On the scale-dependence of precipitation predictability

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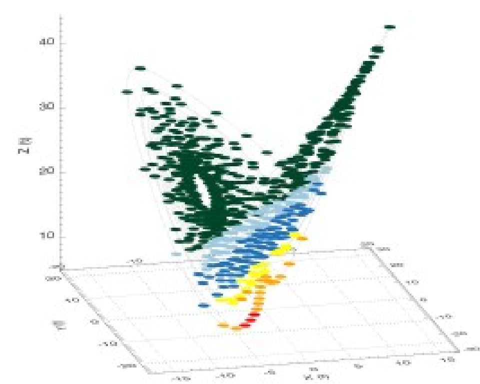
Acknowledgements: Adam J. Clark, Ming Xue, Fanyou Kor

Atmospheric predictability

Intrinsic

Related to the *non-linear nature of atmospheric dynamics*: very small errors in ICs grow exponentially to result in a finite limit of atmospheric predictability

$$\frac{\mathrm{d}x}{\mathrm{d}t} = \sigma(y - x),$$
$$\frac{\mathrm{d}y}{\mathrm{d}t} = x(\rho - z) - y,$$
$$\frac{\mathrm{d}z}{\mathrm{d}t} = xy - \beta z.$$



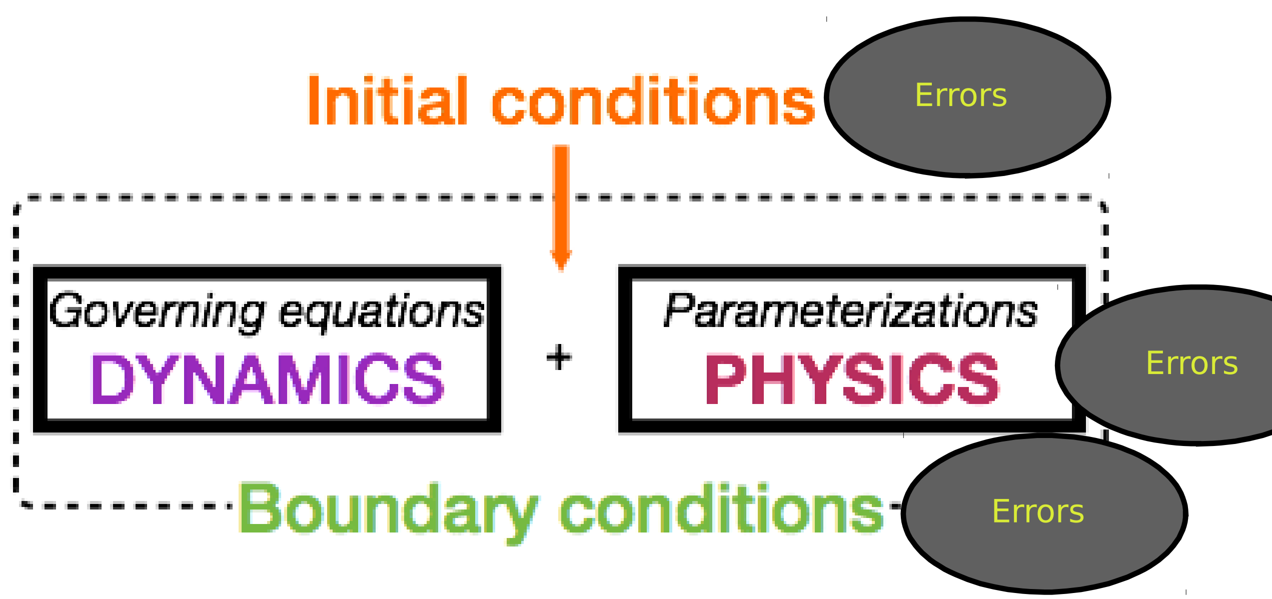
Chaotic behaviour for:

$\sigma = 10$, $\beta = 8/3$ and $\rho = 28$.

Lorenz (1969)

Practical

Related to the loss of predictability due to *errors in ICs and model physics* that could be potentially resolved



What do we know about intrinsic predictability?

- Predictability is scale-dependent
  - Lorenz 1969, Lilly 1990, Kalnay 2003: predictability at scales ~ 10 km is O(1h), at scales ~1000 km is O(10 days)
  - Errors grow faster at convective scales than at synoptic scales (Hohenegger and Schar 2007)
  - Error growth at convective scales is amplified by moist convection (Hohenegger and Schar 2007, Zhang et al. 2002)
  - Once errors saturate at convective scale, they propagate upscale where they continue to grow – the three stage error growth model (Zhang et al. 2007, Selz and Craig 2015):
    - 1st stage: error growth and saturation due to moist convective instability
    - 2nd stage: geostrophic adjustment
    - 3rd stage: continuing growth at synoptic scales through baroclinic instability

Intrinsic versus practical predictability

- While in some cases intrinsic predictability limitations can lead to a very rapid loss of forecasts skill (Zhang et al. 2003, Melhauser and Zhang 2012), generally practical predictability limitations are the main reason for forecast errors (Durran and Gingrich 2014).
- Most previous studies were based on a limited set of cases.
- ***Investigate the intrinsic and practical limitations for convection-allowing models using a large data set of storm-scale ensemble forecasts.***

Quantify the limits of precipitation predictability

Intrinsic

Practical

Investigate the growth of very small IC perturbations in model simulations

Characterizing the growth of different types of model perturbations in model simulations

Predictability of the model state

Comparing forecasts to observations Evaluating forecast skill

Model predictability of the atmospheric state

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Methodology

- ***A statistical approach to studying predictability***
  - Use a large set of data
  - Quantify predictability as a function of spatial scale
  - Determine the role of different types of errors forensemble predictability
  - Characterize the relationship between predictability limits and the environment

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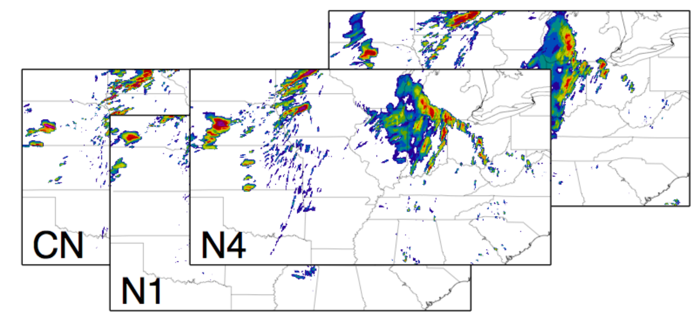
Large data set

Acknowledging Adam Clark (NSSL), Ming Xue (OU, CAPS) and Fanyou Kong (OU,CAPS)

Storm-scale ensemble forecasting system
WRF-based, 4-km grid spacing, radar DA
Multi-physics, multi-model



Now more than 10 years of high-resolution ensemble forecasts during the severe weather season in the US.

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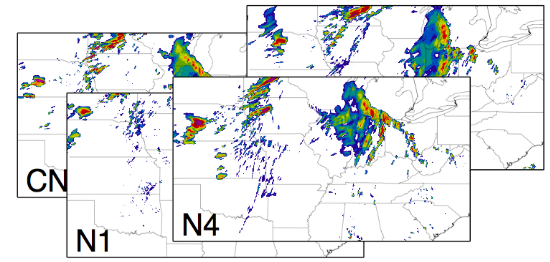
. Our experience in mesoscale redictability

Ensemble precipitation forecasts



Initial conditions — Errors

- IC/LBC perturbations from regional-scale ensemble - resolution of 32-45 km
- Random IC perturbations
- Random correlated IC perturbations - small-scale (12 km horizontal, 3 km vertical)

Governing equations DYNAMICS + Parameterizations PHYSICS — Errors

Boundary conditions — Errors

- Varied MP scheme
- SKEB
- Varied PBL scheme

Practical predictability limits

Intrinsic predictability limits

Practical predictability limits

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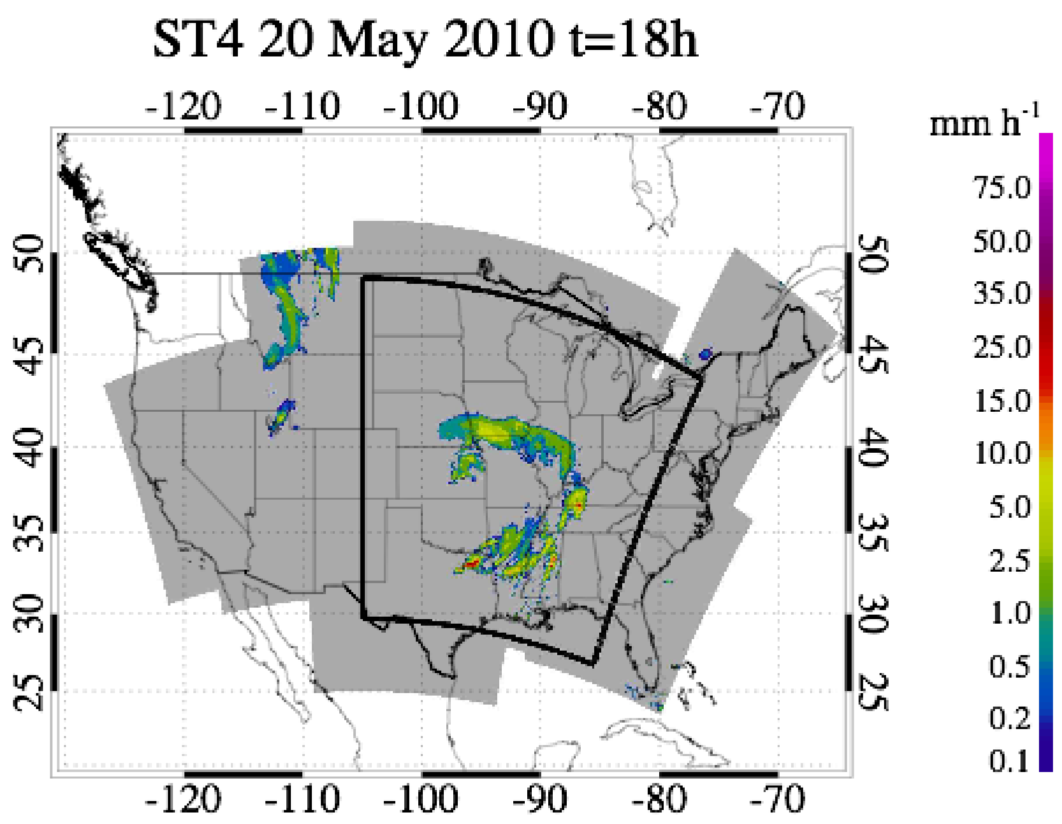
Data set



Precipitation forecasts from CAPS SSEF.
Radar derived QPE.
Stage IV precipitation.

All remapped on the Stage IV grid using nearest neighbor interpolation.

Type	Description	Years
IC/LBC	SREF-derived IC/LBC perturbations	2008
IC/LBC/PHYS	SREF-derived IC/LBC perturbations and mixed PHYS	2008–11, 2013
RAND	Uncorrelated random noise added to the initial moisture and temperature fields	2010
RC	Correlated random noise added to the initial moisture and temperature fields	2010
MP	Microphysical parameterization scheme different than for CN (Thompson)	2010–13
PBL	Planetary boundary layer scheme different than for CN (MYJ)	2010–13
SKEB	Stochastic kinetic energy backscatter scheme	2012

Quantify predictability as a function of scale

- As mentioned before, Zhang et al. 2003 etc. – errors saturate with scale and forecast time
- Does this apply to our definitions of predictability and to our data set?
- Determine the range of scales where predictability is lost: **the decorrelation scale**

The decorrelation scale

- Define the power ratio for a pair of precipitation fields:

$$R(\lambda) = \frac{\mathrm{Var}_X(\lambda) + \mathrm{Var}_Y(\lambda)}{\mathrm{Var}_{X+Y}(\lambda)}$$

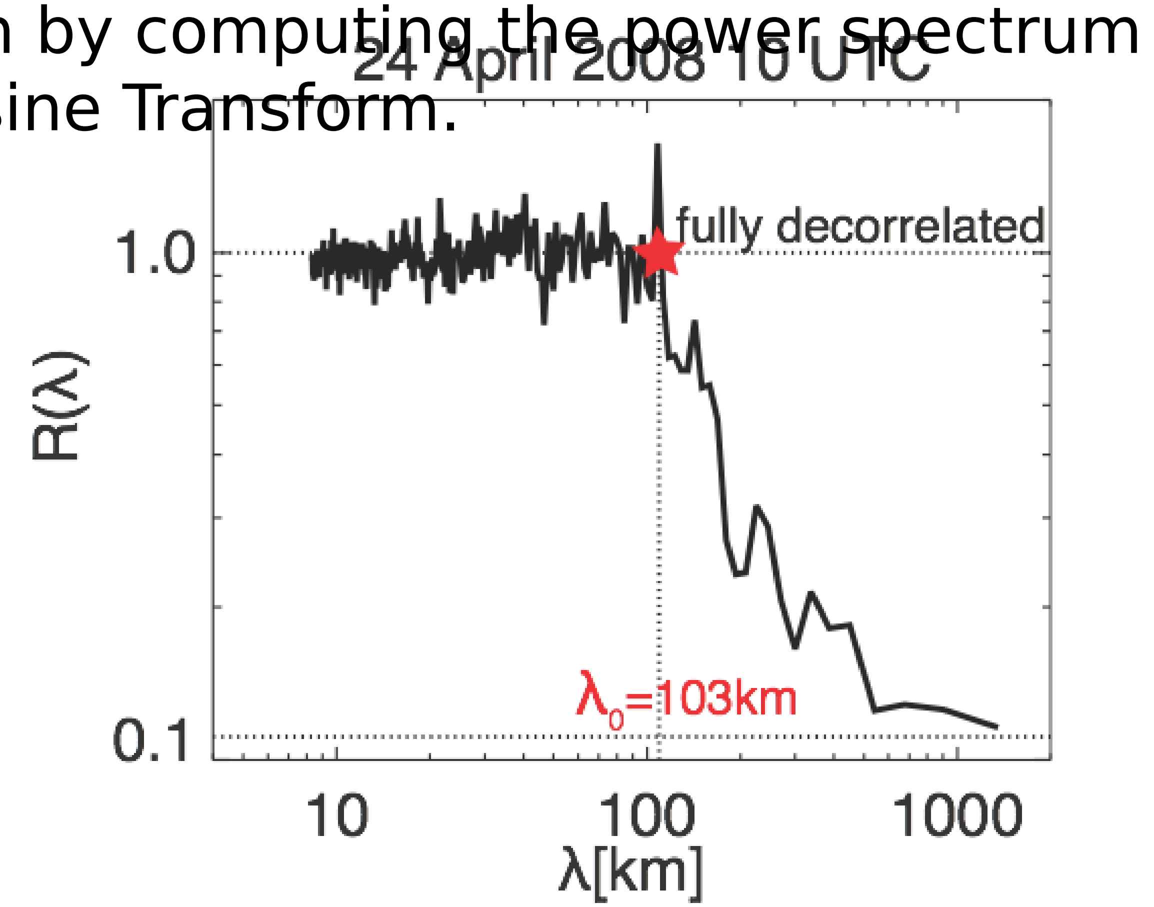
X, Y are 2D precipitation fields and $\mathrm{Var}_X(\lambda)$ and $\mathrm{Var}_Y(\lambda)$ represent the variance of the fields at scale λ

- When the power ratio is 1, the two precipitation fields are fully decorrelated.

