

# The Image Warp for Evaluating Gridded Weather Forecasts

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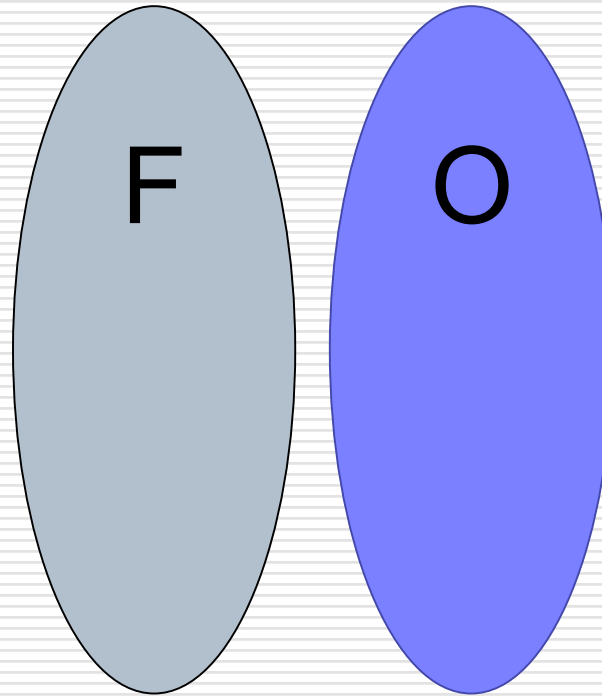


12 June 2008

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# User-relevant verification: Good forecast or Bad forecast?

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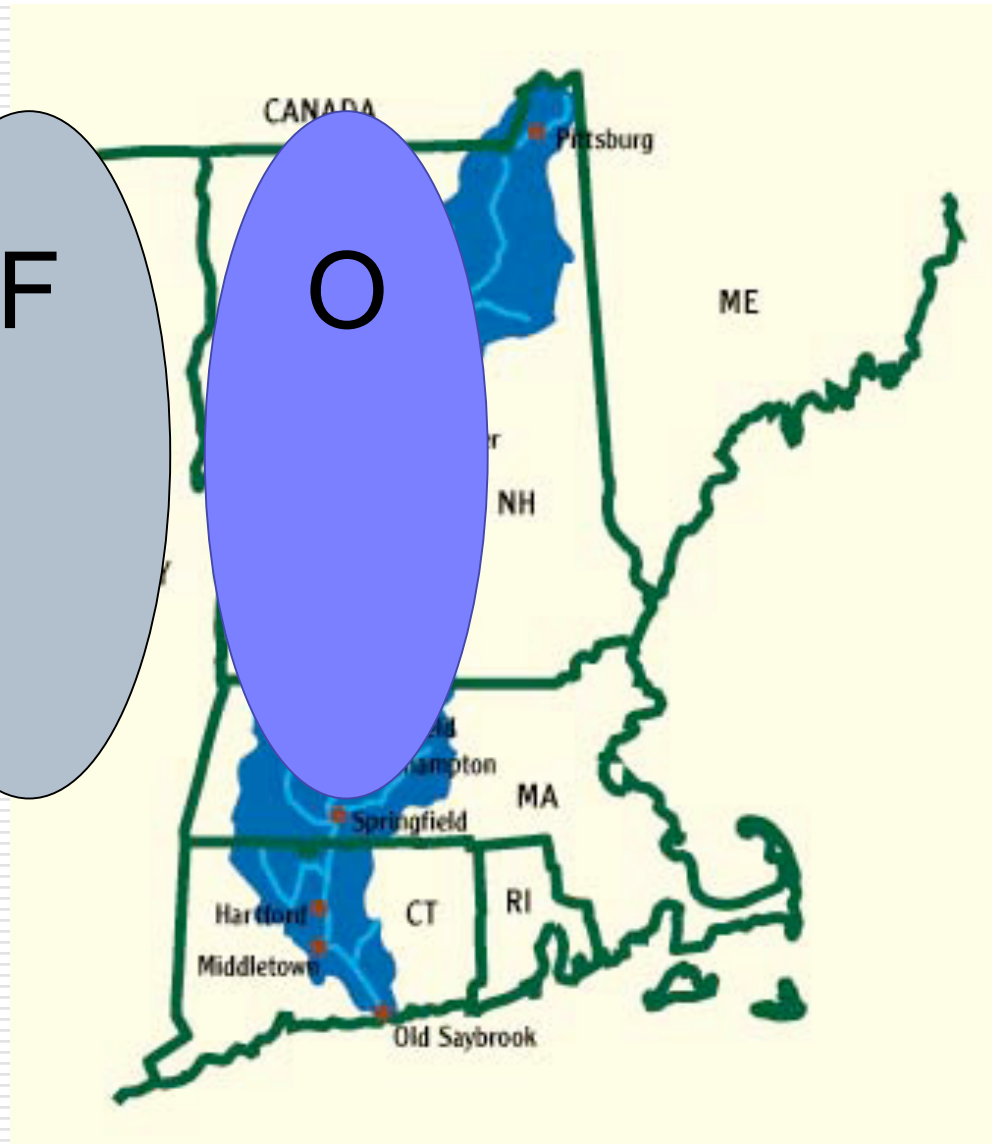


# User-relevant verification: Good forecast or Bad forecast?

If I'm a water manager for this watershed, it's a pretty bad forecast...

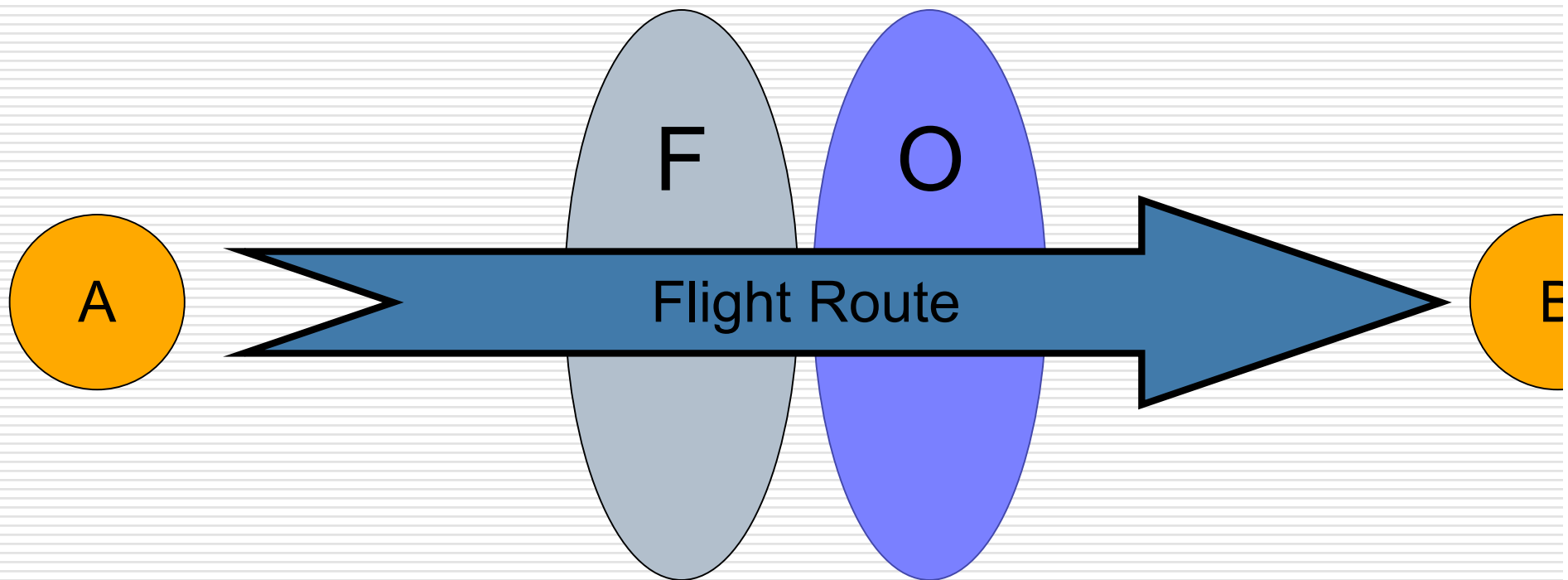
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# User-relevant verification: Good forecast or Bad forecast?

