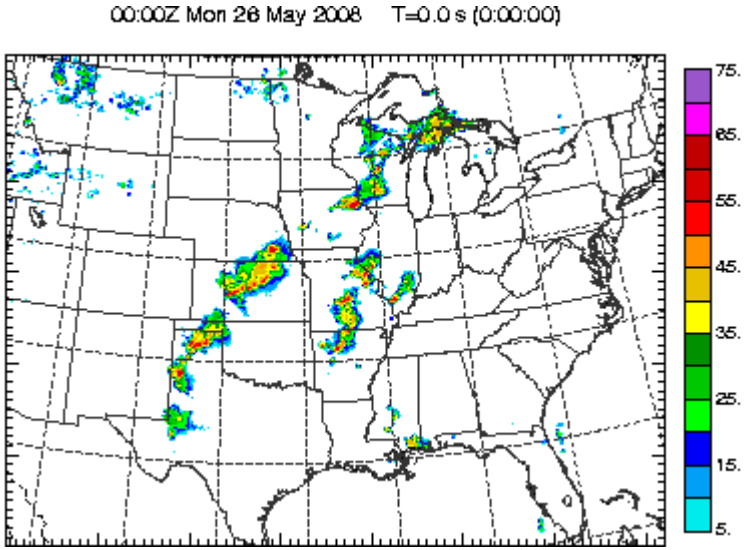
2008 – first year to assimilate radar data