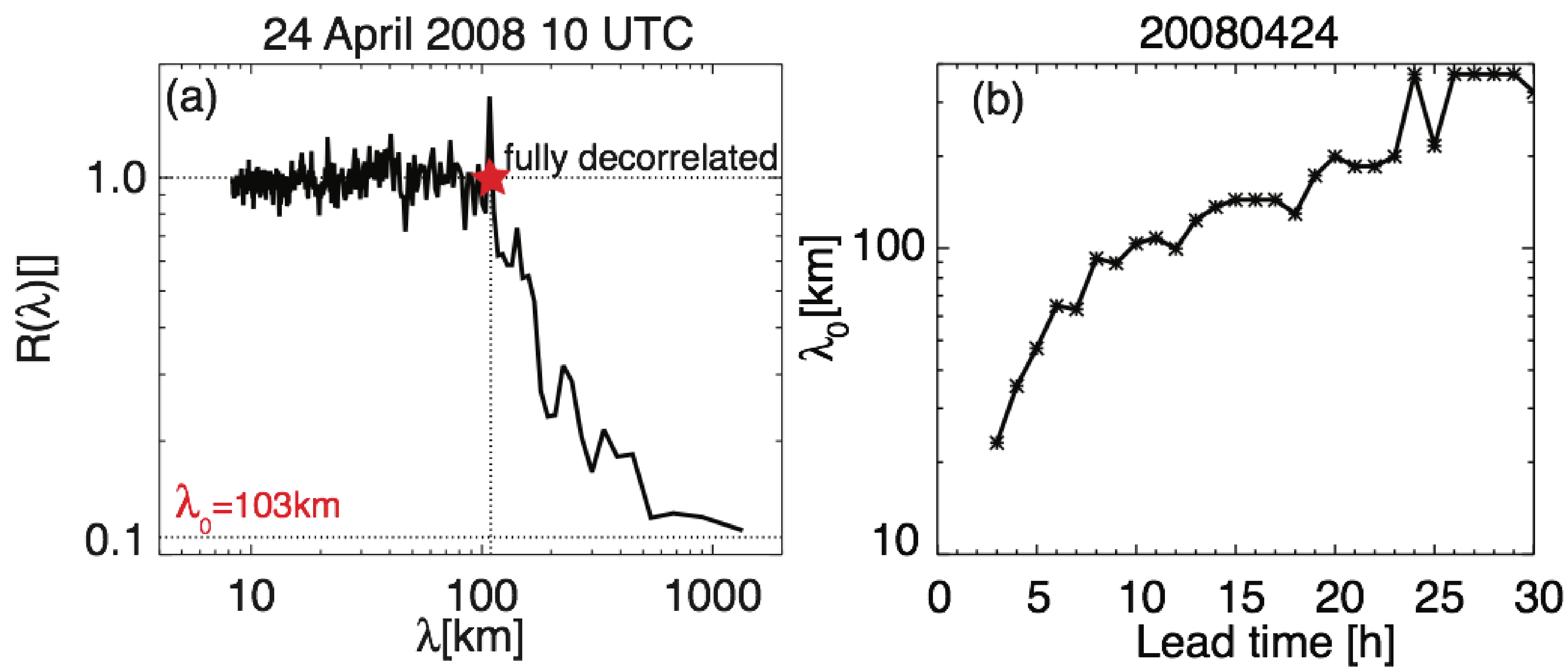
- The variance at a given scale is obtain by computing the power spectrum of precipitation using the Discrete Cosine Transform.

Example of the power ratio for a pair of two precipitation forecasts, one unperturbed, one with IC/LBC perturbations.

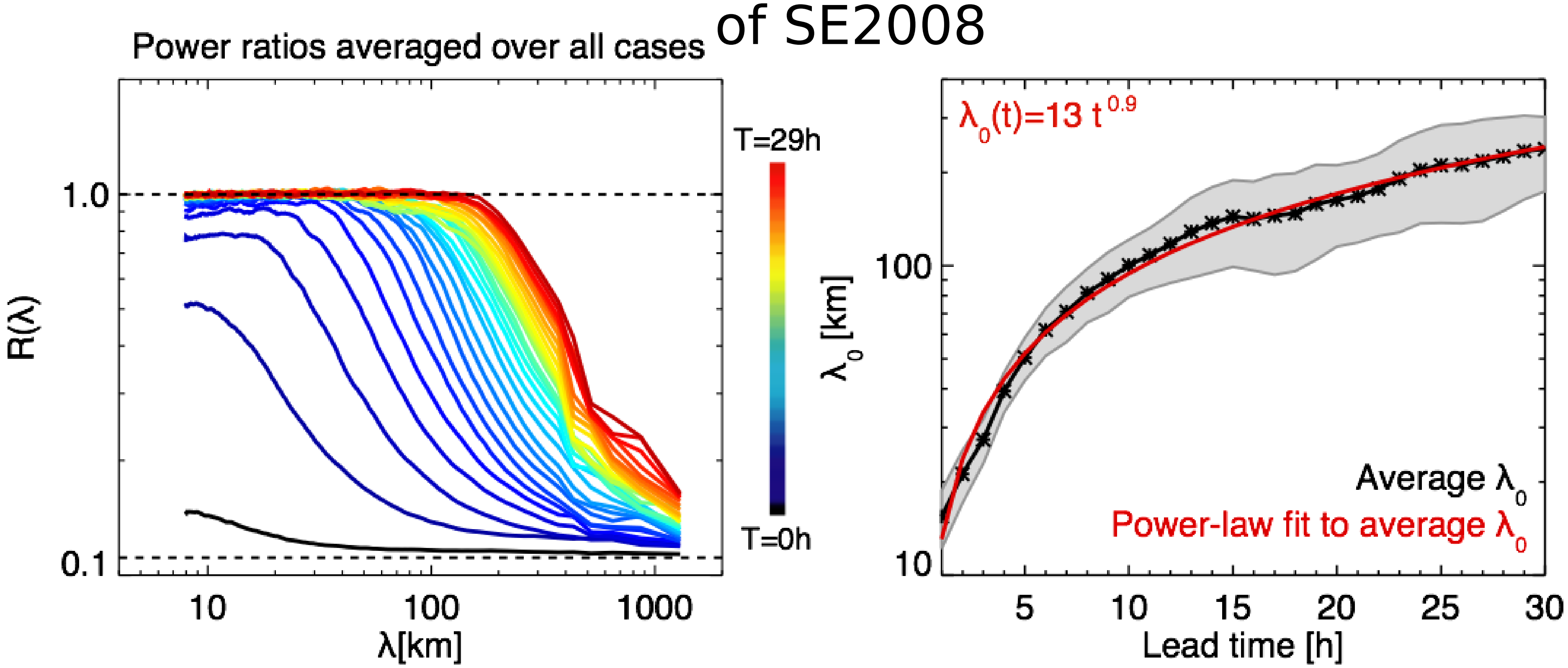
At 10-hour lead time, the decorrelation scale is 103 km. This means that ***IC/LBC errors in this case cause predictability loss at scales smaller than 100 km after 10 forecast hours***!



The decorrelation scale as a function of forecast lead-time for one event



The decorrelation scale as a function of forecast lead-time averaged over all cases of SE2008



Other measures to quantify predictability

- The Normalized Root Mean Square Error:

$$\mathrm{NRMSE} = \frac{\sum_{i=1}^{I}\sum_{j=1}^{J}[X(i,j)-Y(i,j)]^2}{\sum_{i=1}^{I}\sum_{j=1}^{J}[X(i,j)+Y(i,j)]^2}$$

X, *Y* are precipitation fields of dimensions *I* and *J*.
This measure is also applied to band-pass components of the fields.

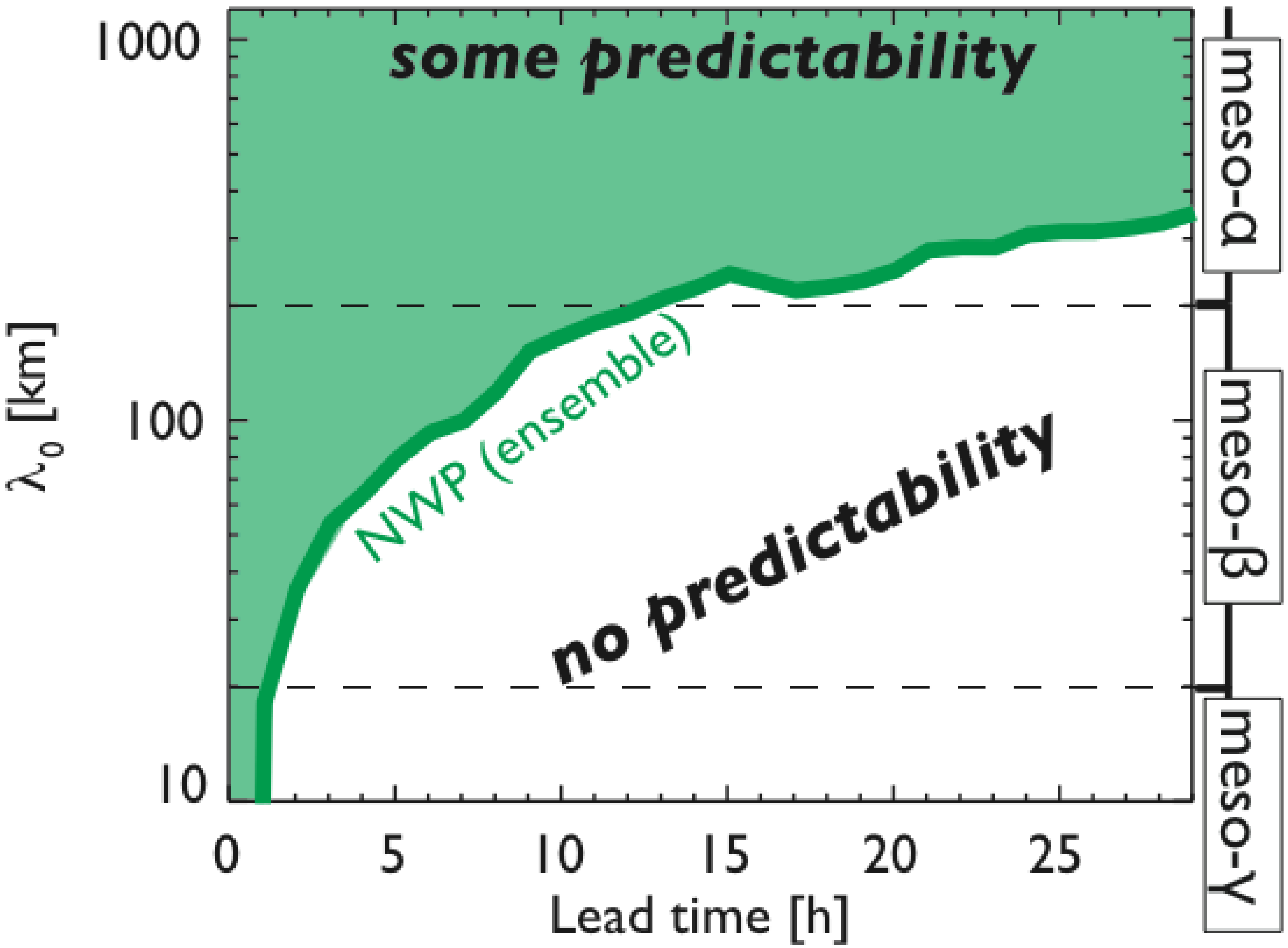
- The Fractions Skill Score (FSS, Roberts and Lean 2005)

$$\mathrm{FSS} = 1 - \frac{\sum_{i=1}^{I}\sum_{j=1}^{J}[f_X(i,j)-f_Y(i,j)]^2}{\sum_{i=1}^{I}\sum_{j=1}^{J}f_X^2(i,j) + \sum_{i=1}^{I}\sum_{j=1}^{J}f_Y^2(i,j)}.$$

f_X, f_Y are fraction fields

Results – the decorrelation scale

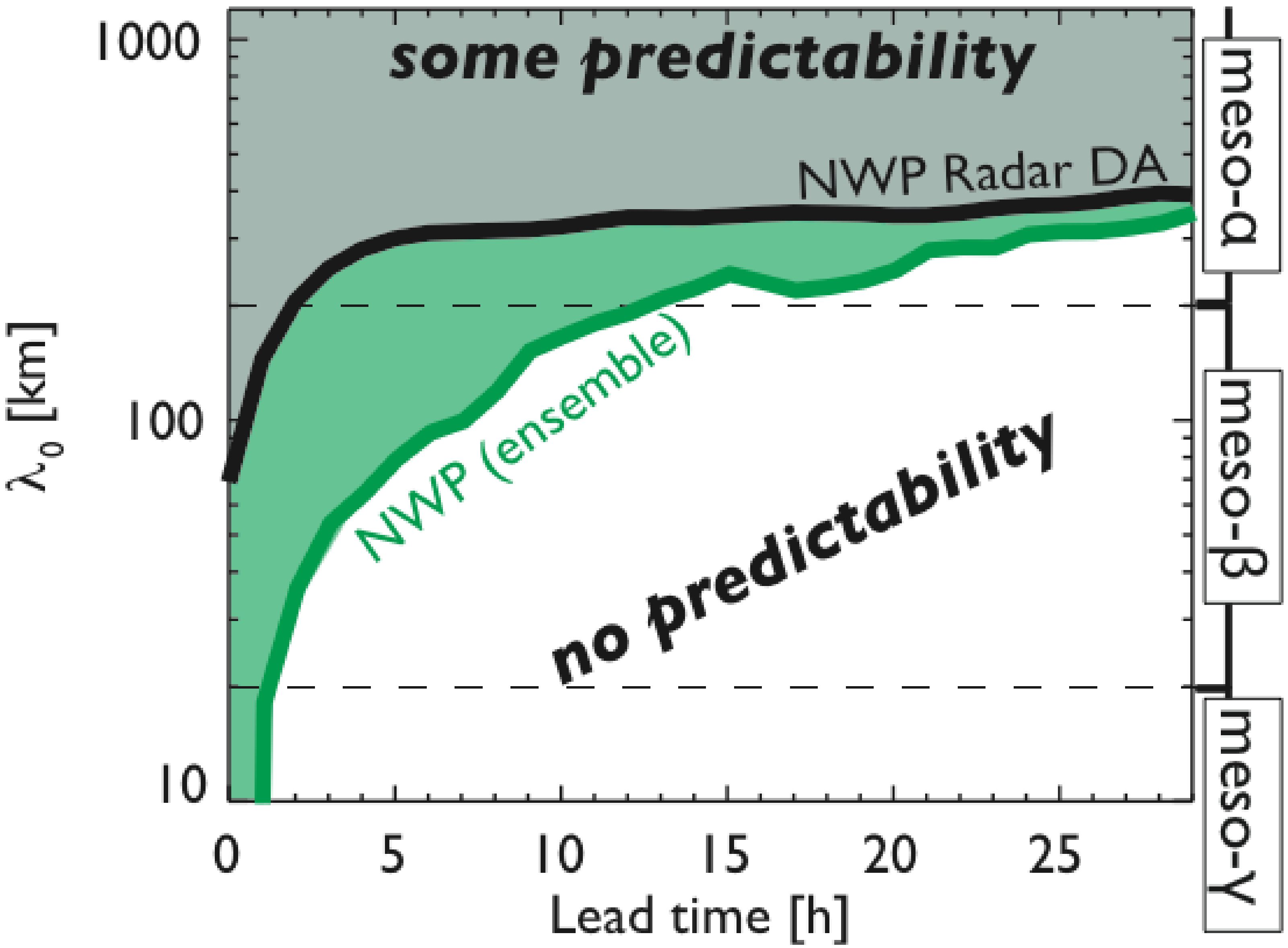
Results are presented for hourly rainfall accumulations and averaged for 22 cases during 2008



Predictability of the model state – effect of IC/LBC/PHYS errors

Results – the decorrelation scale

Results are presented for hourly rainfall accumulations and averaged for 22 cases during 2008



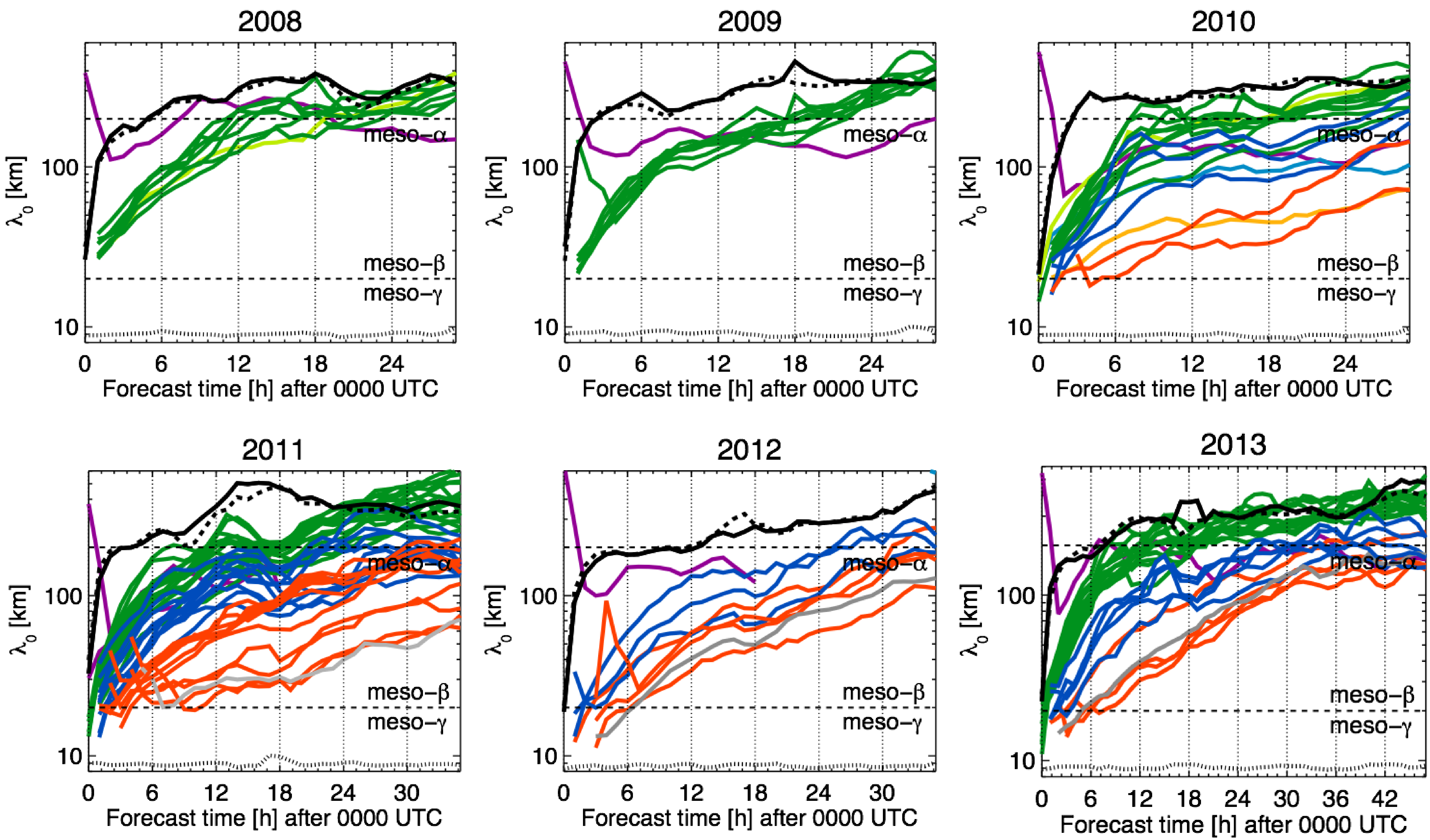
Predictability of the model state – effect of IC/LBC/PHYS errors

Model predictability of the atmospheric state – effect of IC/LBC/PHYS errors on forecast skill

Predictability is lost very rapidly. Significant difference between spread and skill.