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If I'm an aviation traffic strategic planner...

It might be a pretty good forecast

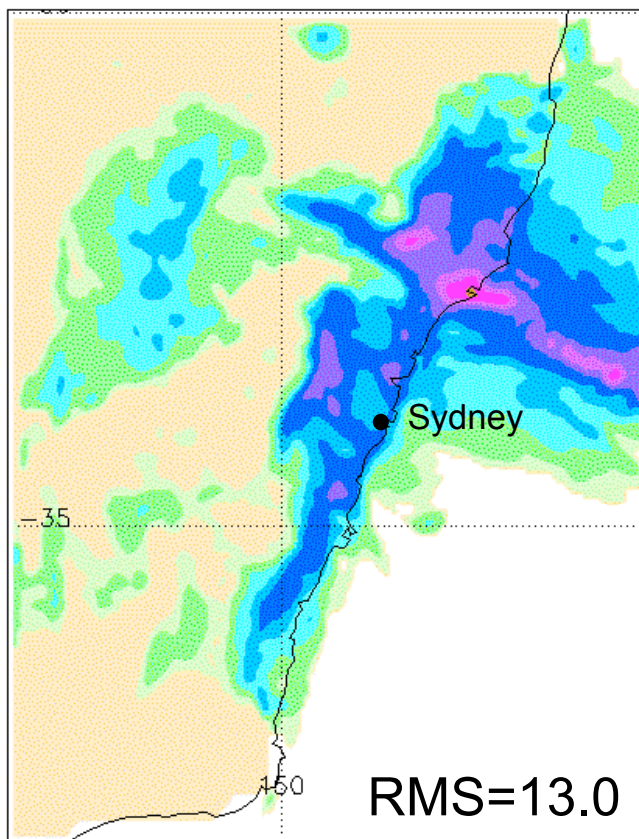
Different users have different ideas  
about what makes a good forecast



