Spatial Forecast Verification: The Image Warp


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Spatial Forecast Verification Methods

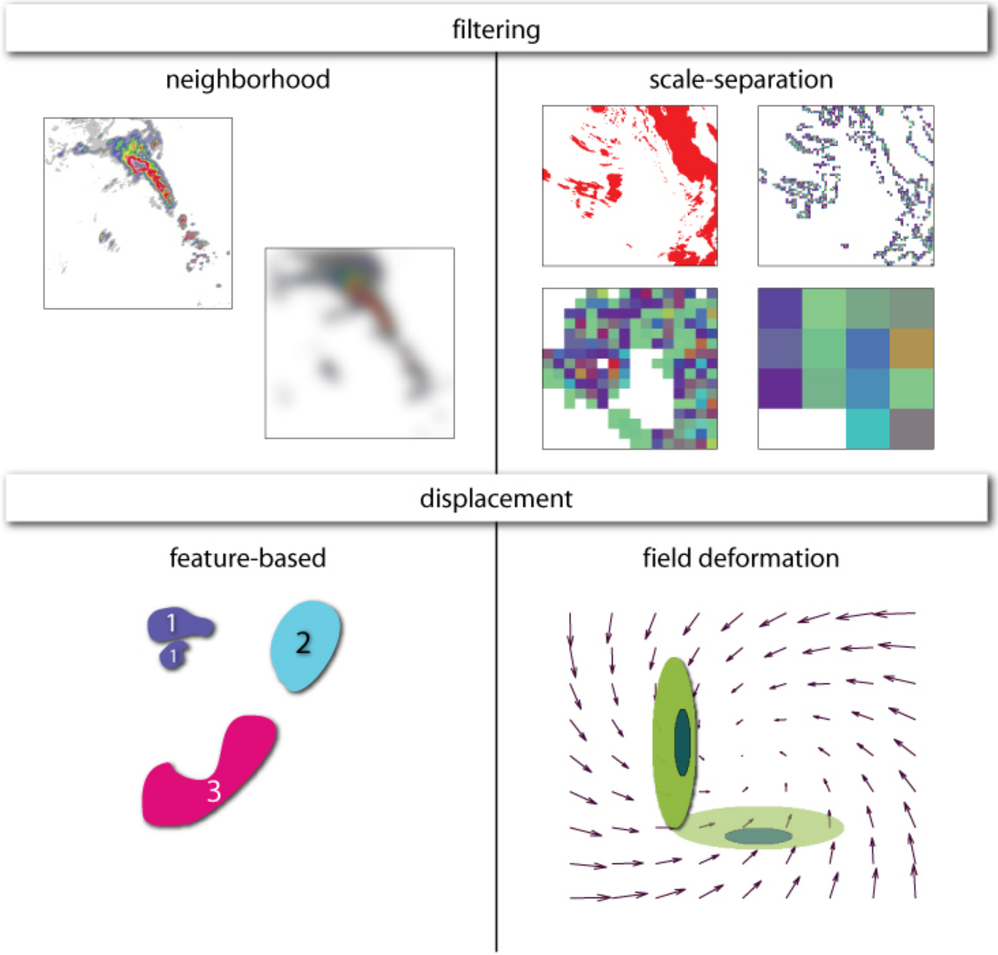
Neighborhood

Scale-separation

Features-based

Field Displacement

(Distribution)



Field Deformation Methods

Objective

Deform the forecast field, F, to better match the observed field, O.

Calculate measures of forecast performance based on:

(i) the original field,

(ii) the amount of displacement, and

(iii) the improvement in performance of the deformed forecast over the original.

Background

Literature

Among the earliest spatial forecast verification methods:

Polynomial Image Warping

Dickinson and Brown (1996); Alexander et al. (1999)

Other

Nehrkorn et al. (2003)

More recently:

Optical Flow (or similar)

Marzban et al. (2009a,b); Keil and Craig (2007, 2009)

Field Deformation Methods result in a vector field describing an *optimal* deformation of the forecast that better compares with the observed field.

Image Warp Methodology

The image warp:
A likelihood function is used to find the optimal warp function (among a class of warp functions).

$$\tilde{F}(x, y) = F(W(x, y)),$$

where $W(x, y)$ maps coordinates from the undeformed image, F, to the deformed image, $\tilde{F}$.