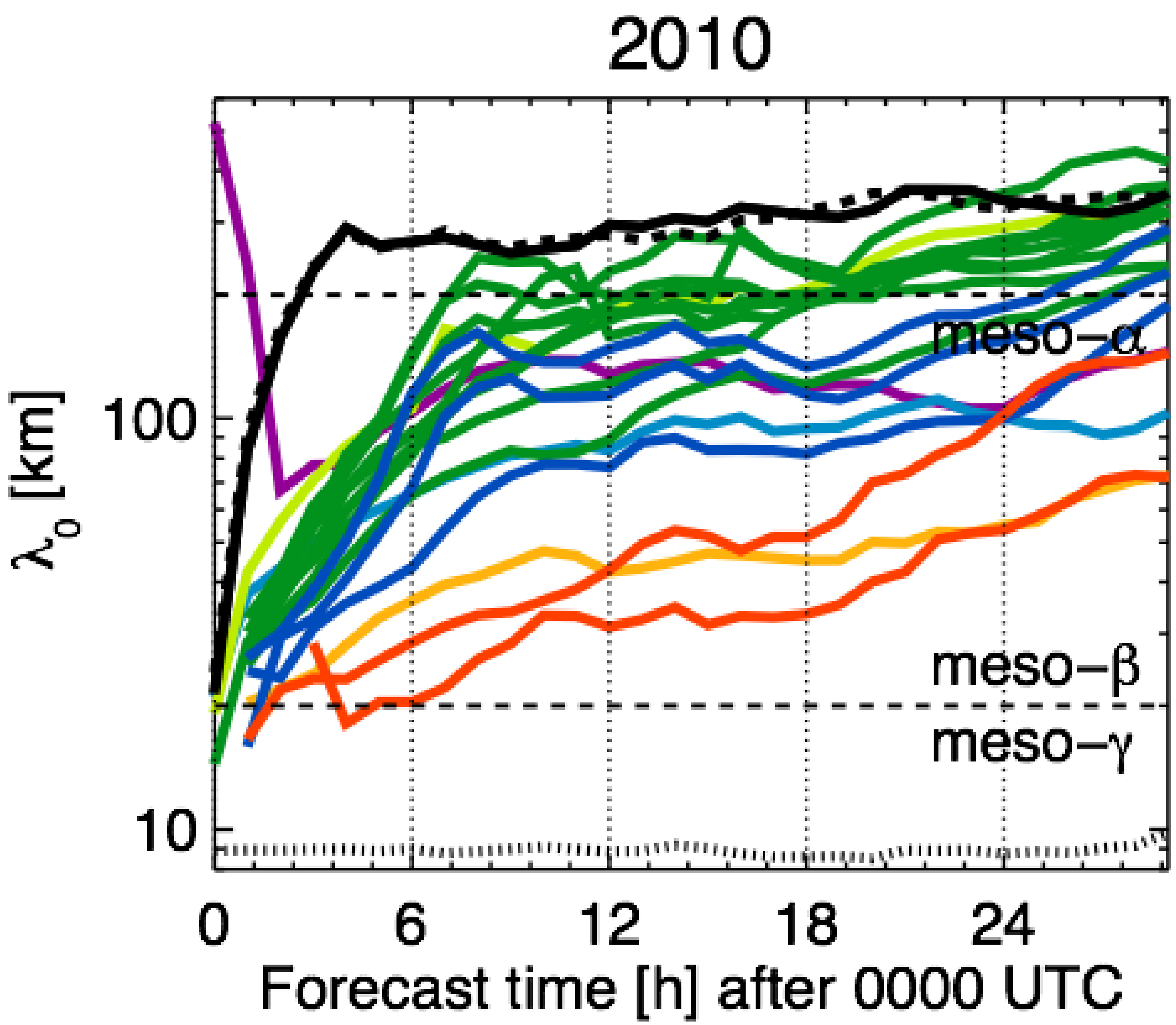
2008-2013 averages

Forecast error IC/LBC/PHYS+RC IC/LBC/PHYS MP RC PBL RAND Radar DA SKEB



2008-2013 averages

Forecast error IC/LBC/PHYS+RC IC/LBC/PHYS MP
RC PBL RAND Radar DA SKEB



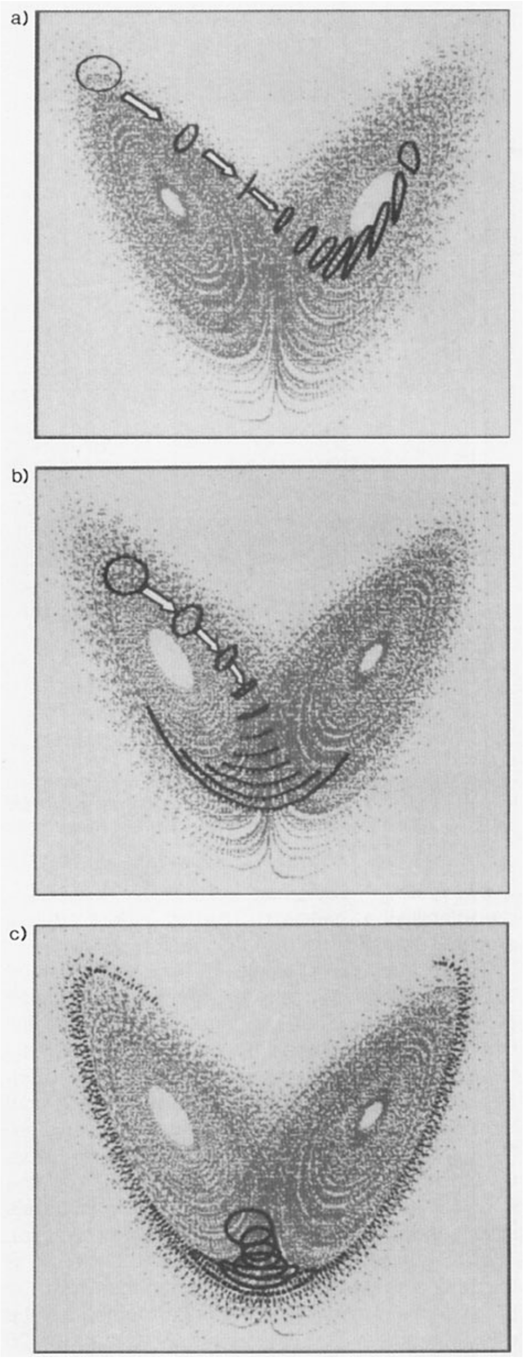
IC/LBC errors most important – spread comparable to forecast error after 20 h.

MP perturbations most important PHYS perturbations

Practical predictability limits far from intrinsic predictability limits

Random perturbations: 0.5 K and 5 % humidity – larger than usually used for intrinsic predictability studies

Case-to-case variability



Palmer 1993

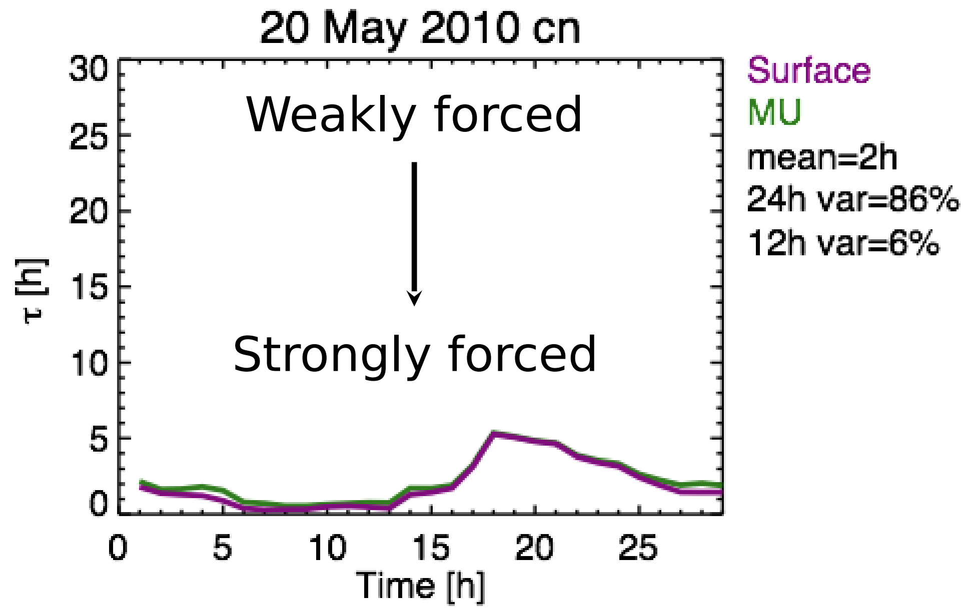
Predictability is not only scale-dependent, but also case-dependent.

Impossible to build the entire atmospheric attractor, so different indicators of where we are situated in the atmospheric attractor are necessary.

Where do the events situate in the atmospheric attractor?

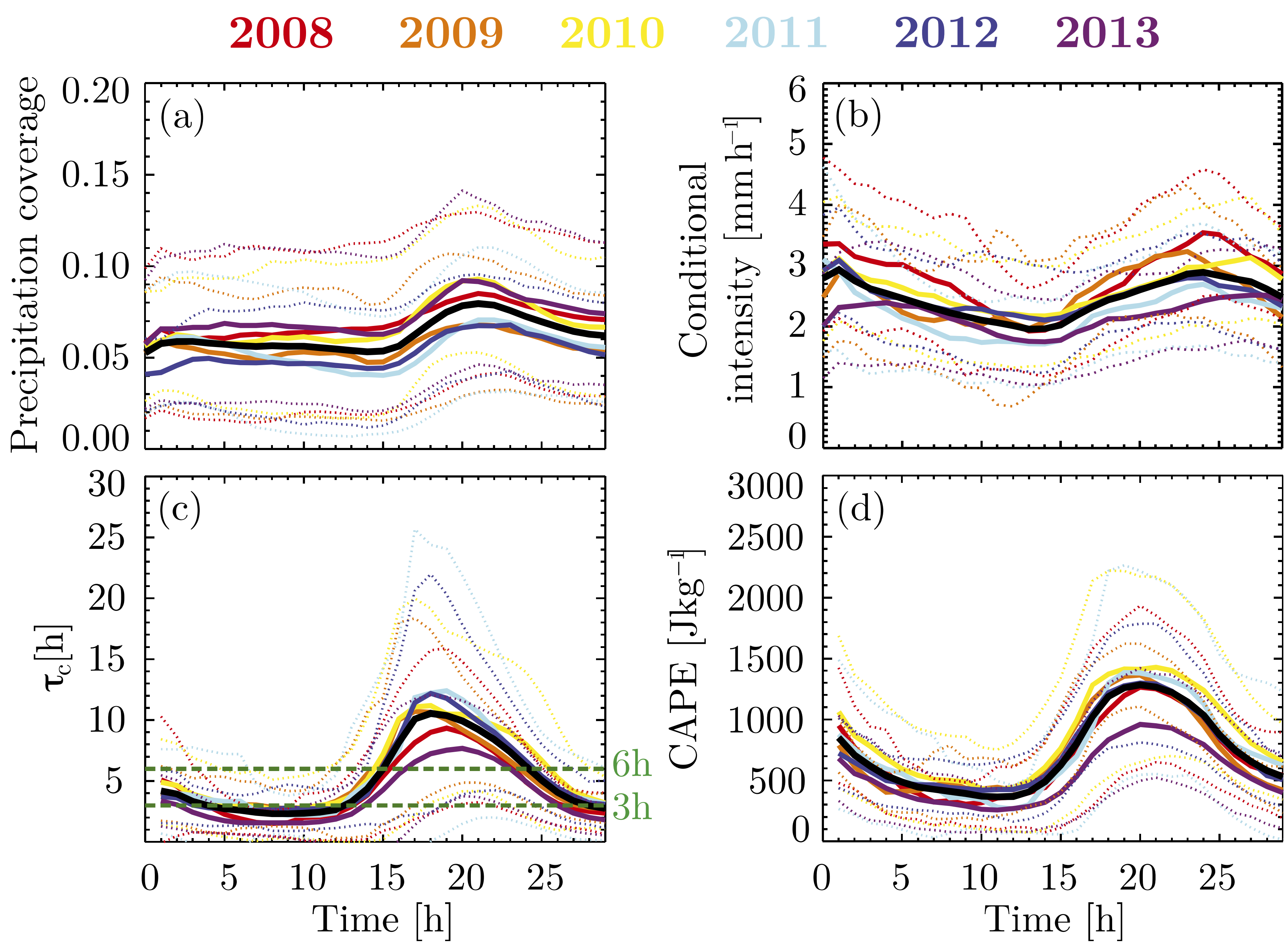
- Use several indices to characterize the events:
  - Fractional precipitation coverage
  - The convective adjustment time scale (Done et al. 2006, Keil et al. 2014) - An indicator of whether convection is in equilibrium with the large-scale flow or not - proxy for strength of large-scale forcing.

$$\tau_c \sim \frac{\text{CAPE}}{d(\text{CAPE})/dt}. \qquad \tau_c = \frac{1}{2}\frac{\text{CAPE}}{P} \times 49.58\,\text{mm}\,\text{s}^3\,\text{m}^{-2}\,\text{h}^{-1},$$



Average the spatial convective-adjusment time-scale over all regions of hourly rainfall accumulations larger than 1 mm.

Where do the events situate in the atmospheric attractor?