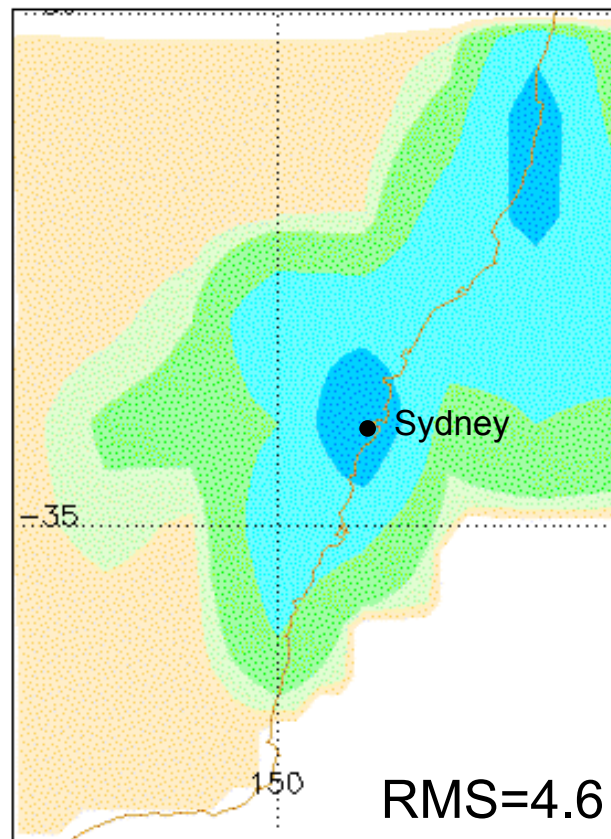
# High vs. low resolution

## Which rain forecast is better?

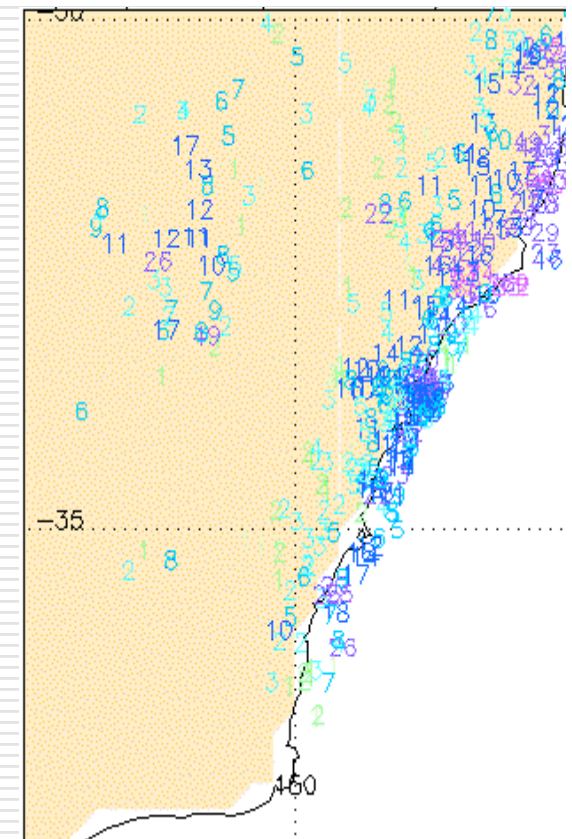
Mesoscale model (5 km) 21 Mar 2004



Global model (100 km) 21 Mar 2004



Observed 24h rain

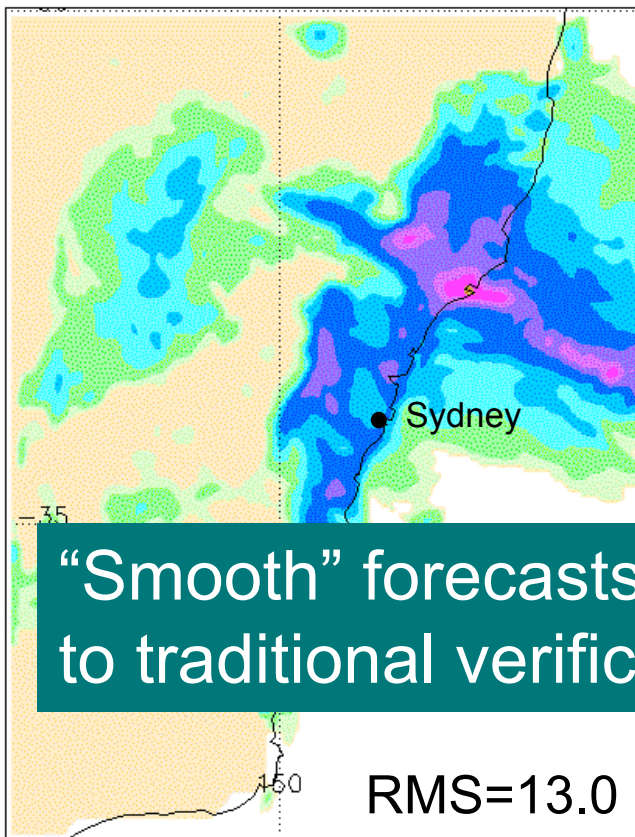


From E. Ebert

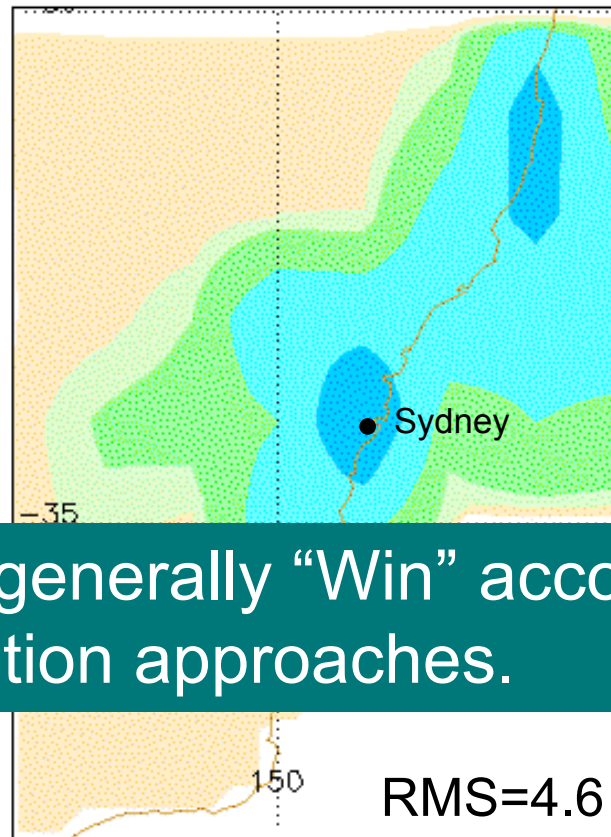
# High vs. low resolution

Which rain forecast is better?

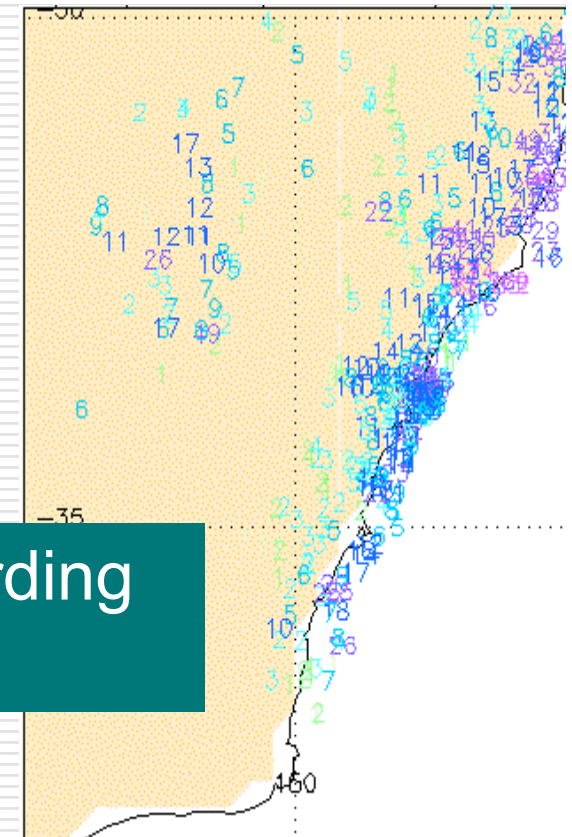
Mesoscale model (5 km) 21 Mar 2004



Global model (100 km) 21 Mar 2004



Observed 24h rain



“Smooth” forecasts generally “Win” according to traditional verification approaches.

From E. Ebert

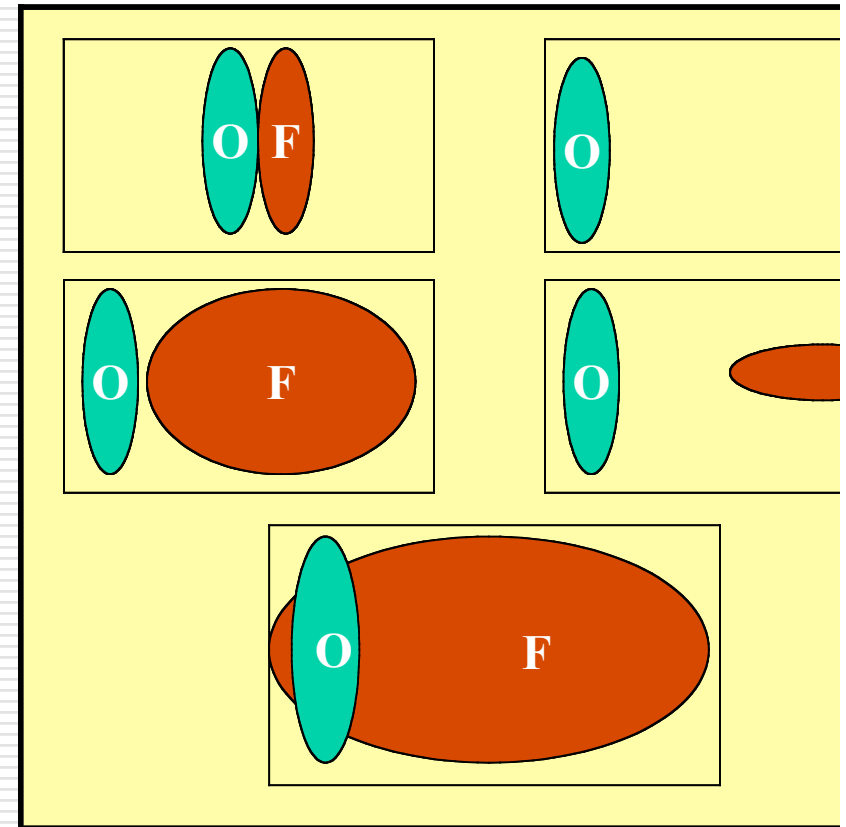
# Traditional “Measures”-based approach

Consider forecasts and observations of some dichotomous field on a grid:

**Some problems with this approach:**

*(1) **Non-diagnostic** – doesn't tell us what was wrong with the forecast – or what was right*

*(2) **Ultra-sensitive** to small errors in simulation of localized phenomena*

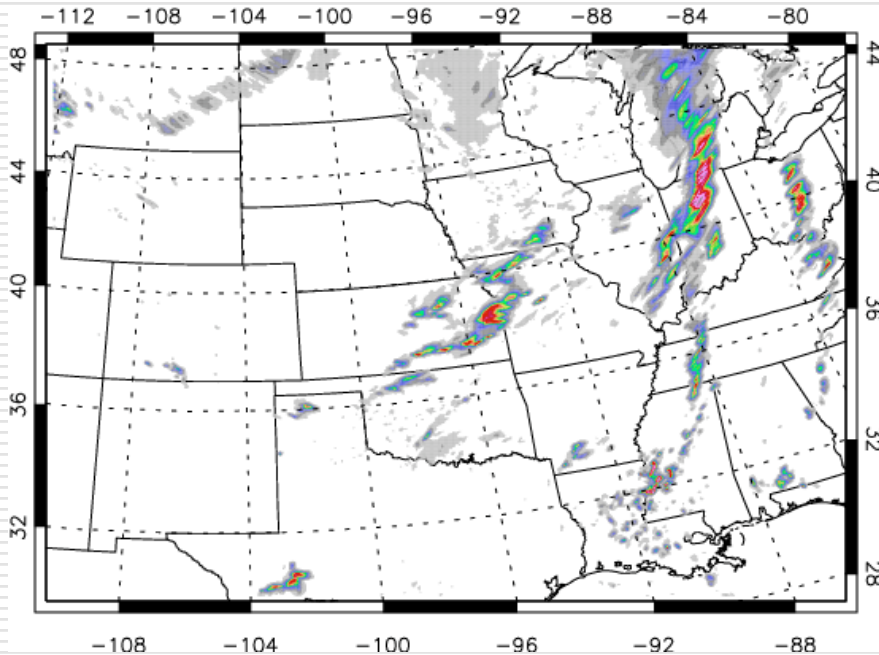


CSI = 0 for first 4;  
CSI > 0 for the 5th



# Spatial forecasts

Weather variables defined over spatial domains have **coherent structure and features**



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Spatial verification techniques aim to

- account for uncertainties in time and location
- account for field spatial structure
- provide information on error in physical terms
- provide information that is
  - diagnostic
  - meaningful to forecast users

# Recent research on spatial verification methods

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- Filter Methods
  - Neighborhood verification methods
  - Scale decomposition methods
- Motion Methods
  - Feature-based methods
  - Image deformation
- Other
  - Cluster Analysis
  - Variograms
  - Binary image metrics
  - Etc...

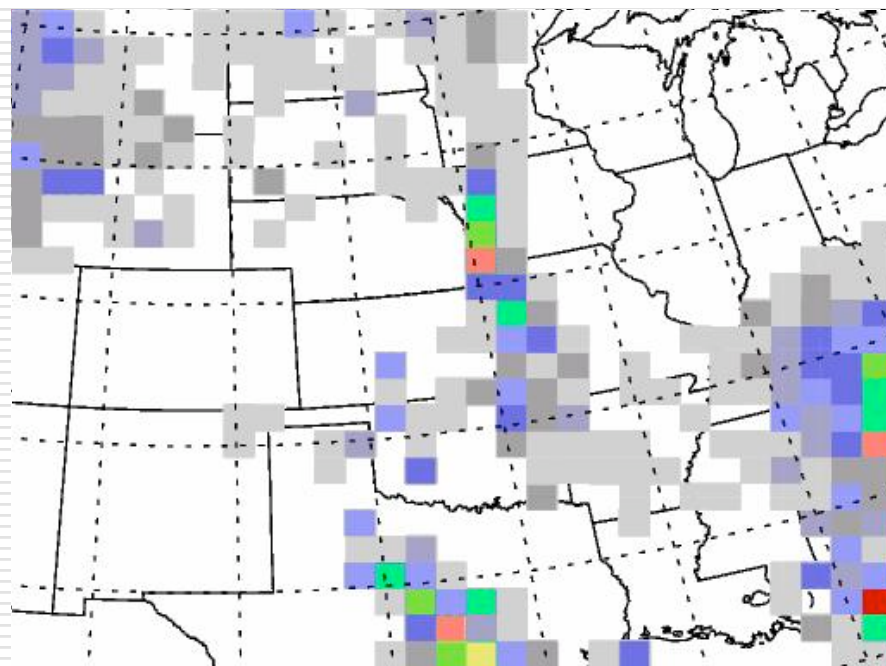


# Filter Methods

## Neighborhood verification

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- Also called “fuzzy” verification
- Upscaling
  - put observations and/or forecast on coarser grid
  - calculate traditional metrics



*Ebert (2007; Met Applications) provides a review and synthesis of these approaches*

Fractions skill score (Roberts 2005; Roberts and Lean 2006)

# Filter Methods

## Single-band pass

- Errors at different scales of a single-band spatial filter (Fourier, wavelets,...)
  - Briggs and Levine, 1997
  - Casati *et al.*, 2004
- Removes noise
- Examine how different scales contribute to traditional scores
- Does forecast power spectra match the observed power spectra?