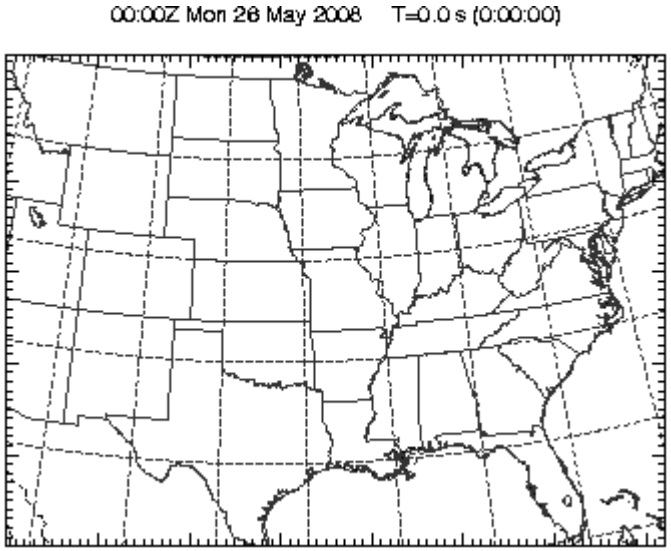
t = 0 h

Observed Reflectivity



I.C. with radar





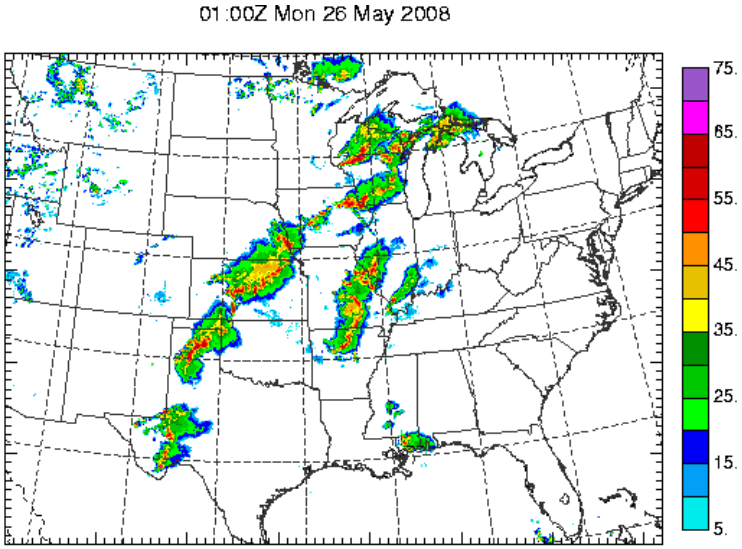
I.C. without radar

dx=4km

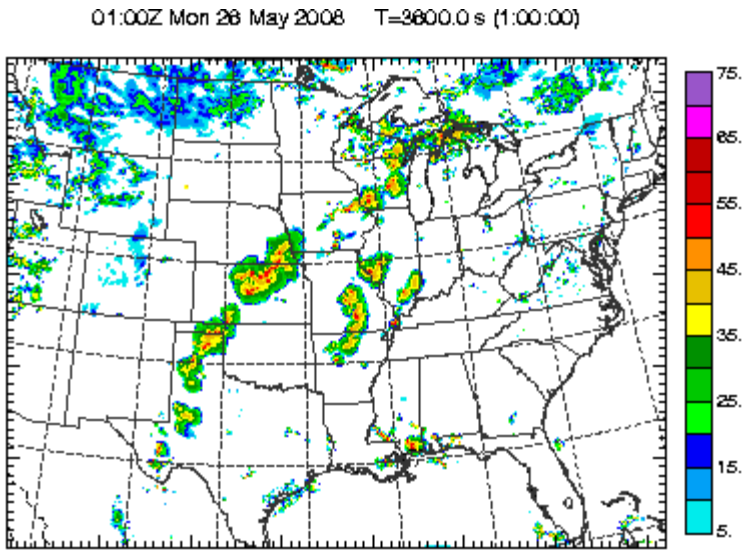
May 26, 2008 Example

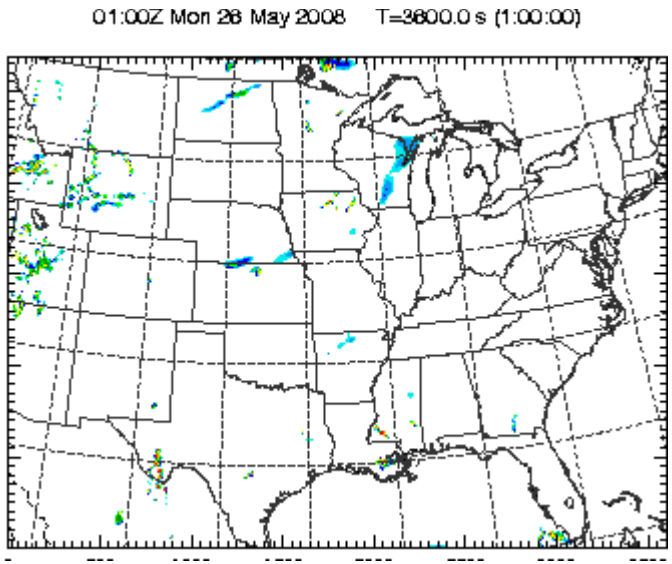
t = 1 h

Observed Reflectivity



fcst with radar



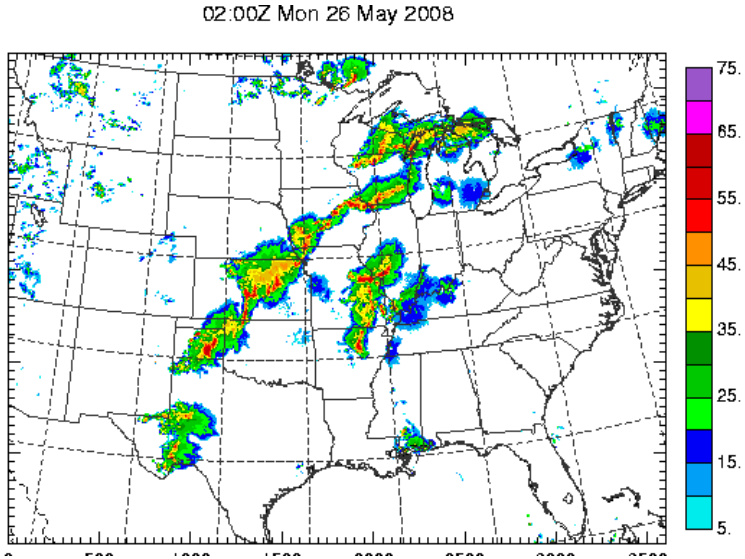


fcst without radar

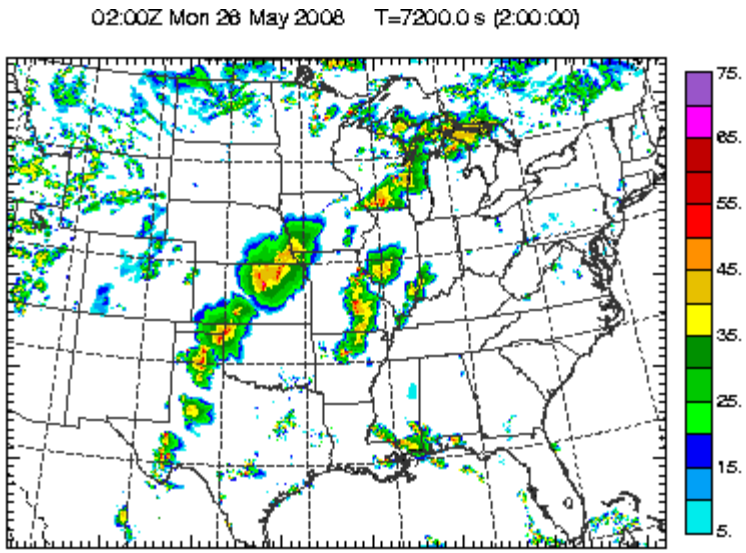
May 26, 2008 Case

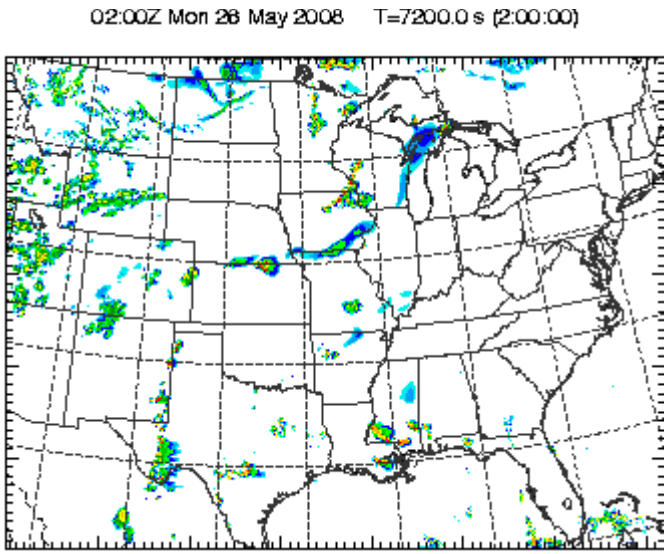
t = 2 h

Observed Reflectivity



fcst with radar



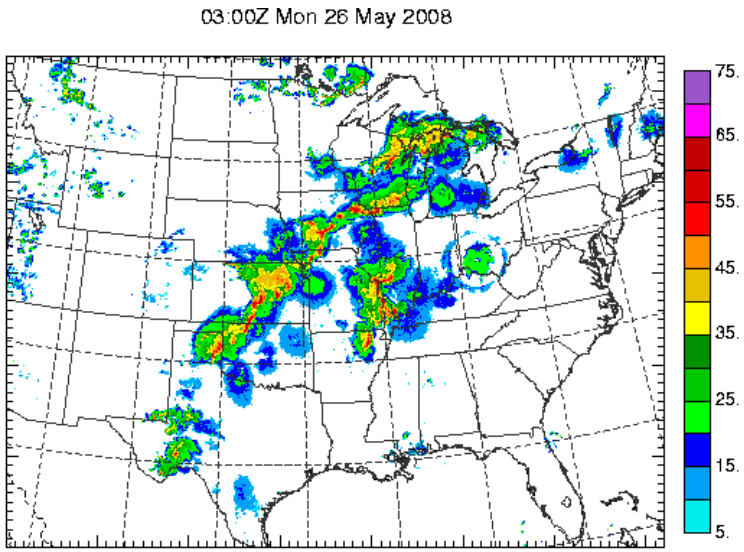


fcst without radar

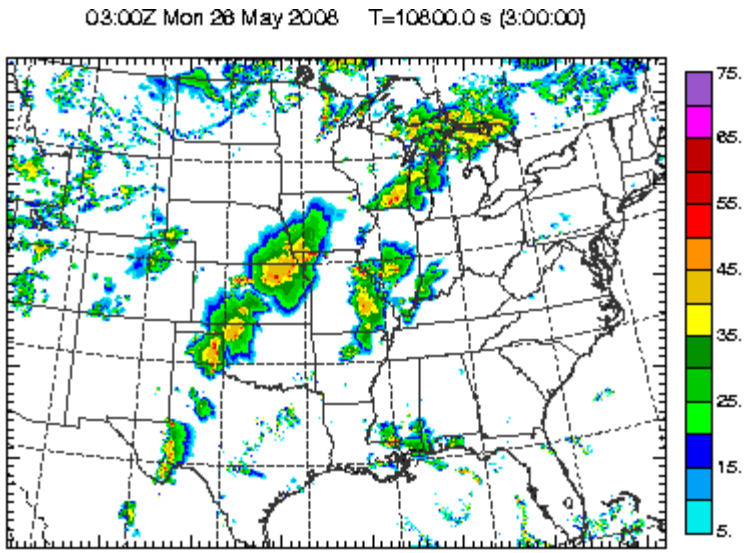
May 26, 2008 Case

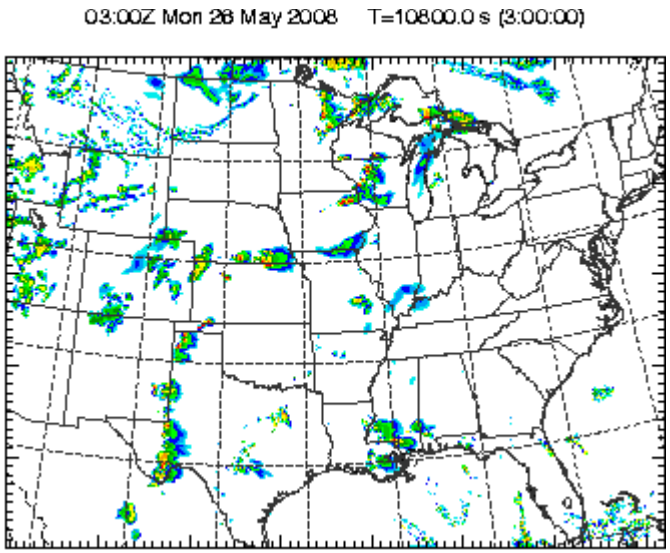
t = 3 h

Observed Reflectivity



fcst with radar





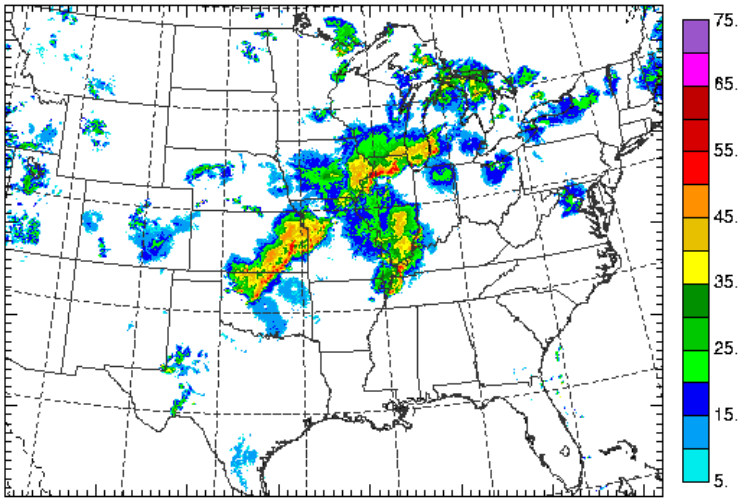
fcst without radar

May 26, 2008 Case

t = 6 h

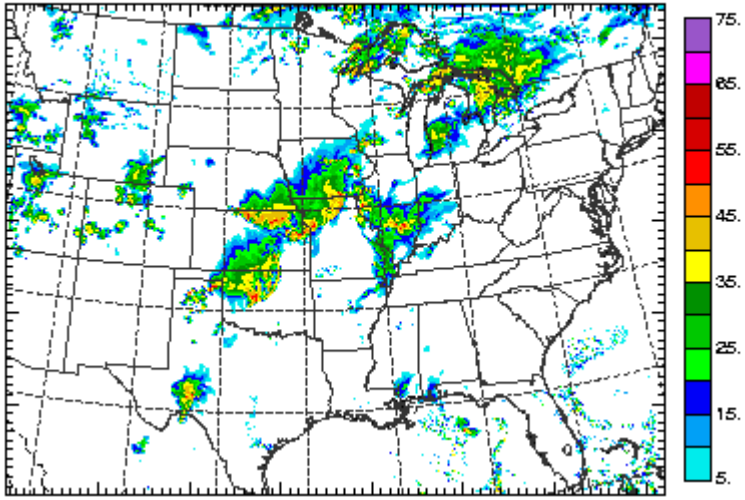
06:00Z Mon 26 May 2008

Observed Reflectivity

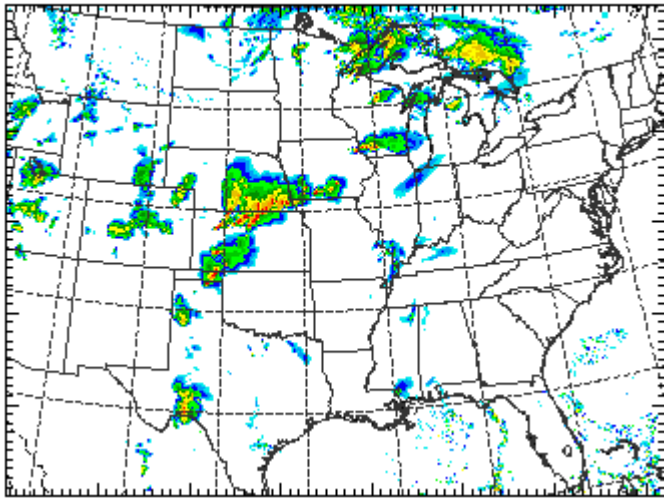


06:00Z Mon 26 May 2008 T=21600.0 s (6:00:00)

fcst with radar



06:00Z Mon 26 May 2008 T=21600.0 s (6:00:00)