Methodology

Many choices for W. A few popular choices.

- polynomials
- thin-plate splines
- B-splines

Motivation

For computational concerns, use control points, $\boldsymbol{p}^F$ and $\boldsymbol{p}^O$, to determine the warp.

Introduce *log*-likelihood to measure dissimilarity between $\tilde{F}$ and O. This is different from measuring via a forecast verification score!

$$\log \mathrm{p}(O|F, \boldsymbol{p}^F, \boldsymbol{p}^O) = h(\tilde{F}, O) \tag{1}$$

where choice of error likelihood h depends on the forecast variable.

Methodology

Must penalize non-physical warps!

Introduce a smoothness prior for the warps

Behavior determined by the control points. Assume $\boldsymbol{p}^O$ are fixed and apriori *known*, in order to reduce the prior on the warping function to $\mathrm{p}(\boldsymbol{p}^F|\boldsymbol{p}^O)$.

$$\mathrm{p}(\boldsymbol{p}^F|O, F, \boldsymbol{p}^O) = \log \mathrm{p}(O|F, \boldsymbol{p}^F, \boldsymbol{p}^O)\mathrm{p}(\boldsymbol{p}^F|\boldsymbol{p}^O) \qquad (2)$$

where it is assumed that $\boldsymbol{p}^F$ are conditionally independent of F given $\boldsymbol{p}^O$.