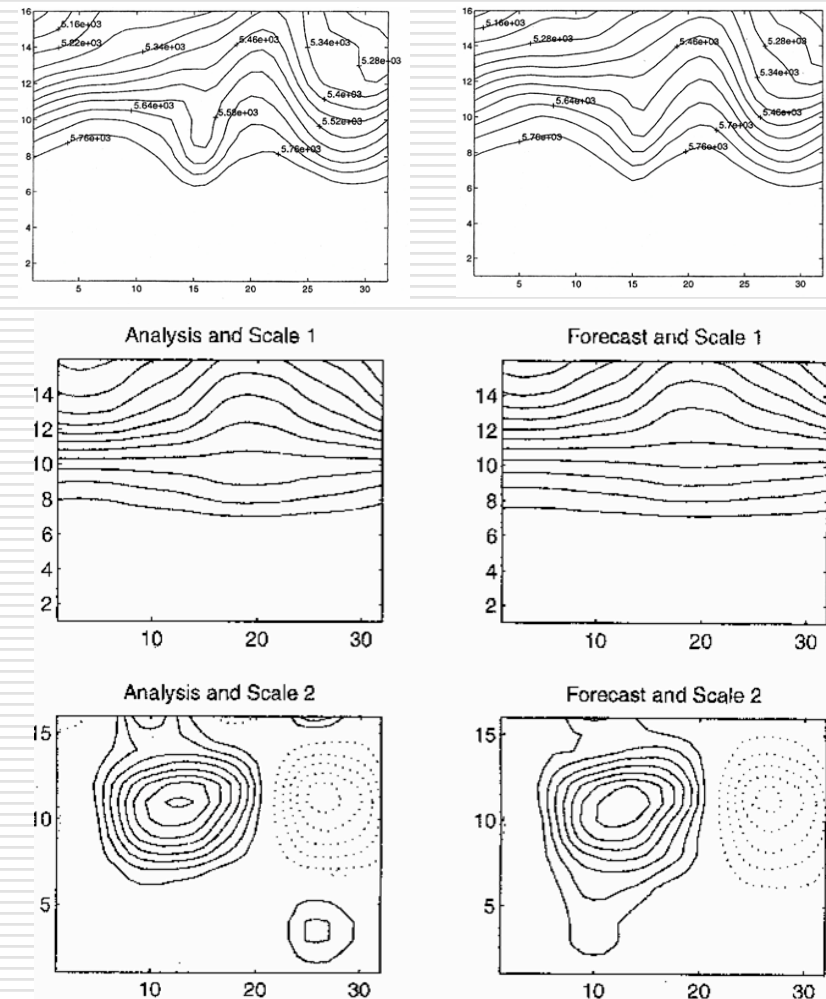


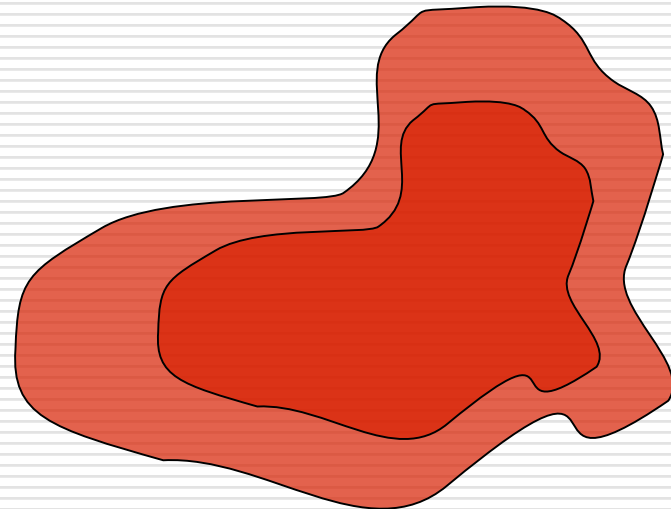
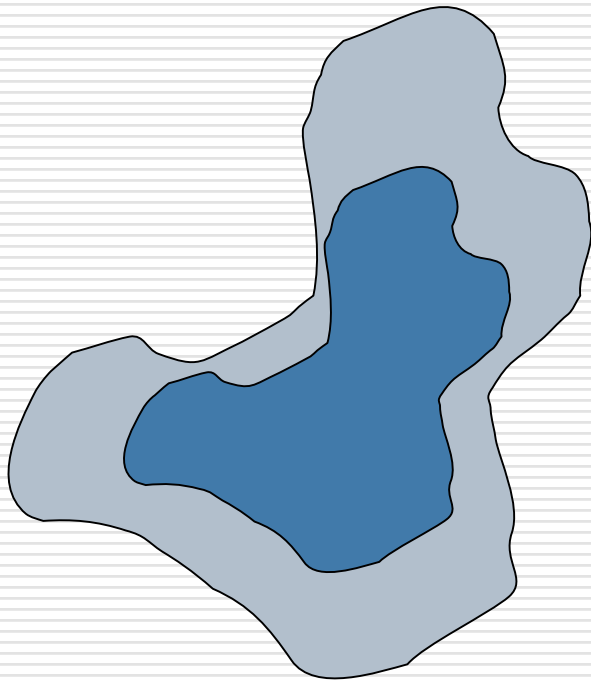
Fig. from Briggs and Levine, 1997

# Feature-based verification

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## Error components

- displacement
- volume
- pattern



# Motion Methods

Feature- or object-based verification

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## Numerous features-based methods

- ❑ Composite approach (Nachamkin, 2004)
- ❑ Contiguous rain area approach (CRA; Ebert and McBride, 2000; Gallus and others)

