GOES-R CI Product Suite

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Overview

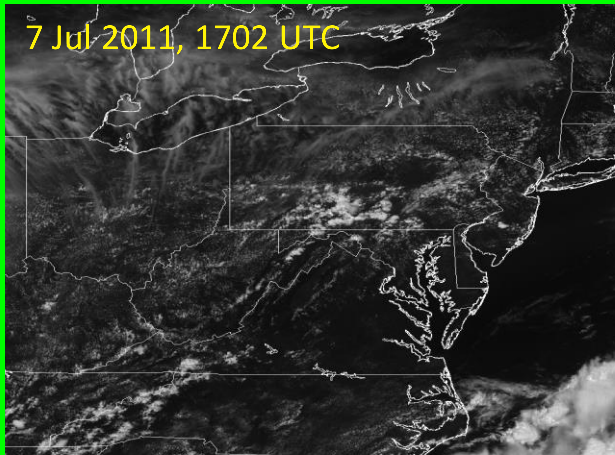
The GOES-R Convective Initiation algorithm is quickly evolving into a suite of products within one main processing methodology and construct. Providing several products within this single framework is the plan, thereby making it easier for users (NASA SPoRT, EWP/HWT/AWT, NWS) to incorporate them into the forecasting process.

1. Basic 0–1 hour CI (object based)
2. Severe CI prediction
3. Early CI – Focuses on use of 1–min SRSOR observations
4. 1–4 hour CI (probabilistic)
5. “mesoscale Atmospheric Motion Vector” (mAMV) storm type delineation
6. HRRR & WRF model data assimilation

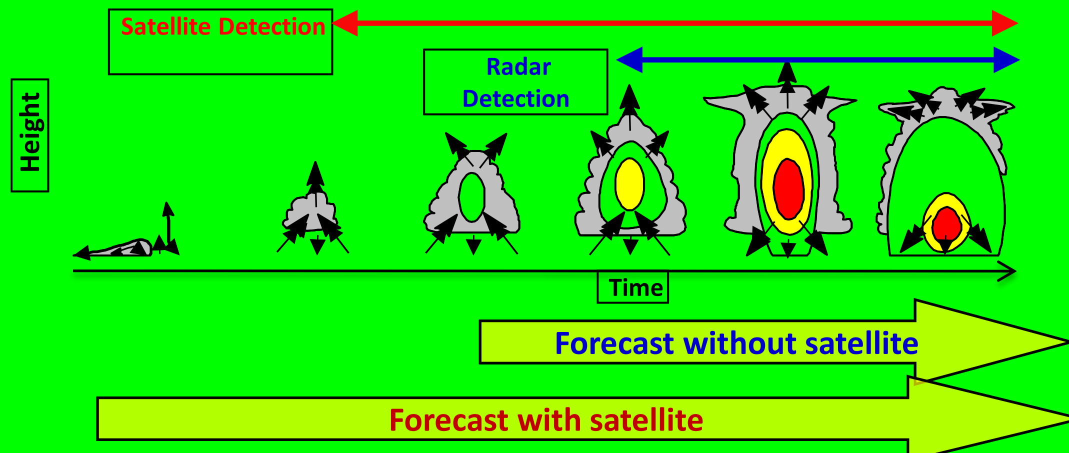
Products 1 and 2 are combined into a single output file.

GOES-R CI Flowchart as Running Operationally

Download latest satellite imagery…



Monitor Cumulus Cloud Development



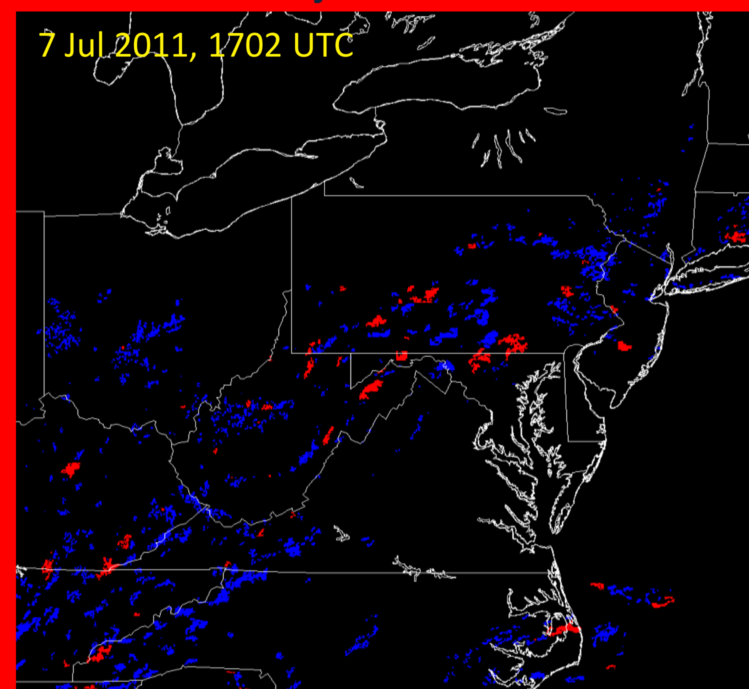
Make Cloud Mask

Produce MAMVs

Track "Cloud Objects" from 'T1' to 'T2' (Similar to "Cb-TRAM" Zinner et al. 2008)

Determine CI forecast for each tracked Cloud Object using Logistic Regression with 24 GOES & RAP Model fields.

Per-Object CI forecast



CI Definition: 1st ≥35 dBZ echo at ground, or at –10 ºC altitude

Current Methodology & Accuracy

Method	**LR-Sat**		**LR-SatNWP**		**RF-Sat**		**RF-SatNWP**	
Probability of Detection	0.54	0.80	**0.68**	**0.85**	0.49	0.74	**0.72**	**0.87**
Probability of False Detection	0.20	0.51	**0.20**	**0.36**	0.21	0.40	**0.27**	**0.40**
False Alarm Ratio	0.32	0.30	**0.28**	**0.22**	0.36	0.27	**0.33**	**0.24**
Accuracy/Total Performance	0.69	0.67	**0.74**	**0.76**	0.66	0.68	**0.72**	**0.76**
% correct CI nowcasts	53.7%	79.8%	**67.6%**	**84.6%**	49.5%	73.5%	**71.9%**	**87.2%**
% correct non-CI nowcasts	80.2%	48.6%	**79.6%**	**64.3%**	78.8%	59.5%	**72.5%**	**60.4%**
Positive Predictive Value	67.8%	69.5%	**72.1%**	**77.7%**	64.5%	72.8%	**67.0%**	**76.4%**
Negative Predictive Value	69.0%	62.1%	**75.9%**	**73.9%**	66.7%	60.5%	**76.8%**	**76.3%**
Bias	1.98	0.98	**1.81**	**1.18**	1.96	1.13	**1.54**	**1.12**
Area under ROC Curve	0.73	0.71	**0.81**	**0.83**	0.69	0.73	**0.80**	**0.82**
Critical Success Index	0.43	0.59	**0.54**	**0.68**	0.39	0.58	**0.53**	**0.69**
Equitable Threat Score	0.21	0.17	**0.31**	**0.33**	0.17	0.20	**0.28**	**0.33**
True Skill Statistic	0.34	0.28	**0.47**	**0.49**	0.28	0.33	**0.44**	**0.48**

- The present 0–1 hour Convective Initiation algorithm is 85-87% accurate (Mecikalski et al. 2015) using Logistic Regression with 24 predictors (9 satellite/15 RAP model).

- Convective storm initiation identified beneath higher clouds, and at night using satellite-based cloud property information.

Indicators being sampled in CI Nowcasting

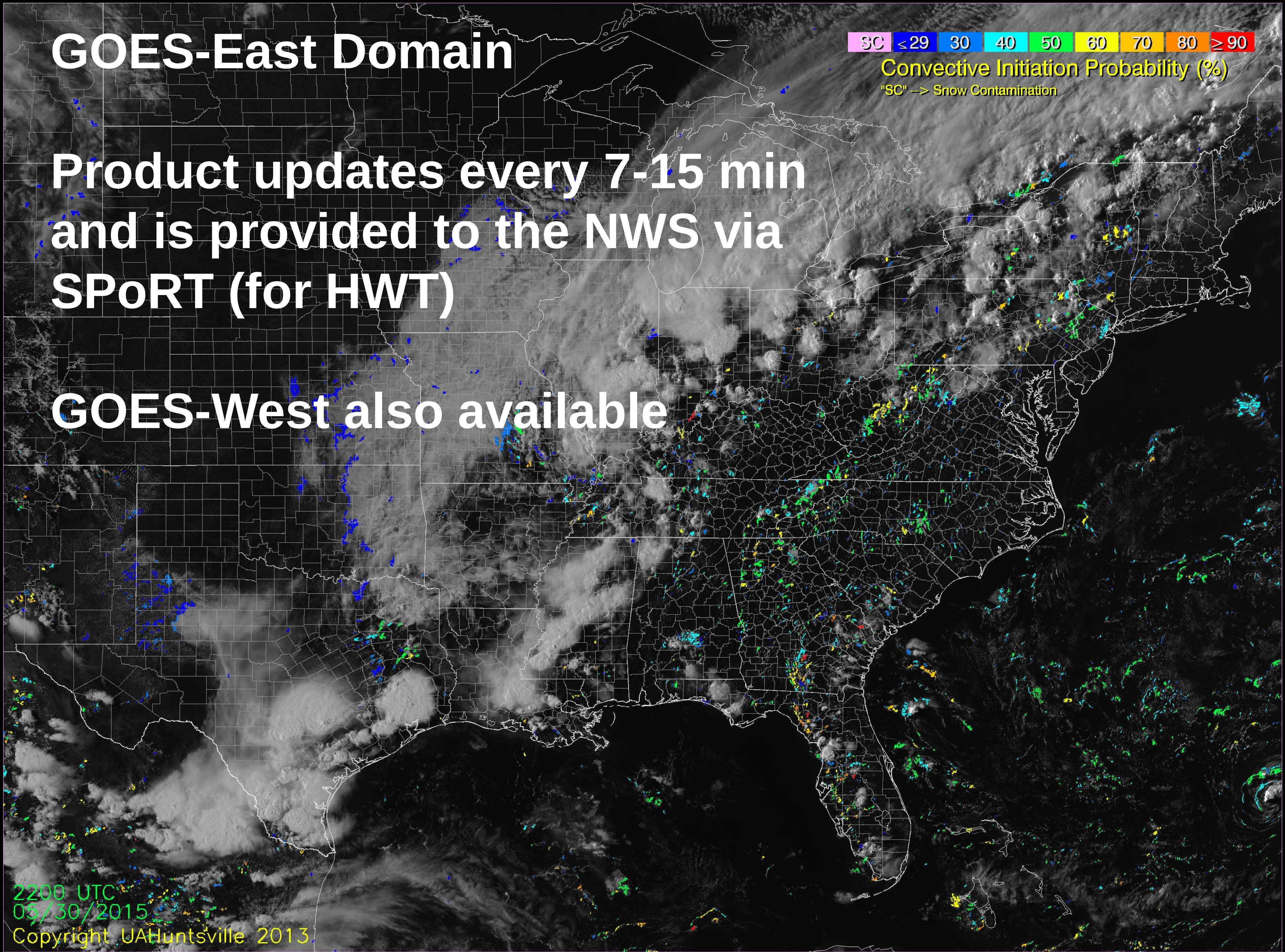
GOES-R CI

- 10.7 µm T_B
- 15 min 10.7 µm Trends
- 6.7–10.7 µm T_B difference & 15-min trend
- 13.3–10.7 µm T_B difference & 15-min trend
- Convective cloud mask at t1 and t2
- Convective cloud mask change (i.e., cumulus to towering cumulus, cumulus staying cumulus, etc.)
- Object size at t1 and t2
- Change in object size for t1 and t2
- Geographical locations (latitude/longitude)
- Solar time

Environmental (RAP–NWP)

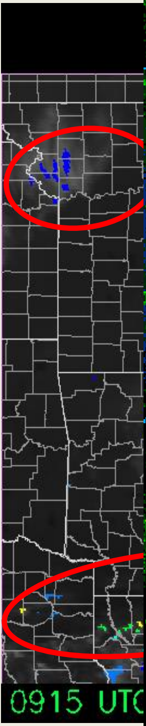
- Surface and most unstable convective available potential energy (CAPE)
- Surface and most stable convective inhibition (CIN)
- Surface and best lifted index (LI)
- Lifted Condensation Level (LCL)
- Level of Free Convection (LFC)
- Convective Condensation Level (CCL)
- Bulk Wind Shear and Low Level Wind Shear
- Height of Freezing Level

Use an automated >120,000+ event database


GOES-East Domain
Product updates every 7-15 min and is provided to the NWS via SPoRT (for HWT)
GOES-West also available
SC ≤29 30 40 50 60 70 80 ≥90
Convective Initiation Probability (%)
"SC" --> Snow Contamination
2200 UTC
05/30/2015
Copyright UAHuntsville 2013

Nighttime Algorithm

Origi



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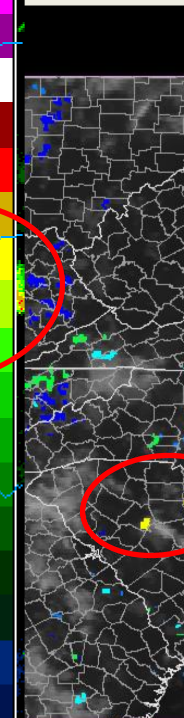