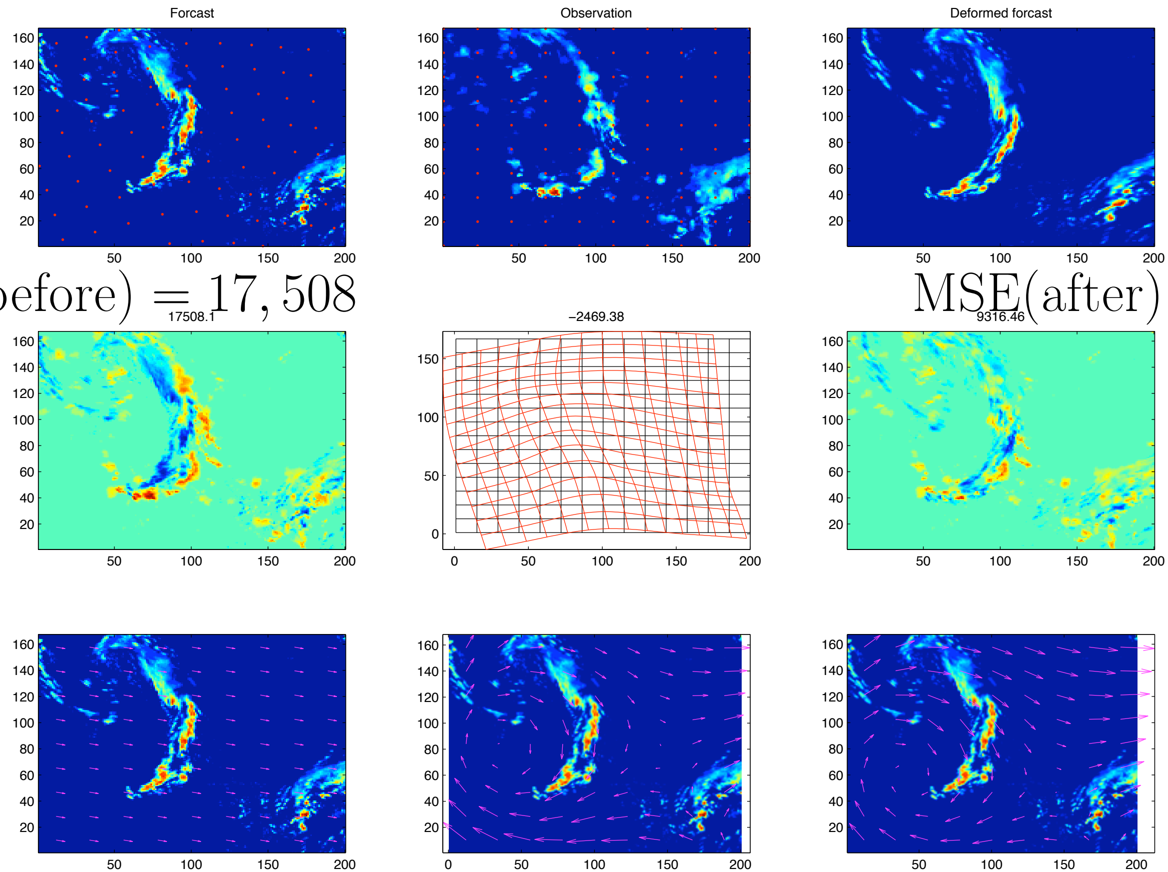
Methodology

Estimation

To find the optimal deformation (based on $\boldsymbol{p}^F$ and $\boldsymbol{p}^O$), maximize the likelihood given by (2). From (1) and (2), we get

$$\begin{aligned}
\ell(\boldsymbol{p}^F|O, F, \boldsymbol{p}^O) &= \log \mathrm{p}(O|F, \boldsymbol{p}^F, \boldsymbol{p}^O) + \log \mathrm{p}(\boldsymbol{p}^F|\boldsymbol{p}^O) \\
&= h(\tilde{F}, O) + \log \mathrm{p}(\boldsymbol{p}^F|\boldsymbol{p}^O).
\end{aligned}$$