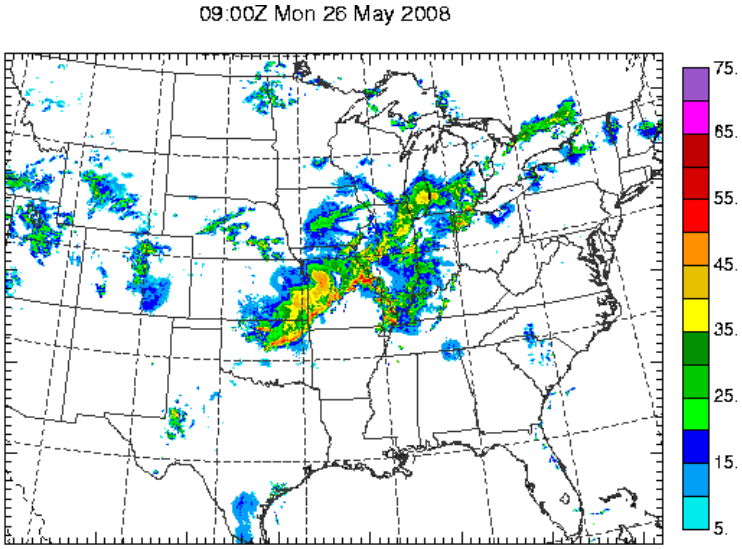


fcst without radar

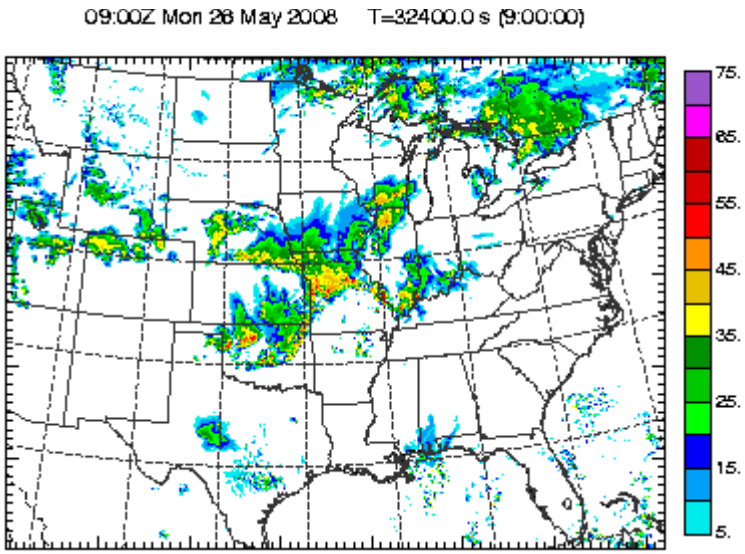
May 26, 2008 Case

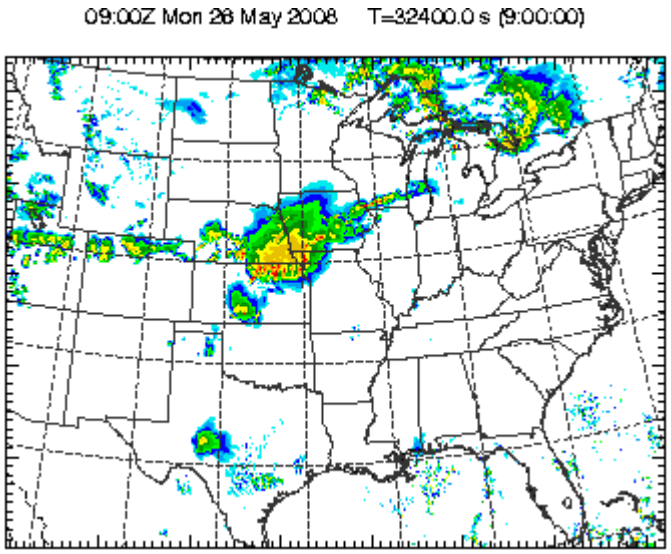
t = 9 h

Observed Reflectivity



fcst with radar





fcst without radar

May 26, 2008 Case

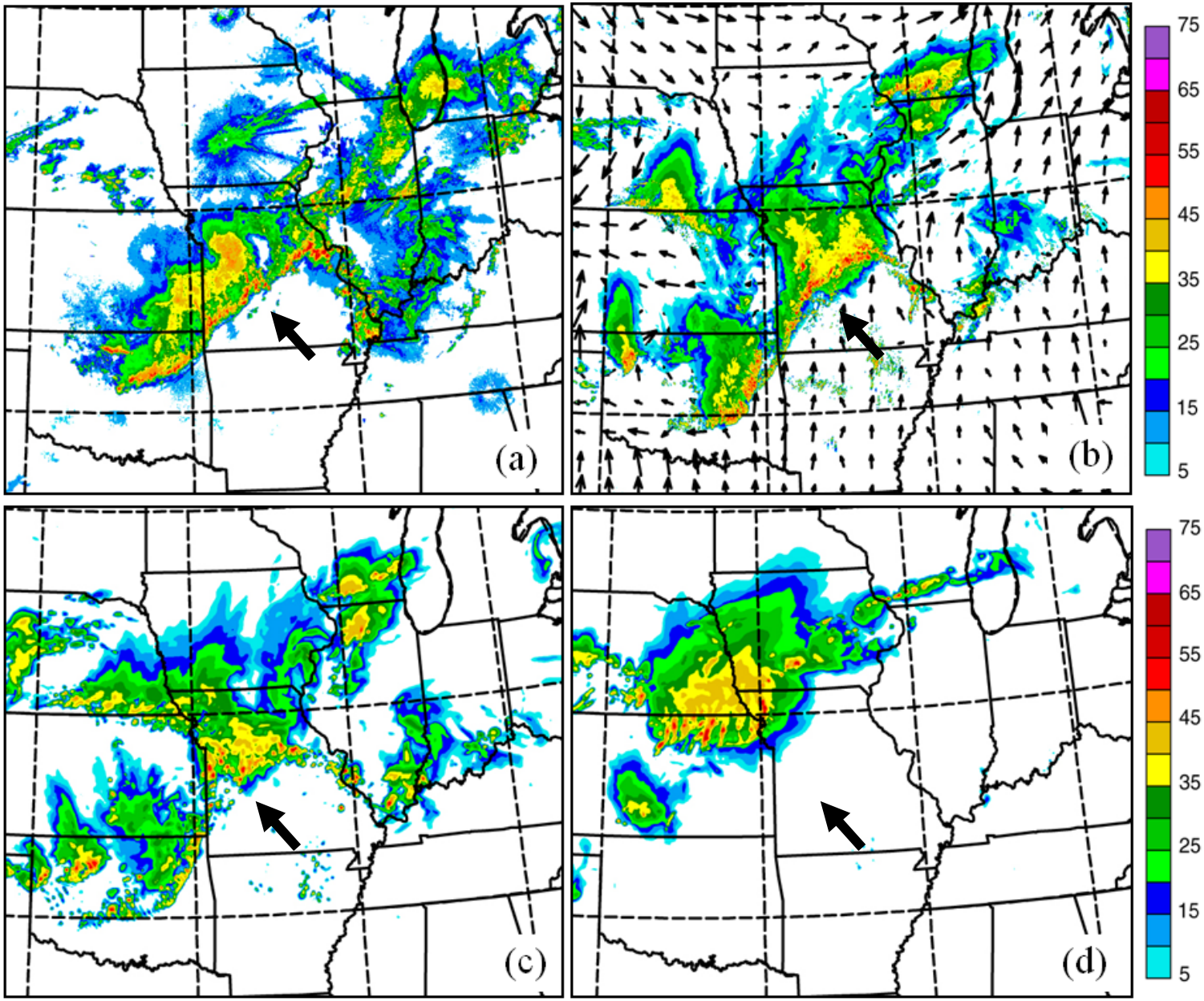
t = 9 h

OBS

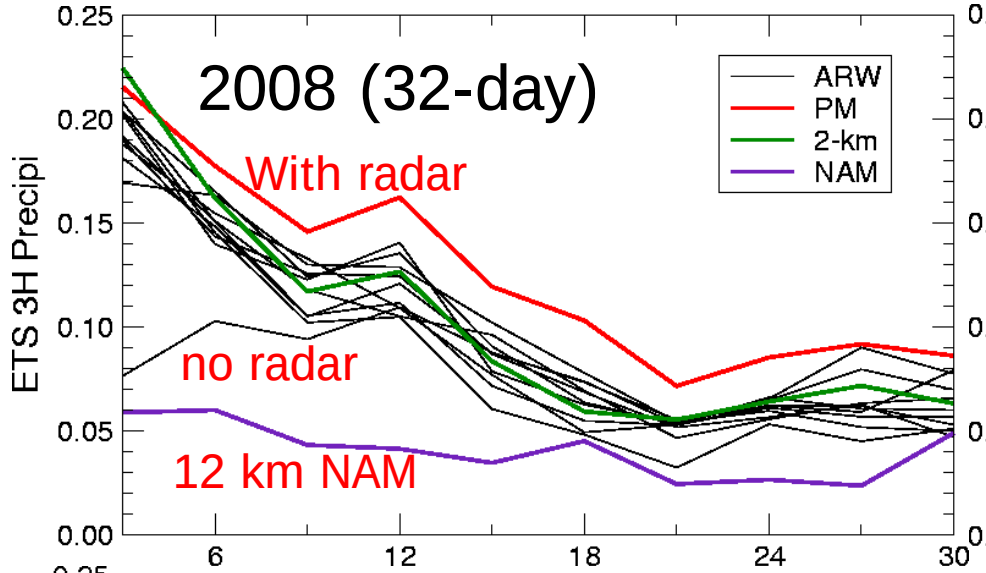
1 km with radar

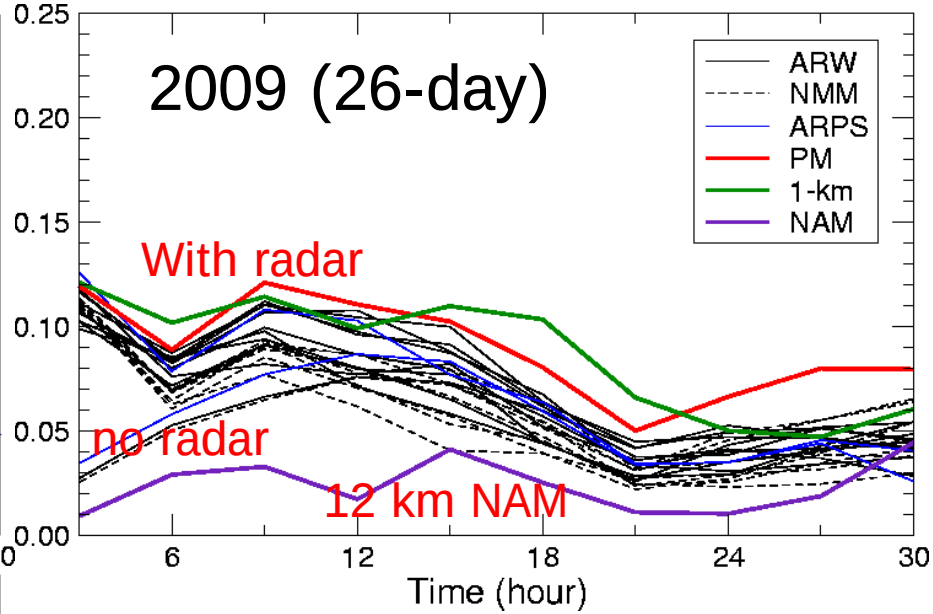
4 km with radar

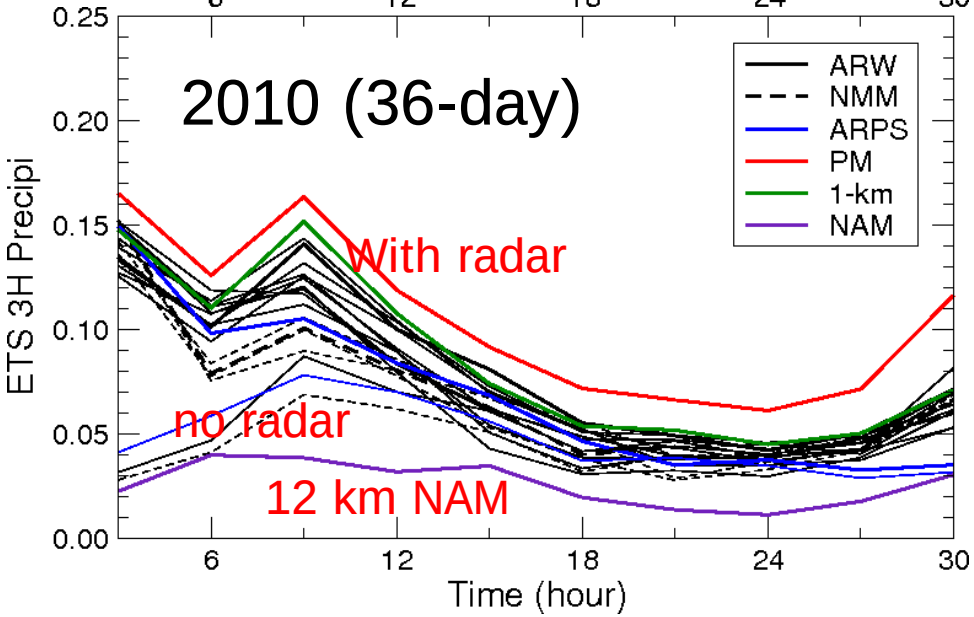
4 km no radar



Euitable Threat Scores for 3-hourly Precip. ≥ 0.5 in







Radar data impact lasts up to in 12 hours

All high-res models outperform 12km NAM

Probability-matched score generally better than any ensemble member

2 km score no-better than the best 4-km ensemble member – may be due to physics

1-km score better than any 4-km member and than the 4 km PM score in 2009.

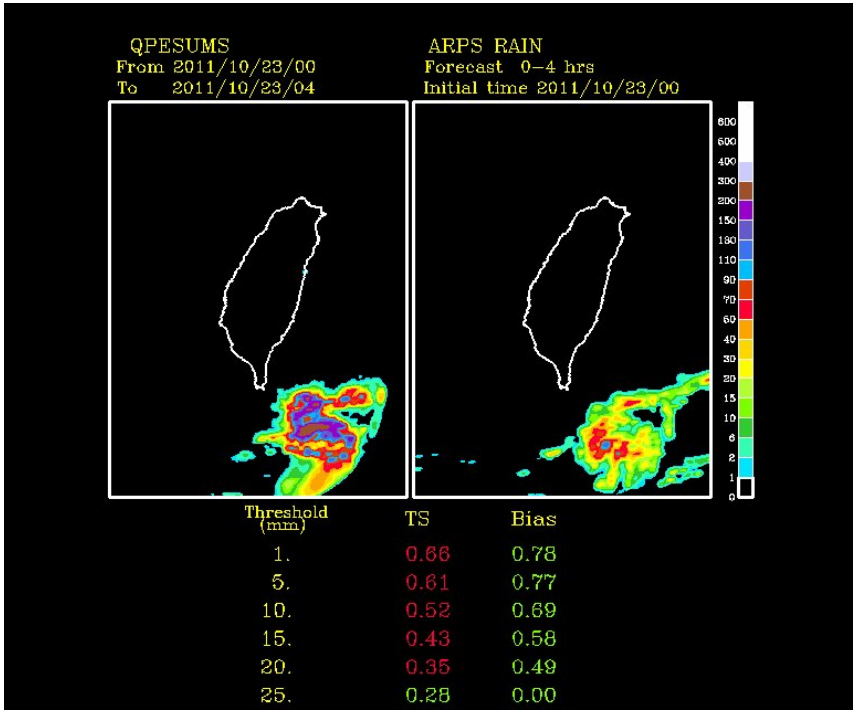
Central Weather Bureau Taiwan
Hourly Updated ARPS Forecasting System

Hourly updated 4-hour forecasts at dx=4km

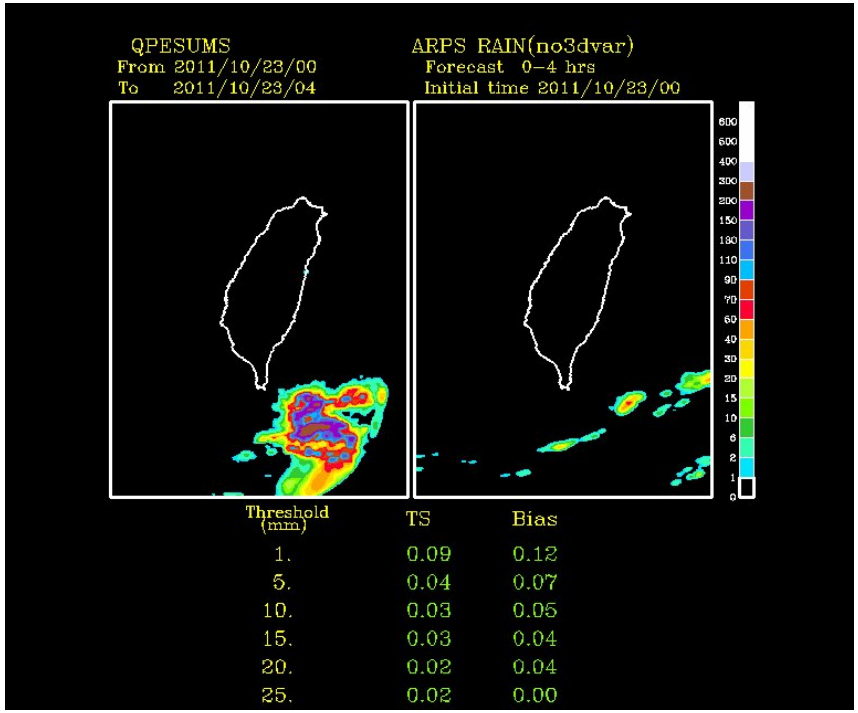
Using ARPS 3DVAR+Cloud Analysis and ARPS Forecast Model