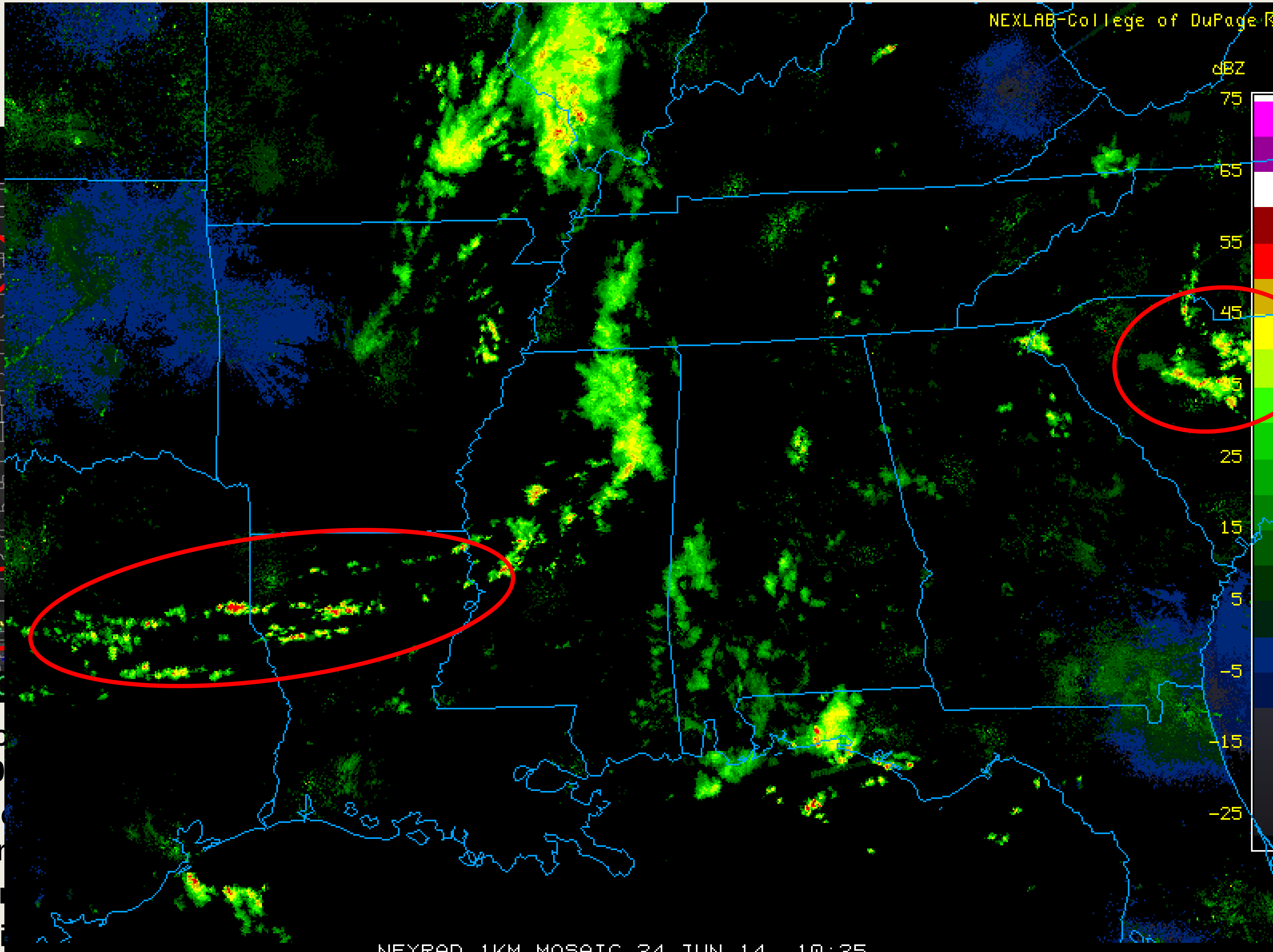

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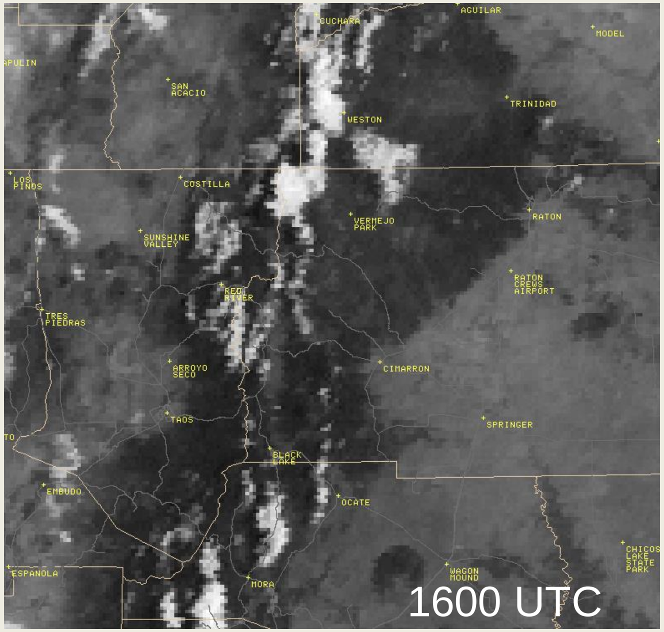
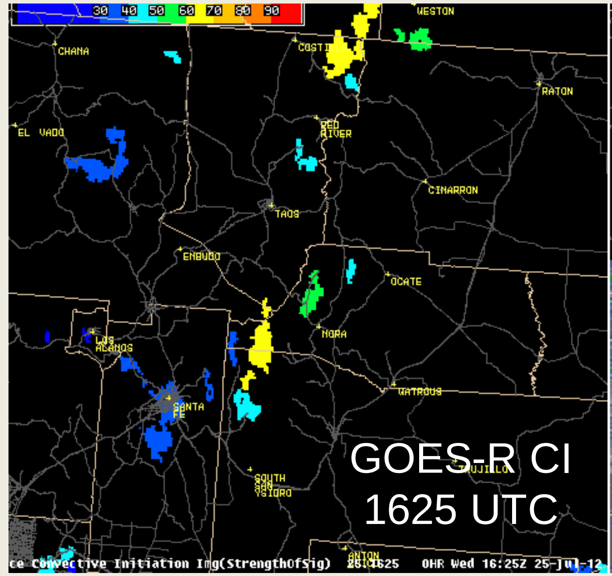
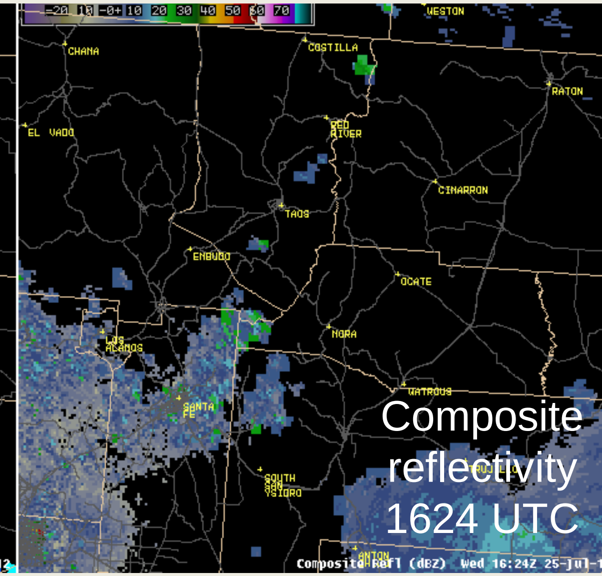
reducing much of the noise.

GOES-R CI Probability Product

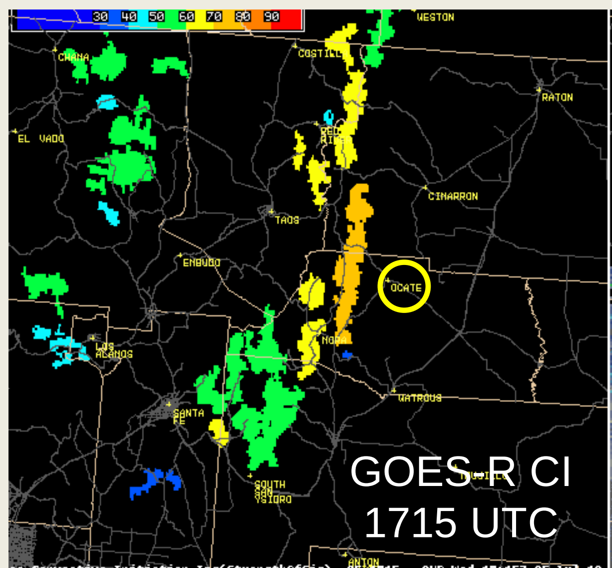
mountainous region – limited radar coverage

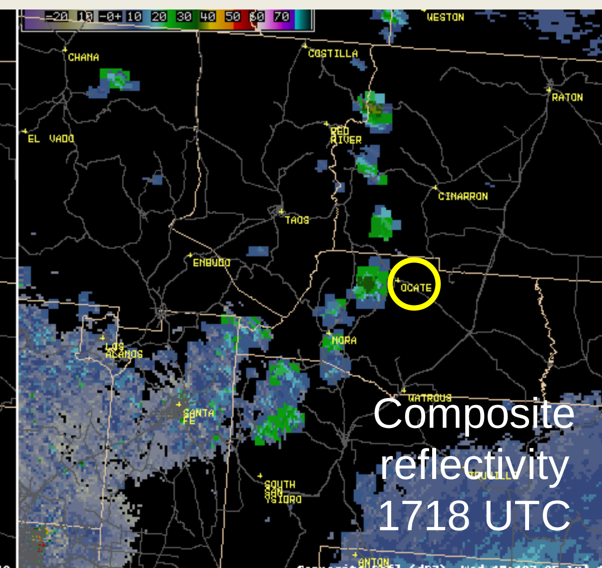






July 25, 2012: NWS-ABQ



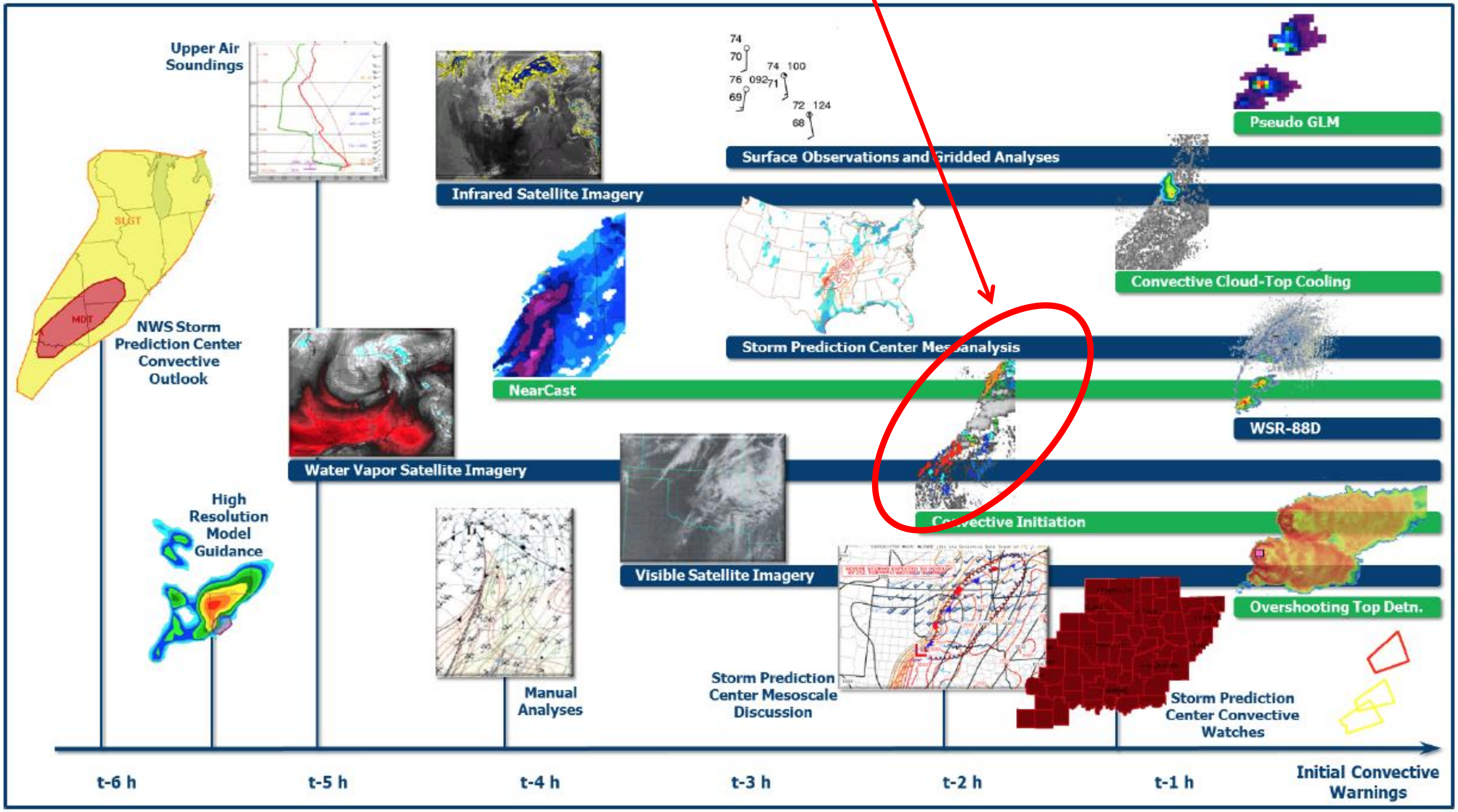


1600: GOES satellite observed towering cumulus clouds
1625: 70 strength of signal reached
1718: 35 dBZ in *composite* reflectivity

First lightning strike in Ocate, New Mexico shortly after.

The –3 to 0 hour Convective Forecasting Timeline

GOES-R CI is the Earliest Satellite Indicator of Intense Storms



Gravelle et al. (2015)

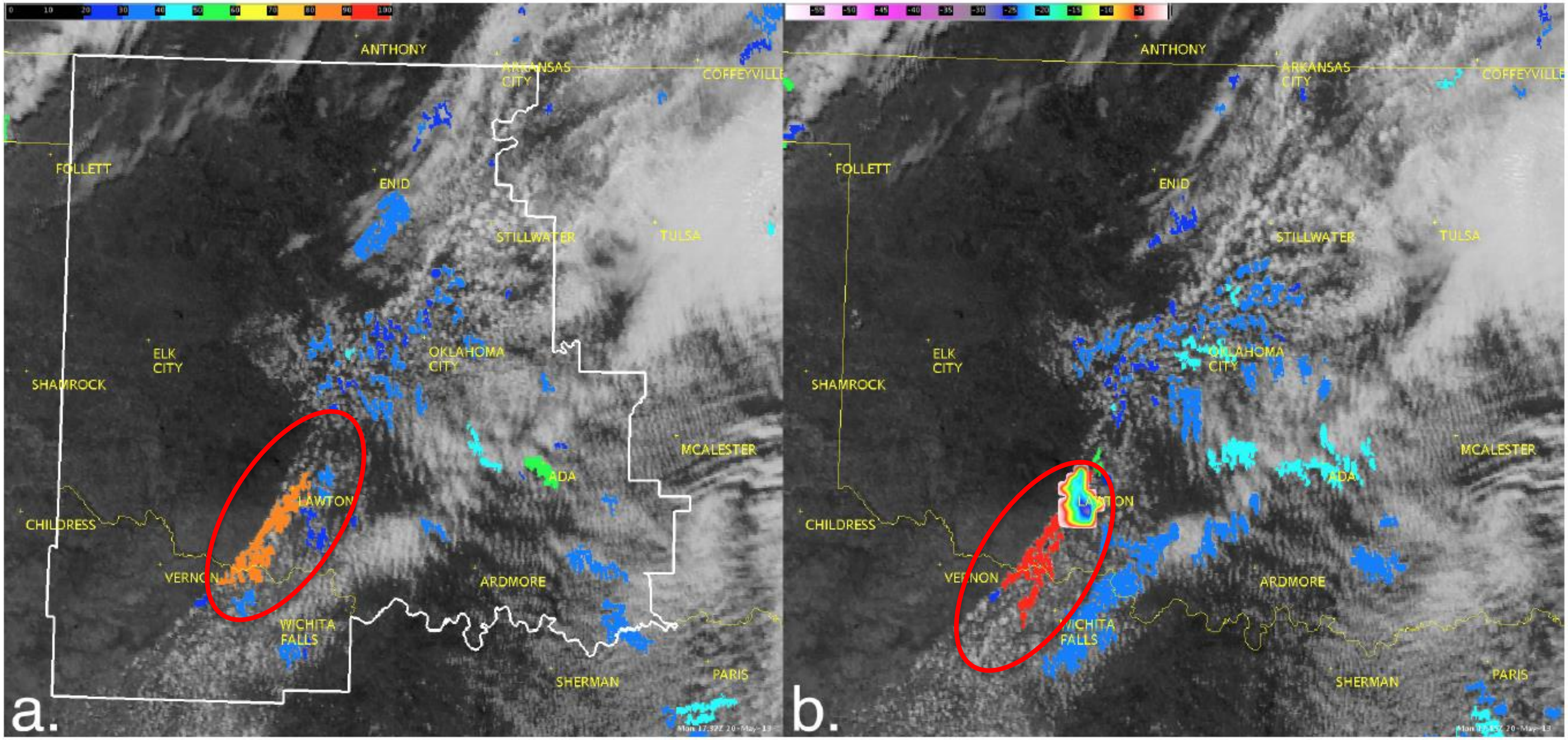


FIG. 4. (a) 1732 UTC 20 May 2013 visible satellite image from the GOES-13, convective initiation (%, shaded according to scale), and convective cloud-top cooling (C 15 min^{-1}, shaded according to scale) and (b) as in (a) except valid at 1745 UTC 20 May 2013. The Norman, Oklahoma NWS County Warning Area boundary is shown in (a).