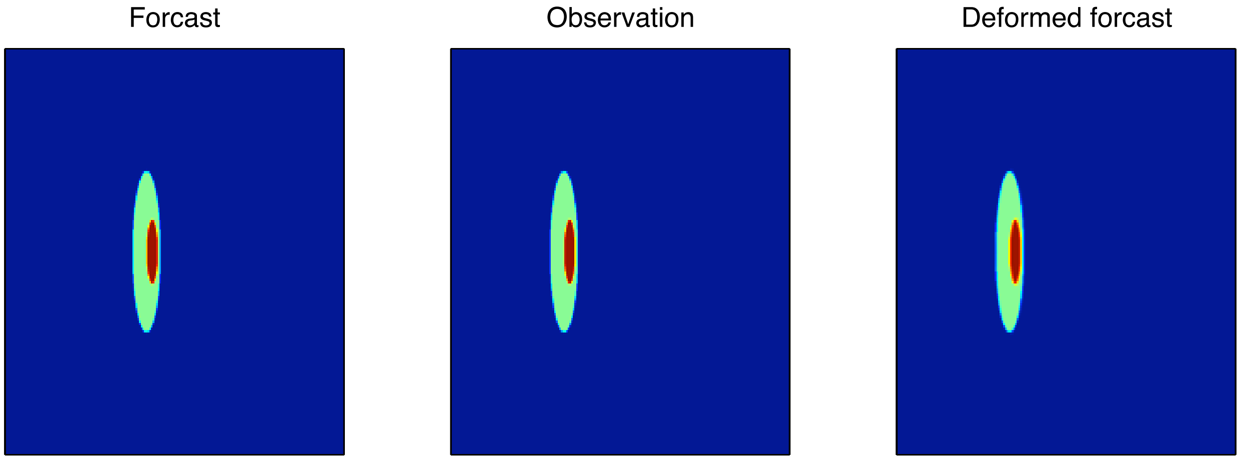
ICP Test Cases



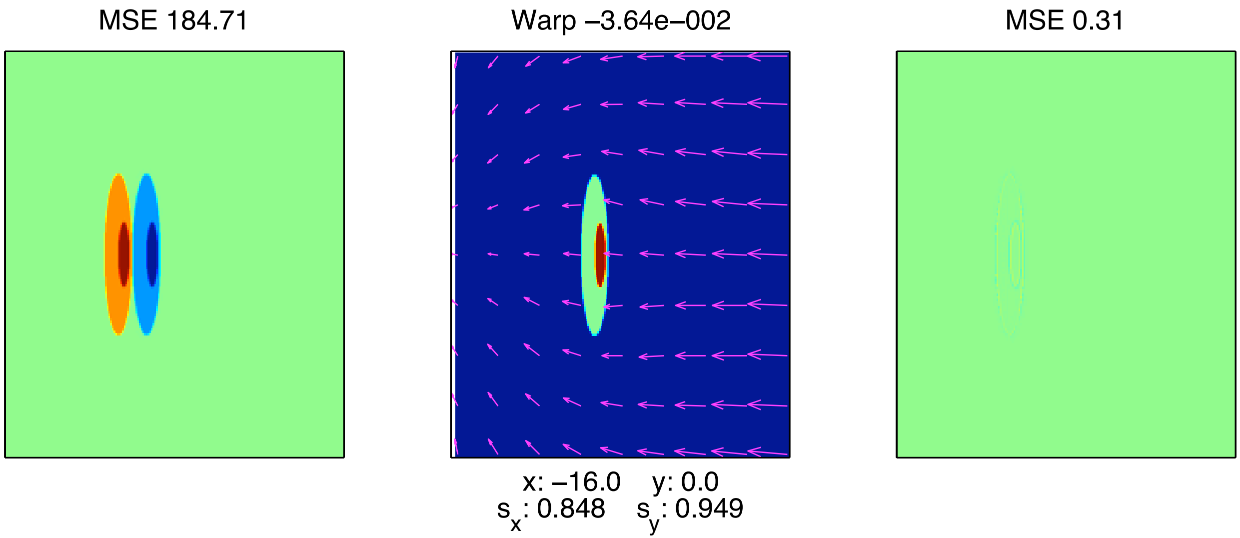
$\text{MSE(before)} = 17,508$