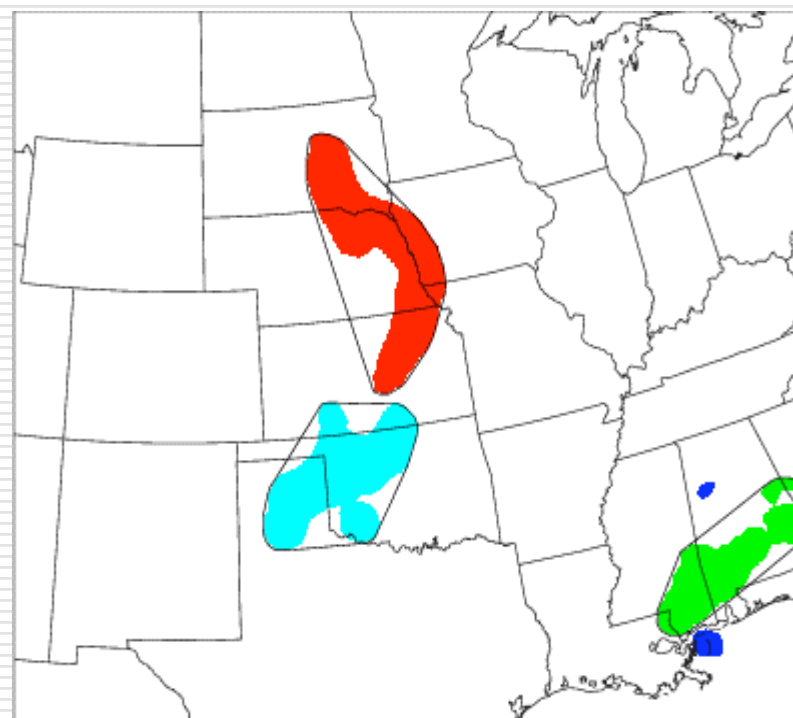


Gratuitous photo from Boulder open

# Motion Methods

Feature- or object-based verification

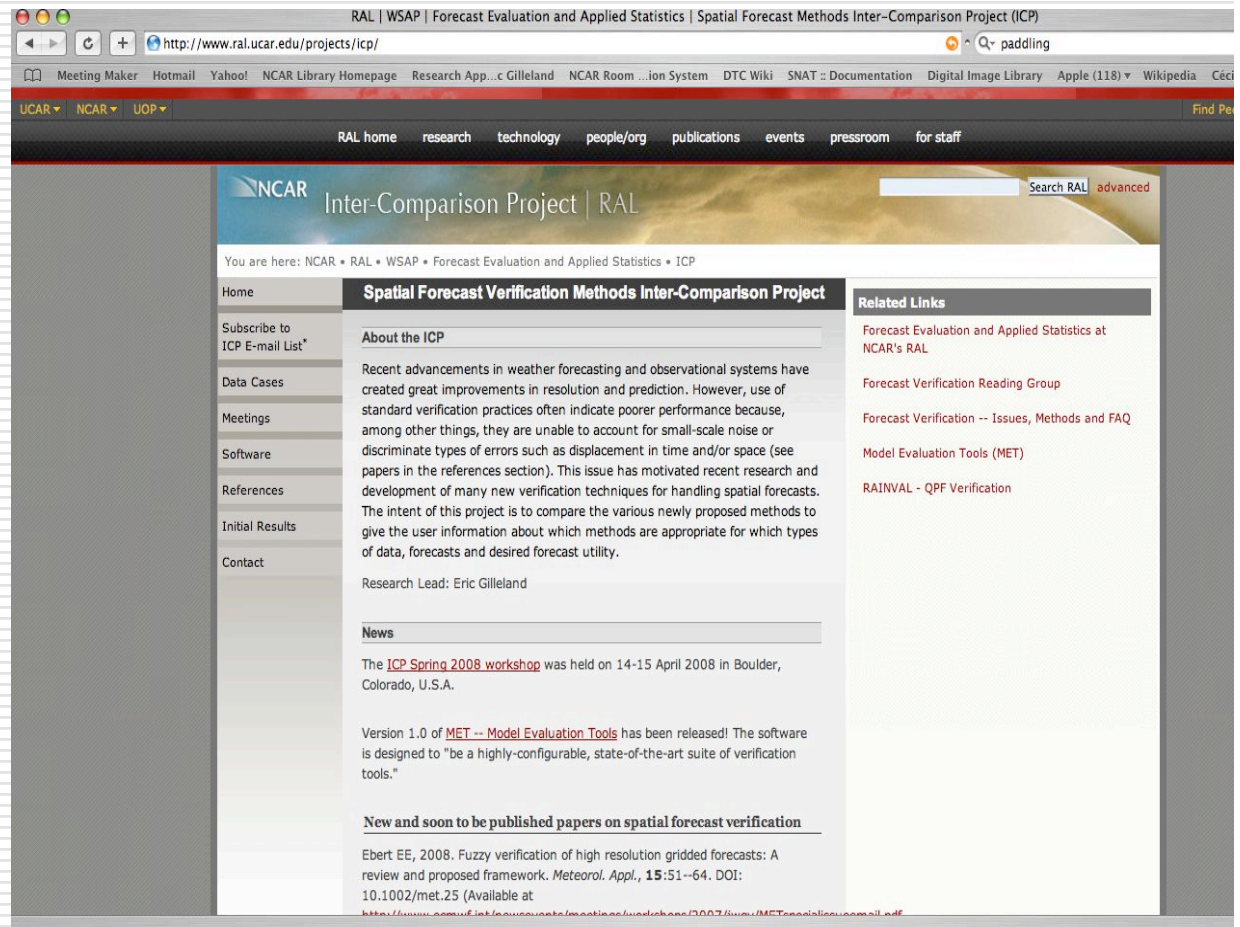
- ❑ Baldwin object-based approach
- ❑ Method for Object-based Diagnostic Evaluation (MODE)
- ❑ Others...





# Inter-Comparison Project (ICP)

- References
- Background
- Test cases
- Software
- Initial Results



<http://www.ral.ucar.edu/projects/icp/>

# The image warp

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# The image warp

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# The image warp

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- Transform forecast field,  $F$ , to look as much like the observed field,  $O$ , as possible.
- Information about forecast performance:
  - Traditional score(s),  $\Theta$ , of un-deformed field,  $F$ .
  - Improvement in score,  $\eta$ , of deformed field,  $F'$ , against  $O$ .
  - Amount of *movement* necessary to improve  $\Theta$  by  $\eta$ .

# The image warp

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## □ More features

- Transformation can be decomposed into:
  - Global affine part
  - Non-linear part to capture more local effects
- Relatively fast (2-5 minutes per image pair using MatLab).
- Confidence Intervals can be calculated for  $\eta$ , affine and non-linear deformations using distributional theory (*work in progress*).



# The image warp

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- Deformed image given by
  - $F'(\mathbf{s}) = F(W(\mathbf{s}))$ ,  $\mathbf{s} = (x, y)$  a point on the grid
  - $W$  maps coordinates from deformed image,  $F'$ , into undeformed image  $F$ .
  - $W(\mathbf{s}) = W_{\text{affine}}(\mathbf{s}) + W_{\text{non-linear}}(\mathbf{s})$
- Many choices exist for  $W$ :
  - Polynomials
    - (e.g. Alexander et al., 1999; Dickinson and Brown, 1996).
  - Thin plate splines
    - (e.g. Glasbey and Mardia, 2001; Åberg et al., 2005).
  - B-splines
    - (e.g. Lee et al., 1997).
  - Non-parametric methods
    - (e.g. Keil and Craig, 2007).

# The image warp

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- Let  $F'$  (*zero-energy* image) have control points,  $p_{F'}$ .
- Let  $F$  have control points,  $p_F$ .
- We want to find a warp function such that the  $p_{F'}$  control points are deformed into the  $p_F$  control points.  $W(p_{F'}) = p_F$
- Once we have found a transformation for the control points, we can compute warps of the entire image:  $F'(s) = F(W(s))$ .

# The image warp

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Select control points,  $p_o$ , in  $O$ .

Introduce log-likelihood to measure dissimilarity between  $F'$  and  $O$ .

$$\log p(O \mid F, p_F, p_o) = h(F', O),$$

Choice of *error likelihood*,  $h$ , depends on field of interest.

# The image warp

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Must penalize non-physical warps!