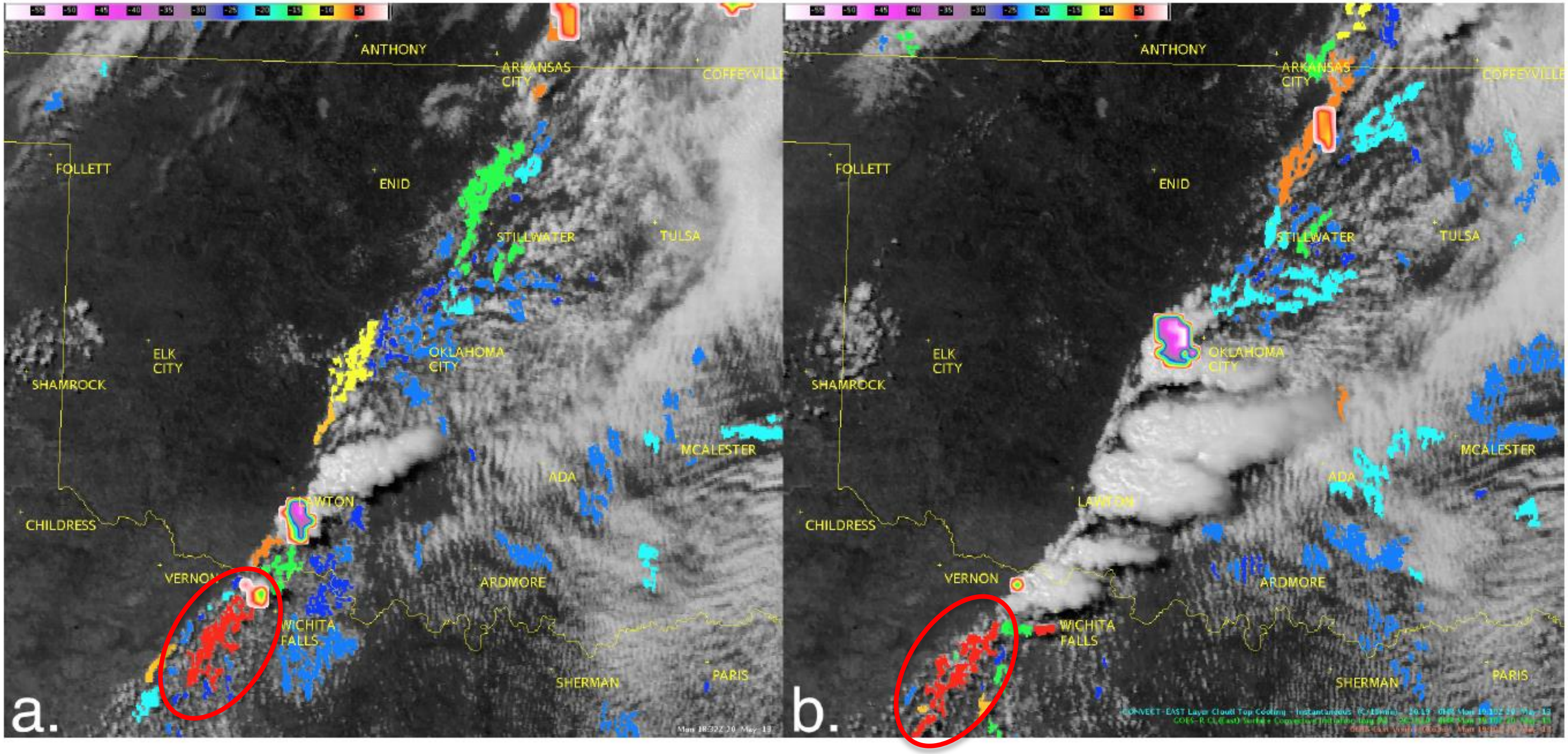
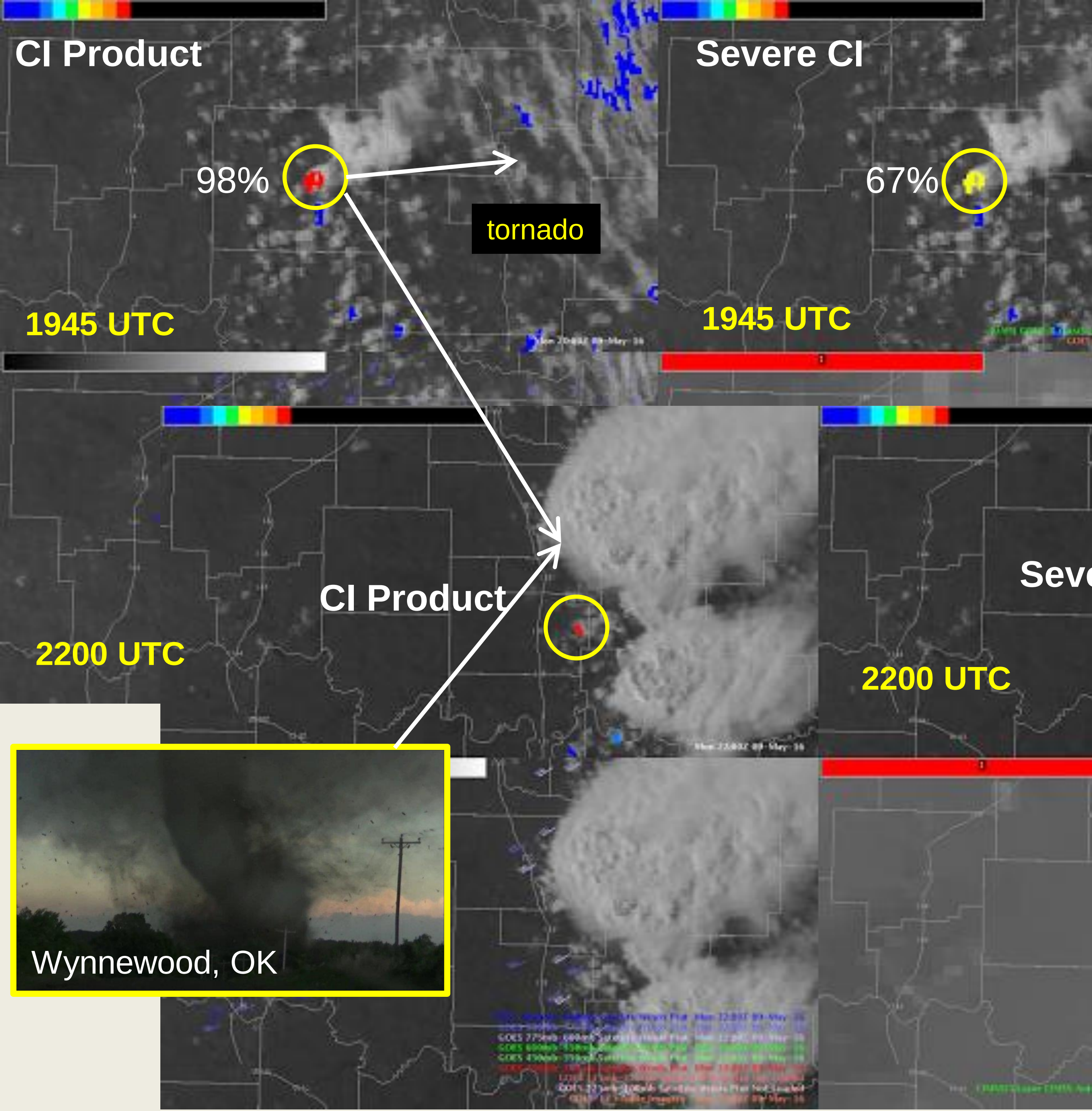
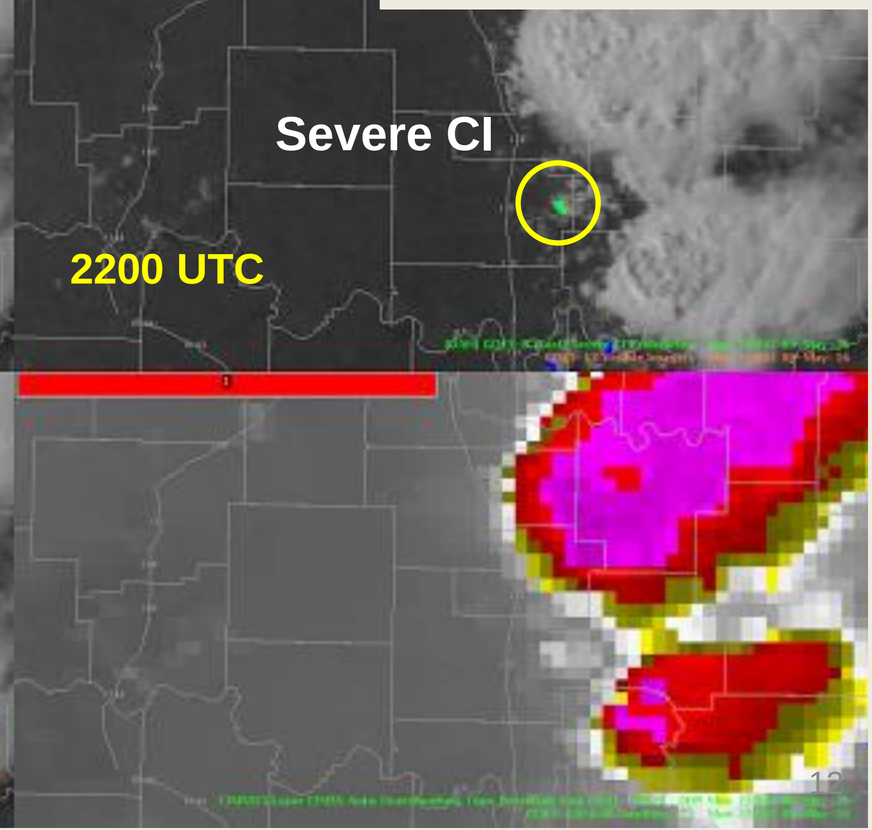


FIG. 5. (a) As in Fig. 2, except valid at 1832 UTC 20 May 2013 and (b) as in Fig. 2, except valid at 1910 UTC 20 May 2013.

May 9, 2016

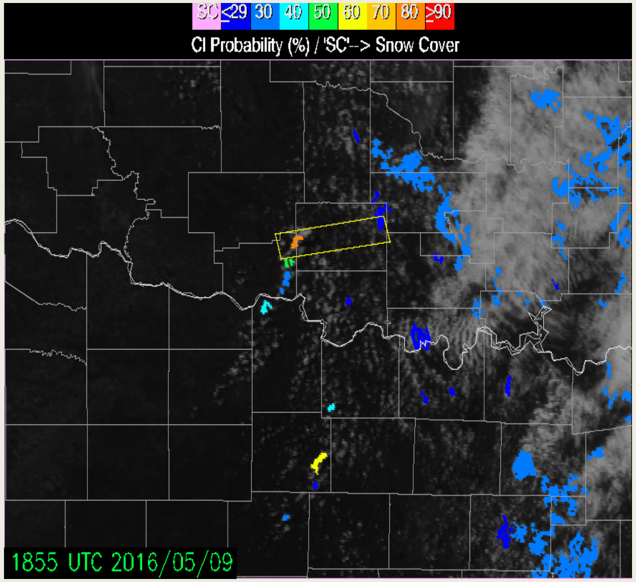
An ~75 min lead time was provided then by the CI algorithm to the occurrence of a tornado in Wynnewood, OK at ~2110 UTC.



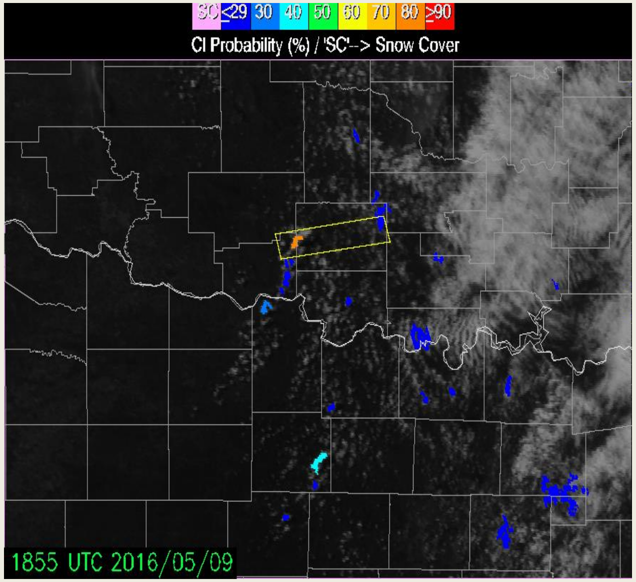


NextStorm Severe Convective Initiation Product
May 09, 2016 Oklahoma tornado

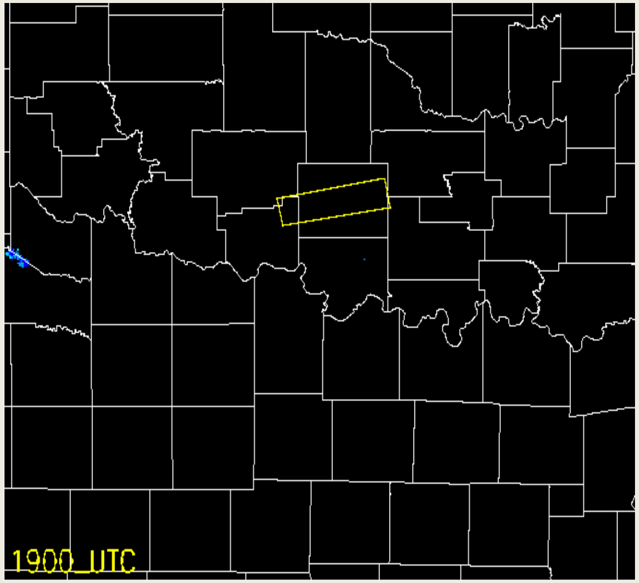
Regular CI Product



Severe CI Product

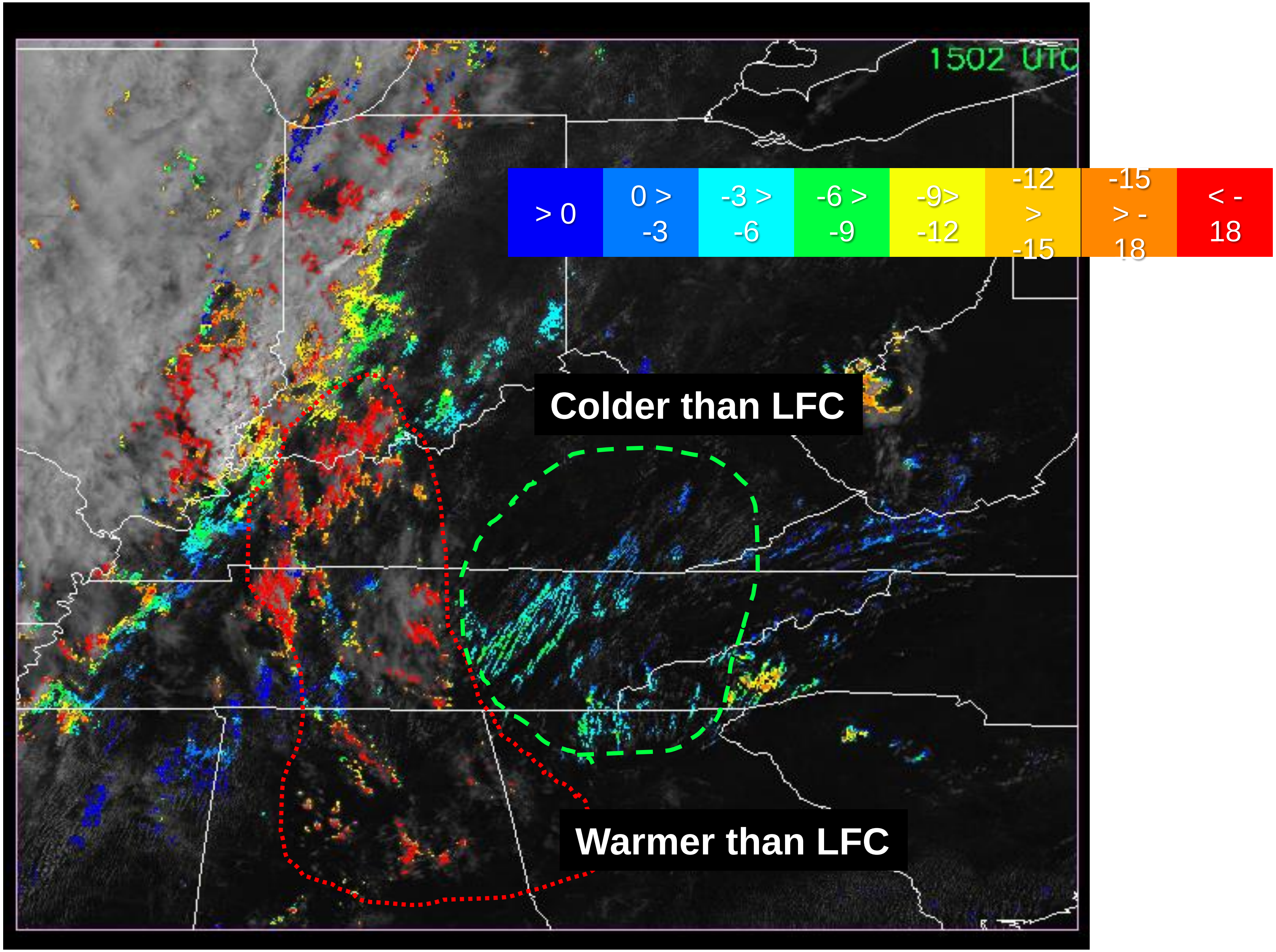


Radar reflectivity at -10 C



- Shown at 1855 UTC is initiation of the parent storm which produced an EF3 tornado in Garvin County, OK.
- Storm actually took time to develop a robust updraft capable of insulating itself from the surrounding environment (note radar imagery).
- Secondary development around 2000 UTC also depicted by the CI algorithms, merged with this parent supercell enhancing the updraft and mesocyclone rotation

“Early Convective Initiation” Product based on SRSOR Data



Feature Selection

- Feature attribute selection using **information-gain algorithm** on combined (1 and 2 hour) feature set which ranks each of 234 features in decreasing order of importance

- Using Information-gain algorithm, the identified top 20 features are aspect_count, TCUM_CLOUD_sum_1hr_dif, TCUM_CLOUD_count, cape2_min, cape0_min, cape3_mean, cape3_max, cape1_min, cape2_max, cape1_mean, cape0_mean, cape0_max, cape2_mean, cape1_max, cape3_min, TCUM_CLOUD_mean, aspect_sum, cin3_min, cin2_min, RAP_REFL_SUM_1hr_dif

- Using **Random Forest** classifier with 10 fold cross validation, 12 experiments were run by selecting top 1, 3, 10, 20, 30, 50, 60, 90, 120, 150, 180 and 210 sub-features respectively which led to overall accuracies of 58.62%, 60.03%, 62.22%, 64.78%, 65.21%, 67.28%, 68.19%, 68.54%, 68.50%, 68.96%, 68.95%, 68.61%

- Based on above results we determine optimal number of features is between 50 to 60 and **optimum accuracy is around 69%**.