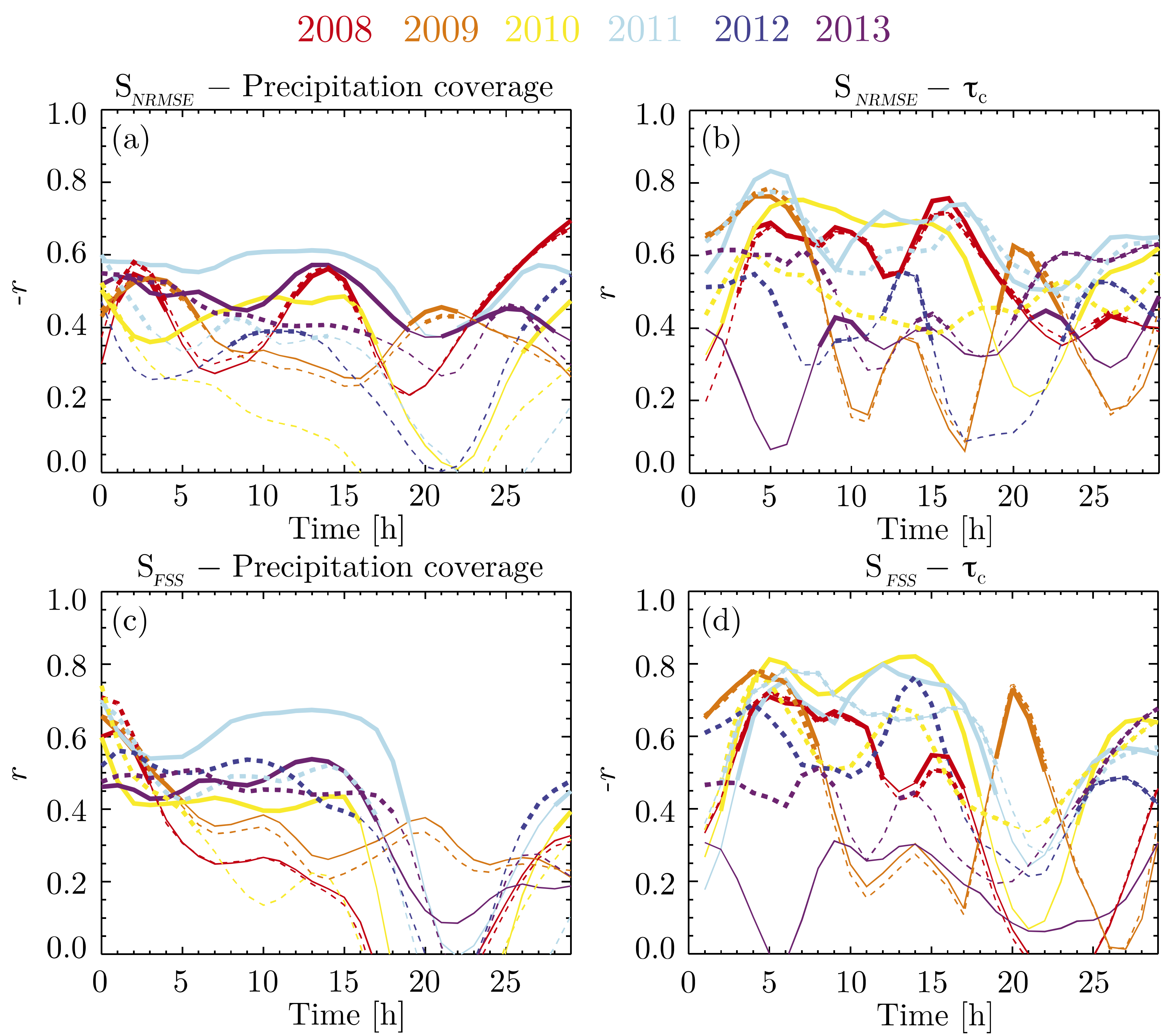
Relate predictability to precipitation coverage and $\boldsymbol{\tau}_c$

- The decorrelation scale does not show any case-dependence
- Case-dependence of spread and skill measures at large scales (more than ~200 km)
- Spread measures:

$$S_{\mathrm{NRMSE}} = \frac{1}{N} \sum_{\text{all members}} \mathrm{NRMSE}_{\text{member-CN}}$$

$$S_{\mathrm{FSS}} = \frac{1}{N} \sum_{\text{all members}} \mathrm{FSS}_{\text{member-CN}}.$$

Relate predictability to precipitation coverage and τ_c



Correlation coefficient between spread and precipitation coverage or $\tau_{c.}$

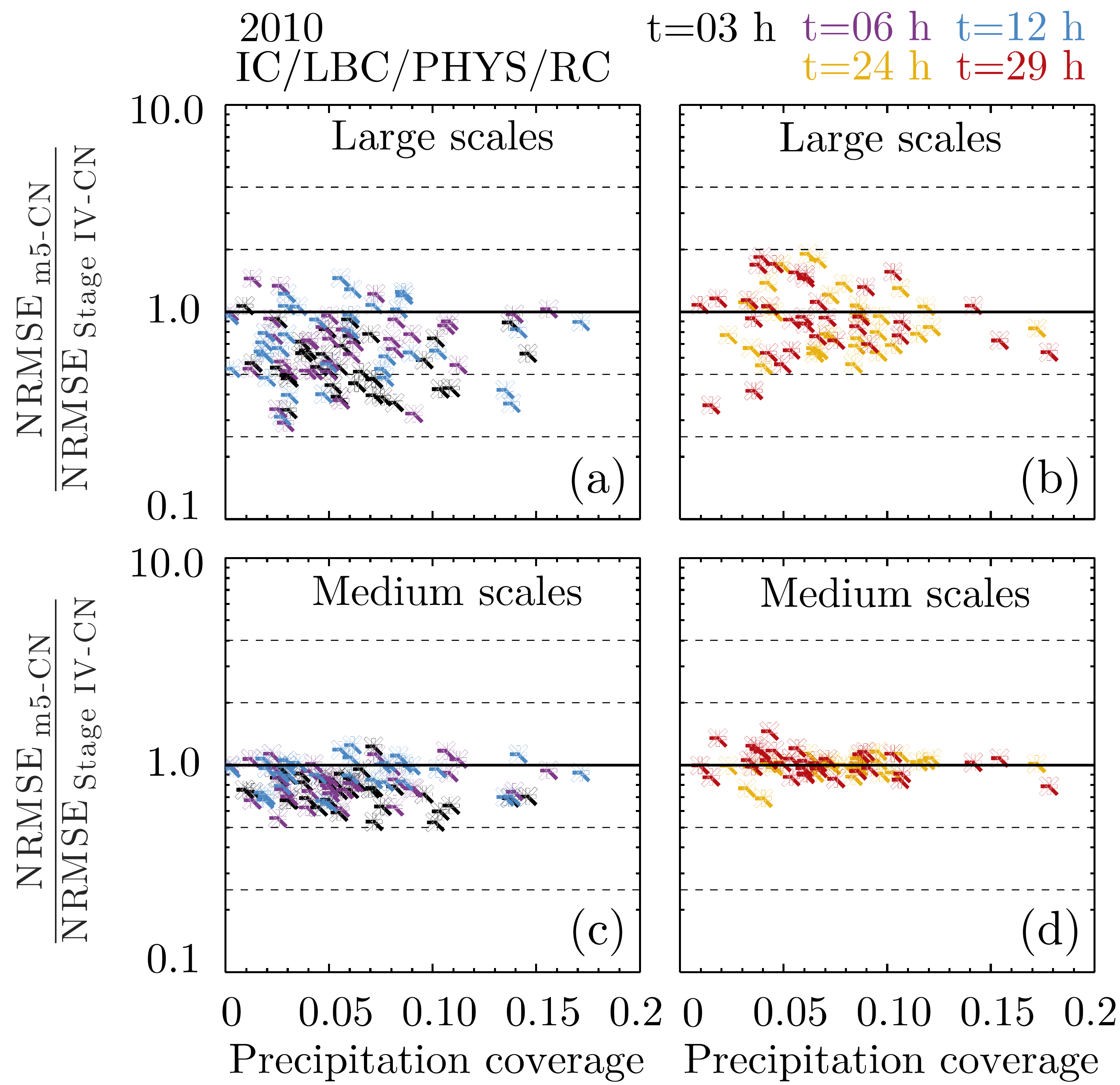
Solid lines – IC/LBC/PHYS ensemble
Dashed lines – MP ensemble

Relationship is not statistically significant during the diurnal cycle precipitation minimum.

No apparent difference between the two types of ensembles

Forecasting skill at scales > 256 km shows more relation to event type than spread

Do the error sources considered in this system ever capture the entire forecast error?



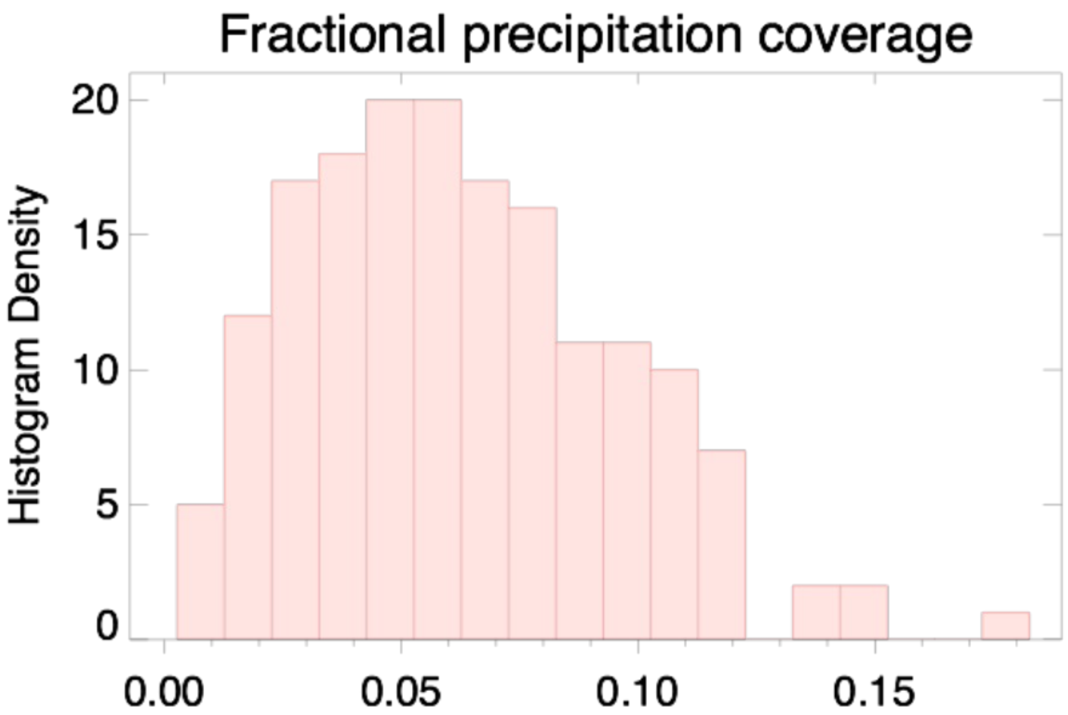
How does the effect of IC/LBC/PHYS/RC perturbations compare to forecast skill?

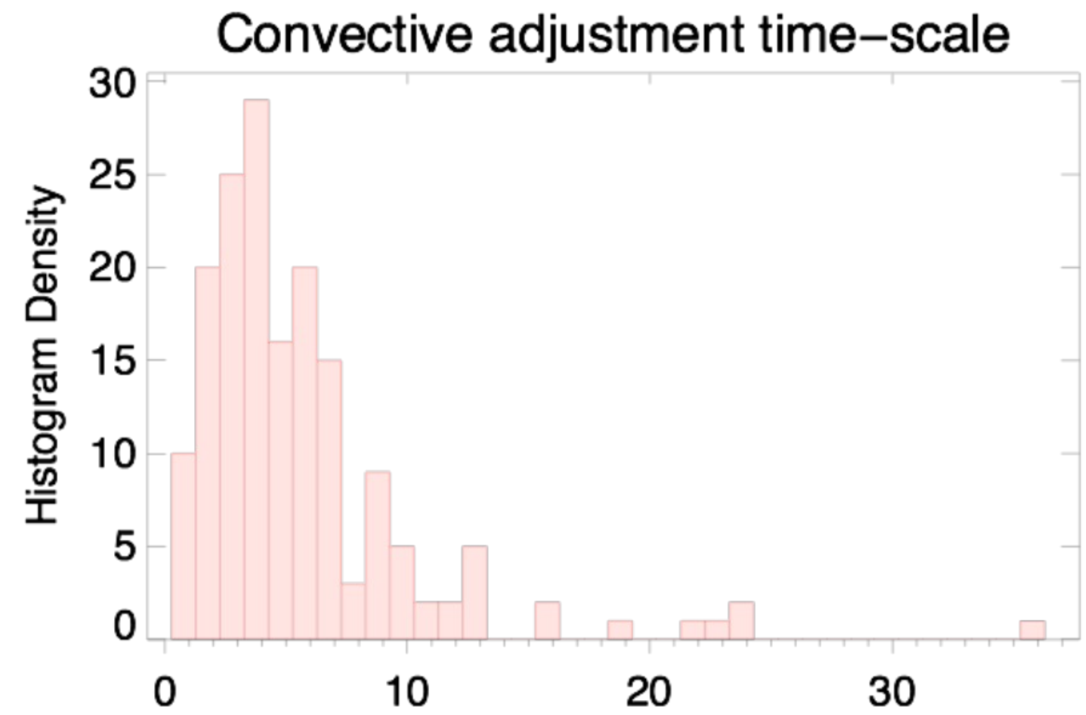
During the first 12 forecast hours the spread is insufficient.

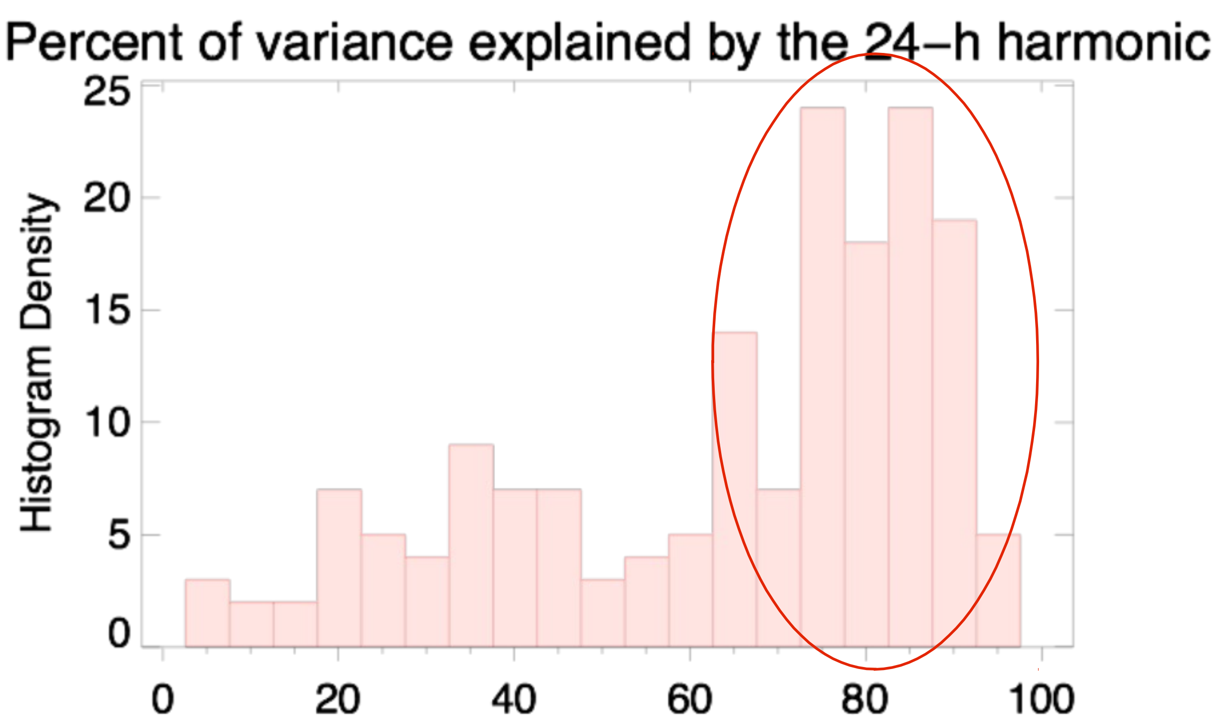
After 24 hours, the errors considered generate sufficient spread, and at medium scale (128-256 km) the error caused by the perturbations is even larger than forecast error.
No relationship to the type of event.

Maybe the distribution of cases we have is not wide enough!

Averages for each case - total of 179 cases over 6 years







For most of the case, most of the variability in fractional precipitation coverage is explained by the diurnal cycle of precipitation.

Summary

- We were interested in characterizing the precipitation predictability limits by convection-allowing models.
- Indeed, predictability at small scales is short lived.
- Furthermore, while there seems to be some relationship between predictability at scales larger than ~200 km and type of event, predictability is always lost rapidly at convective scales.
- Despite the many types of errors sampled by the ensemble system used here, spread for short lead times (<12 h) is still insufficient.

Impacts

- Serious implications of these findings:
  - Small scale predictability always rapidly lost – what does this mean for data assimilation of storm scale observations? How long can the duration of the effect of assimilating such data be?
  - Producing operational forecast products - information is lost rapidly at small scales, therefore, shouldn’t probabilistic forecasts of precipitation reflect that?
    - Schwartz and Sobash 2016: neighbourood approaches for producing POPs
    - The neighbourhood size should change with forecast lead time – work in progress
    - Already explored for lagrangian extrapolation nowcasting systems (ex. MAPLE , Germann and Zawadzki 2004)
    - Careful interpretation of ensemble mean products, which become increasingly filtered with increasing forecast time.