Introduce a *smoothness* prior for the warps

Behavior determined by the control points. Assume these points are fixed and a priori *known*, in order to reduce prior on warping function to  $p(p_F | p_O)$ .

$$p(p_F | O, F, p_O) =$$

$$\log p(O | F, p_F, p_O) p(p_F | p_O) =$$

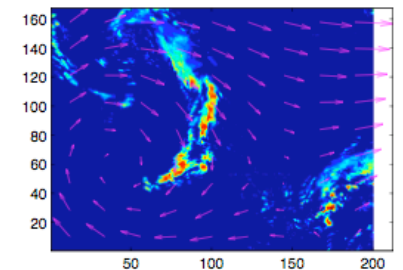
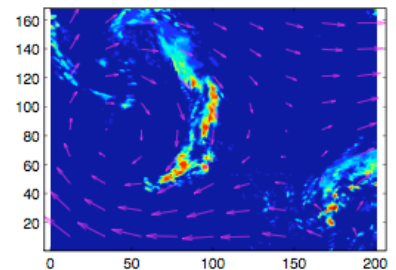
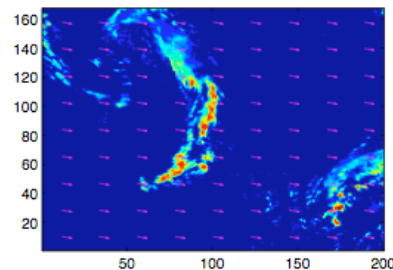
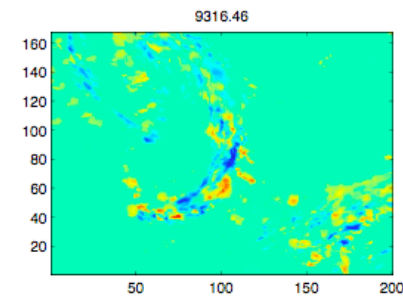
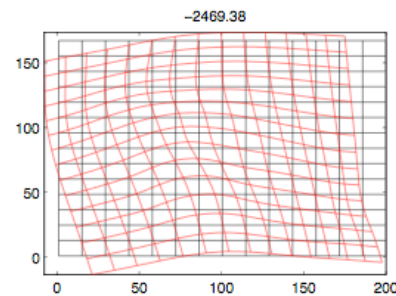
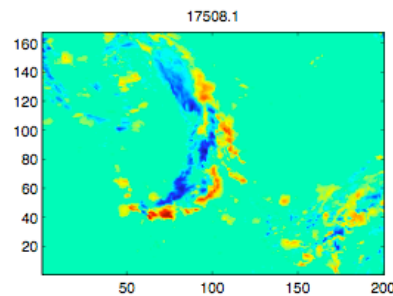
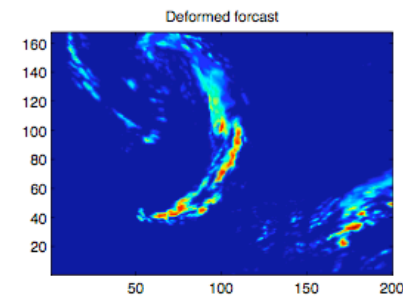
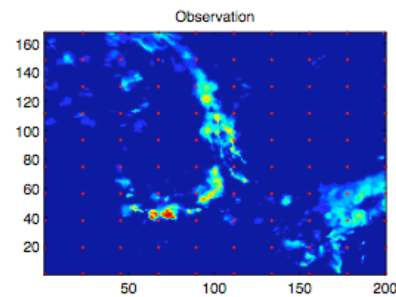
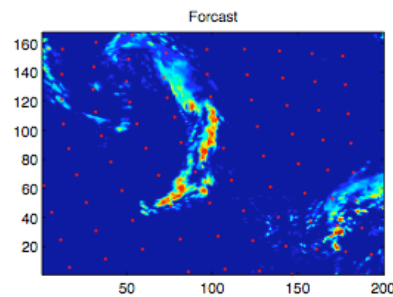
$$h(F', O) + \log p(p_F | p_O),$$

where it is assumed that  $p_F$  are conditionally independent of  $F$  given  $p_O$ .

# ICP Test case 1 June 2006

WRF  
ARW  
(24-h)

Stage  
II

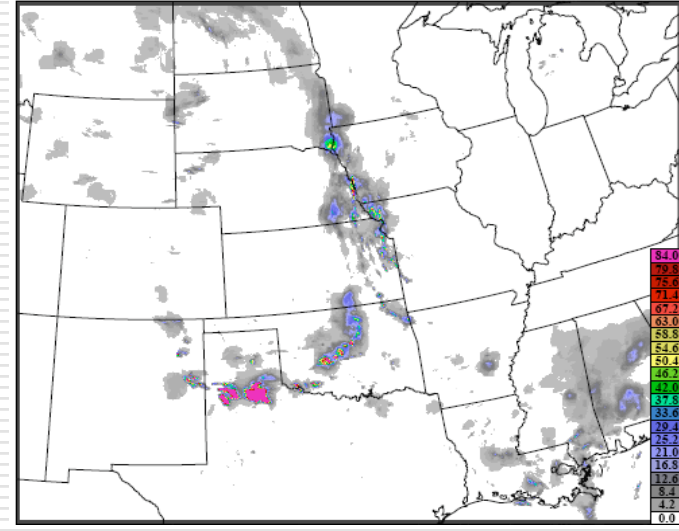
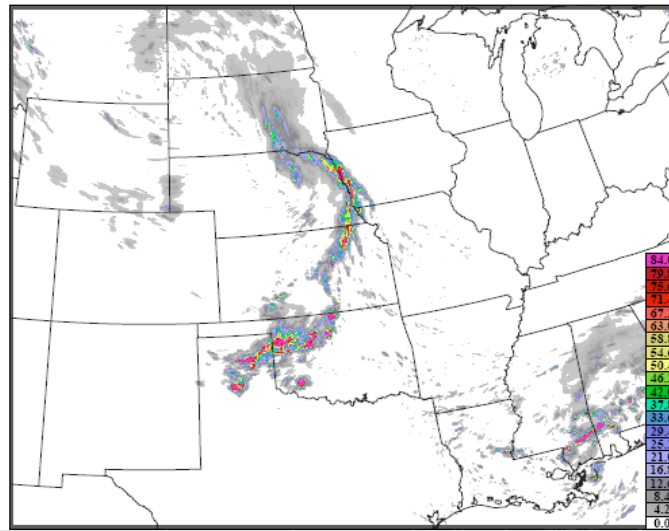