- Using information gain algorithm results and some domain knowledge we manually selected **59 out of 234 features** for training algorithm

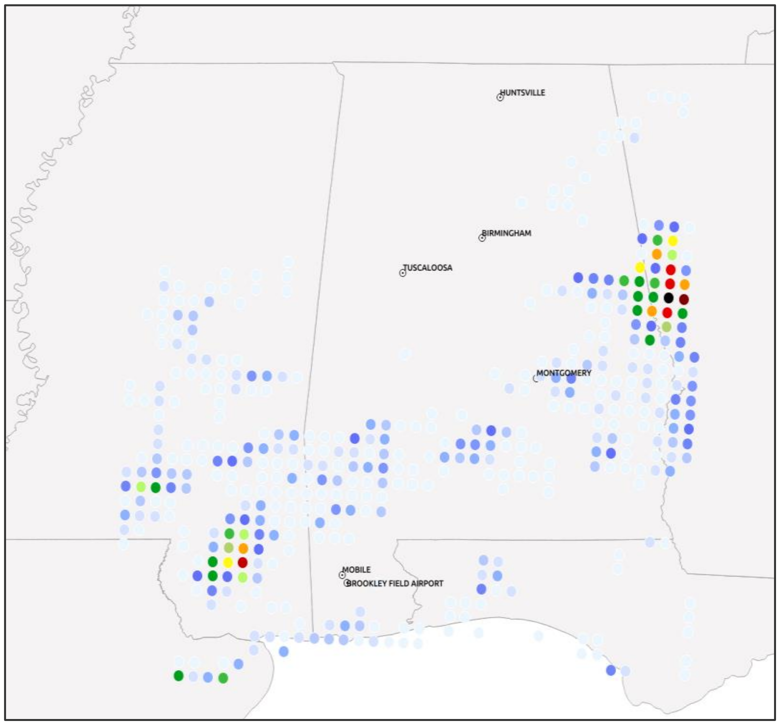
Training (Evaluation of Algorithms)

- 7 classification algorithms are used – **BayesNet** (BN), **Naive Bayes** (NB), **Logical Model Trees** (LMT), **Logistic Regression** (LR), **Multilayer Perceptron** (MP), **Random Forest** (RF), **Support Vector Machines** (SMO). *Waikato Environment for Knowledge Analysis* (WEKA) package was used for machine learning analysis

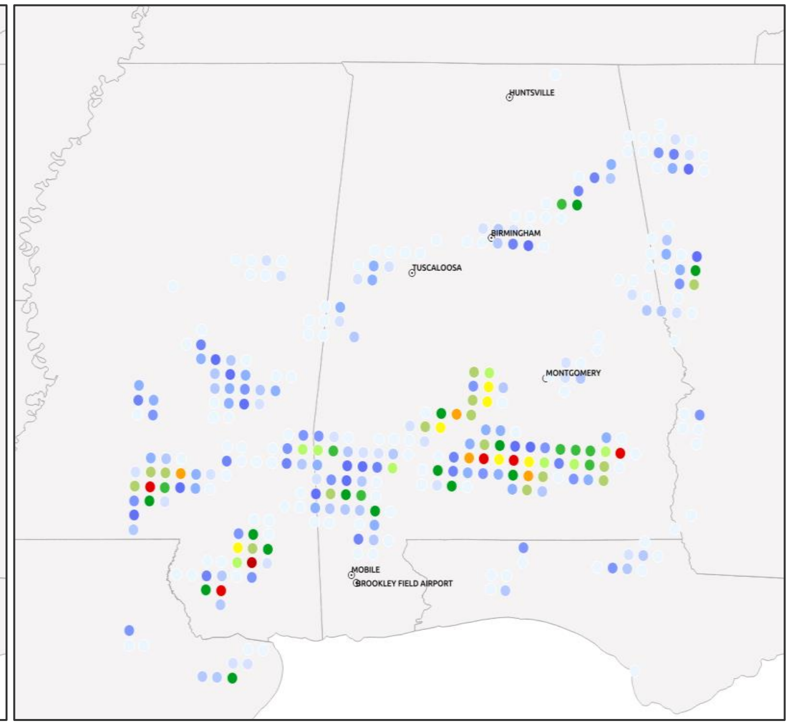
- **August data (59 features) was used to train each model** and **tested on July data**. For classifiers that allow parameter optimization (Random Forest, SMO, etc.) a range of parameter options are tested and best models were selected

	1hr Training	1hr Testing	2hr Training	2hr Testing
BN	58.6%	62.9%	54.6%	58.0%
NB	57.6%	64.7%	54.9%	58.7%
LMT	61.4%	65.0%	55.2%	56.8%
LR	59.7%	66.8%	55.8%	58.5%
MP	59.8%	64.7%	55.9%	59.5%
RF	**63.4%**	**66.8%**	**58.0%**	**59.1%**
SMO	64.0%	66.4%	59.3%	59.1%

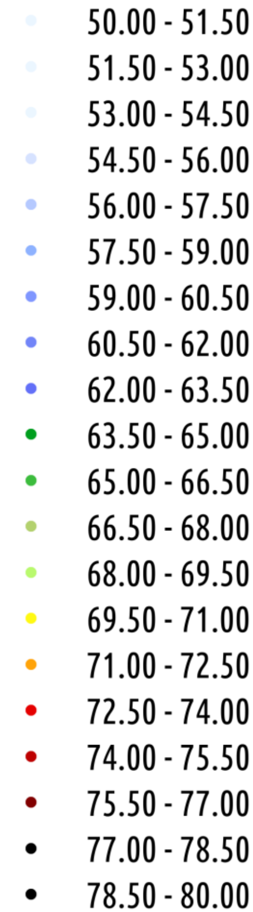
CI Probability for 2014-07-24 2300 UTC



2 hour CI prediction

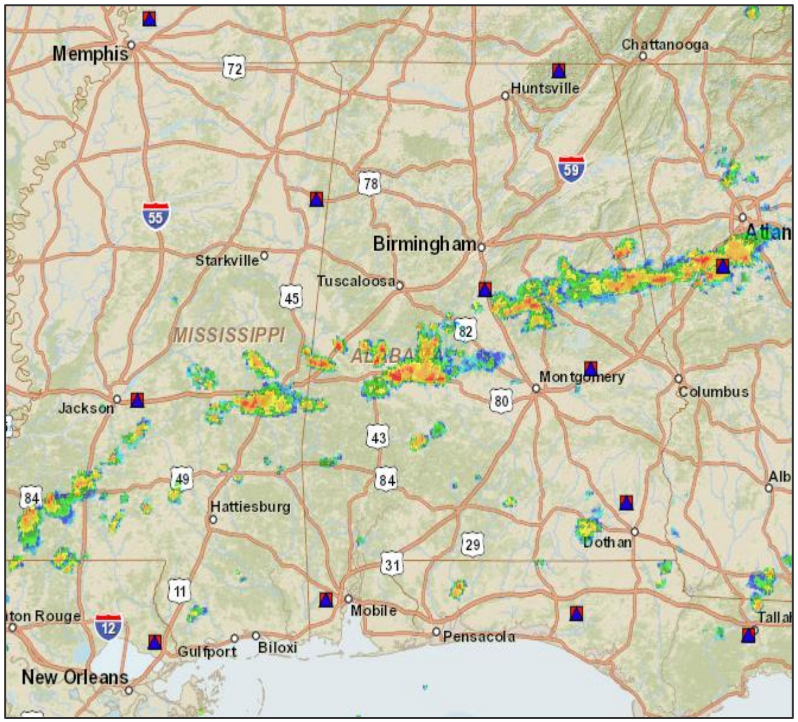


1 hour CI prediction

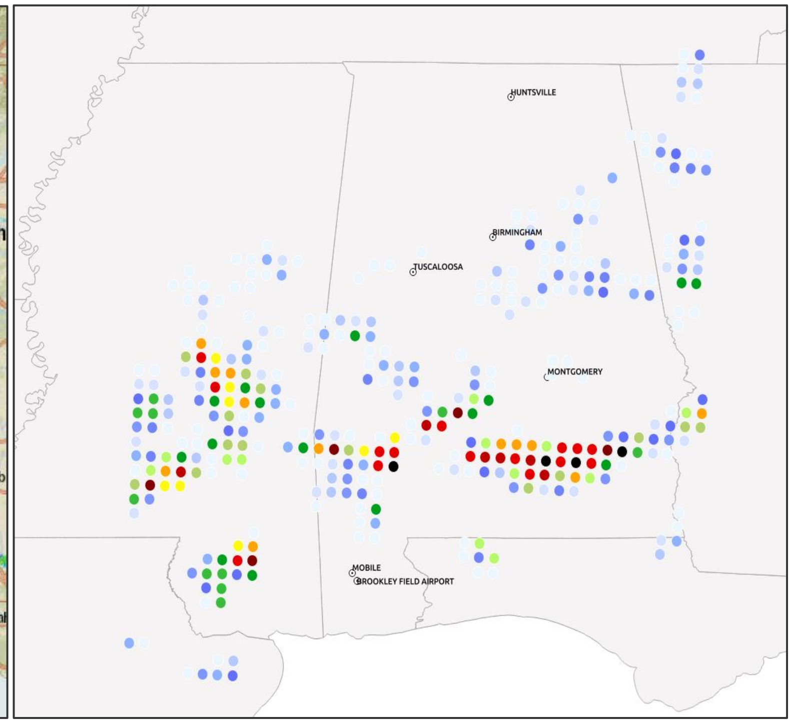


CI probabilities <50% not shown

CI Probability for 2014-07-24 2300 UTC

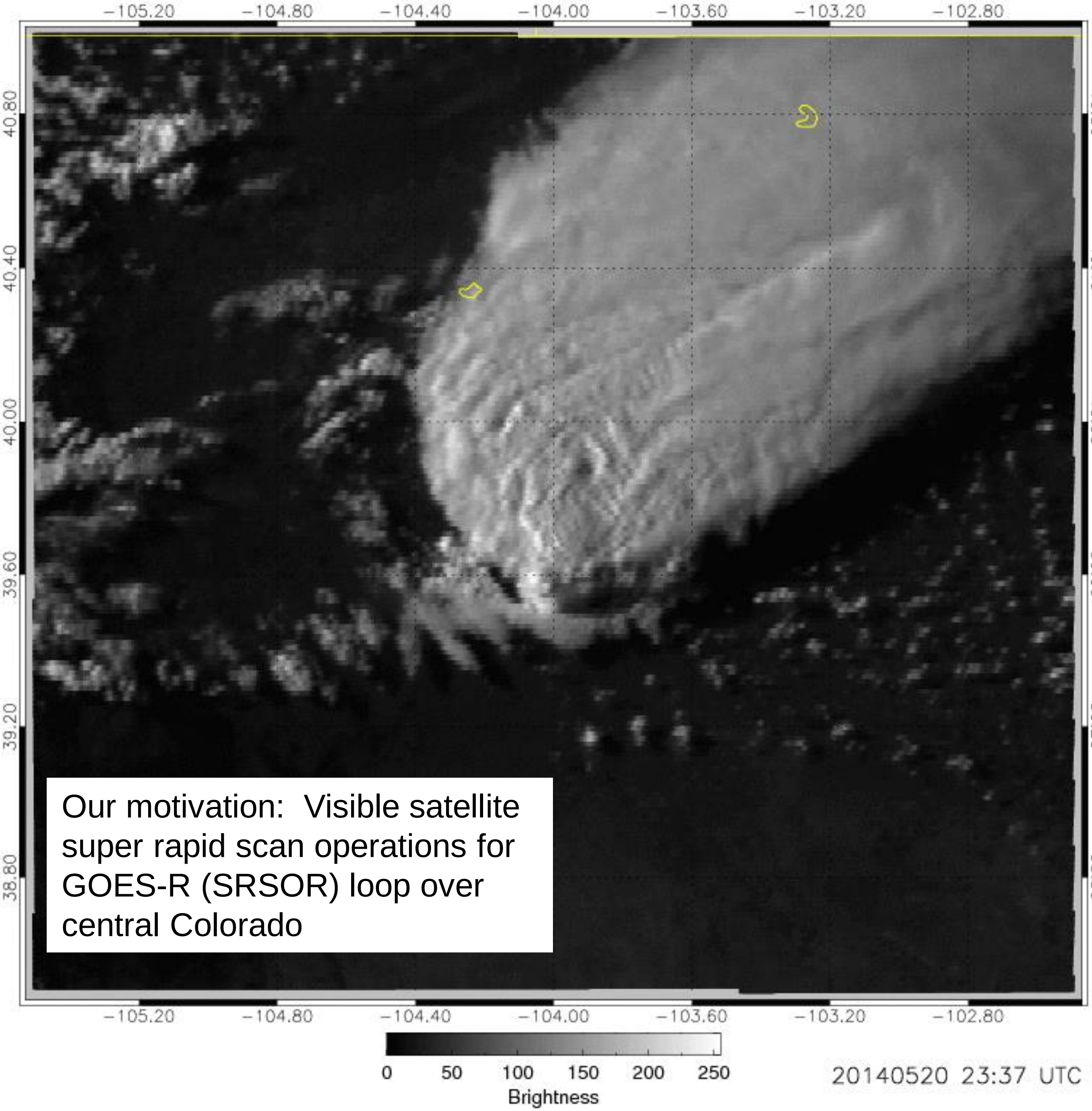


NEXRAD Radar composite



0 hour (CI nowcast)