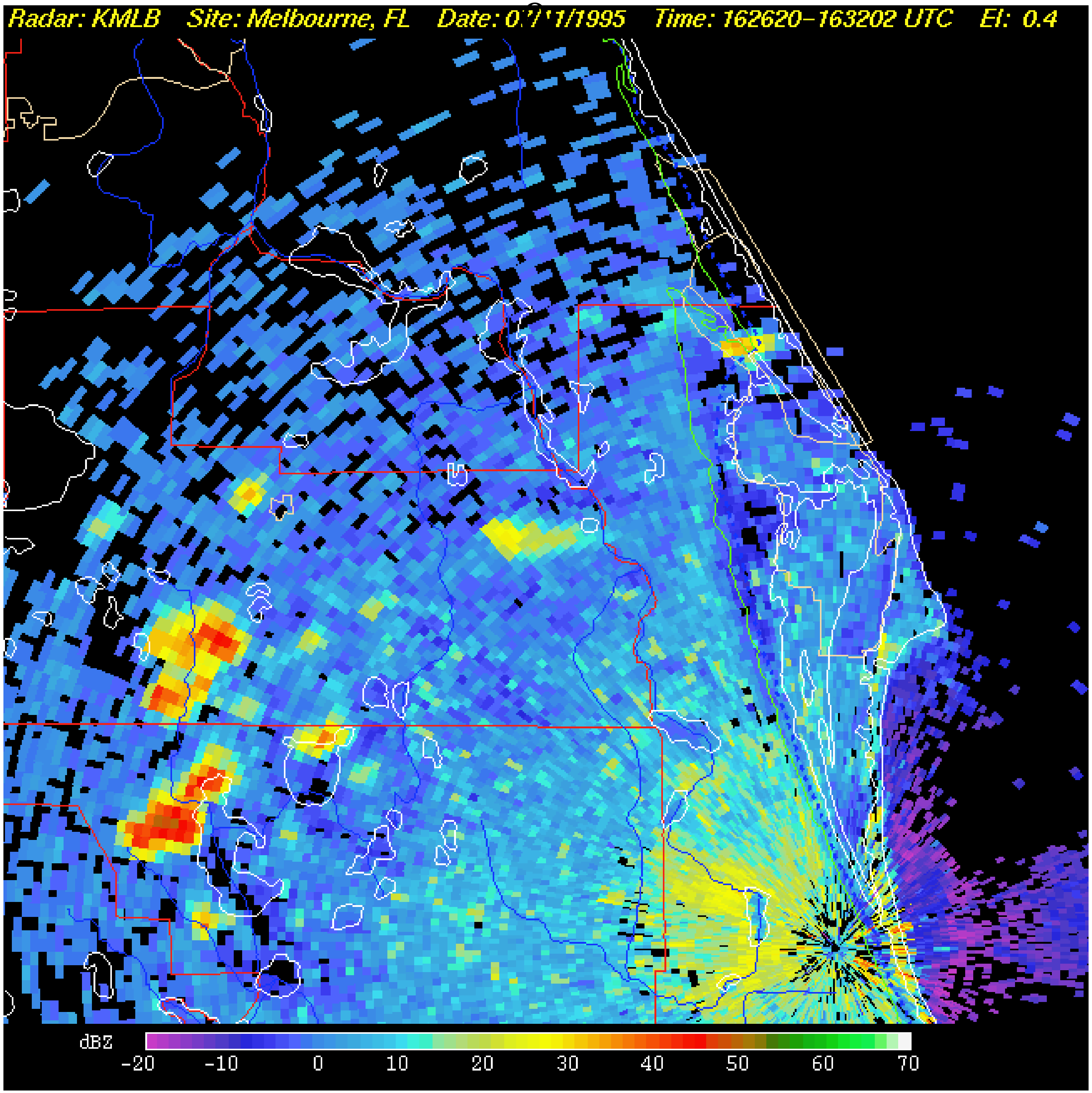
Caveats

- Main problem of our study: using data produced for other purposed made it difficult to control the experiment
- Only precipitation data available – How do predictability estimates differ when other variables are analyzed?
    - Expecting less spread for other variables such as temperature and wind – problem for DA!
    - Understanding the relationship between error growth in mass variables and error growth in precipitation is important
- No perfect knowledge of the IC perturbation structure which is needed to properly understand error growth
- Predictability estimates are sensitive to the model used for estimation

To end the presentation

- An example of how difficult convective scale predictability could be

16:3



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Site: Melbourne, FL
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El: 0.4
dBZ
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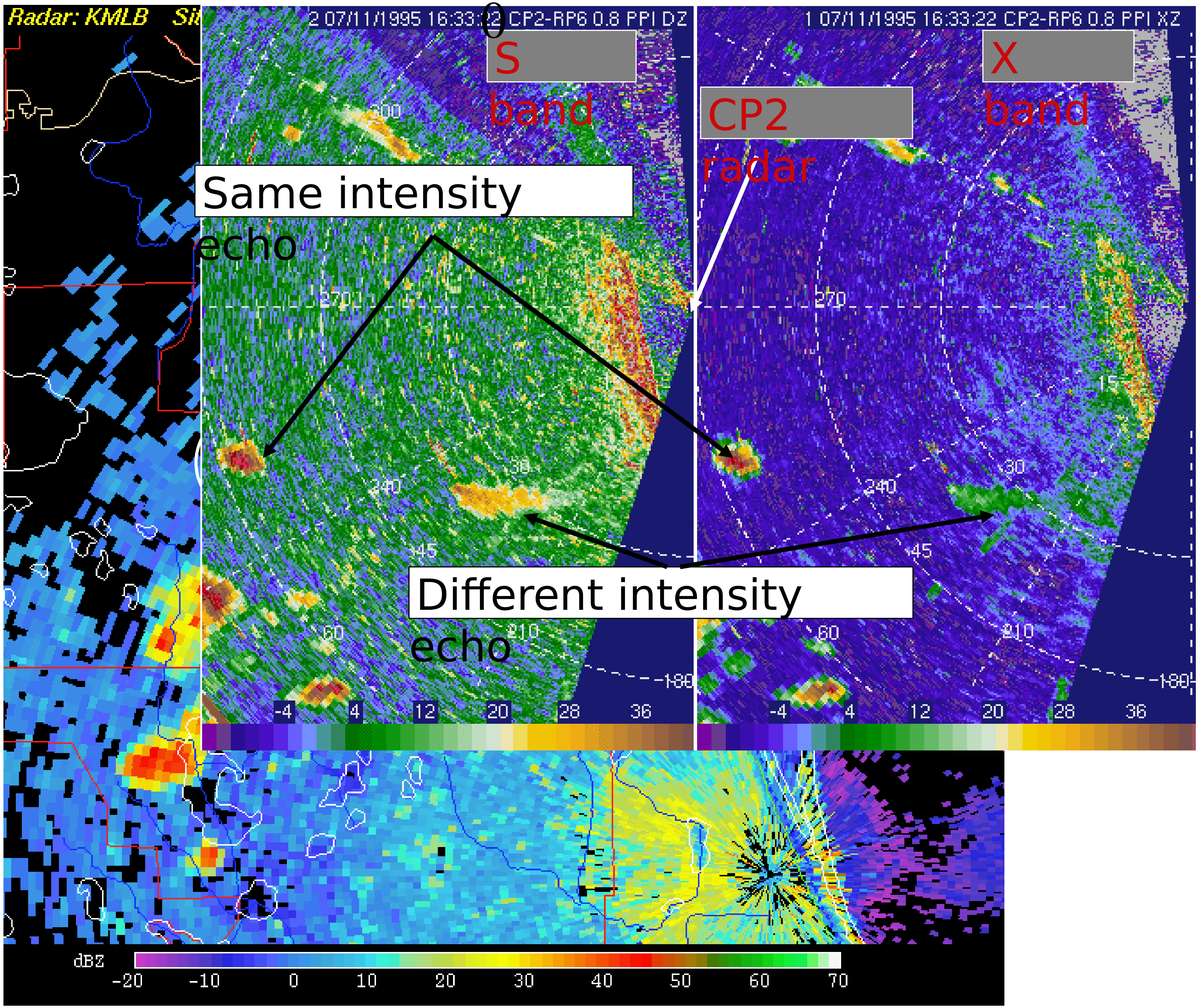
16:30


Radar: KMLB
2 07/11/1995 16:33:22 CP2-RP6 0.8 PPI DZ
1 07/11/1995 16:33:22 CP2-RP6 0.8 PPI XZ
S band
X band
CP2 radar
Same intensity echo
Different intensity echo
-4 4 12 20 28 36
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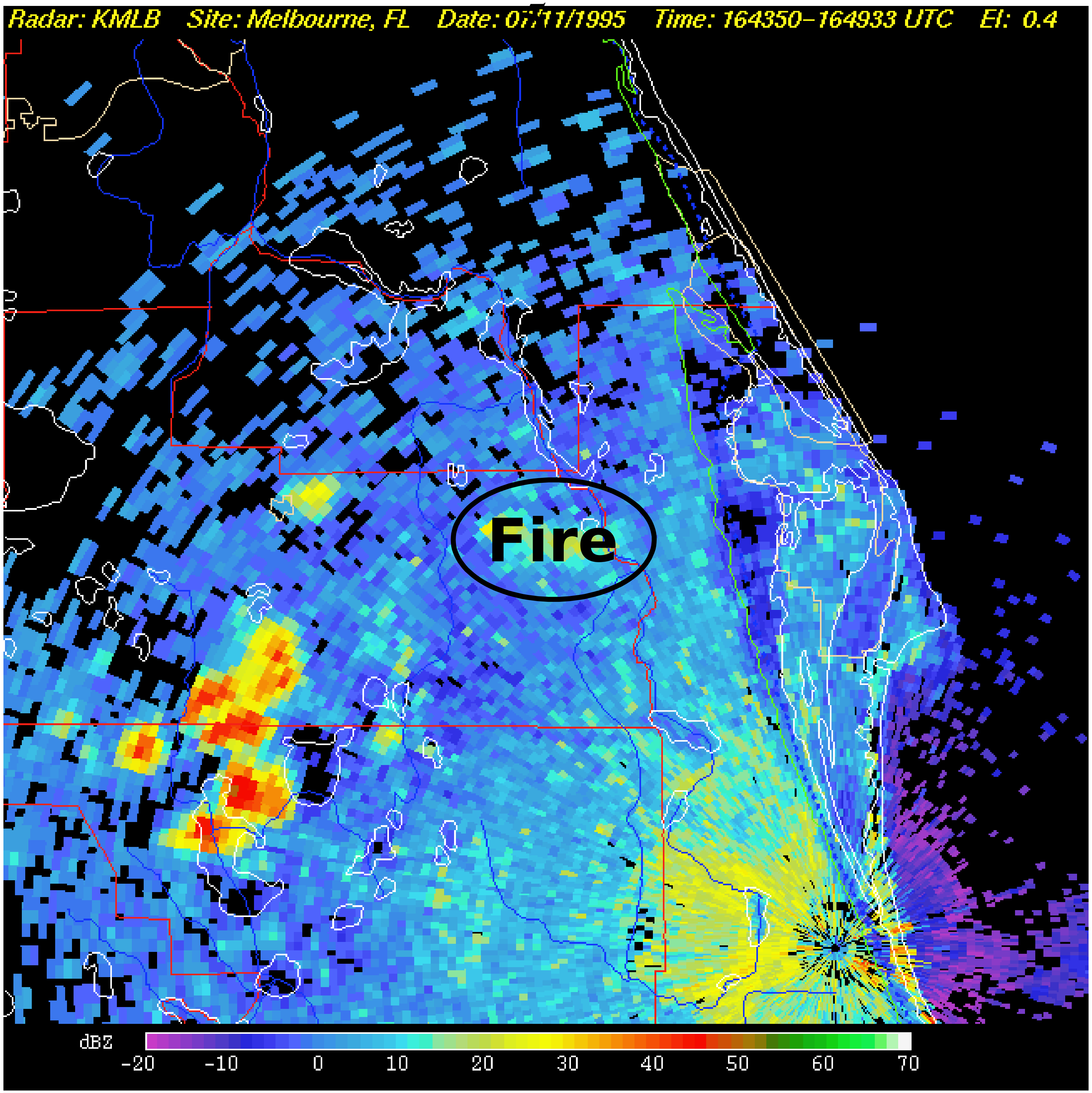
-20 -10 0 10 20 30 40 50 60 70

16:4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Fire
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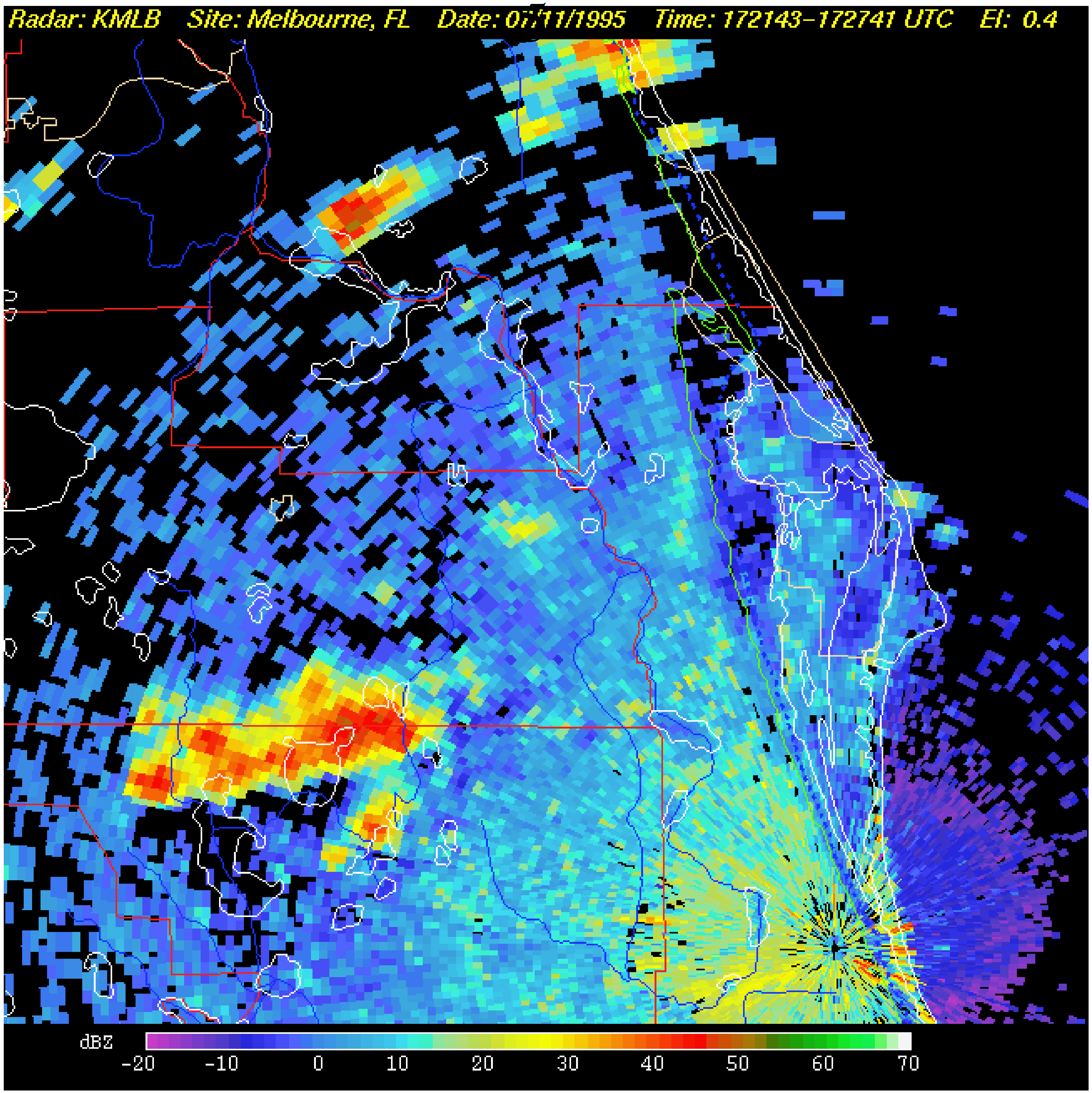
17:2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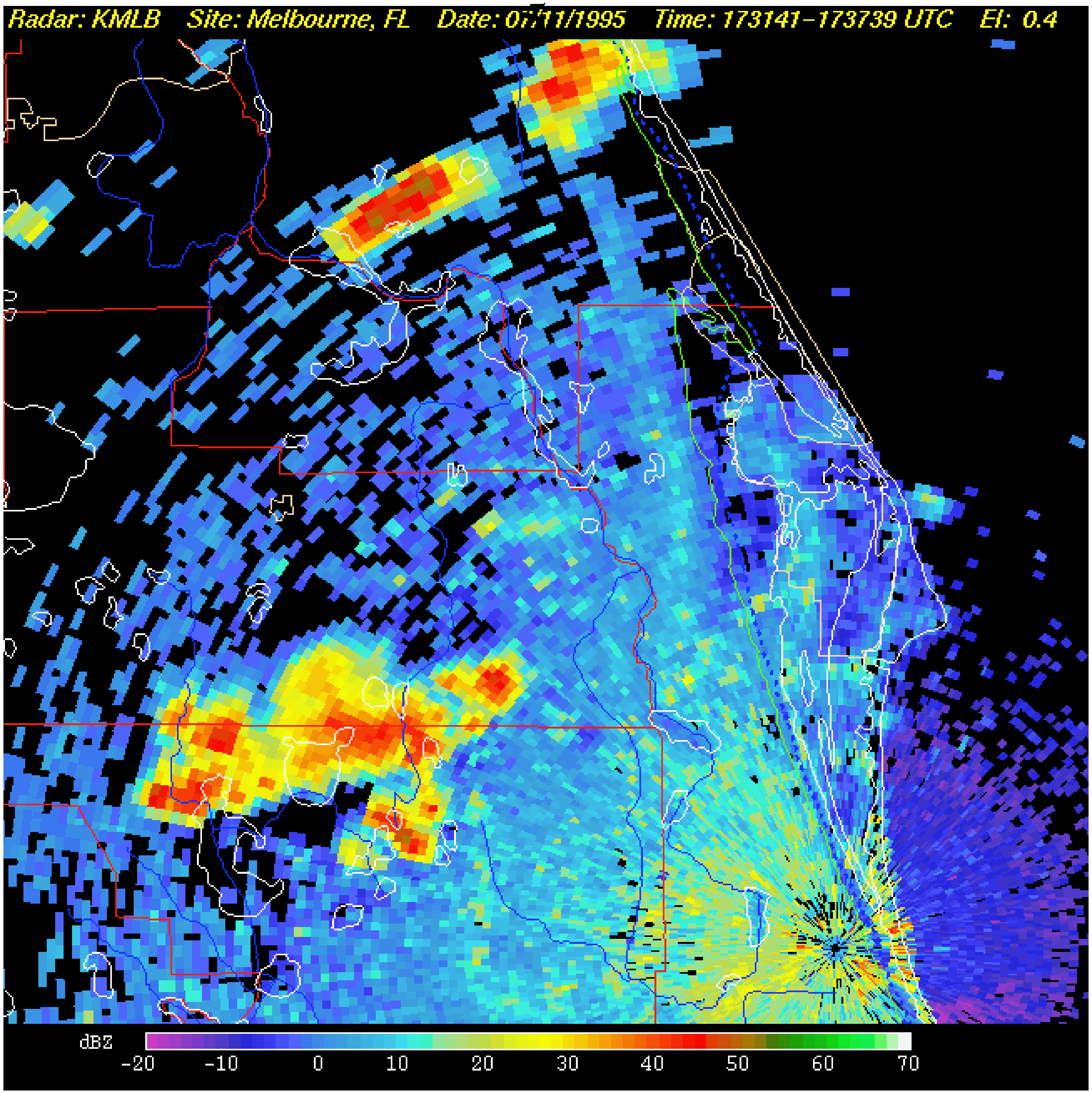