$\text{MSE(after)} = 9,316$

$$\frac{17{,}508 - 9316}{17{,}508} \approx 47\%$$

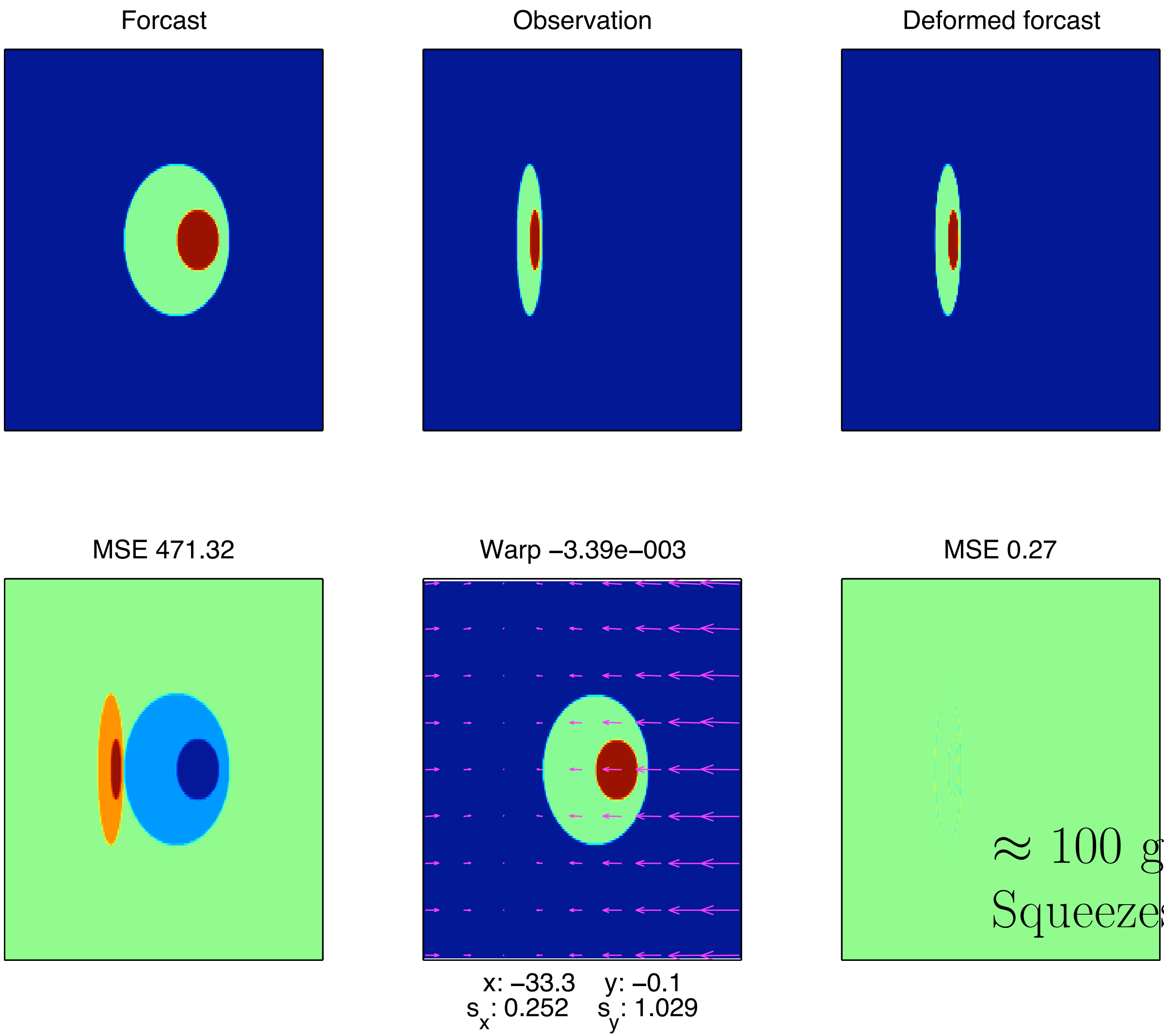


$\approx$ 99.8% reduction in MSE.