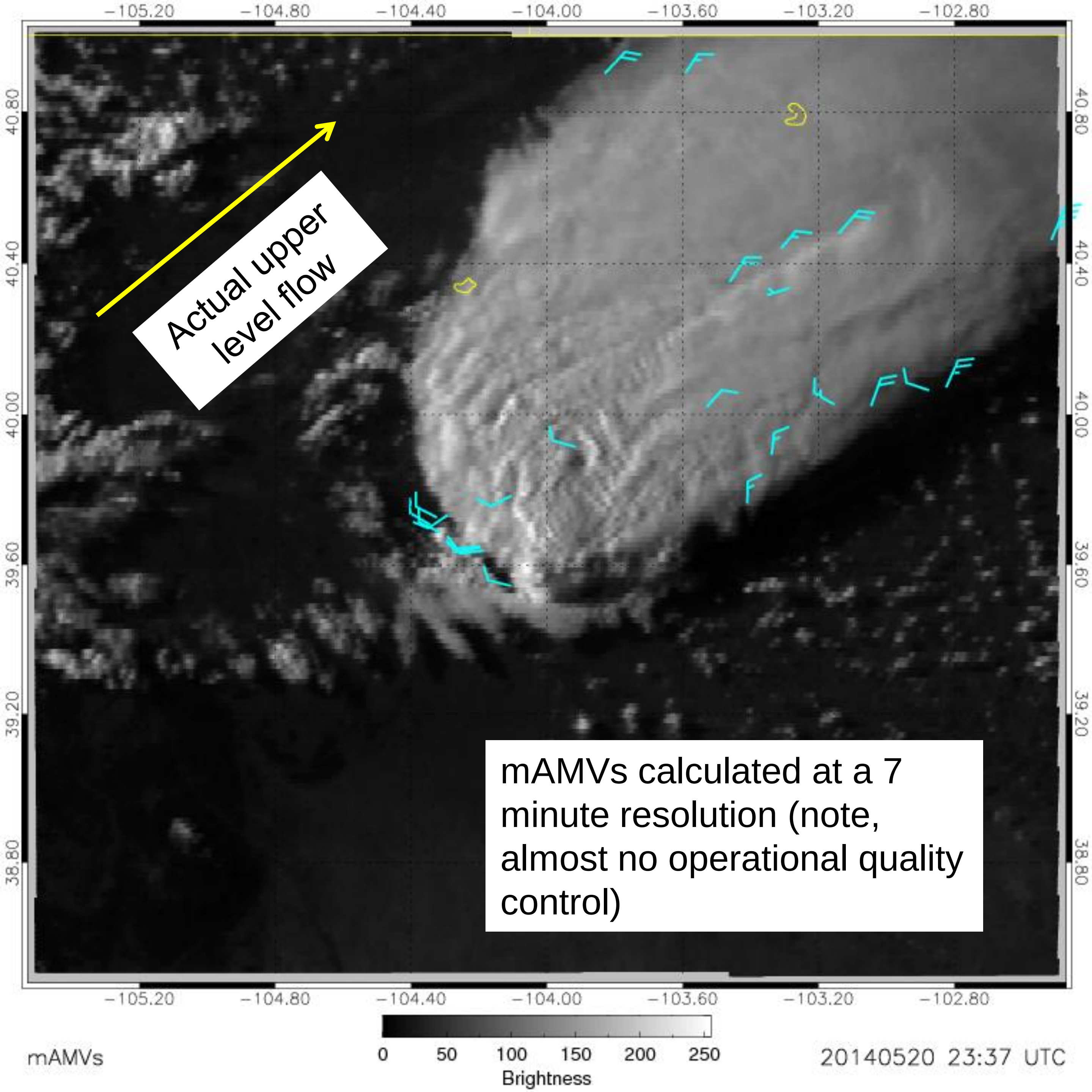
- 50.00 - 51.50
- 51.50 - 53.00
- 53.00 - 54.50
- 54.50 - 56.00
- 56.00 - 57.50
- 57.50 - 59.00
- 59.00 - 60.50
- 60.50 - 62.00
- 62.00 - 63.50
- 63.50 - 65.00
- 65.00 - 66.50
- 66.50 - 68.00
- 68.00 - 69.50
- 69.50 - 71.00
- 71.00 - 72.50
- 72.50 - 74.00
- 74.00 - 75.50
- 75.50 - 77.00
- 77.00 - 78.50
- 78.50 - 80.00



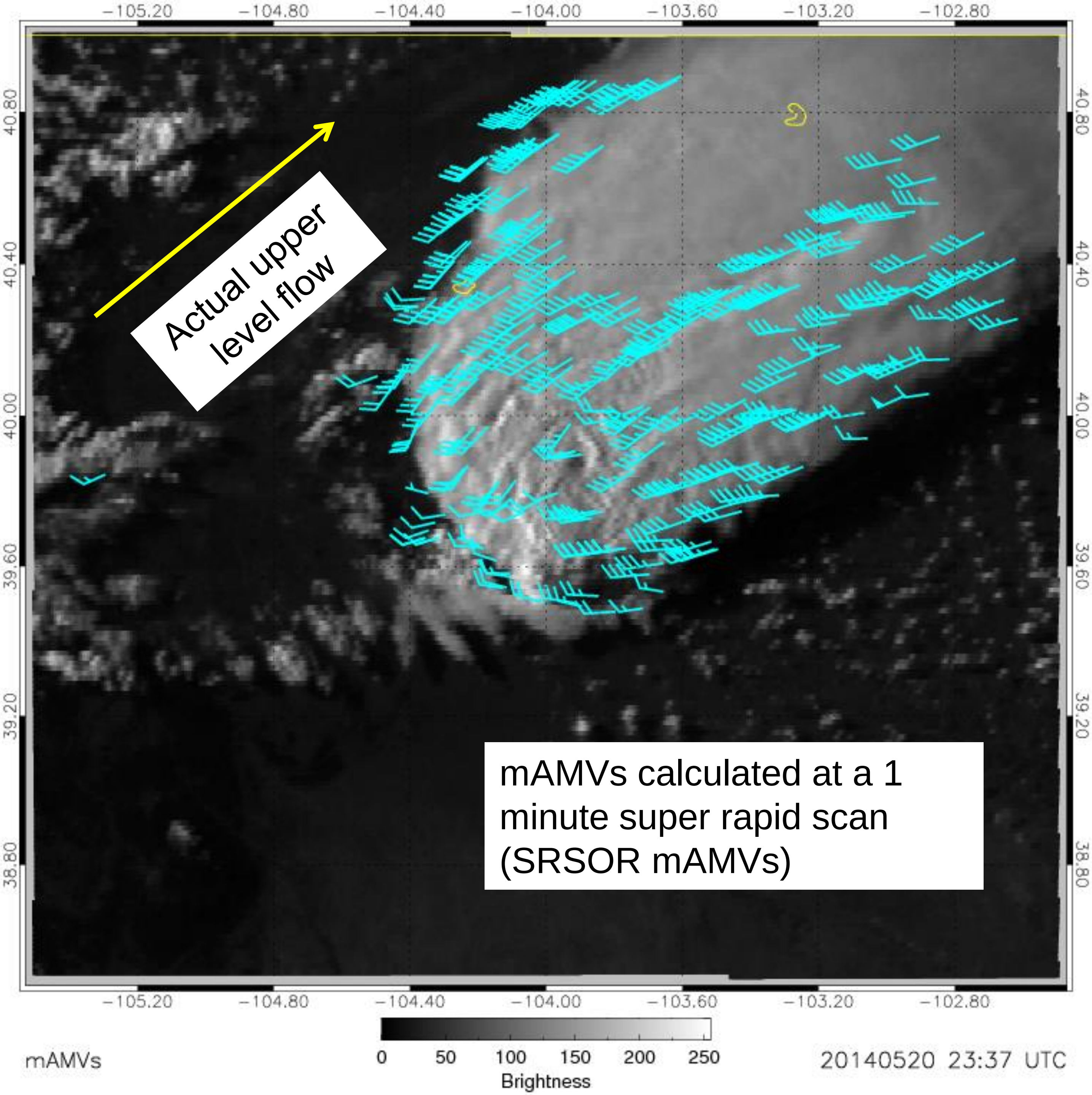
Our motivation: Visible satellite super rapid scan operations for GOES-R (SRSOR) loop over central Colorado

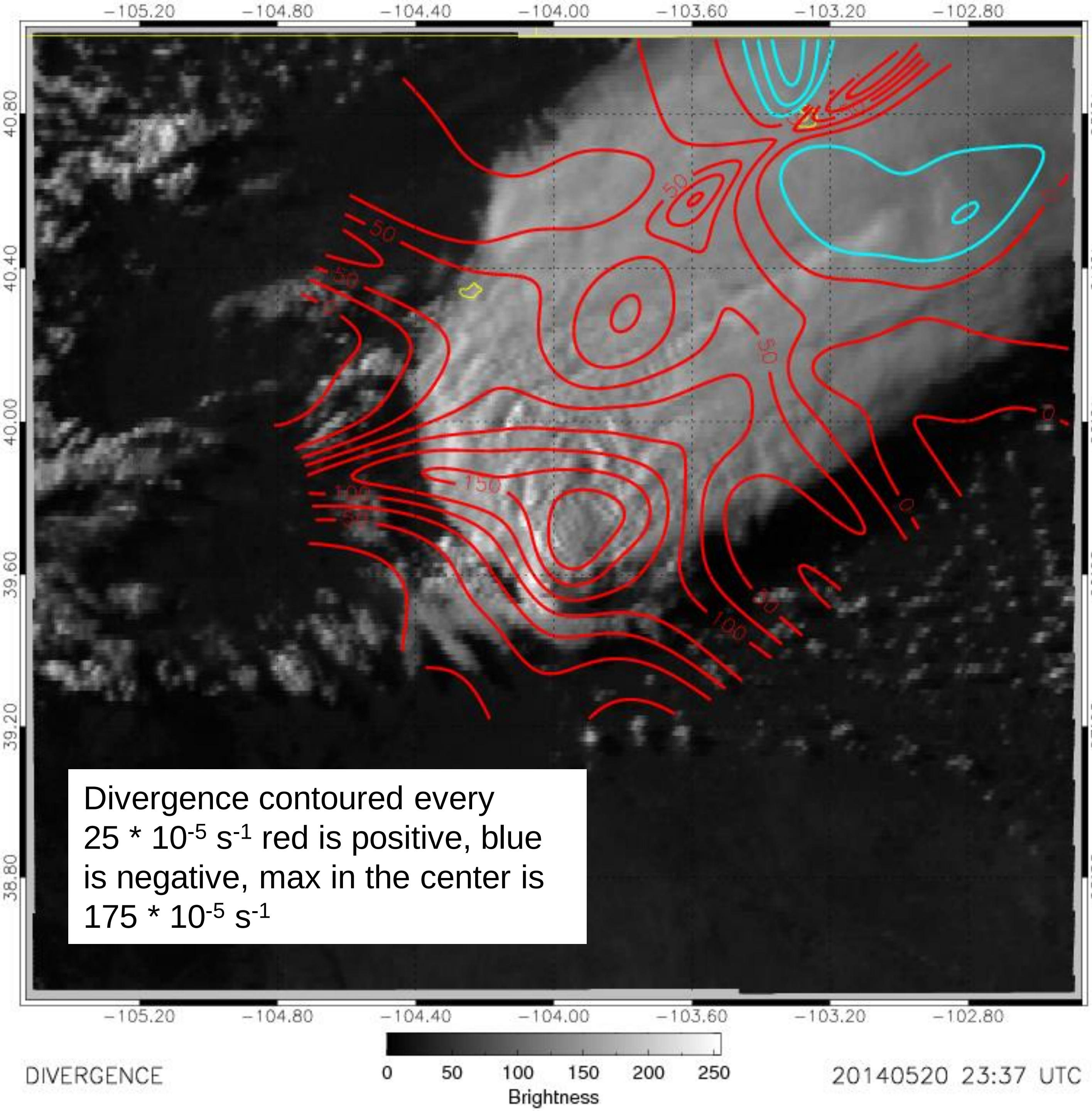
Background

- The mesoscale atmospheric motion vector (mAMV) program (Velden et al. 1997, 1998; Bedka and Mecikalski, 2005) is already used for experimental algorithms such as GOES-R CI (Mecikalski and Bedka, 2006; Walker et al. 2012; Mecikalski et al. 2015)
  - Generates wind estimates by tracking targets of interest, such as boundaries, minima and maxima in Visible/IR using cross-correlation techniques
- Now we are repurposing it to resolve winds at higher levels (above 500 mb) with higher temporal resolution
- Several cases are analyzed with this presentation, five instances of supercells, one ordinary convective events
- A single pass Barnes analysis is used to interpret flow characteristics such as divergence and vorticity at cloud top (Apke et al. 2016, JAMC, *In review*)

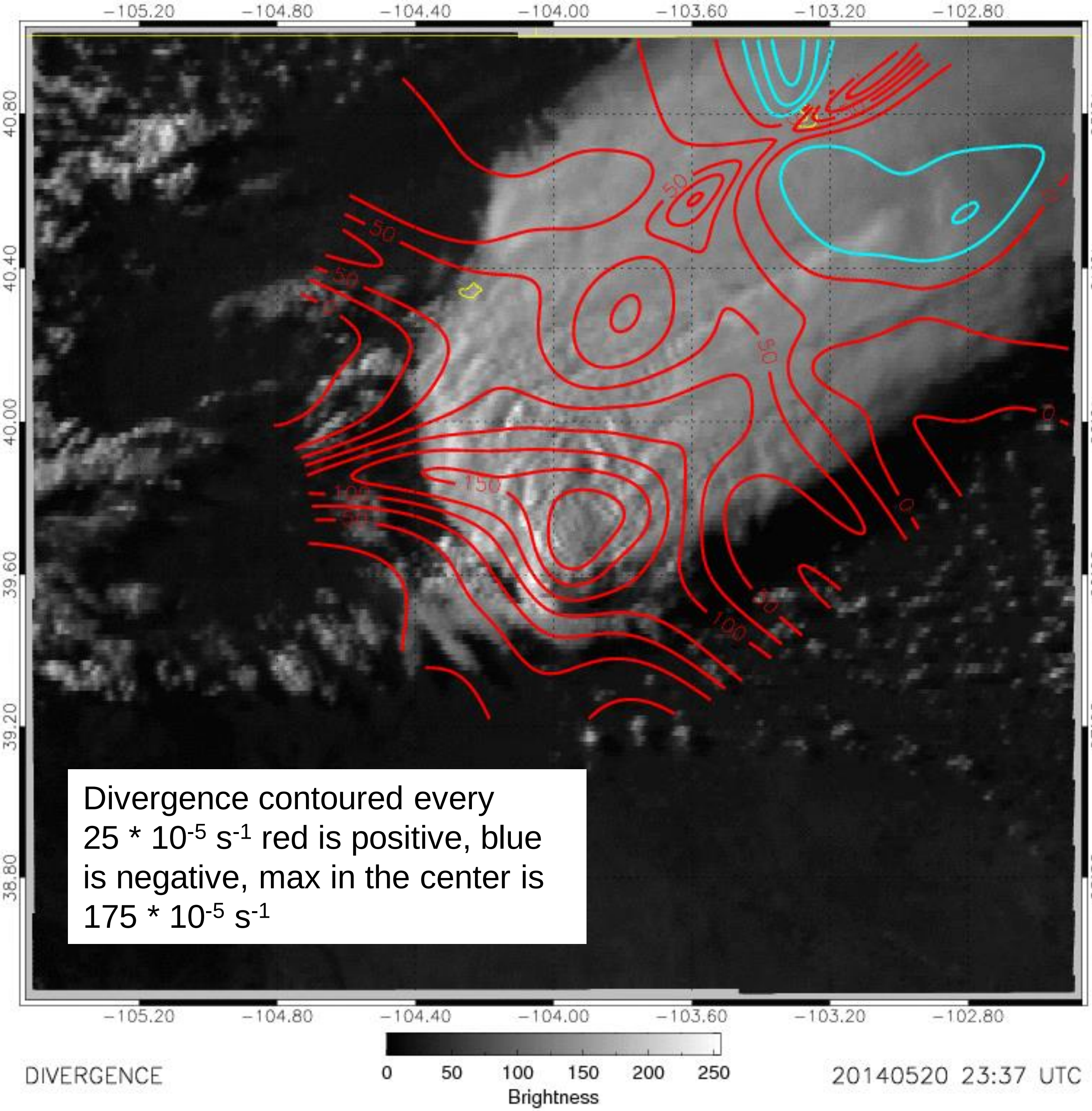


−105.20
−104.80
−104.40
−104.00
−103.60
−103.20
−102.80
40.80
40.40
40.00
39.60
39.20
38.80
Actual upper level flow
mAMVs calculated at a 7 minute resolution (note, almost no operational quality control)
mAMVs
0
50
100
150
200
250
Brightness
20140520 23:37 UTC