MSE=17,508 → 9,316

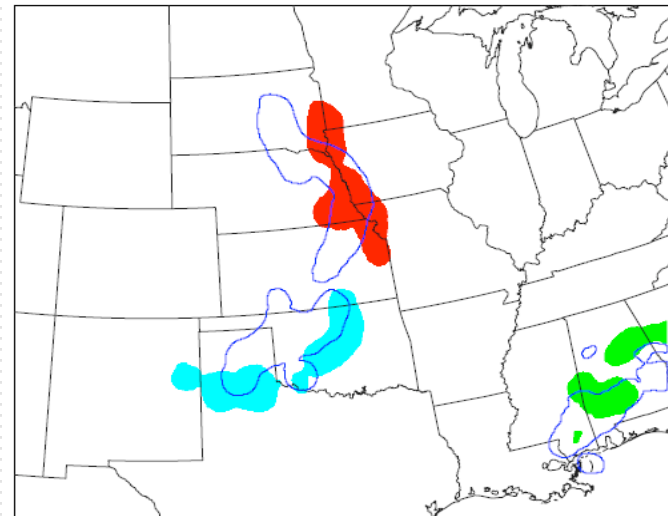
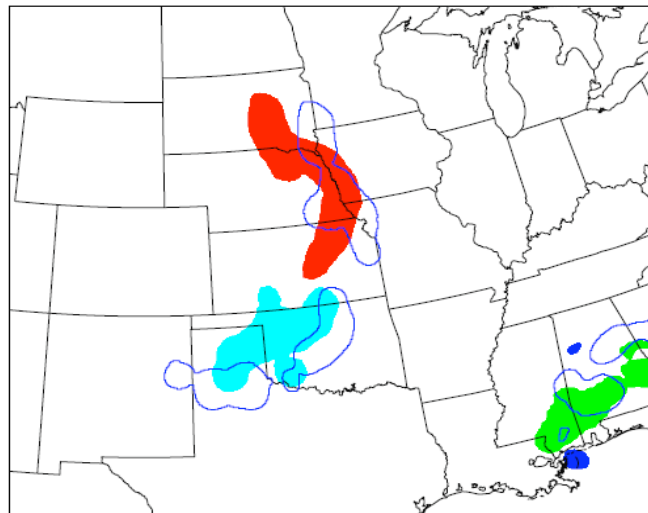


# Comparison with MODE (Features-based)

WRF  
ARW  
(24-h)

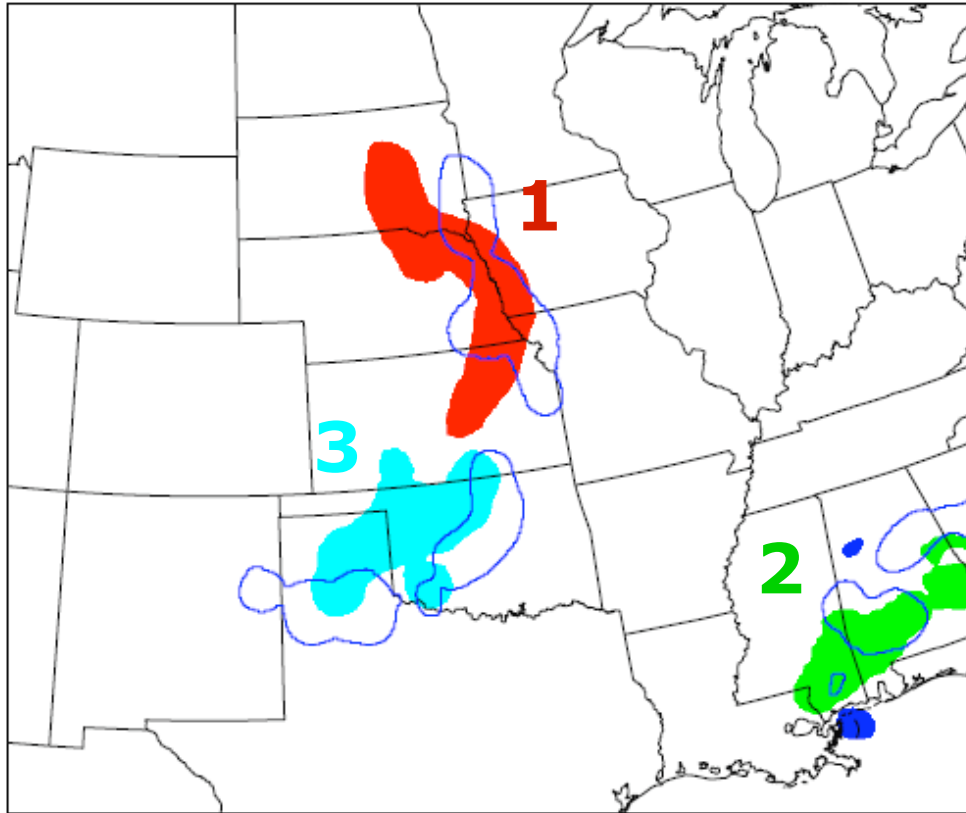


Sta  
II



Radius = 15 grid  
squares  
Threshold =  
0.05"

# Comparison with MODE (Features-based)



WRF ARW-2 Objects with Stage II Objects overlaid

- Area ratios
  - (1) 1.3 ☁️ All forecast
  - (2) 1.2 areas were
  - (3) 1.1 somewhat too large
- Location errors
  - (1) Too far West
  - (2) Too far South
  - (3) Too far North
- Traditional Scores
  - POD = 0.40
  - FAR = 0.56
  - CSI = 0.27

# Acknowledgements

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- **Many slides borrowed:** David Ahijevych, Barbara G. Brown, Randy Bullock, Chris Davis, John Halley Gotway, Lacey Holland

# References on ICP website

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<http://www.rap.ucar.edu/projects/icp/references.html>

# References not on ICP website

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Sofia Åberg, Finn Lindgren, Anders Malmberg, Jan Holst, and Ulla Holst. An image warping approach to spatio-temporal modelling. *Environmetrics*, 16(8):833–848, 2005.

C.A. Glasbey and K.V. Mardia. A penalized likelihood approach to image warping. *Journal of the Royal Statistical Society. Series B (Methodology)*, 63(3):465–514, 2001.

S. Lee, G. Wolberg, and S.Y. Shin. Scattered data interpolation with multilevel B-splines. *IEEE Transactions on Visualization and Computer Graphics*, 3(3):228–244, 1997



# Nothing more to see here...

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# The image warp

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□  $W$  is a vector-valued function with a transformation for each coordinate of  $\mathbf{s}$ .

■  $W(\mathbf{s}) = (W_x(\mathbf{s}), W_y(\mathbf{s}))$

□ For TPS, find  $W$  that minimizes

$$J(W_x) = \iint_{\mathcal{R}^2} \left( \frac{\partial^2 W_x(s)}{\partial s_x^2} \right)^2 + 2 \left( \frac{\partial^2 W_x(s)}{\partial s_x \partial s_y} \right)^2 + \left( \frac{\partial^2 W_x(s)}{\partial s_y^2} \right)^2 ds$$

(similarly for  $W_y(\mathbf{s})$ ) keeping  $W(p_0) = p_1$  for each control point.

# The image warp

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Resulting warp function is

$$W_x(\mathbf{s}) = \mathbf{S}'\mathbf{A} + \mathbf{UB},$$

where  $\mathbf{S}$  is a stacked vector with components  $(1, s_x, s_y)$ ,  $\mathbf{A}$  is a vector of parameters describing the affine deformations,  $\mathbf{U}$  is a matrix of radial basis functions, and  $\mathbf{B}$  is a vector of parameters describing the non-linear deformations.