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15 min

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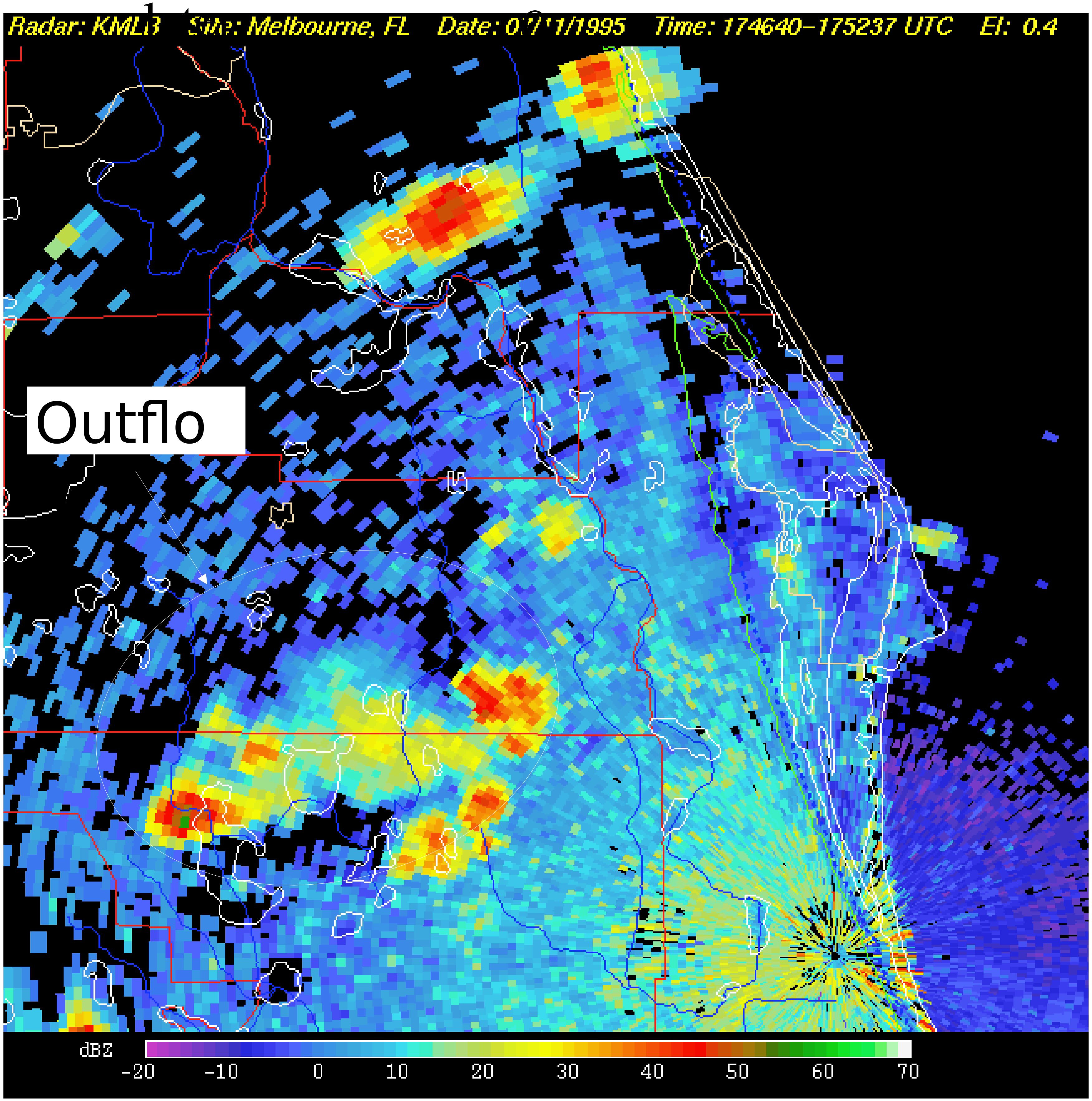

Melbourne, FL
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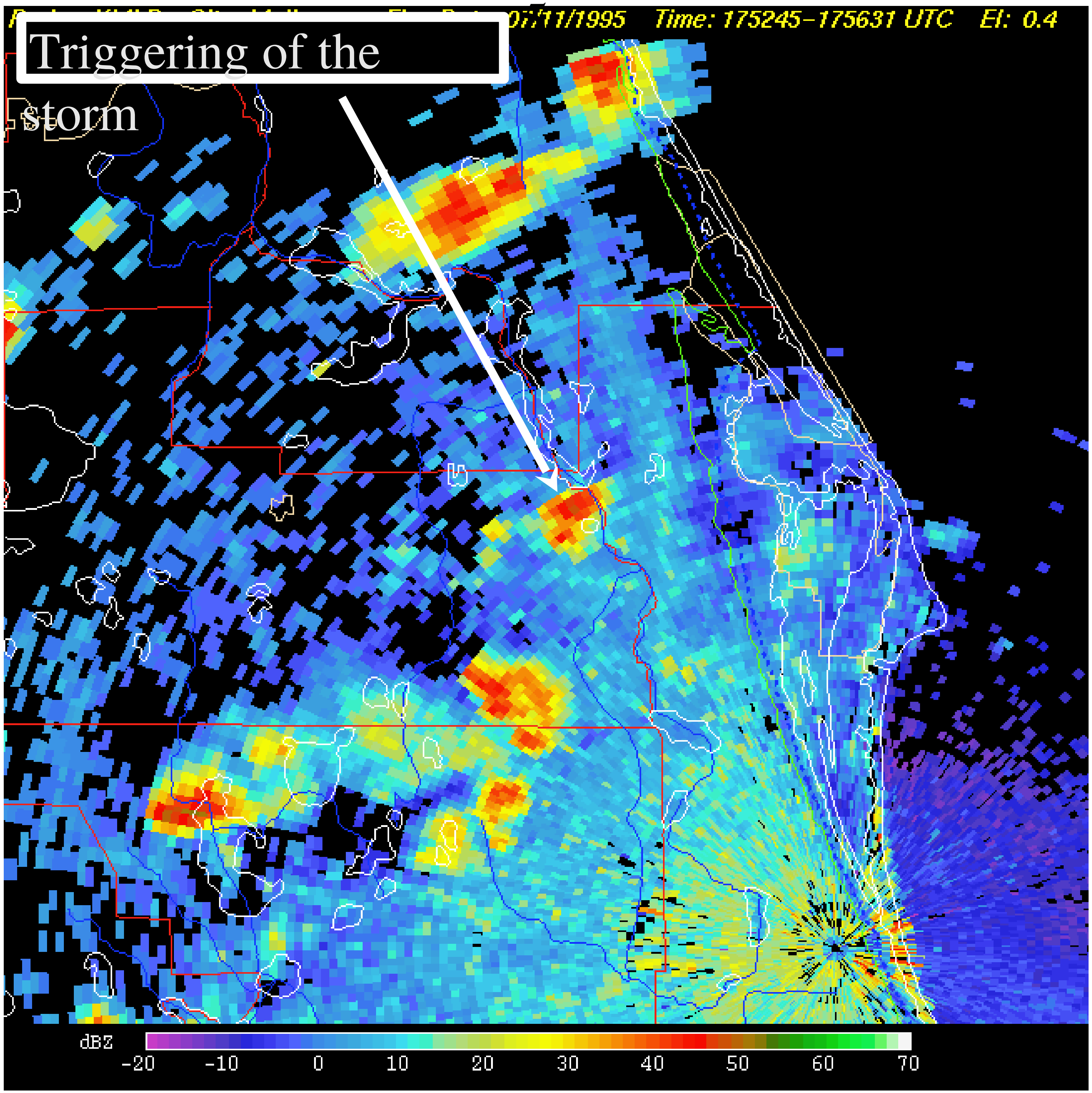
17:5



Time: 175245-175631 UTC
El: 0.4
Triggering of the
storm
dBZ
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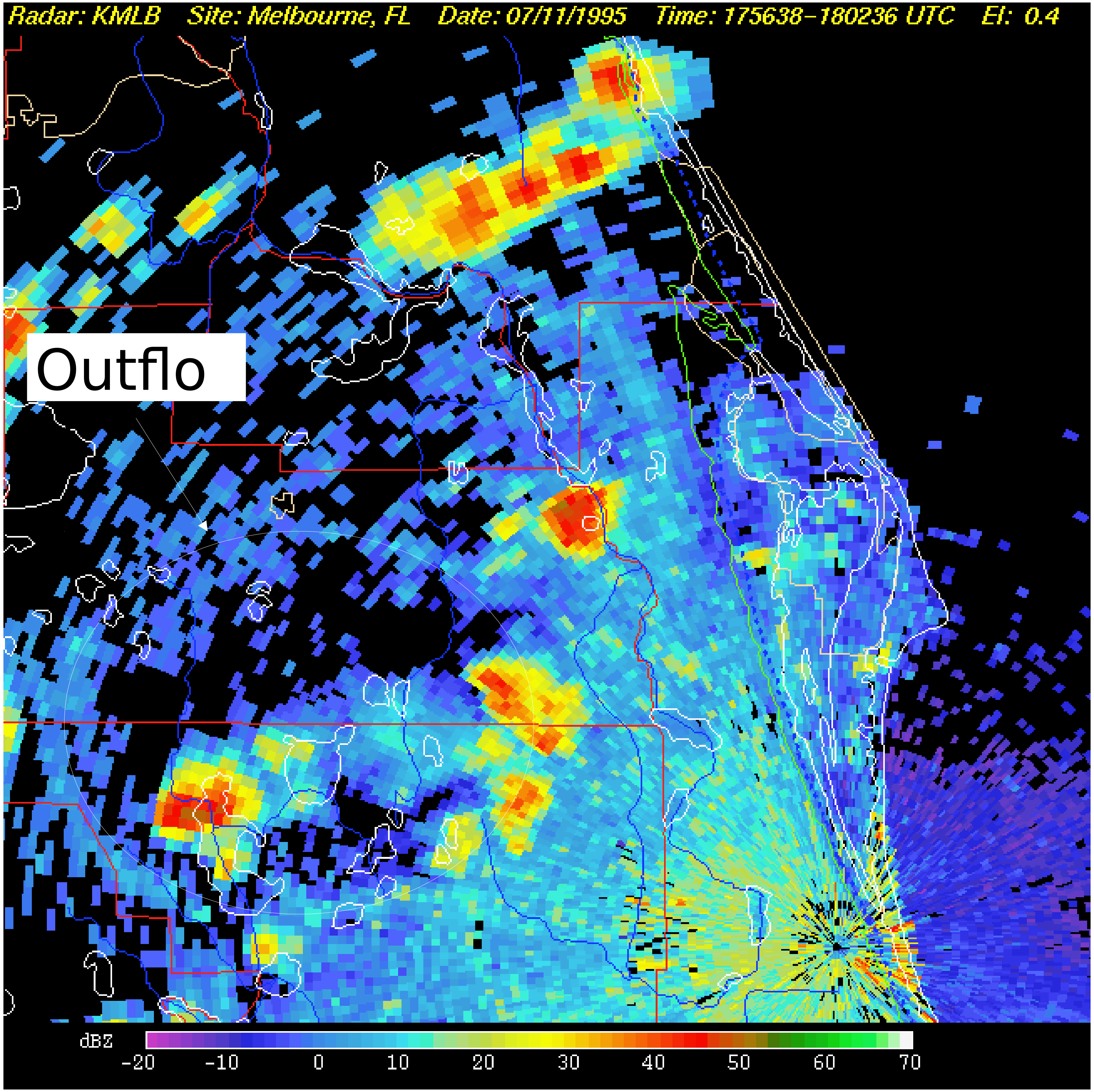
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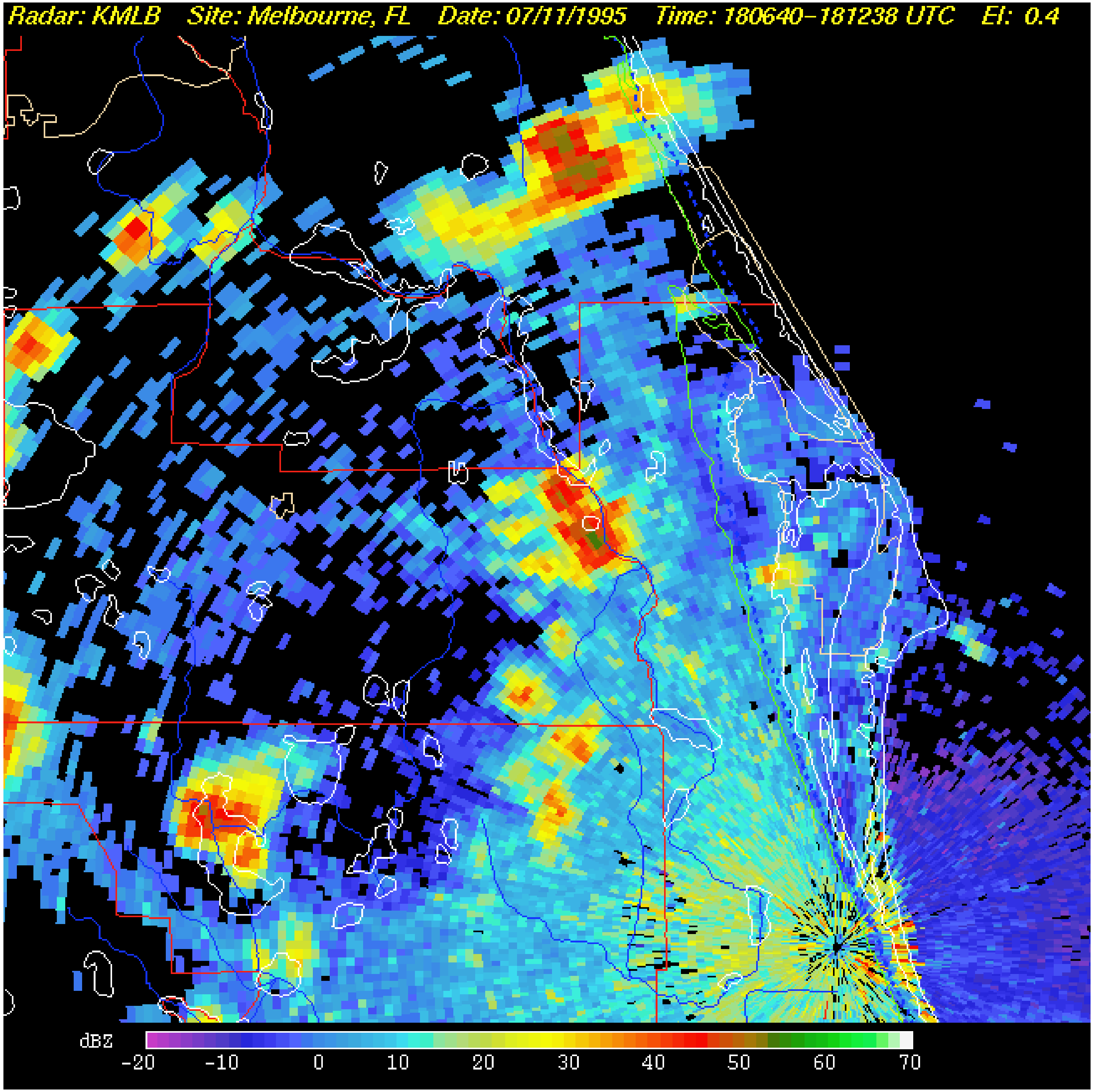