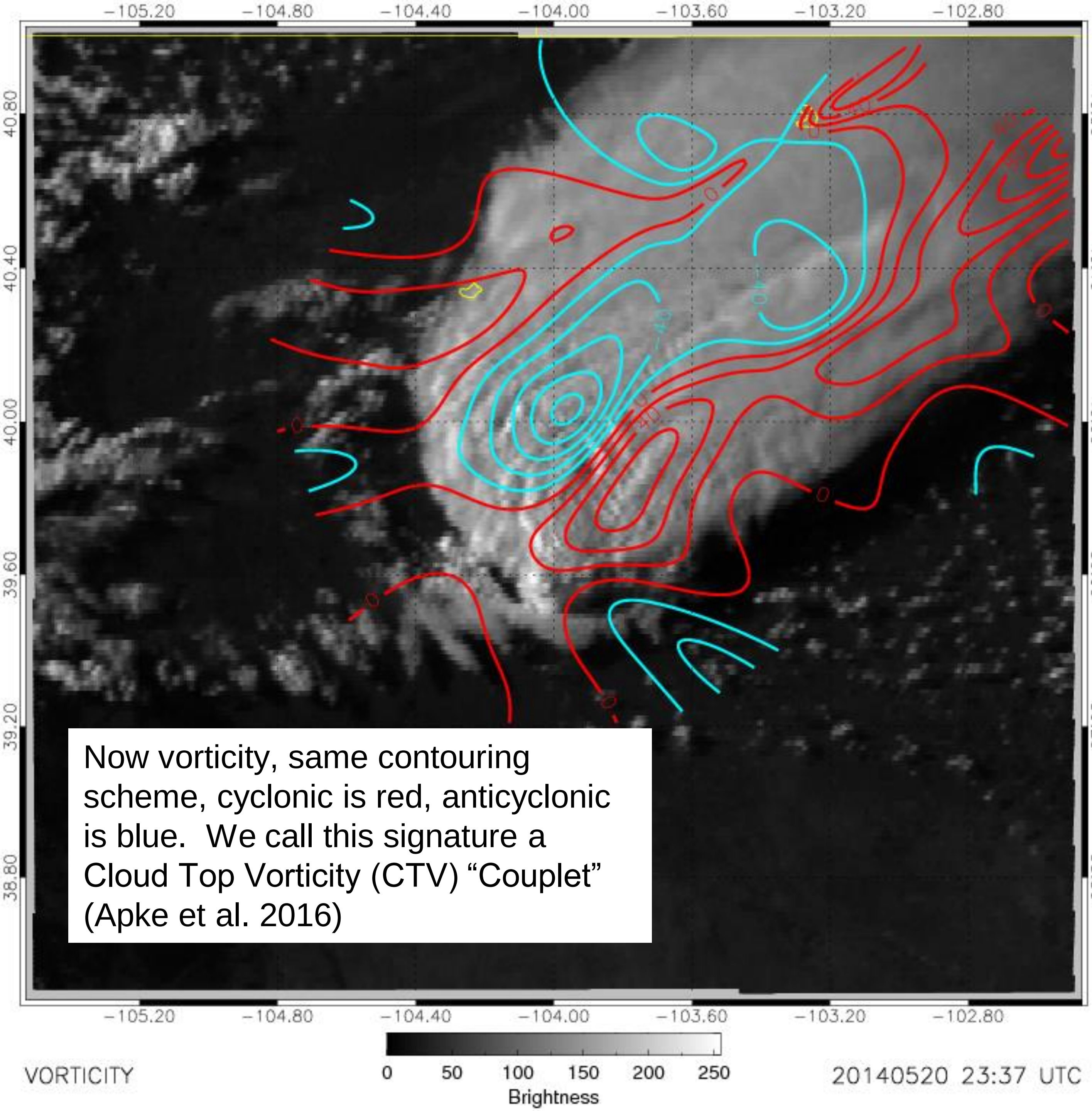

-105.20
-104.80
-104.40
-104.00
-103.60
-103.20
-102.80
40.80
40.40
40.00
39.60
39.20
38.80
Actual upper level flow
mAMVs calculated at a 1 minute super rapid scan (SRSOR mAMVs)
mAMVs
0
50
100
150
200
250
Brightness
20140520 23:37 UTC



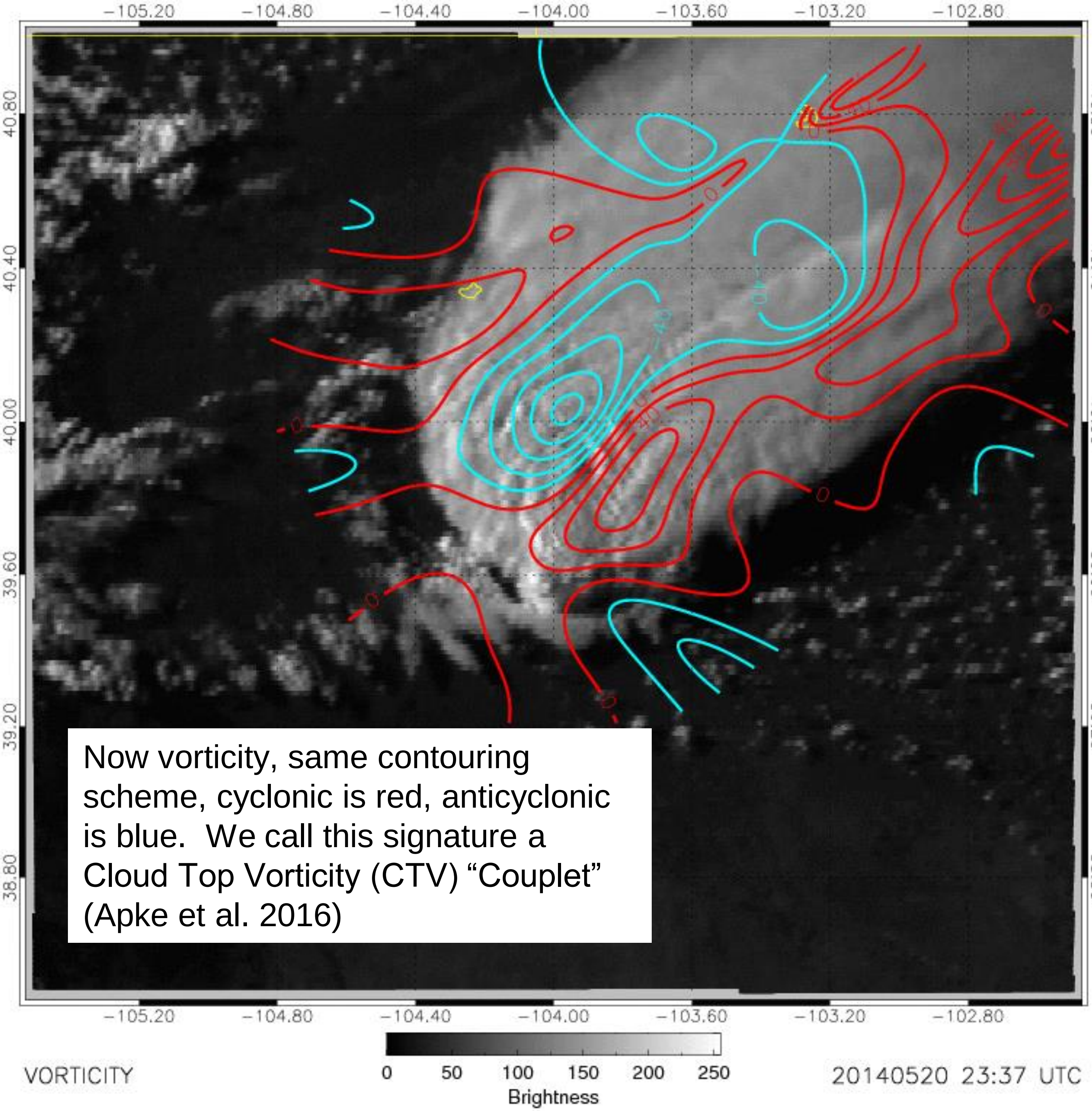
Divergence contoured every $25 * 10^{-5}\ s^{-1}$ red is positive, blue is negative, max in the center is $175 * 10^{-5}\ s^{-1}$



Divergence contoured every $25 * 10^{-5}\ s^{-1}$ red is positive, blue is negative, max in the center is $175 * 10^{-5}\ s^{-1}$



Now vorticity, same contouring scheme, cyclonic is red, anticyclonic is blue. We call this signature a Cloud Top Vorticity (CTV) “Couplet” (Apke et al. 2016)



Now vorticity, same contouring scheme, cyclonic is red, anticyclonic is blue. We call this signature a Cloud Top Vorticity (CTV) "Couplet" (Apke et al. 2016)

Figure 1. 20 May 2014 supercell photographed near Burlington, Colorado.
(*Photo provided courtesy of Roger Hill*)

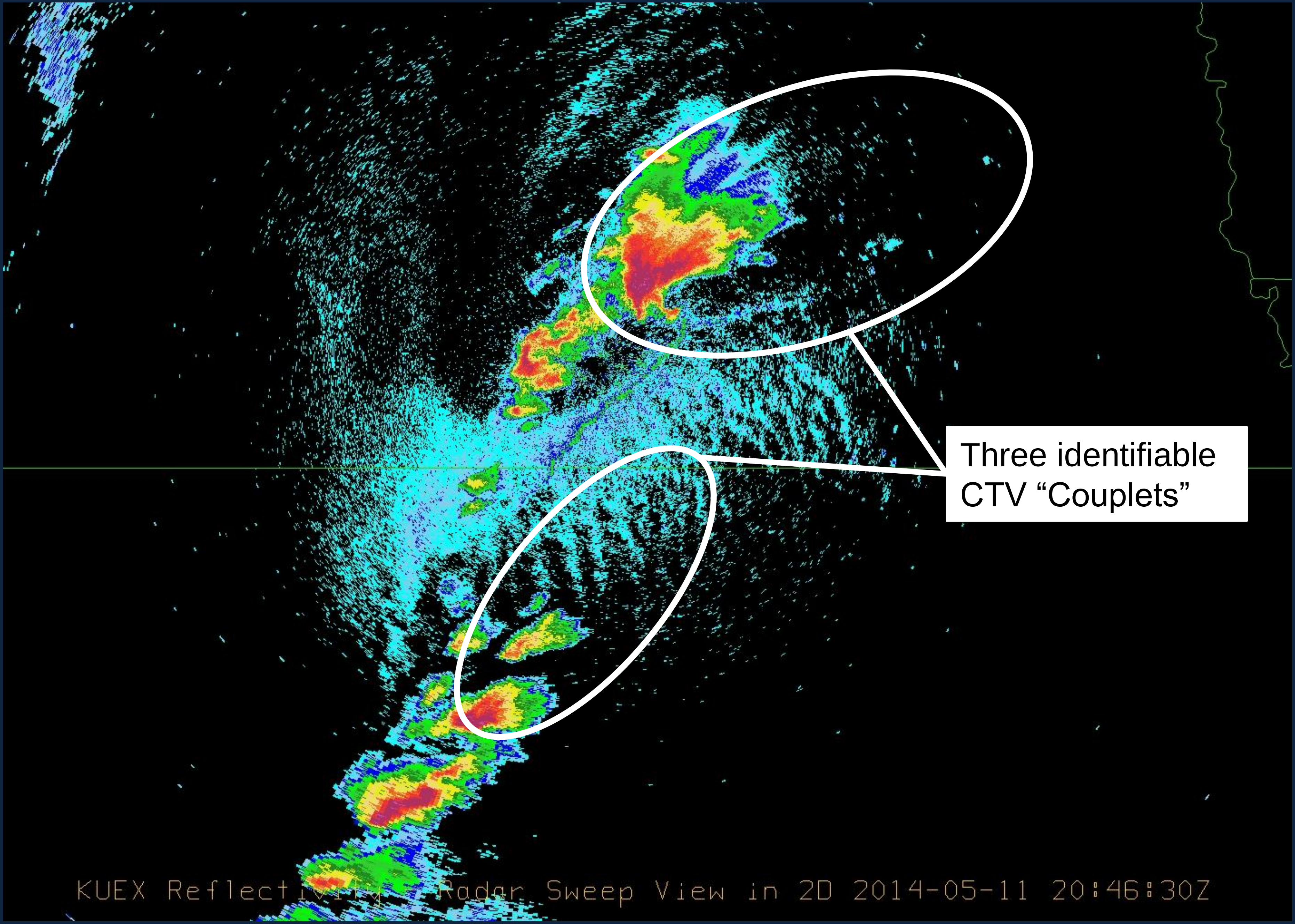
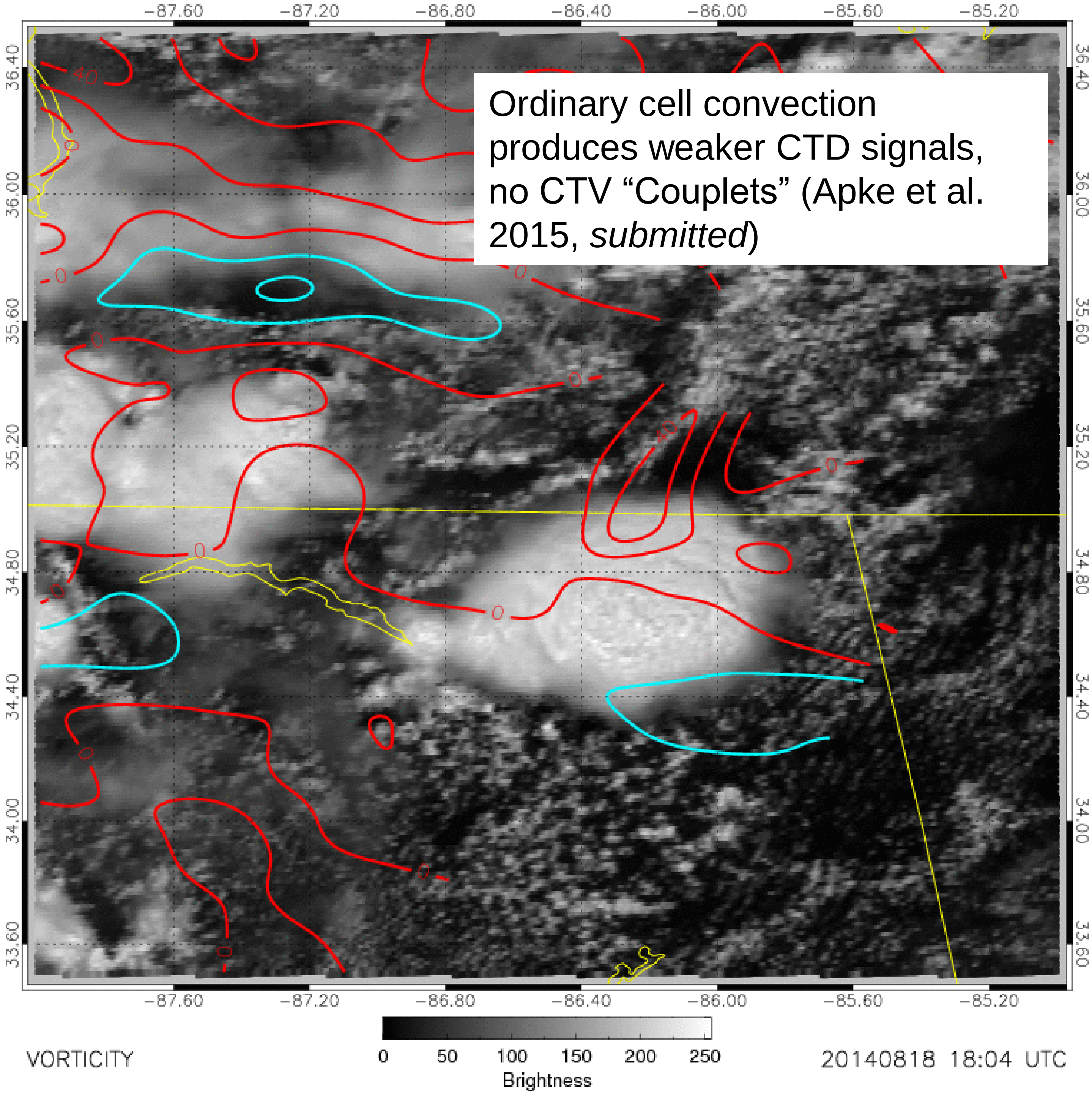
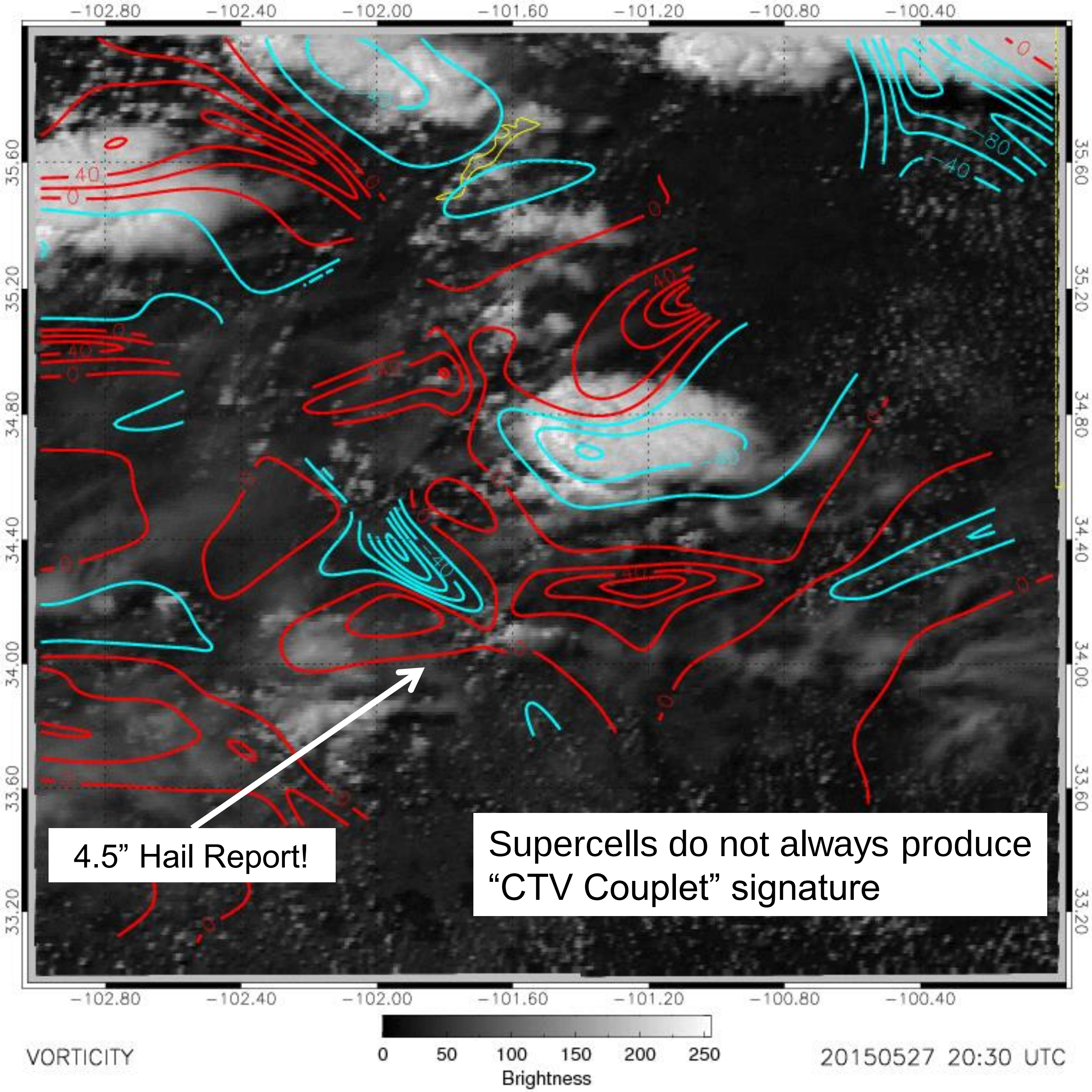