Cases:4 h accumulated precip

3D-VAR vs. no 3D-VAR radar DA



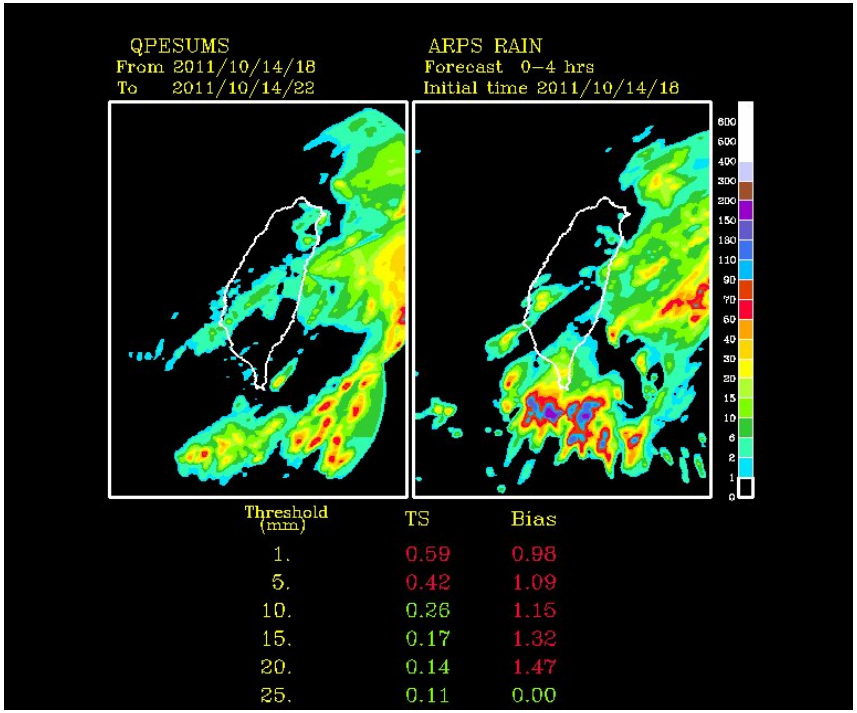
Threshold (mm)	TS	Bias
1.	0.66	0.78
5.	0.61	0.77
10.	0.52	0.69
15.	0.43	0.58
20.	0.35	0.49
25.	0.28	0.00



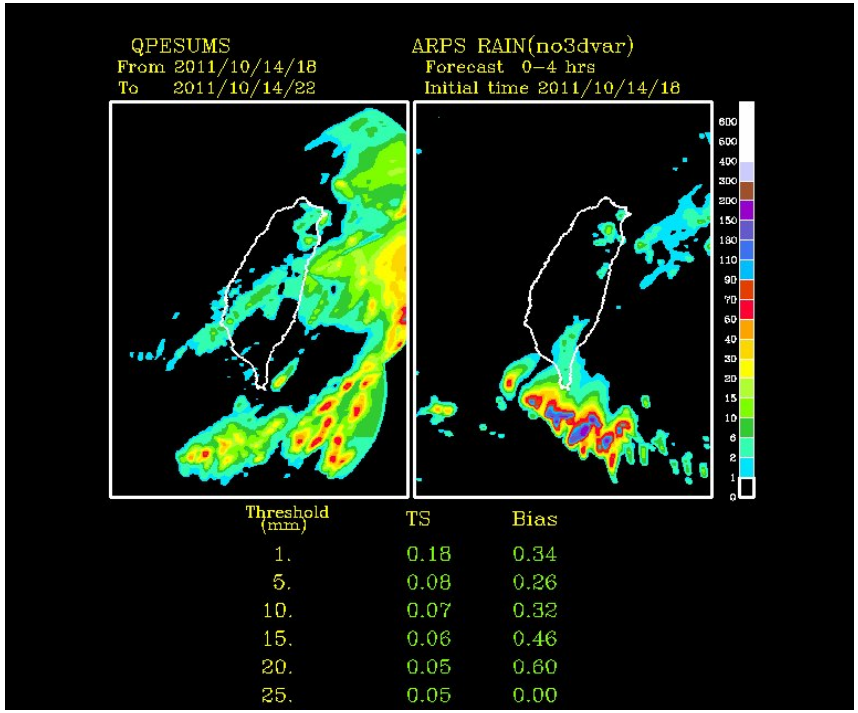
Threshold (mm)	TS	Bias
1.	0.09	0.12
5.	0.04	0.07
10.	0.03	0.05
15.	0.03	0.04
20.	0.02	0.04
25.	0.02	0.00

Cases:4 h accumulated precip

3D-VAR vs. no 3D-VAR radar DA



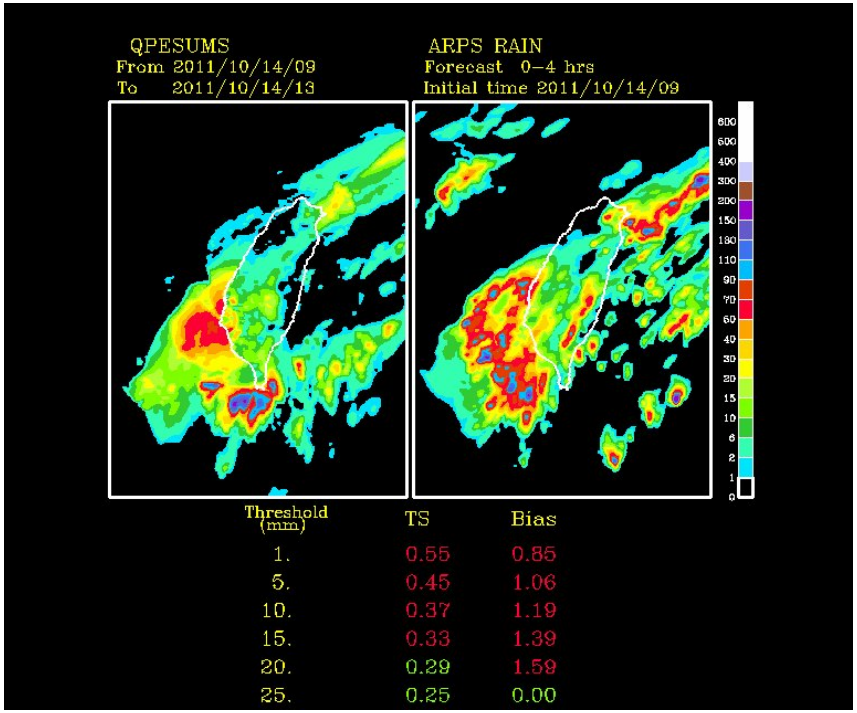
Threshold (mm)	TS	Bias
1.	0.59	0.98
5.	0.42	1.09
10.	0.26	1.15
15.	0.17	1.32
20.	0.14	1.47
25.	0.11	0.00



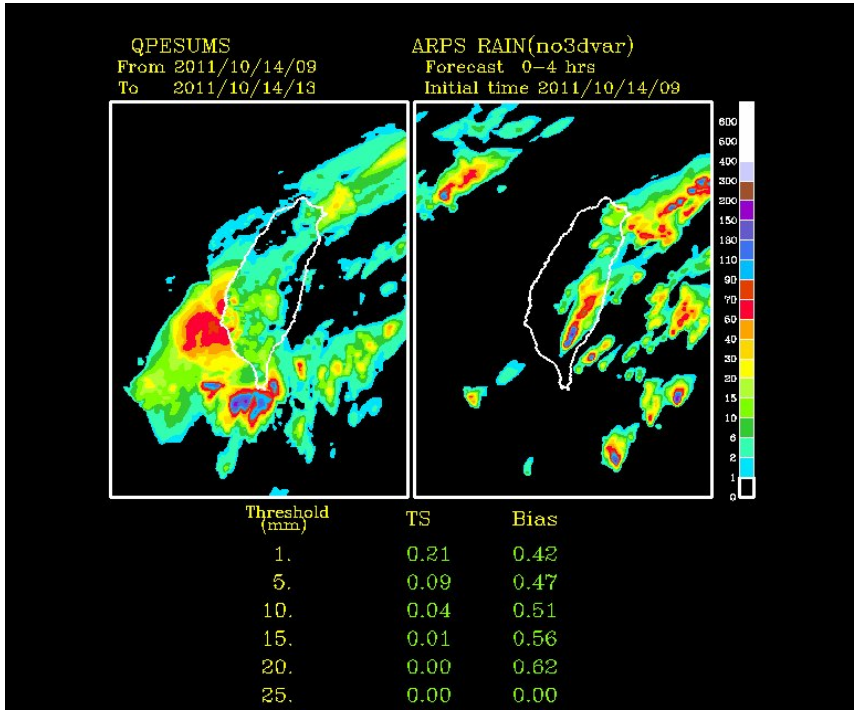
Threshold (mm)	TS	Bias
1.	0.18	0.34
5.	0.08	0.26
10.	0.07	0.32
15.	0.06	0.46
20.	0.05	0.60
25.	0.05	0.00

Cases:4 h accumulated precip

3D-VAR vs. no 3D-VAR radar DA



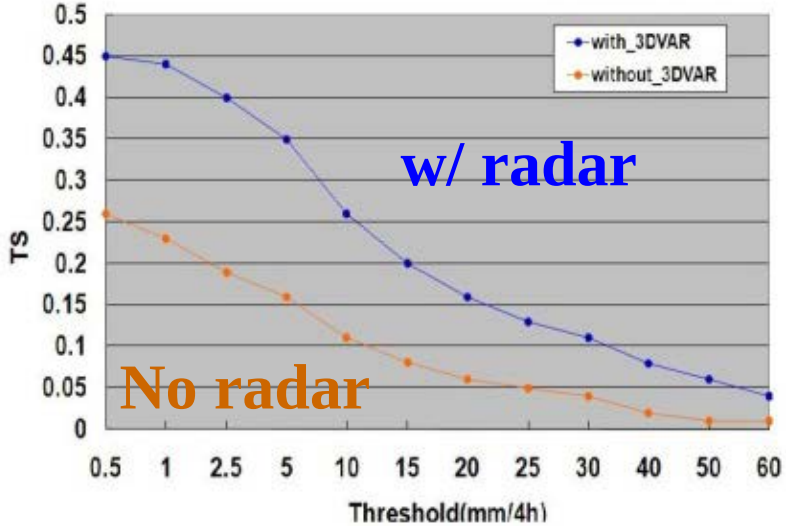
Threshold (mm)	TS	Bias
1.	0.55	0.85
5.	0.45	1.06
10.	0.37	1.19
15.	0.33	1.39
20.	0.29	1.59
25.	0.25	0.00



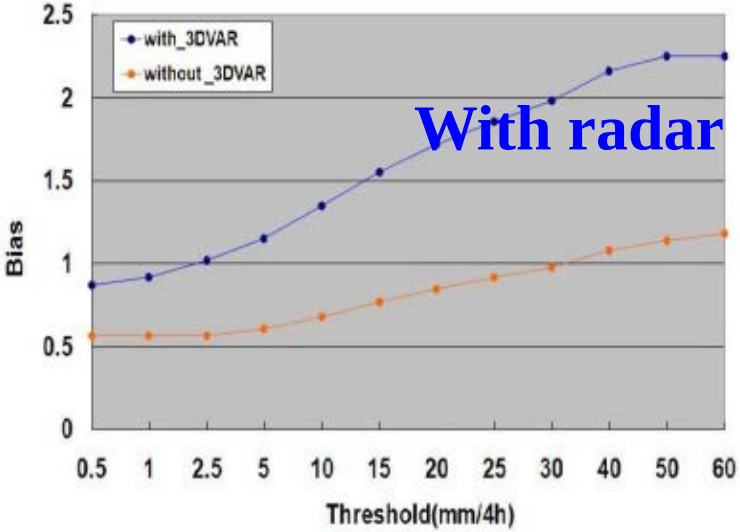
Threshold (mm)	TS	Bias
1.	0.21	0.42
5.	0.09	0.47
10.	0.04	0.51
15.	0.01	0.56
20.	0.00	0.62
25.	0.00	0.00