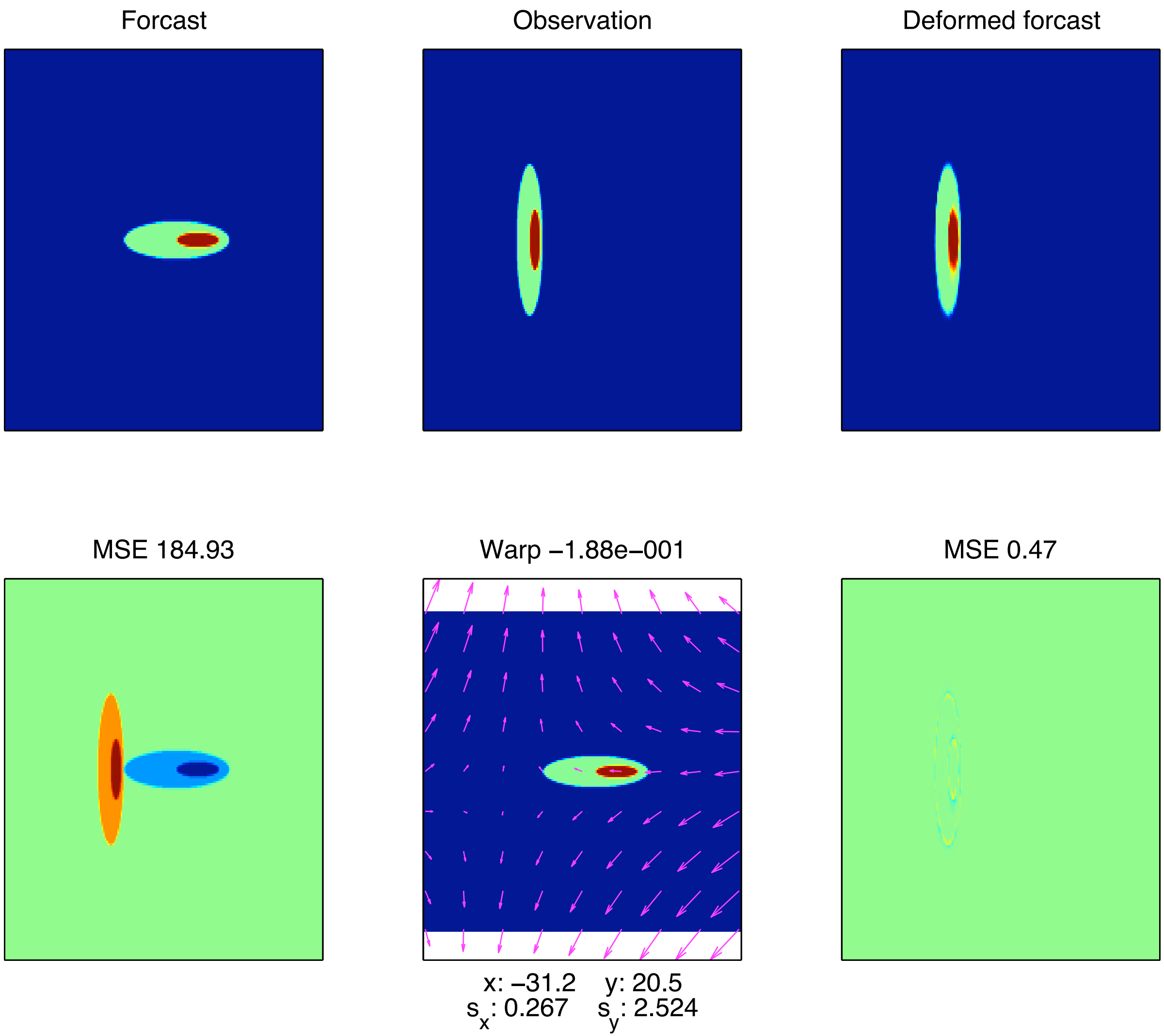
Gemoetric 1; 50 pts too far to the east

$3 \cdot (-16.0) = -48 \equiv$ Moves forecast 48 grid points to the west; negligible re-scaling and nonlinear movement.