Figure 2. 11 May 2014 KUEX radar reflectivity at 0.5˚ tilt

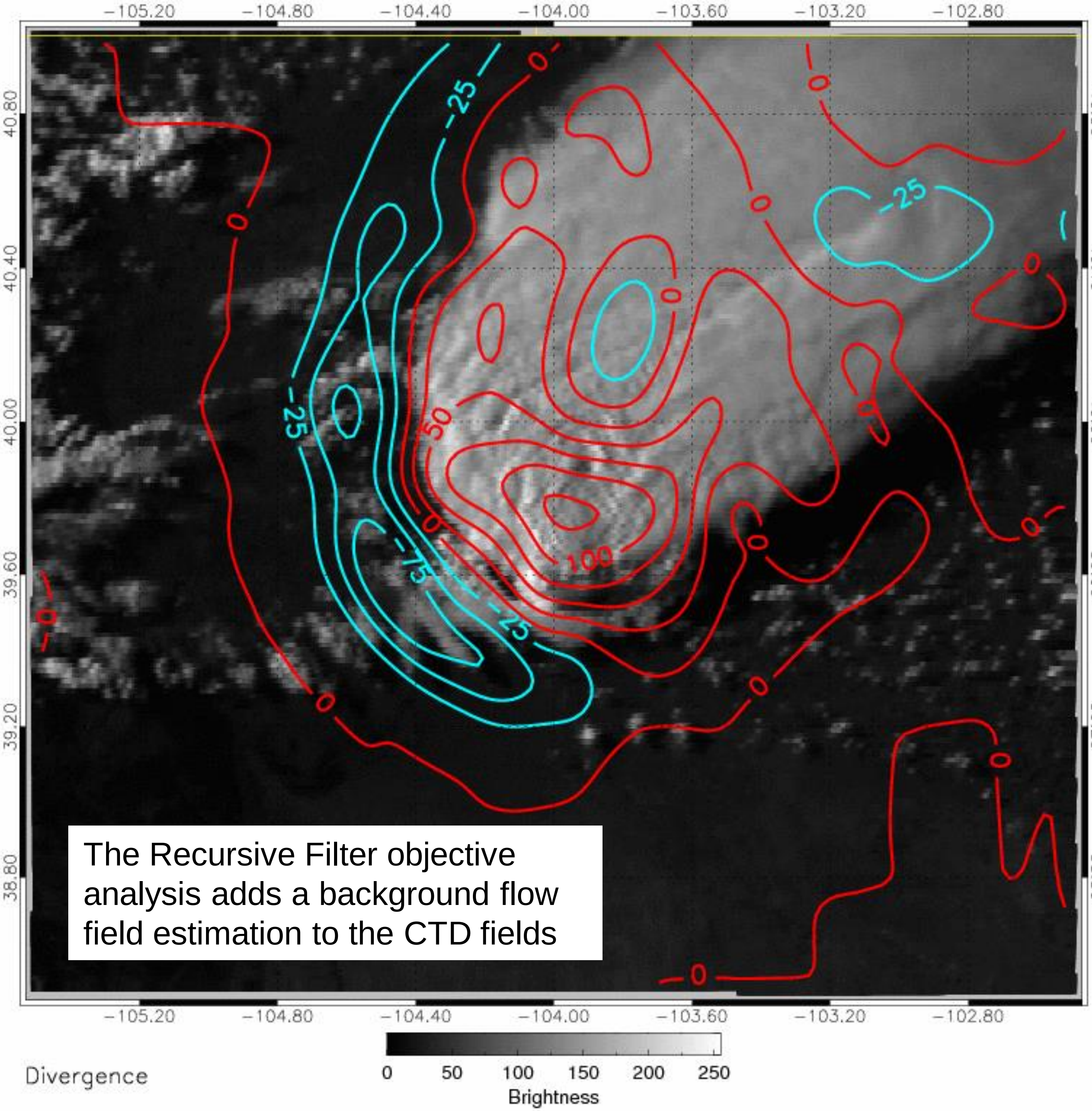
Ordinary cell convection produces weaker CTD signals, no CTV “Couplets” (Apke et al. 2015, *submitted*)



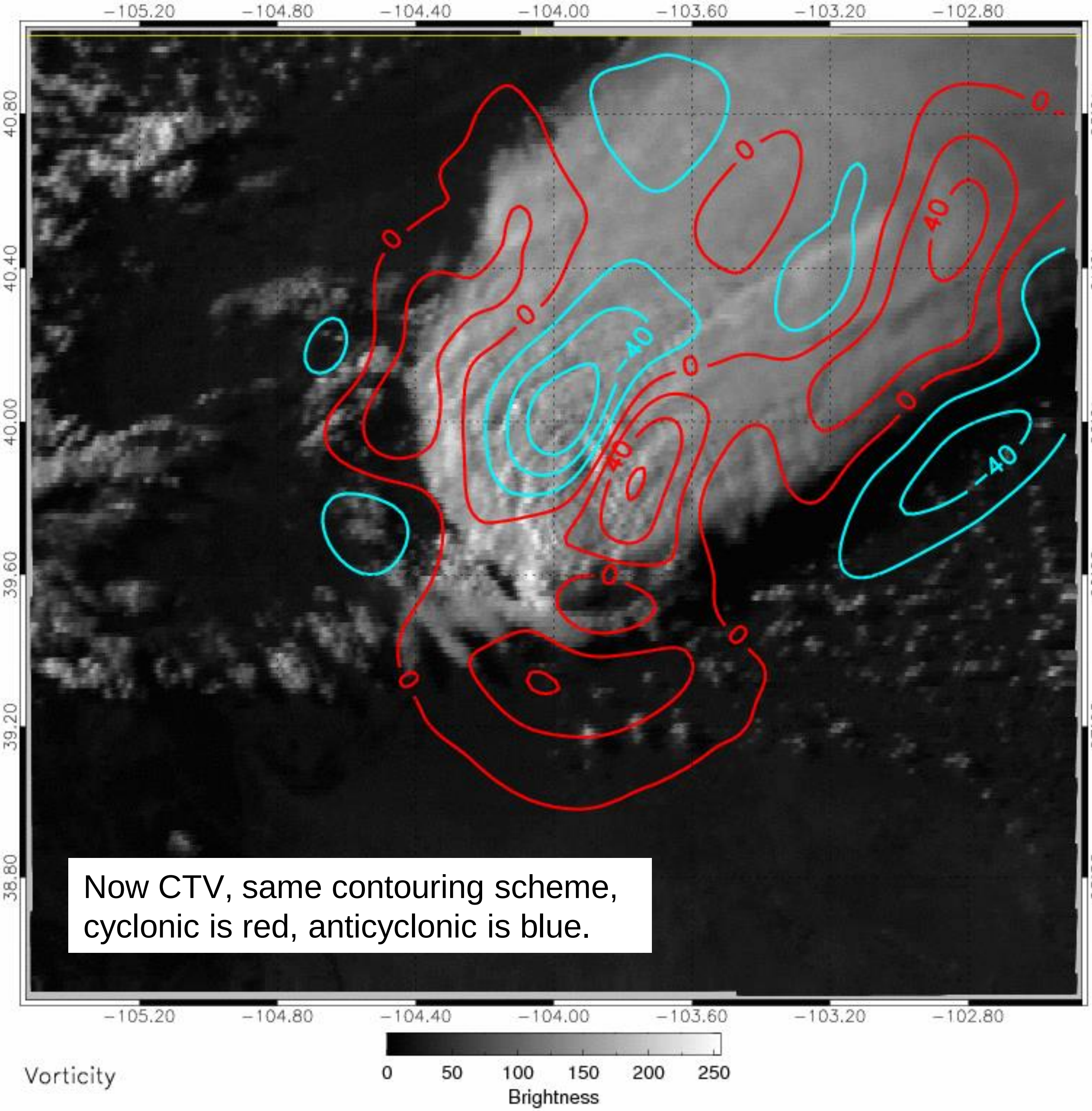

-102.80
-102.40
-102.00
-101.60
-101.20
-100.80
-100.40
35.60
35.20
34.80
34.40
34.00
33.60
33.20
4.5” Hail Report!
Supercells do not always produce “CTV Couplet” signature
VORTICITY
0
50
100
150
200
250
Brightness
20150527 20:30 UTC

Recursive Filter Approach

- The RF approach in one dimension (Hayden and Purser 1995):
- Applies forwards and backwards to a grid of values, where the smoothing parameter controls the spatial scale of the filter
- The analysis is determined by the quality of observations near a grid point
  - The quality is determined by the obs. deviation from a background dataset at the grid point and obs. density
- With multiple forward and backwards passes, the RF approach can be shown to be equivalent to a single pass of a Gaussian (Barnes) filter



The Recursive Filter objective analysis adds a background flow field estimation to the CTD fields



Now CTV, same contouring scheme, cyclonic is red, anticyclonic is blue.

HRRR Model: Diabatic Digital Filter Initialization

1. Translate GOES cloud-top cooling signature into latent heating rates.

2. Heating rate should be proportional to updraft strength, consistent with cumulus convection

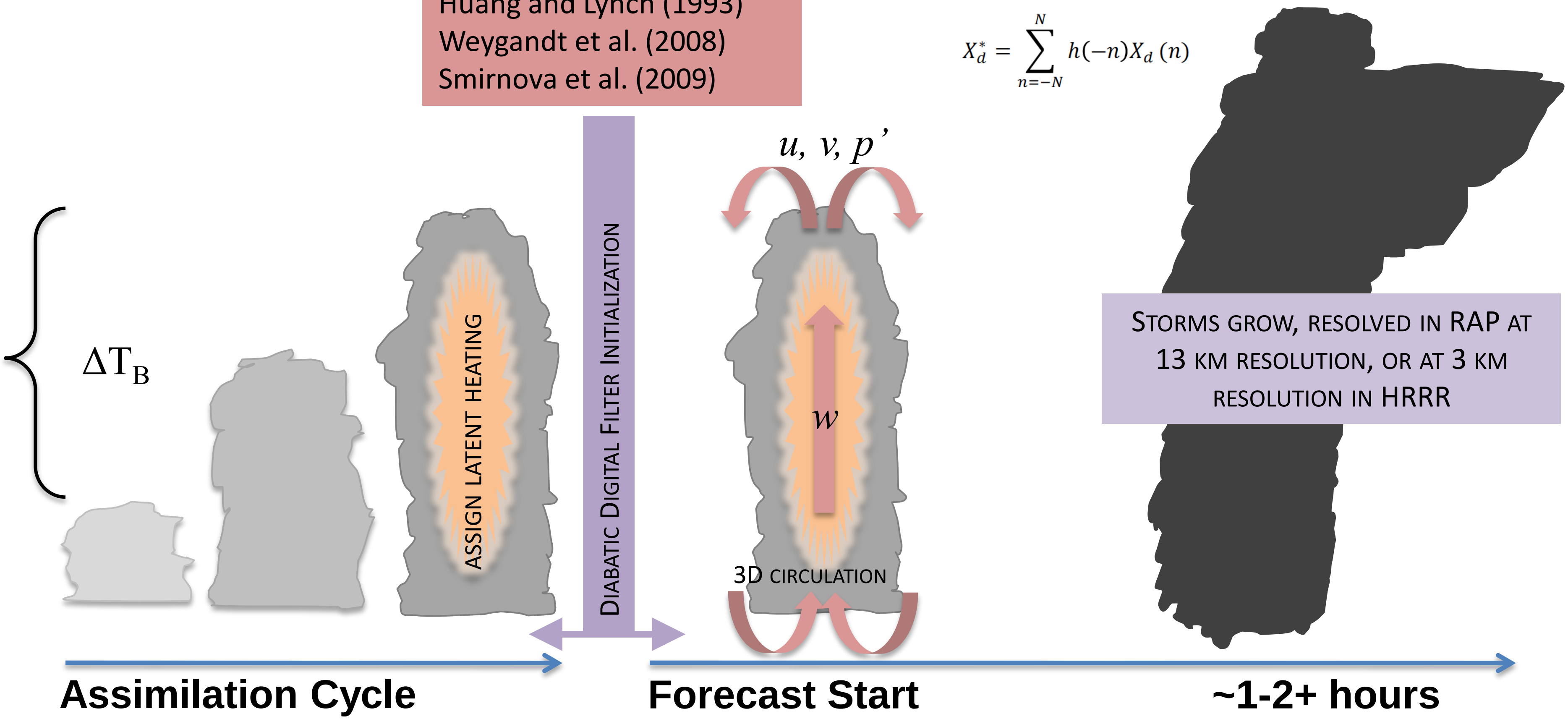
3. In HRRR model form a 3D circulation that then preserves convective feature

4. DDFI is applied to a short time series generated by model integration of the initial data. The model is integrated diabatically forward, and then adiabatically backward, forming a centered time series, $X_d(n)$.