Verification of CWB Experimental Forecasts

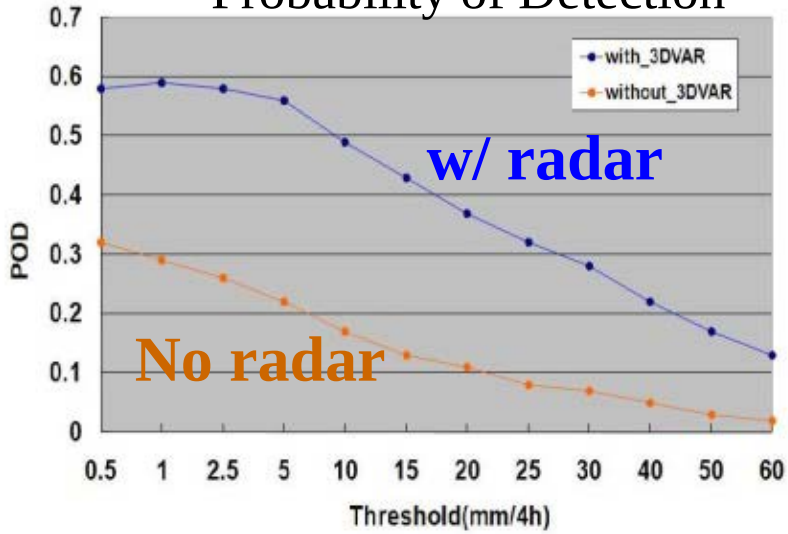
Treat Score



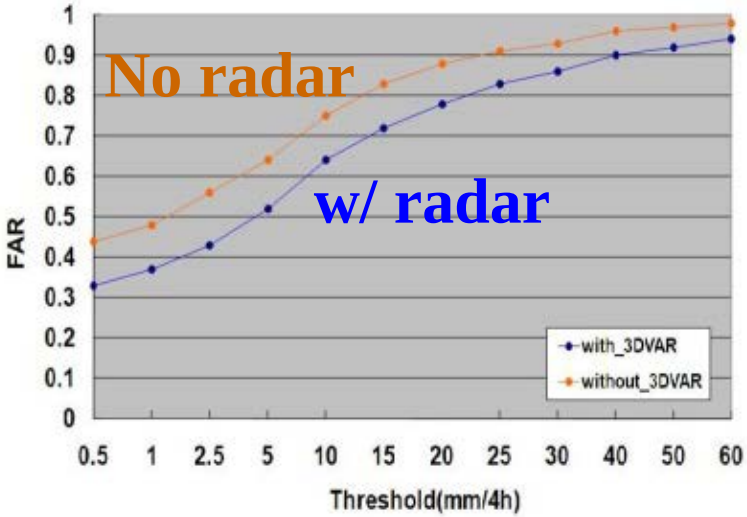
Bias



Probability of Detection



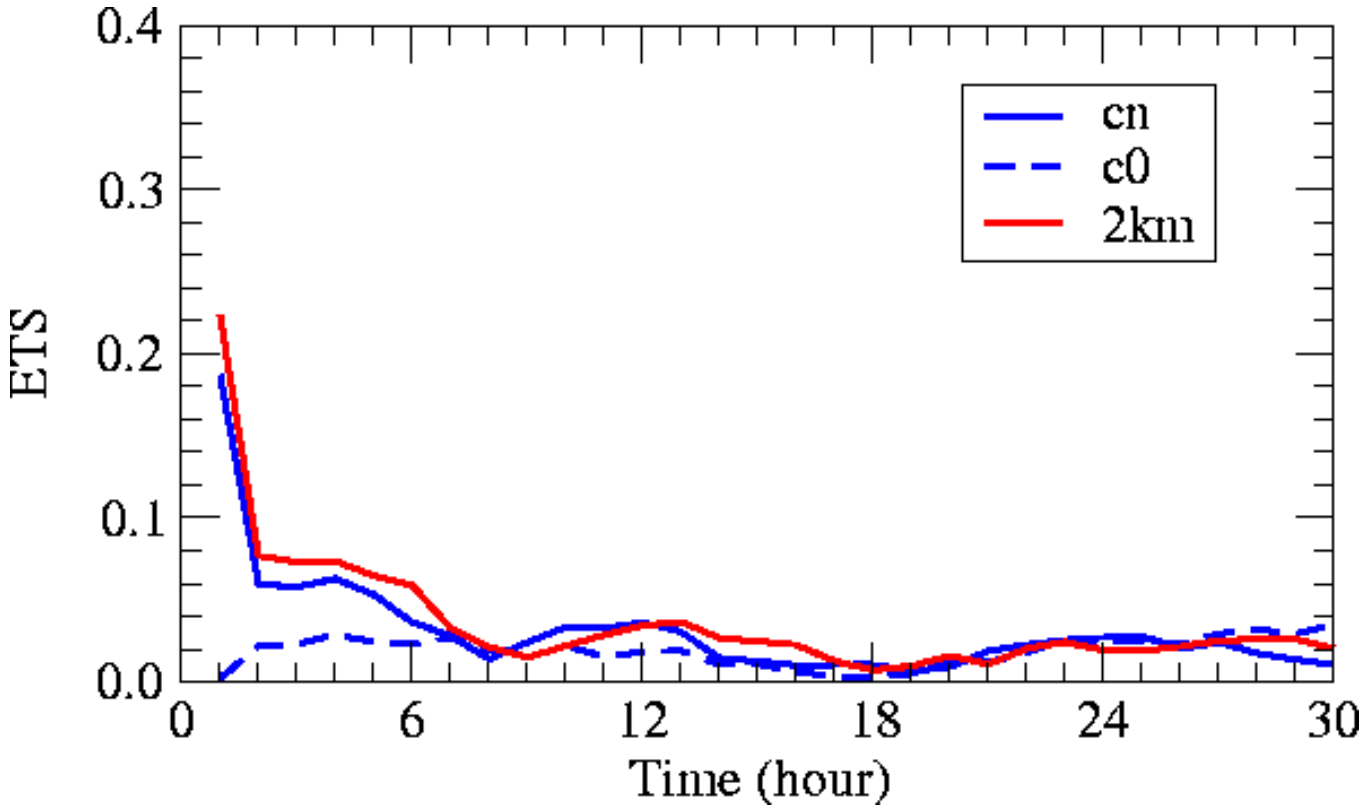
False Alarm Rate



Issues with cloud analysis

- Not ‘optimal’ combination of background and observations – not weighted by error
- Can add, not effectively remove storms
- Semi-emperical hydrometeor partitioning and adjustments to cloud water/ice, T and q_v. No wind adj.
- Analysis imbalances, leading to ‘spin-down’ problem.

ETS of hourly precipitation at 0.5 inch threshold for the 4-km with radar (cn) and without radar (c0), and 2 km forecasts, averaged over the 2008 CAPS HWT forecasts



Problems: Balance issues, no direct update to wind from Z, difficulty in suppressing spurious storms

How does EnKF work?

- Use covariance derived from ensemble

$$\mathbf{x}^a = \mathbf{x}^b + \frac{\mathbf{BH}^{\mathbf{T}}}{\mathbf{R} + \mathbf{HBH}^{\mathbf{T}}}(\mathbf{Z}^o - \mathbf{Z}^b)$$

$\mathbf{x}$ contains u, v, w, T, q_v, p, q's.

Covariance between m^{th} obs and j^{th} state variable:

$$(\mathbf{BH}^{\mathbf{T}})_{j,m} = \frac{1}{N-1}\sum_{i=1}^{N}(Z_{m,i}^b - \overline{Z}_m^b)(x_{j,i}^b - \overline{x}_j^b)$$

- Be able to project limited observations (e.g., Z) to all state variables

EnKF for (Polarimetric) Radar Data Assimilation

$$\begin{pmatrix} u^a \\ v^a \\ w^a \\ \theta^a \\ p^a \\ q_v^a \\ q_c^a \\ q_r^a \\ q_i^a \\ q_s^a \\ q_h^a \end{pmatrix} = \begin{pmatrix} u^f \\ v^f \\ w^f \\ \theta^f \\ p^f \\ q_v^f \\ q_c^f \\ q_r^f \\ q_i^f \\ q_s^f \\ q_h^f \end{pmatrix} + \alpha K \left[\begin{pmatrix} V_r \\ Z_{hh} \\ Z_{vv} \\ Z_{DR} \\ Z_{DP} \\ K_{DP} \end{pmatrix} - H \begin{pmatrix} u^f \\ v^f \\ w^f \\ \theta^f \\ p^f \\ q_v^f \\ q_c^f \\ q_r^f \\ q_i^f \\ q_s^f \\ q_h^f \end{pmatrix} \right]$$

Radar data used:

V_r (Z_{hh} > 10 dBZ)

Z_{hh} (everywhere)

:

K_{DP} (K_{DP} > 0.3 deg./km)

$V_r = V_r\,(u, v, w)$

$Z_{hh} = Z_{hh}\,(q_r, q_s, q_h)$

:

$K_{DP} = K_{DP}\,(qr, qs)$

K is the Kalman Gain, a function of background and obs error covariances

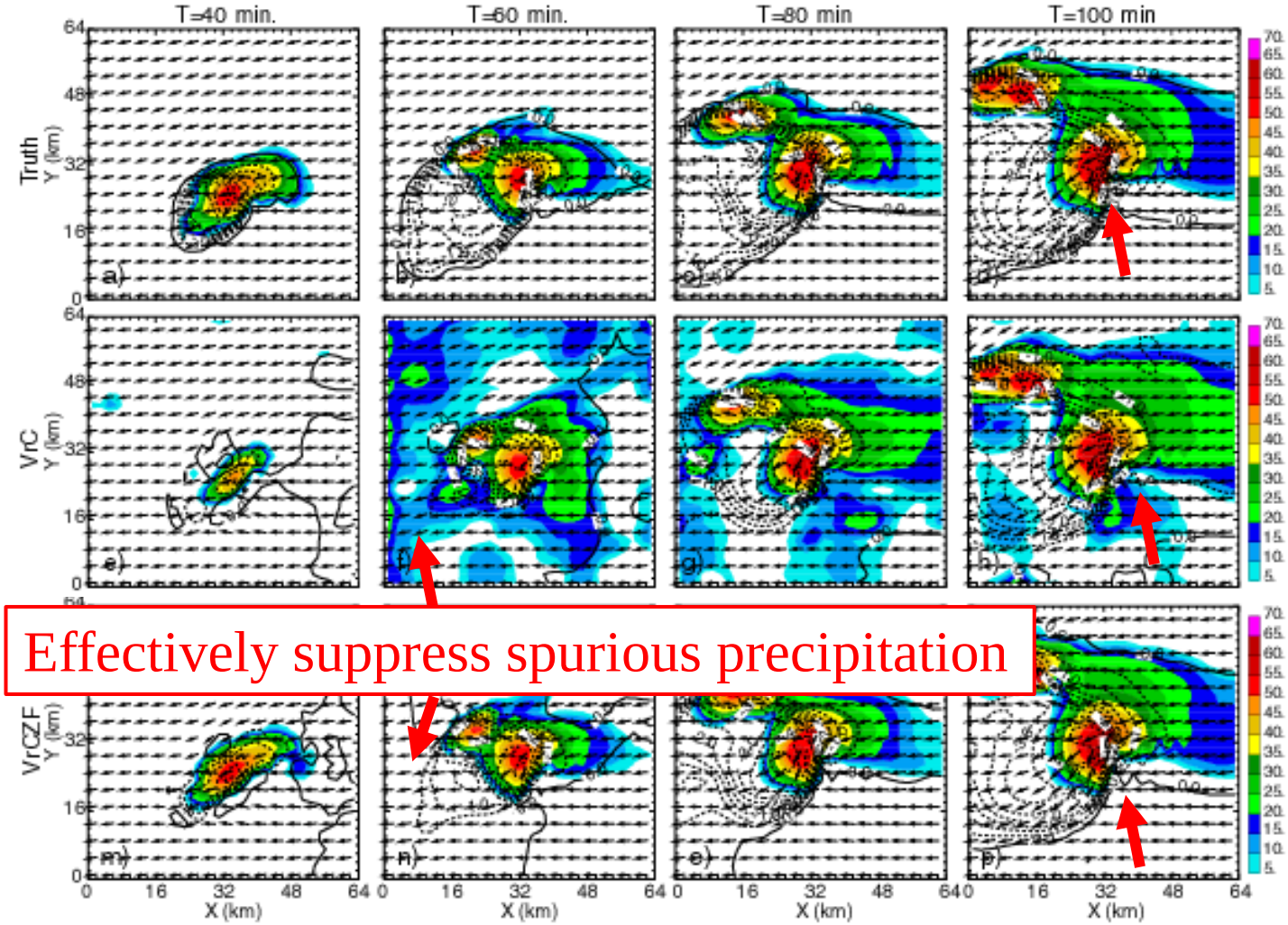
Perfect Model OSSEs

Analyses of Low level cold pool and reflectivity v.s. Truth

Truth

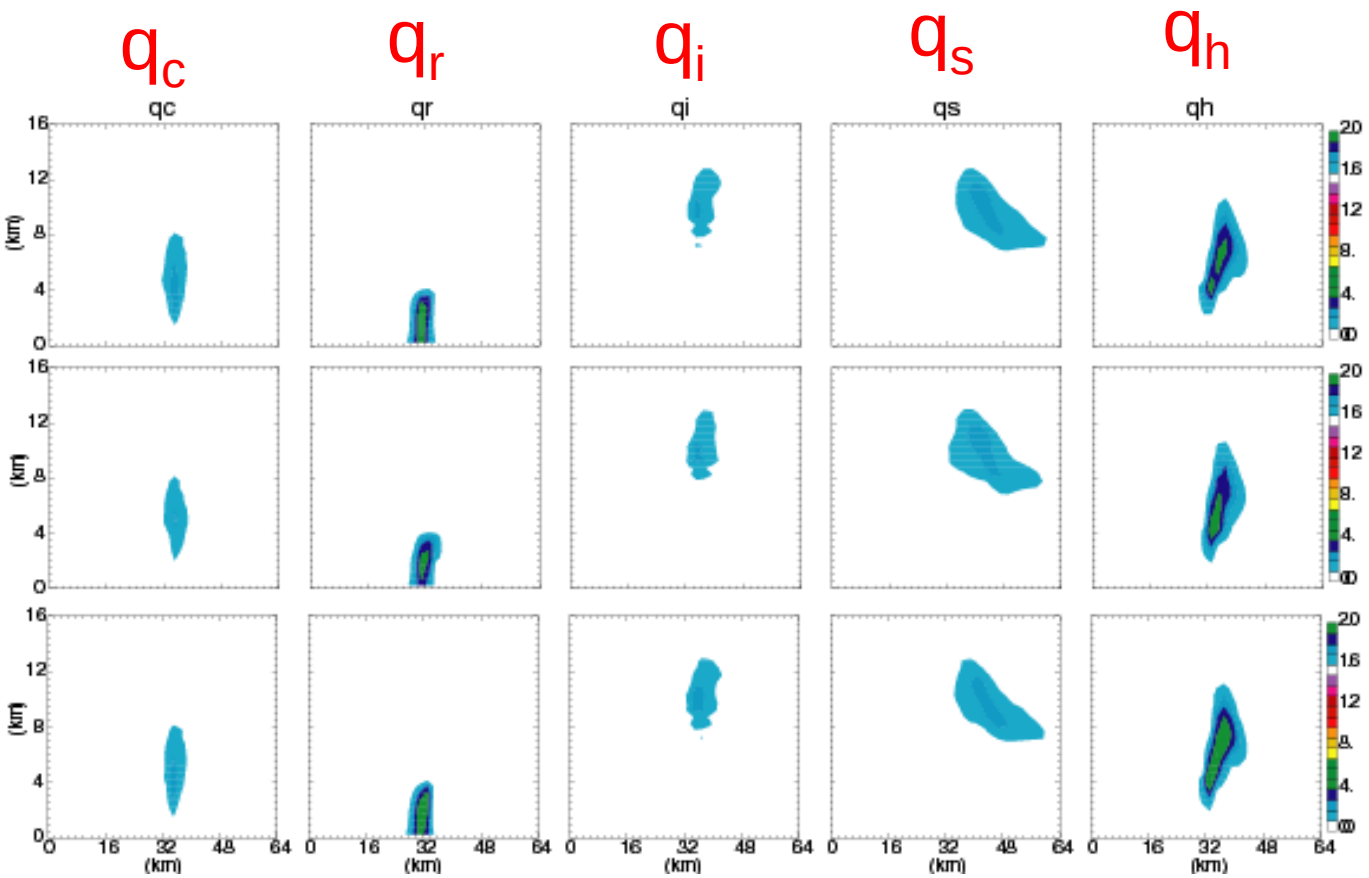
Vr only

Vr + Z



Tong and Xue (2005) – first EnKF study involving Z & ice microphysics

Accurate Analysis of Microphysical Fields

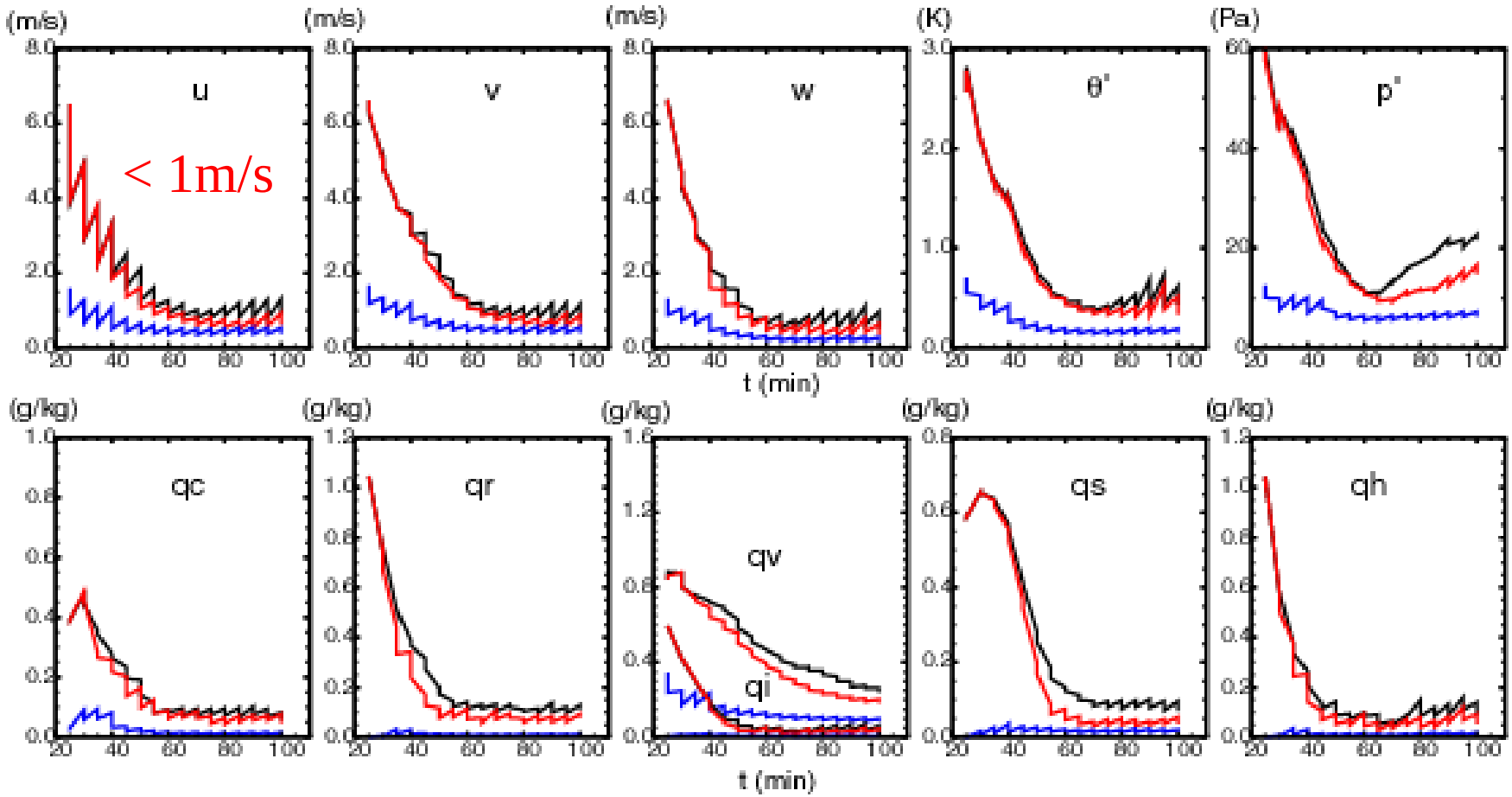


Truth

Vr only

Vr + Z

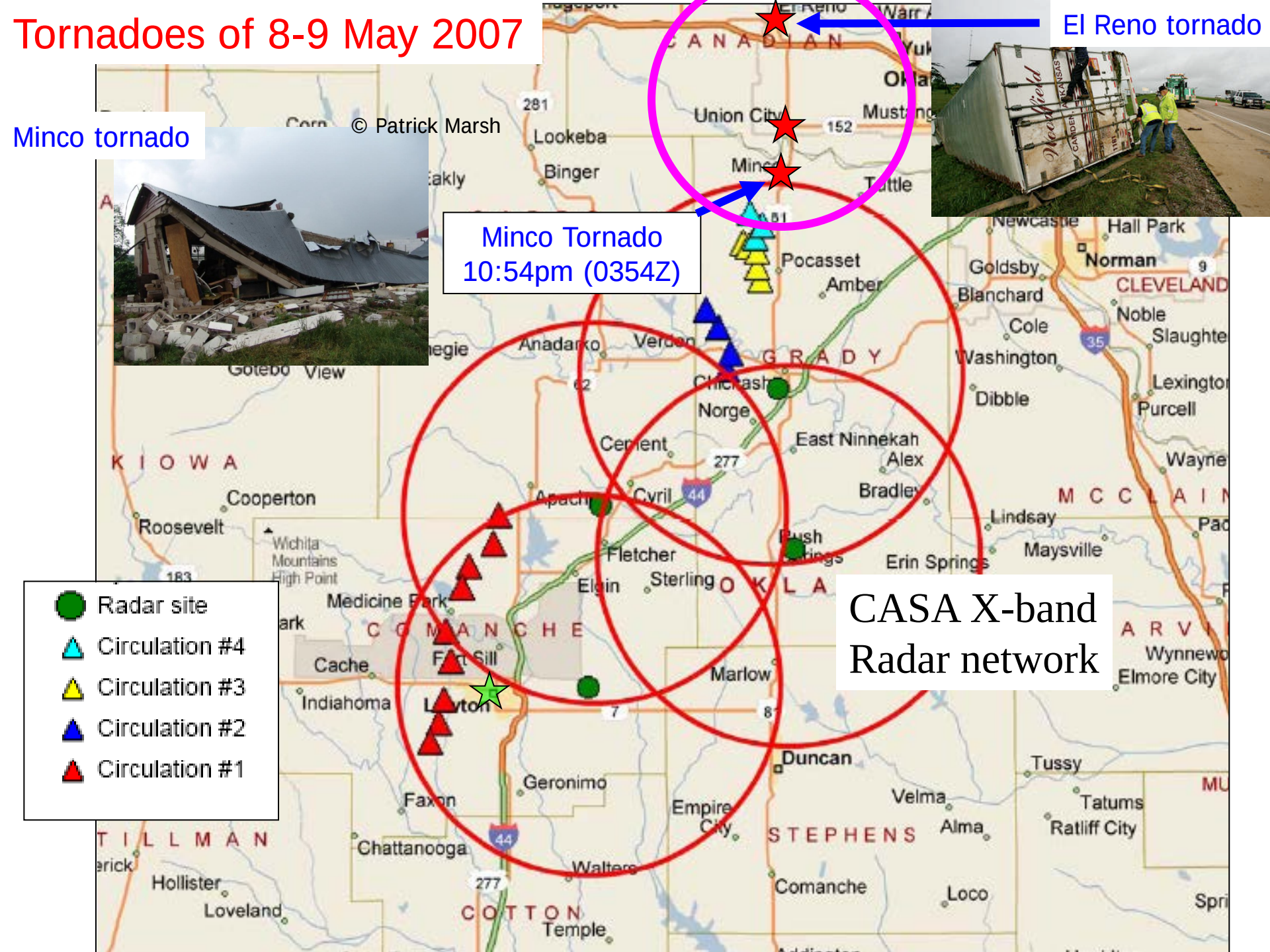
Assimilation of V_r + Z v.s. V_r only
Very Low Ensemble Mean RMS Errors