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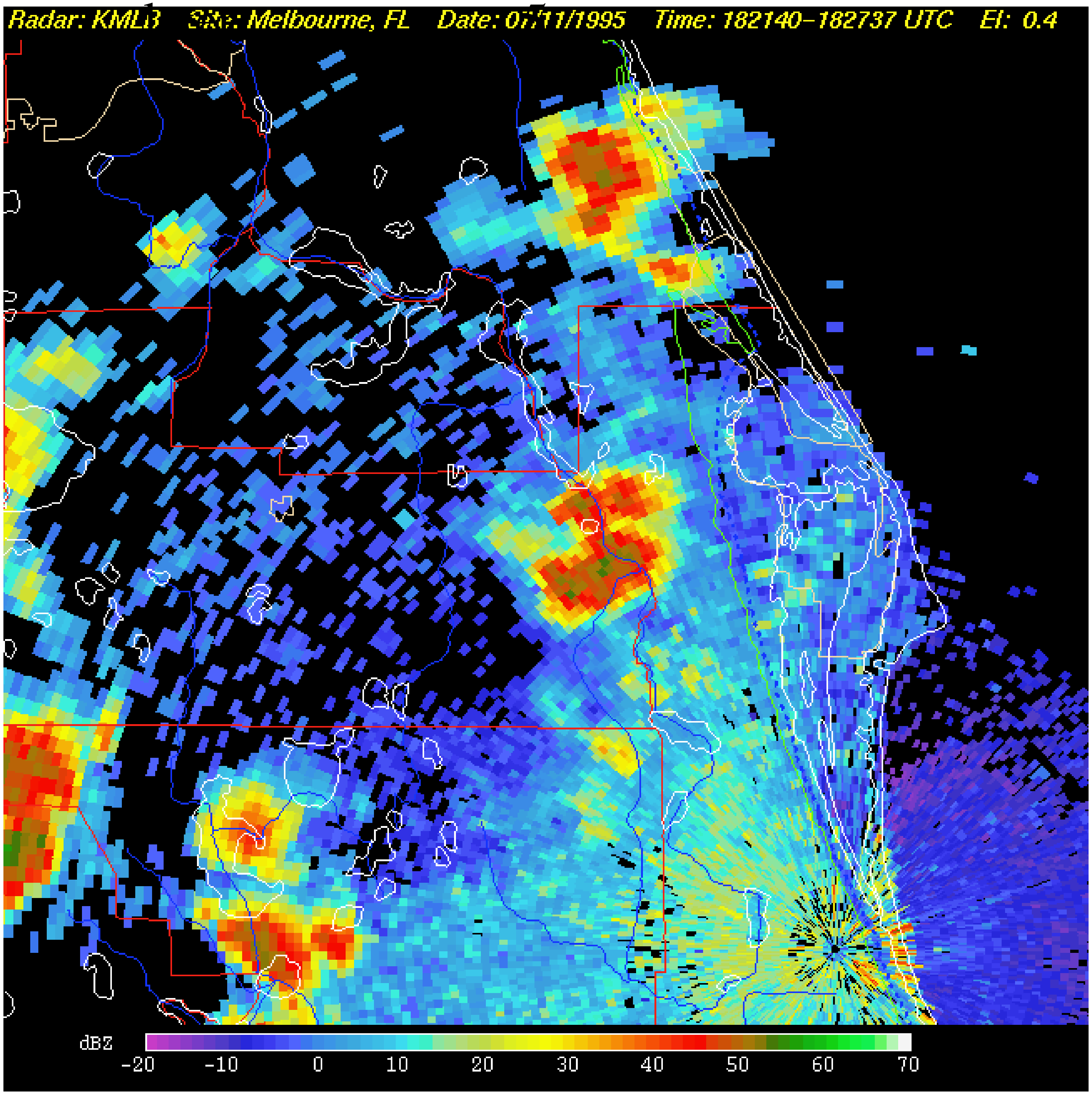
30 min 18:2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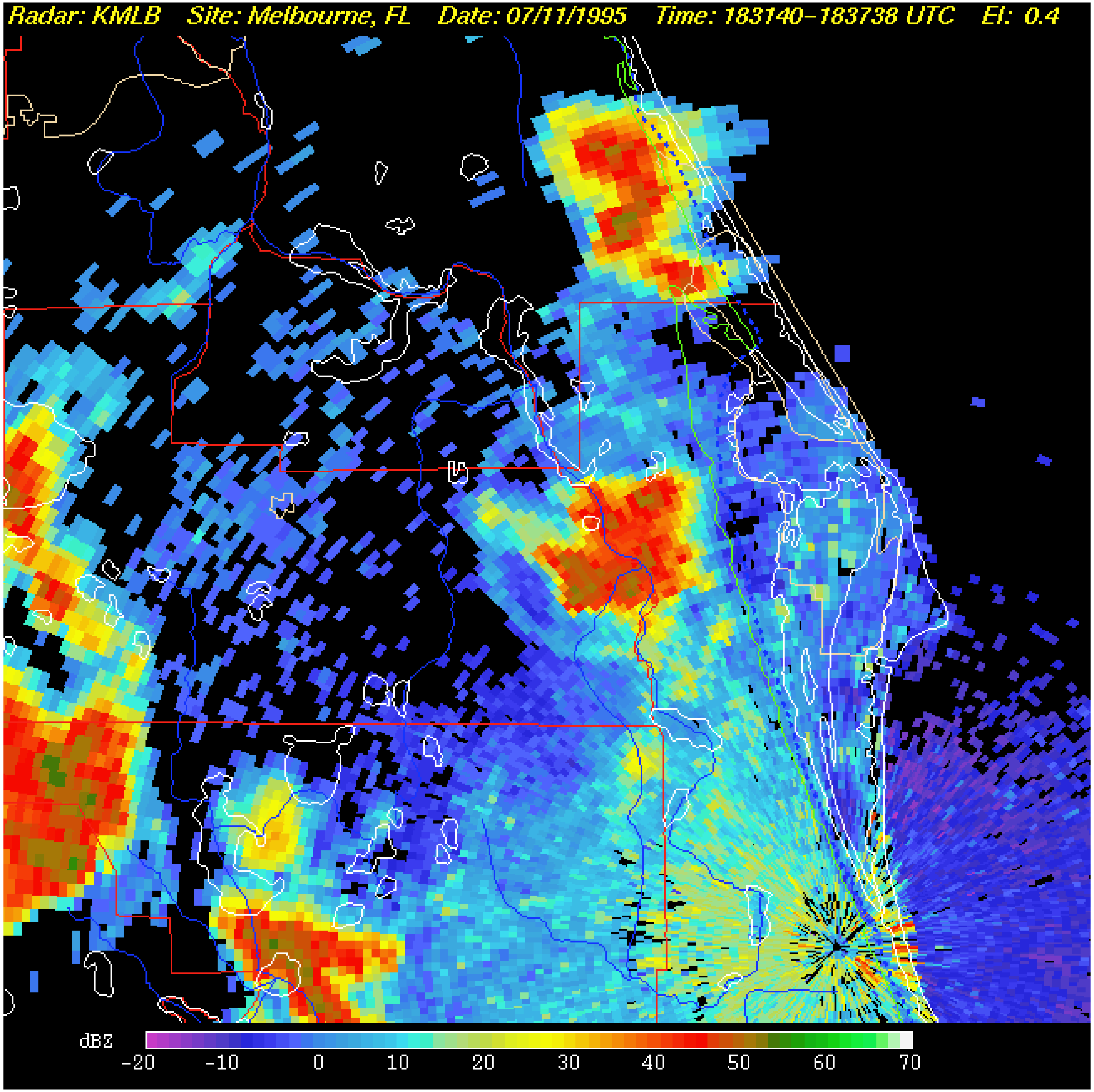
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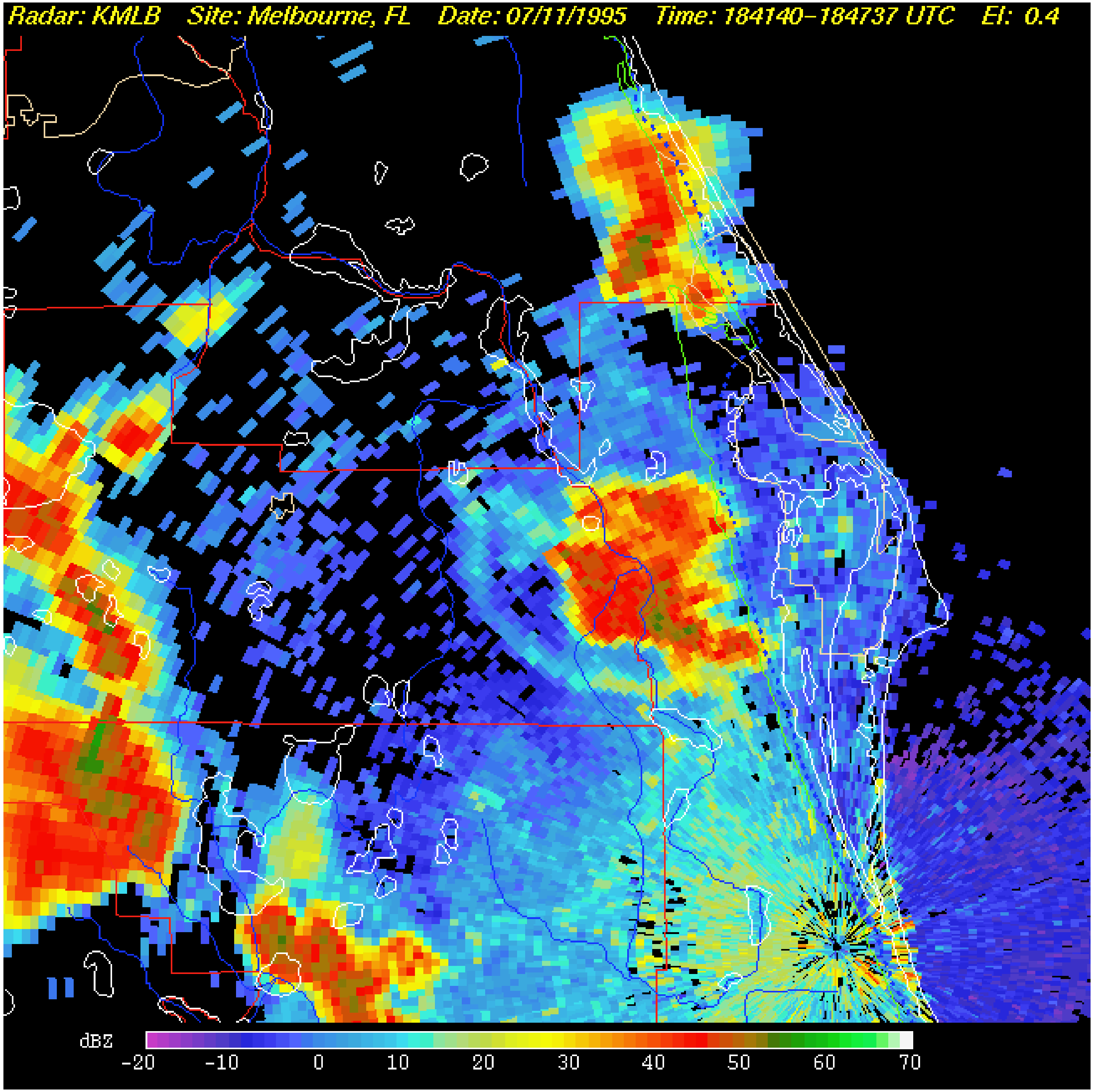
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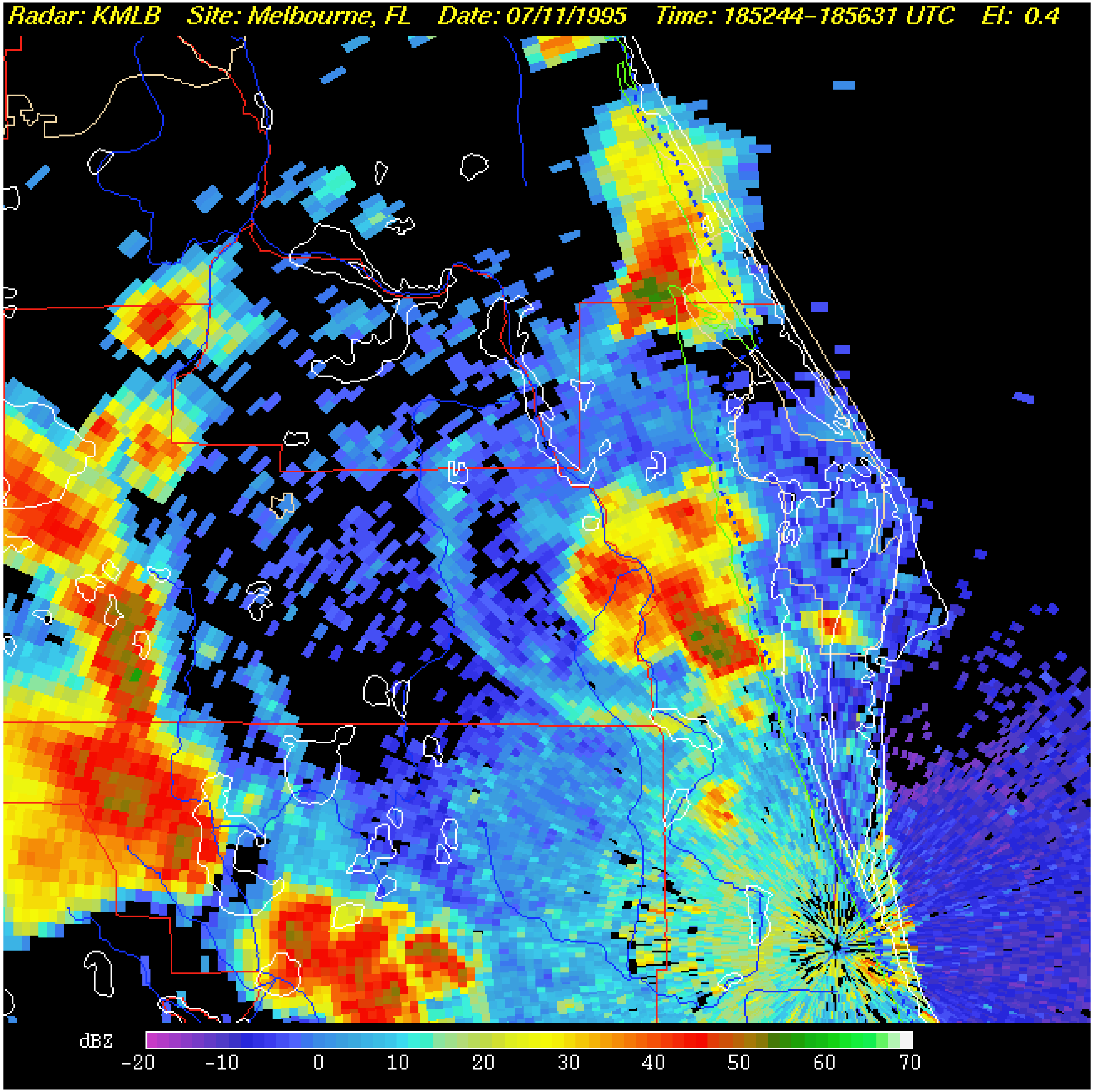
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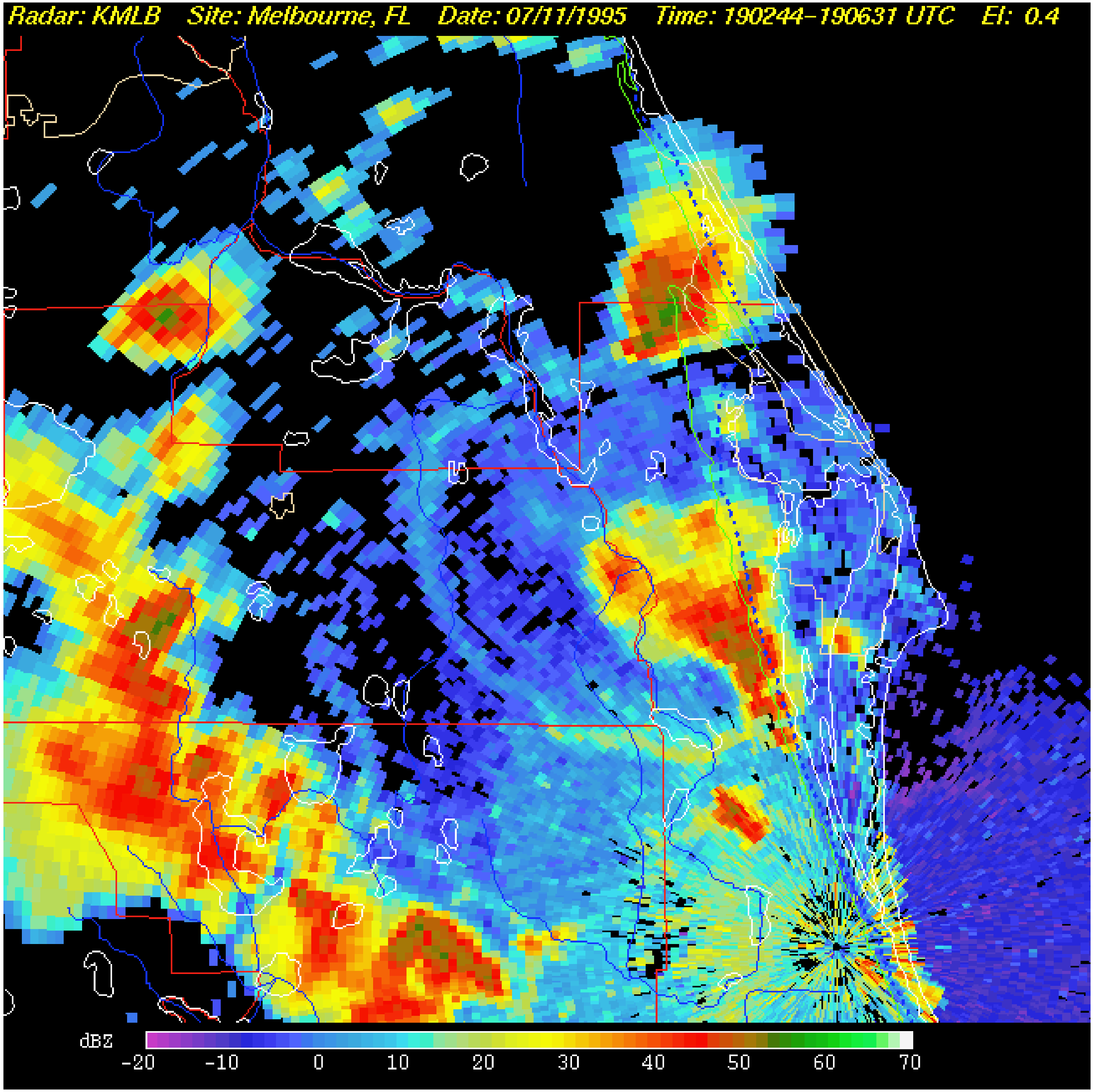