5. The filtered model state time series, X_d^* then initializes the forecast.

$$X_d^* = \sum_{n=-N}^{N} h(-n) X_d(n)$$

Huang and Lynch (1993)
Weygandt et al. (2008)
Smirnova et al. (2009)

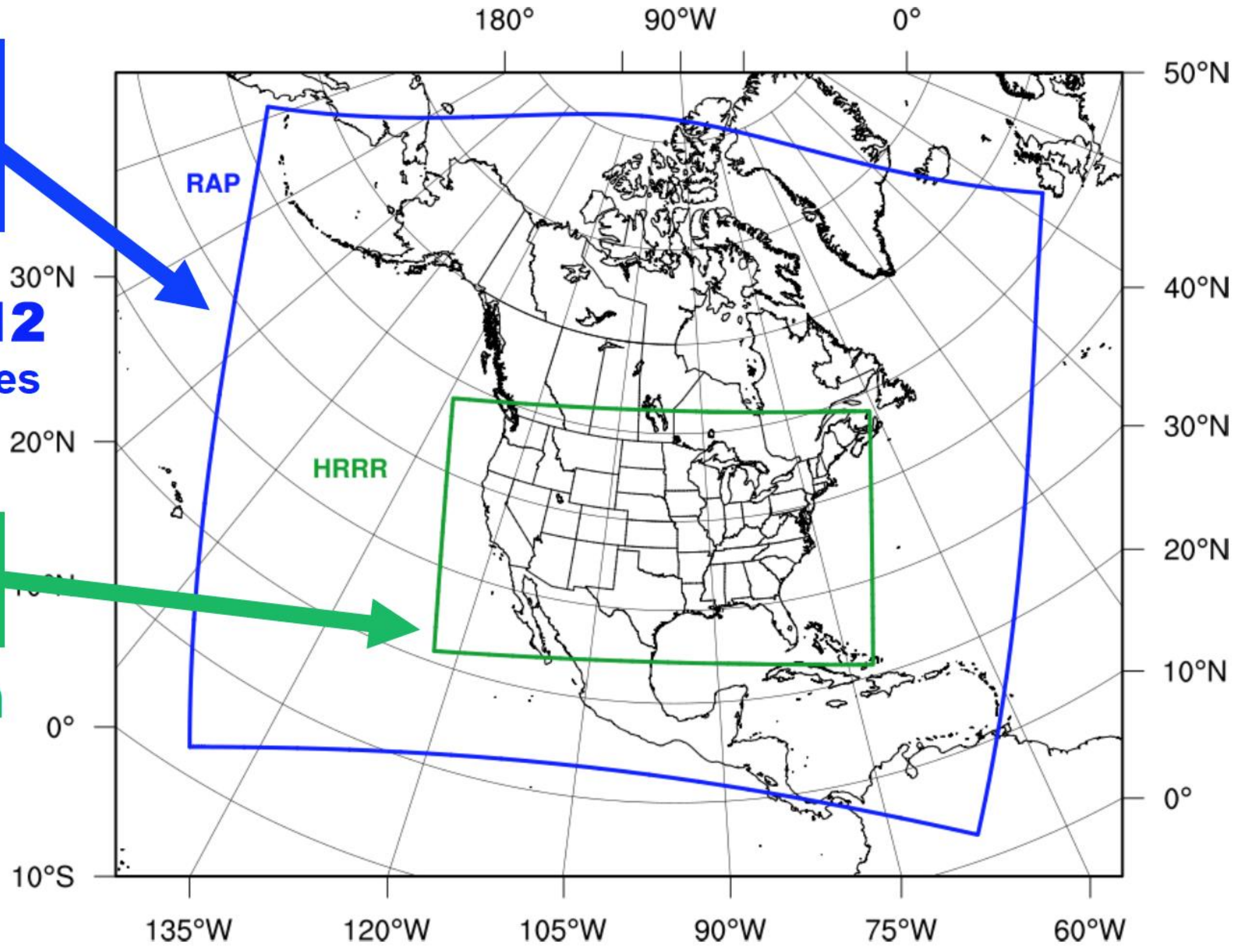


Hourly Updated NWP Models

13km Rapid Refresh (RAP) (mesoscale)

Replaced RUC at NCEP 05/01/12

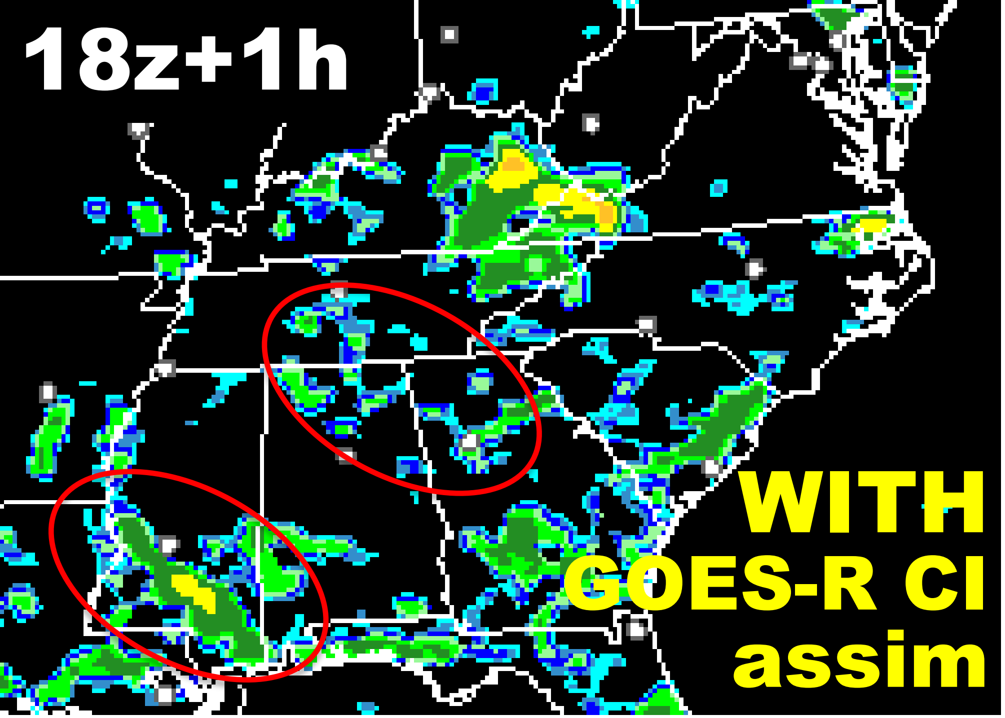
WRF, GSI, RUC features

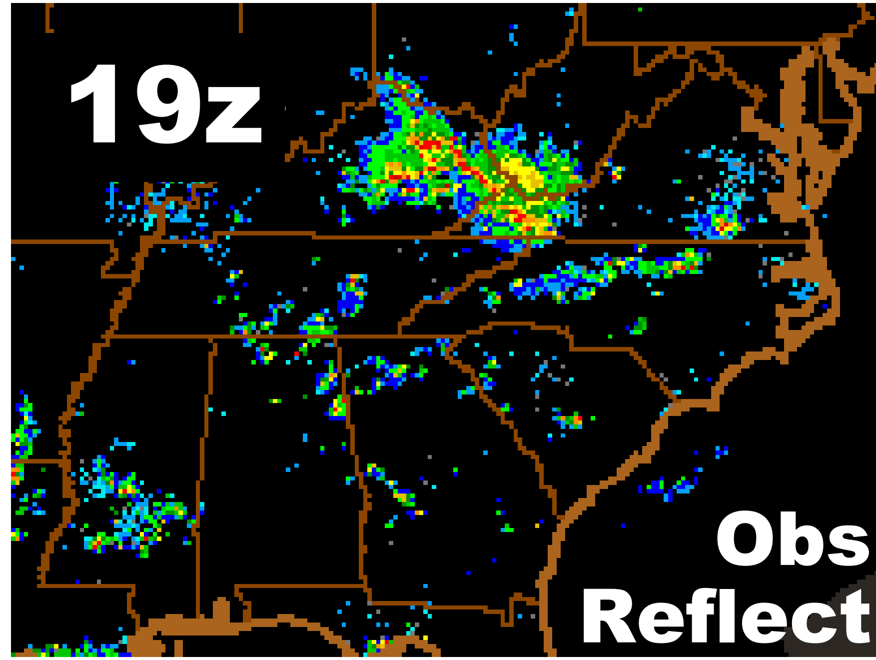


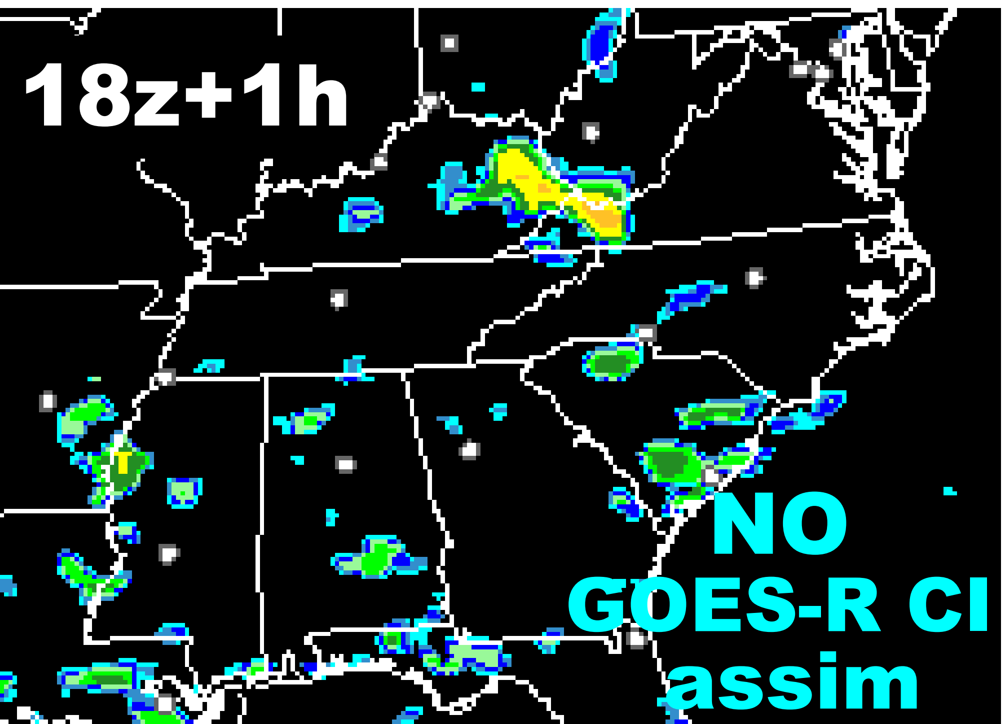
3km HRRR (storm-scale)

High-Resolution Rapid Refresh

Experimental 3km nest inside RAP, hourly 15-h fcst

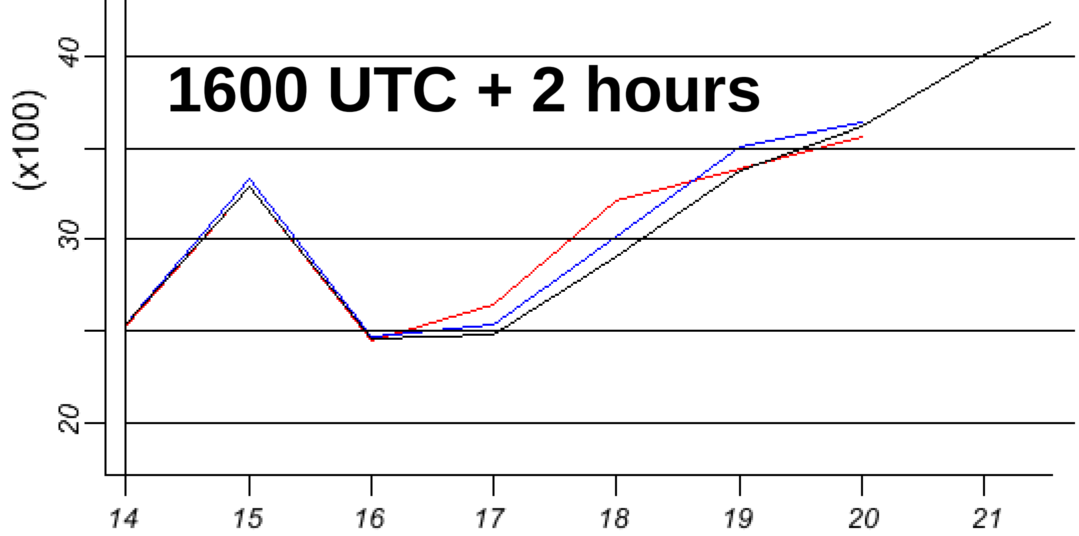


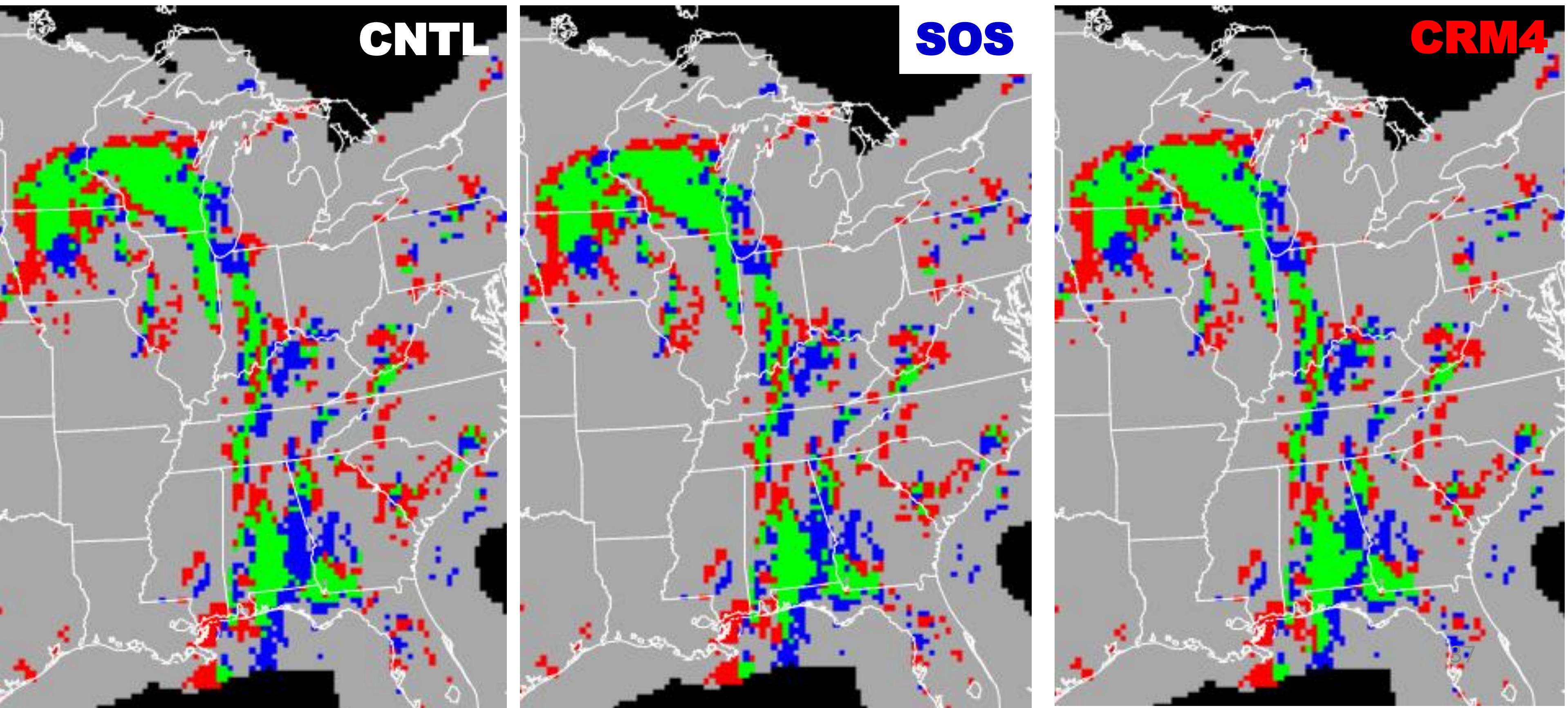




Assimilation of GOES cloud-top cooling rates provides more realistic short-range forecast of convective initiation and development

Measurable improvement in 2-6 hour convective storm forecasts in HRR through the assimilation of GOES-R CI cloud-top cooling rate information.





Overview

The GOES-R Convective Initiation algorithm is quickly evolving into a suite of products within one main processing methodology and construct. Providing several products within this single framework is the plan, thereby making it easier for users (NASA SPoRT, EWP/HWT/AWT, NWS) to incorporate them into the forecasting process.

1. Basic 0–1 hour CI (object based)
2. Severe CI prediction
3. Early CI – Focuses on use of 1–min SRSOR observations
4. 1–4 hour CI (probabilistic)
5. “mesoscale Atmospheric Motion Vector” (mAMV) storm type delineation
6. HRRR & WRF model data assimilation

Products 1 and 2 are combined into a single output file.