Black: V_r only; **Red: V_r + Z;**

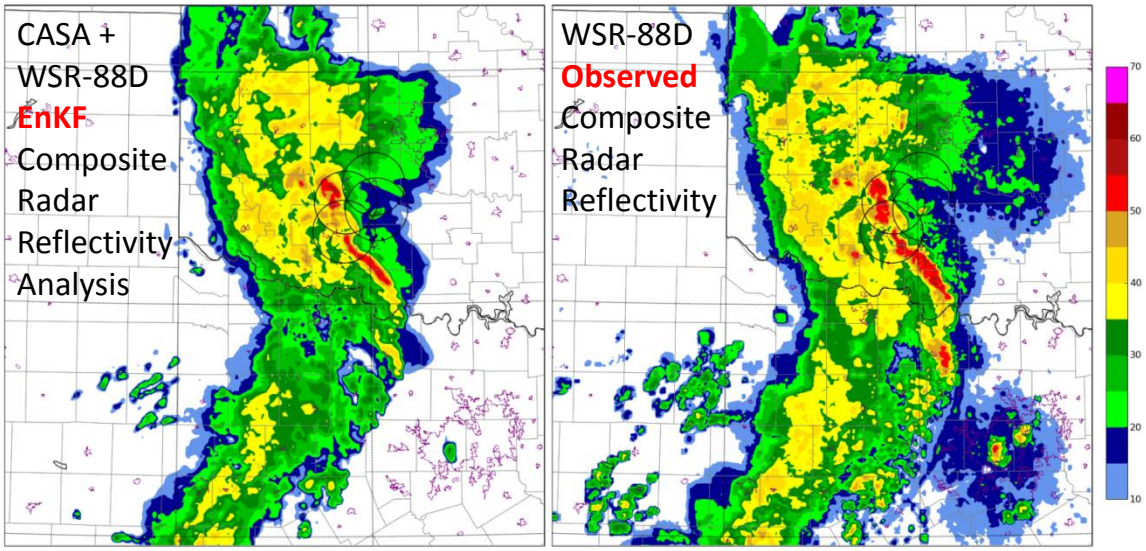
Blue: ensemble spread as an estimate of error

Tornadoes of 8-9 May 2007



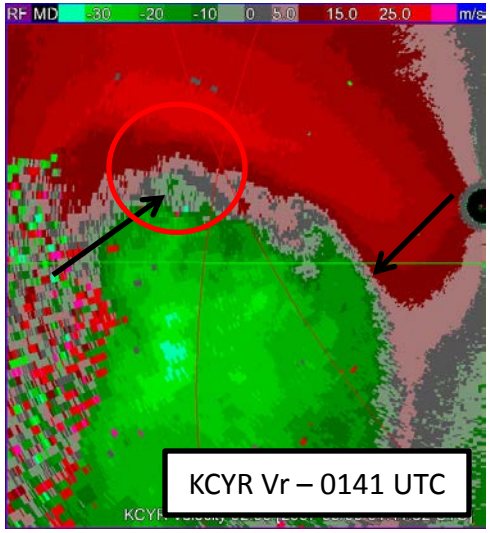
Assimilation of CASA and 88D radar data using mixed-microphysics ensemble: Results of EnKF Analysis using dx=2km

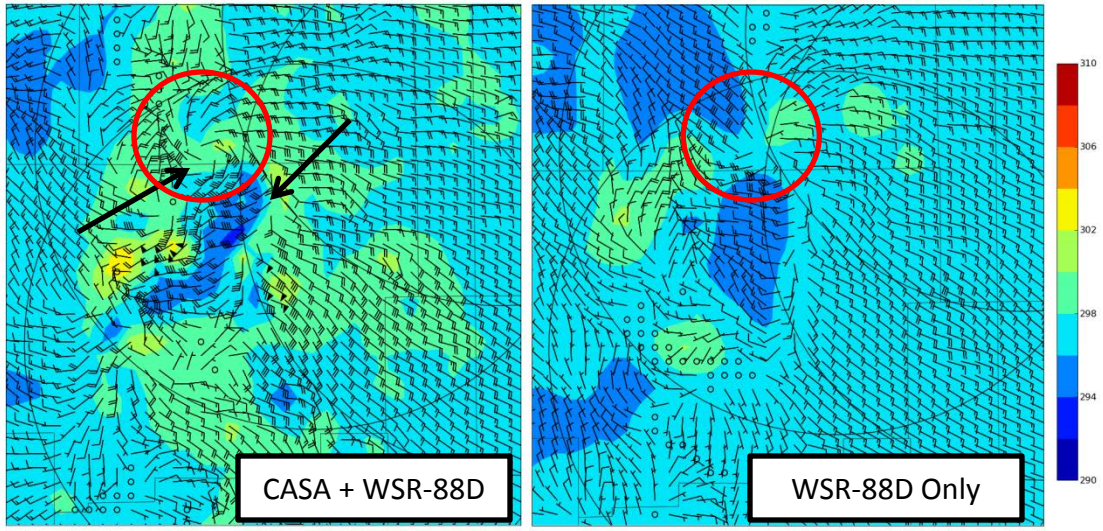
Final analysis (0200 UTC) Reflectivity



Near-surface winds and potential temperature (0140 UTC)

Snook et al
(MWR 2011)

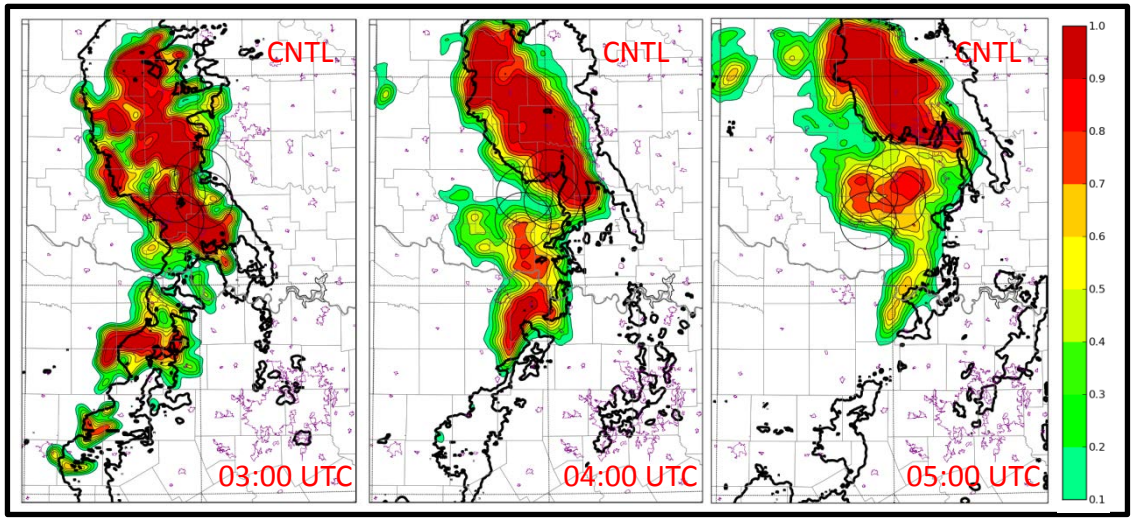




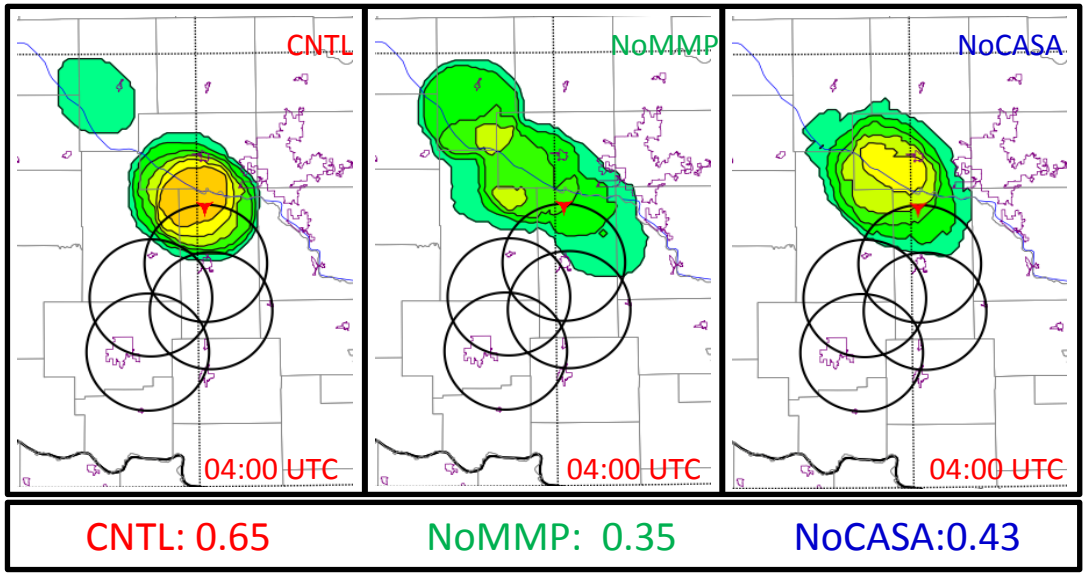
Effects of assimilated CASA data and mixed-microphysics ensemble

Ensemble-based Probabilistic Convective-scale Forecasts

1, 2, and 3-Hour Probabilistic Forecasts for P[Z > 25 dBZ]



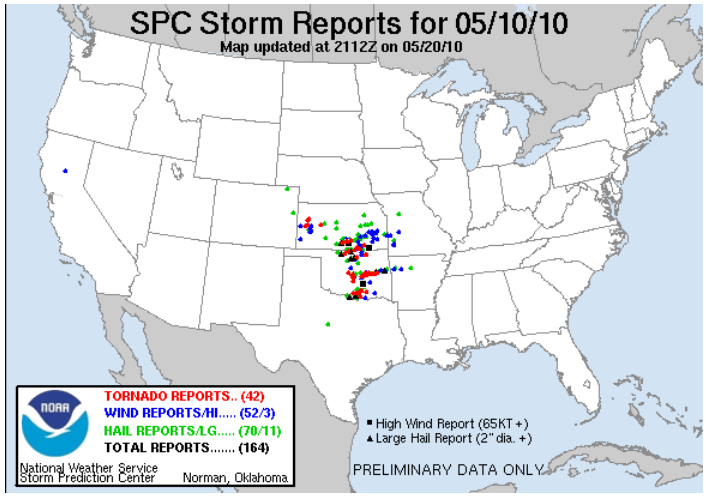
2-Hour Probabilistic Forecasts for Presence of Near-surface Vortices