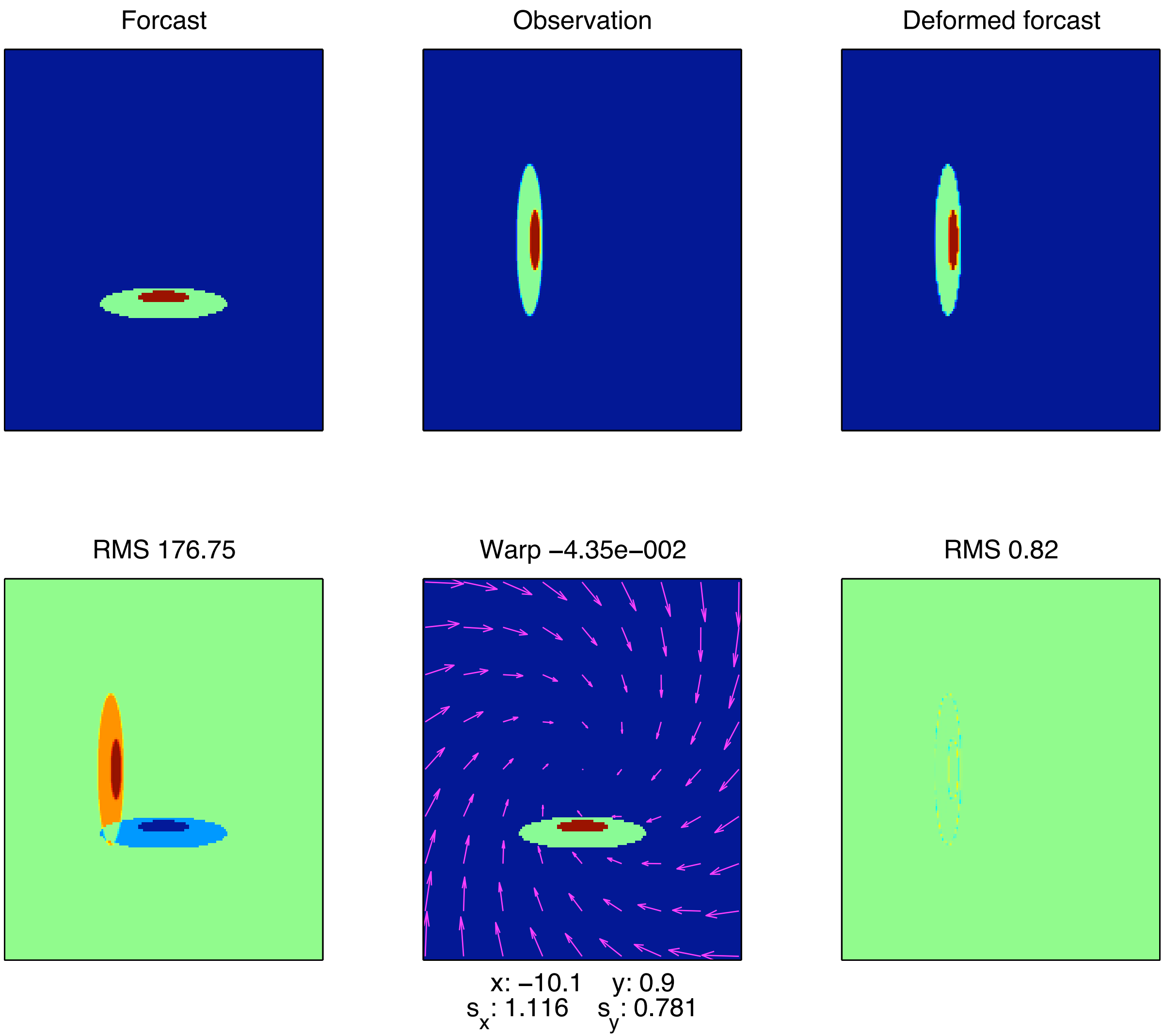


≈ 100 grid points west
Squeezes horizontally.

Geometric 3; 125 grid points too far east and larger spatial coverage



Geometric 4; 125 pts too far east and incorrect orientation



True Rotation

Ranking of multiple forecasts: A proposed statistic

$$\text{IWS}_j = c_{1j}D_j + c_{2j}(1 - \eta_j) + c_{3j}\text{AMP}_j$$

- $j = 1, \ldots, J$ indexes the forecasts being compared,
- D is the (normalized) average displacement of points,
- η represents the reduction in RMSE,
- AMP is the standardized RMSE before deformation, and
- the coefficients, $c_{\cdot j}$ are user-specified weights that can depend on the values of each component (e.g., if D is very large, might want to ignore the first two components).

ICP perturbed cases

Perturbed *real* cases have identical shape, but displaced, and in one case (`prt006`) the amplitude has been everywhere multiplied by 1.5 mm, and another (`prt007`) has it everywhere reduced by 1.27 mm. These last two have the same spatial displacements as `prt003`, and otherwise, the x and y displacements each double with case number, beginning with 3 pts to the right and 5 pts down for case `prt001`.

IWS rank by case results:

prt001	prt002	prt003	prt004	prt005	prt006	prt007
1	2	3	5	6	7	4

Discussion, Ongoing and Future Work

- A fine line between rotations vs. re-scaling, but for real cases, does not seem to be an issue.
- Control points:
  Fewer mean faster computation, but less intricate warps.
- Statistical model will allow for parametric confidence intervals.
- Could be applied to most any field
  (e.g., wind vector fields, temperature, etc.)
- Extendable to multiple dimensions (time, vertical, etc.)
- Gives information about types of error:
  Vector field describing the deformation has potential to give a lot of information, but a few simple statistics also yield very useful results.

That's all . . .

Thank you.

Questions?

References from slides on next slide.

Test cases taken from the Spatial forecast Verification Inter-Comparison Project (ICP)
http://www.ral.ucar.edu/projects/icp

References

Alexander, G., Weinman, J., Karyampudi, V., Olson, W., Lee, A., 1999. The effect of assimilating rain rates derived from satellites and lightning on forecasts on the 1993 superstorm. Mon. Wea. Rev. 127, 1433–1457.

Dickinson, S., Brown, R., 1996. A study of near-surface winds in marine cyclones using multiple satellite sensors. J. Appl. Meteorol. 35, 769–781.

Keil, C., Craig, G., 2007. A displacement-based error measure applied in a regional ensemble forecasting system. Mon. Wea. Rev. 135, 3248–3259.

Keil, C., Craig, G., 2009. A displacement and amplitude error based score employing an optical flow technique. Submitted to Wea. Forecasting.

Marzban, C., Lennon, D., Sandgathe, S., 2009a. Optical flow for verification. Manuscript in preparation.

Marzban, C., Sandgathe, S., Lyons, H., Lederer, N., 2009b. Three spatial verification techniques: Cluster analysis, variogram, and optical flow. Submitted to Wea. Forecasting.

Nehrkorn, T., Hoffman, R., Grassotti, C., Louis, J.-F., 2003. Feature calibration and alignment to represent model forecast errors: Empirical regularization. Q.J.R. Meteorol. Soc. 129, 195–218.