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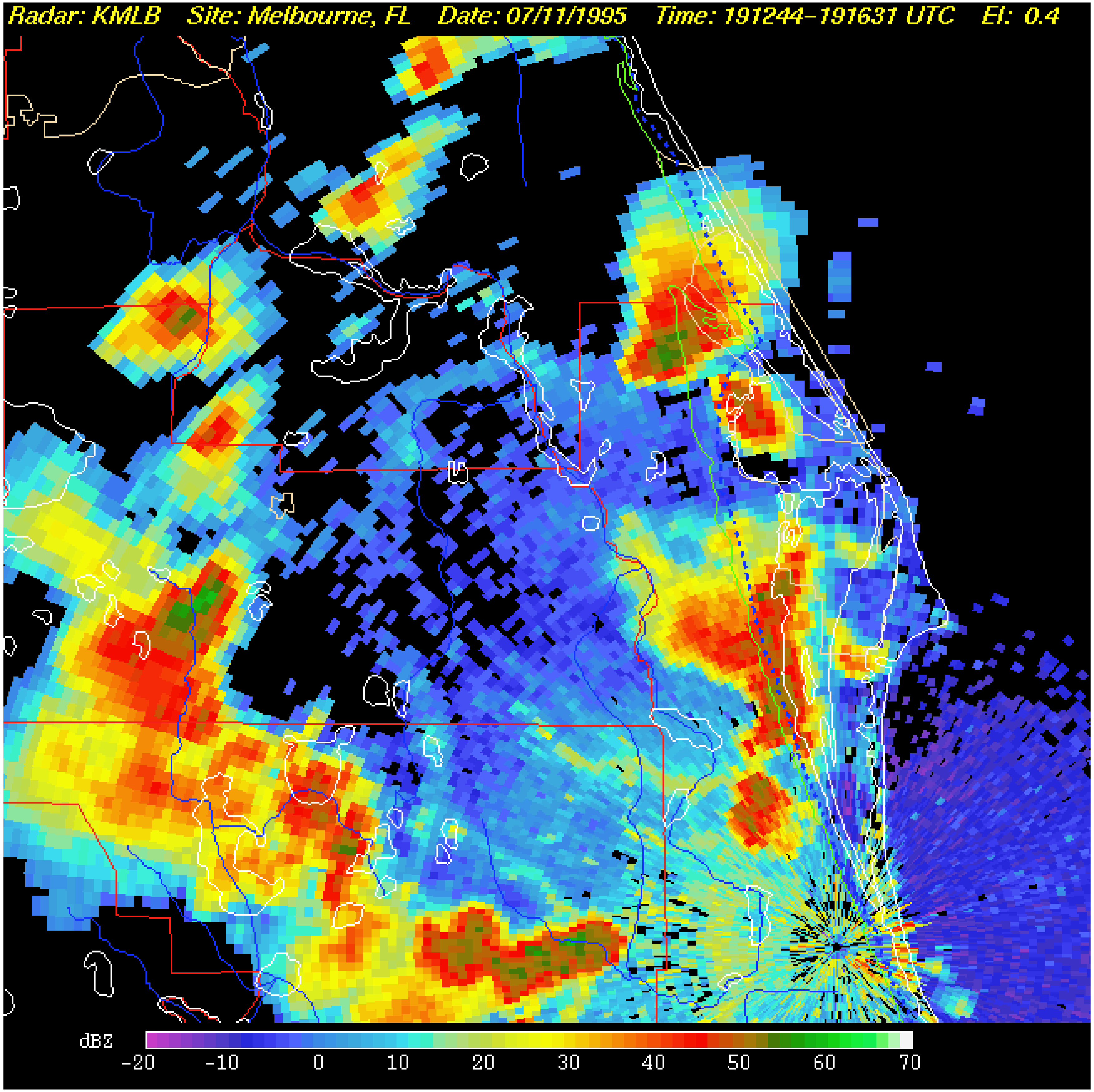
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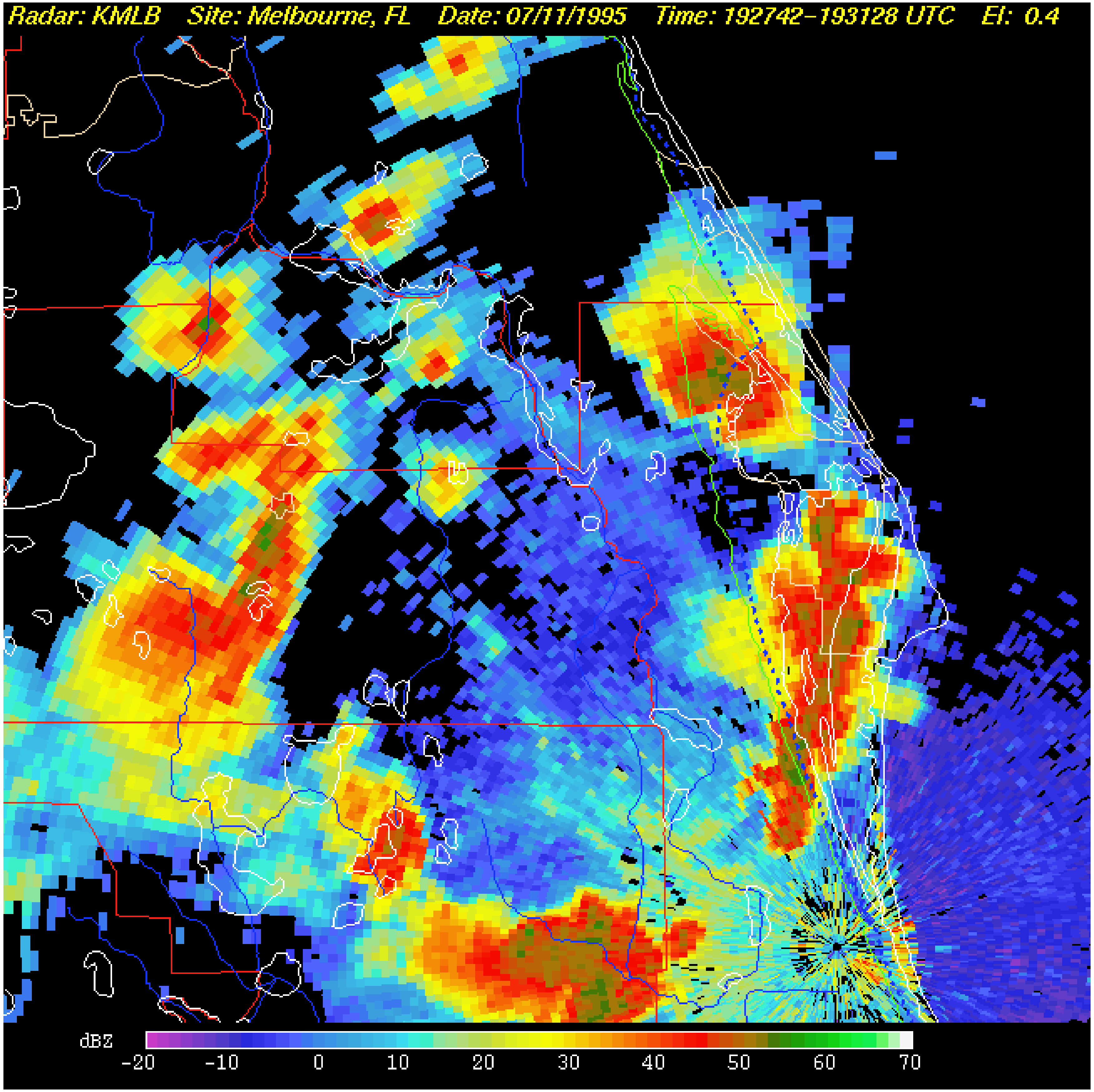
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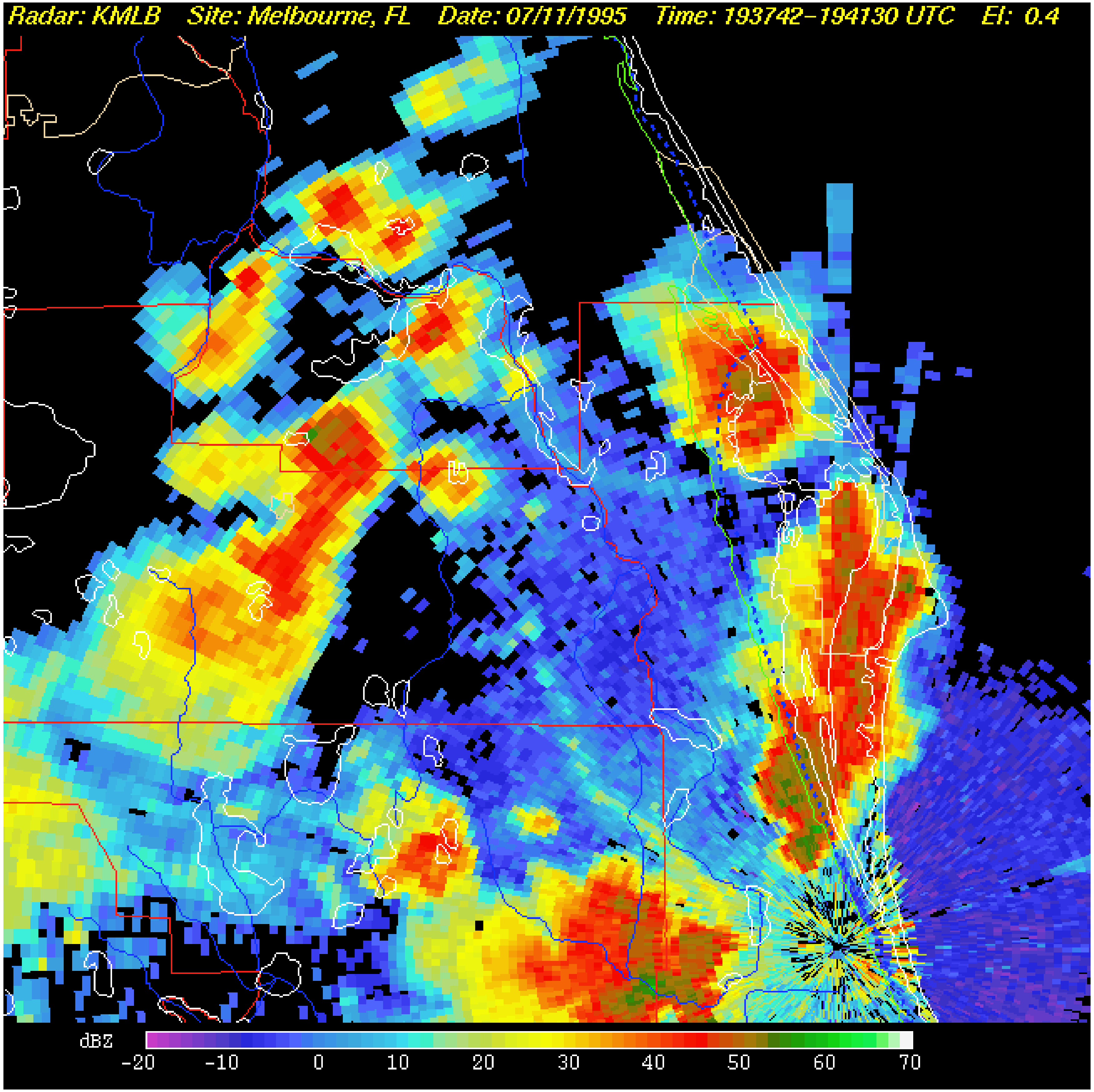

Radar: KMLB Site: Melbourne, FL Date: 07/11/1995 Time: 193742-194130 UTC El: 0.4
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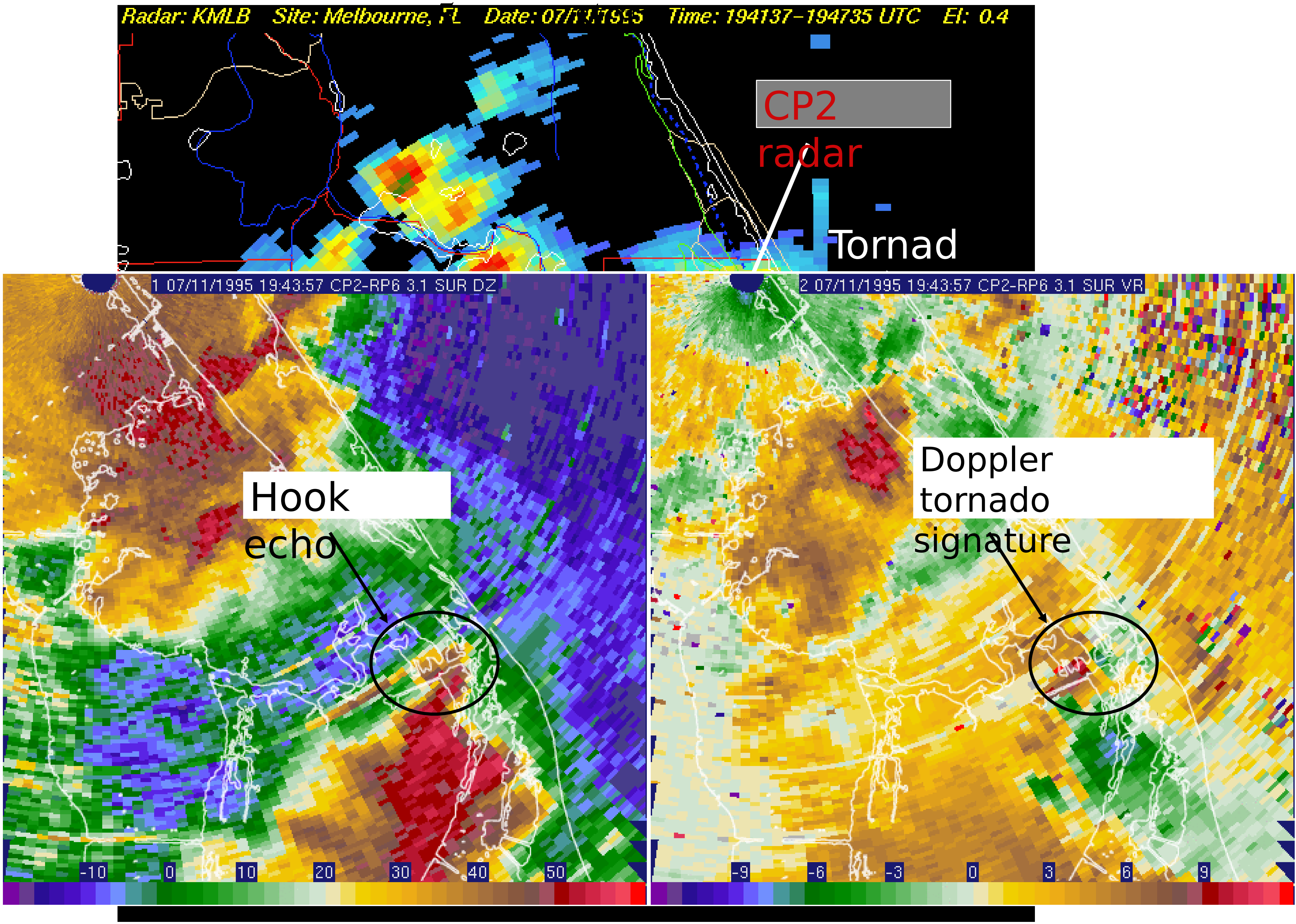
19:4 less than 2h after triggering of the



This is a very extreme case – but what is the impact of other smaller anthropogenic perturbations such as rush hour traffic effects?

Lorenz 1969: is the system represented by convection-allowing models non-deterministic? How can we account for these stochastic effects?

Thank you!