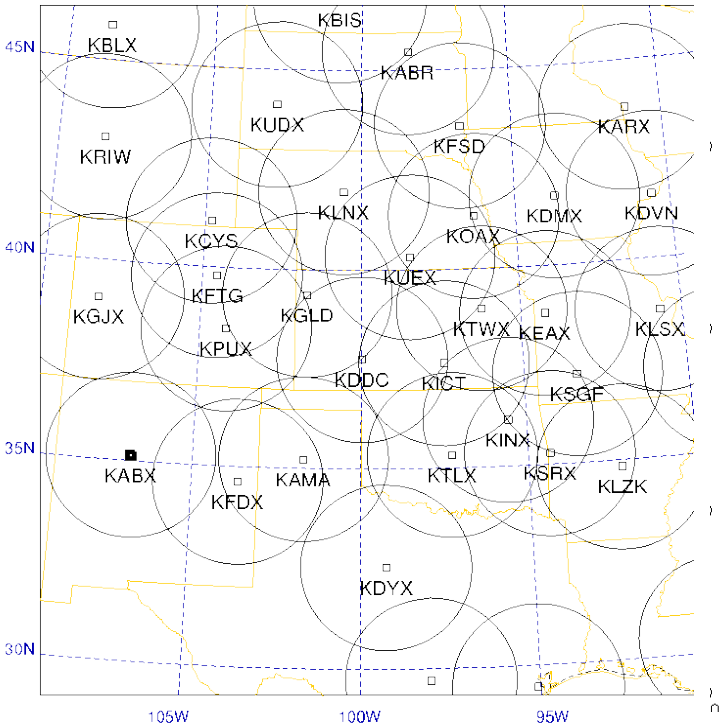


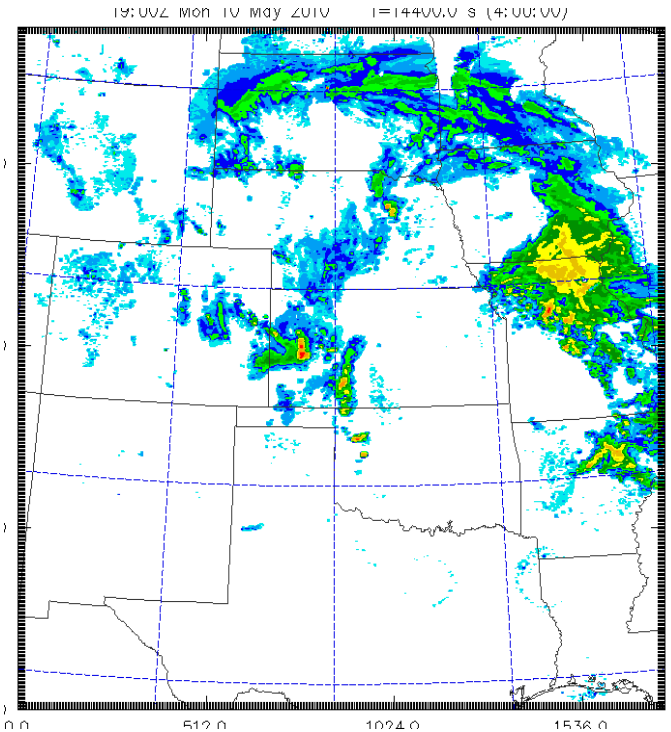
Snook et al
(MWR 2012)

EnKF Analysis of Many Radars

10 May 2010 OK-KS tornado outbreak







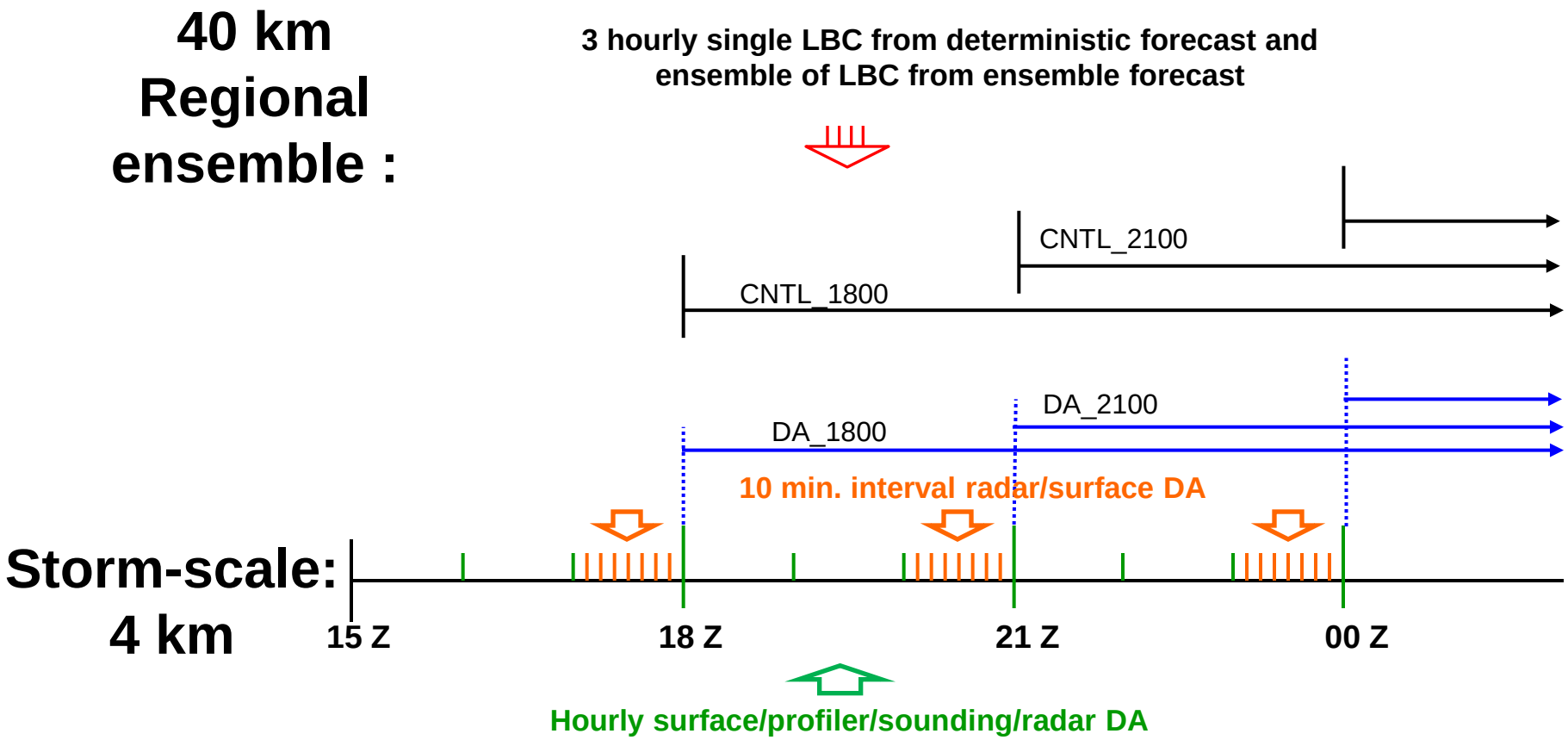
443x483x53 grid
1760 x 1920 km

29-40 radars:
Vr and Z

Surface obs,
Soundings
Profilers

Parallel multi-scale EnKF Algorithm (Wang et al. 2012)

DA procedure



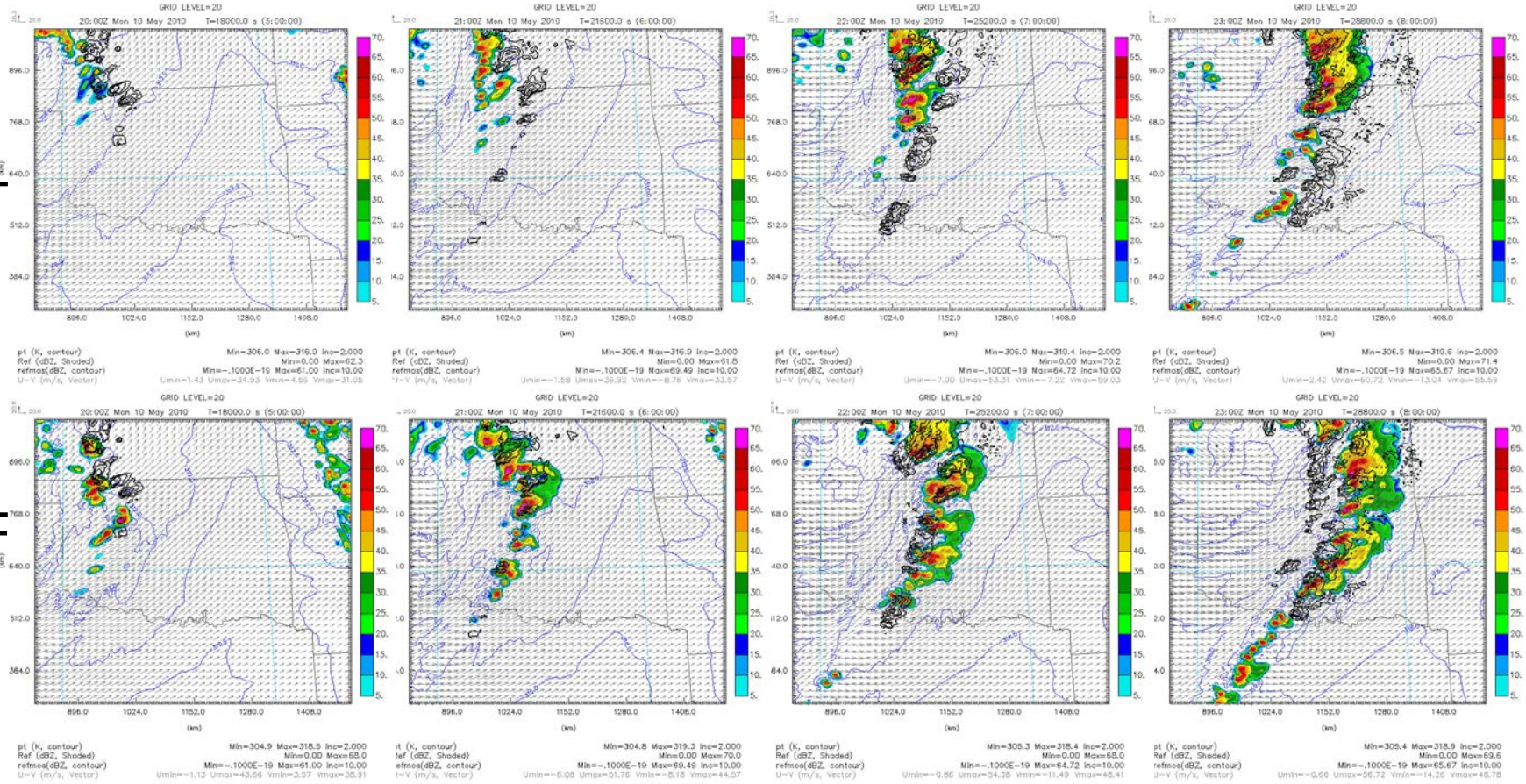
Deterministic forecasts

(contours = Z observation)

1900 UTC 2000 UTC 2100 UTC 2200 UTC

CNTL

EnKF radar



Concluding Remarks

- The semi-empirical complex cloud analysis package in the ARPS DA system, originating from LAPS cloud analysis, has been shown to be rather effective for reflectivity data assimilation for both continental convective storms, and tropical cyclones.
- With the assimilation of radar data, the spin-up problem for precipitation forecast is generally gone, but the spin-down problem can still be major due to dynamic inconsistency among the analyzed fields.
- Utilizing ensemble-derived flow-dependent covariance and being able to handle highly nonlinear ice physics, EnKF method holds much promise.
- But, EnKF method can suffer from model error, poor background estimate, and the presence and difficulty in correcting errors across many scales.
- Further research and development of advanced DA methods and efficient DA systems that maximize information extraction and dynamic consistency of state estimation are still much needed. This is especially important for radar DA given the very limited number of parameters measured.