

Image Warping for Forecast Verification

Eric Gilleland

Research Applications Laboratory,
National Center for Atmospheric Research

Johan Lindström and Finn Lindgren

Mathematical Statistics,
Centre for Mathematical Sciences,
Lund University, Lund, Sweden.

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Methodology

Motivation

Transform (deform) the forecast field, F , to look as much like the observed field, O , as possible.

Information about forecast performance given by:

- Traditional score(s), θ , of un-deformed field, F , against O .
- Percent reduction in θ after Affine deformations (η_1).
- Percent reduction in θ_{affine} after Nonlinear deformations (η_2).
- Amount of movement necessary to improve θ by η_1 .
- Amount of bending energy required to further improve θ_{affine} by η_2 .

Methodology

$$\tilde{F}(\mathbf{s}) = F(W(\mathbf{s})), \mathbf{s} \in \mathcal{D}$$

where \mathcal{D} is the support of the image (i.e., the grid).

$$W(\mathbf{s}) = W_{\text{NL}}(W_{\text{affine}}(\mathbf{s}))$$

maps coordinates from the undeformed image, F , to the deformed image, \tilde{F} .

Methodology

Many choices for W . A few popular choices.

- polynomials (e.g., Alexander et al., 1999; Dickinson and Brown, 1996)
- thin-plate splines (e.g., Sampson and Guttorp, 1992; Glasbey and Mardia, 2001; Åberg et al., 2005).
- B-splines (e.g., Lindström, Gilleland and Lindgren (In Prep))
- Other (e.g. Keil and Craig, 2007)

Motivation

For computational concerns, use control points, \mathbf{p}^F and \mathbf{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!

$$\log p(O|F, \mathbf{p}^F, \mathbf{p}^O) = h(\tilde{F}, O) \quad (1)$$

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 these points are fixed and apriori *known*, in order to reduce the prior on the warping function to $p(\mathbf{p}^F | \mathbf{p}^O)$.

$$p(\mathbf{p}^F | O, F, \mathbf{p}^O) = \log p(O | F, \mathbf{p}^F, \mathbf{p}^O) p(\mathbf{p}^F | \mathbf{p}^O) \quad (2)$$

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

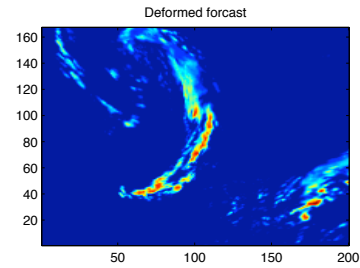
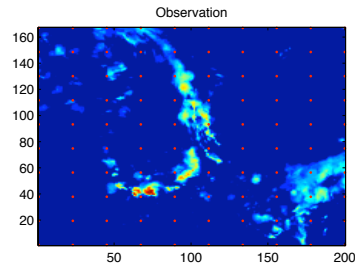
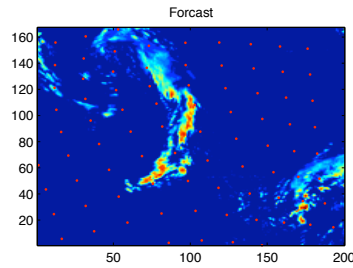
Methodology

Estimation

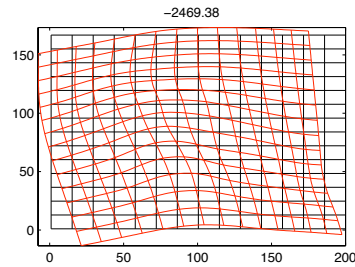
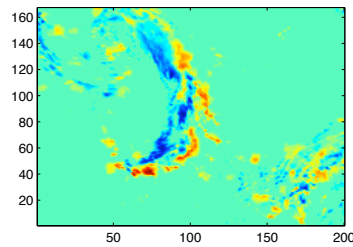
To find the optimal deformation (based on \mathbf{p}^F and \mathbf{p}^O), maximize the likelihood given by (2). From (1) and (2), we get

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

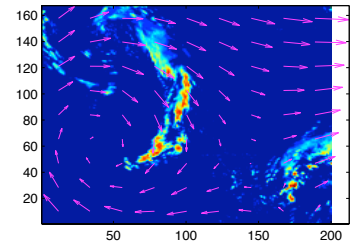
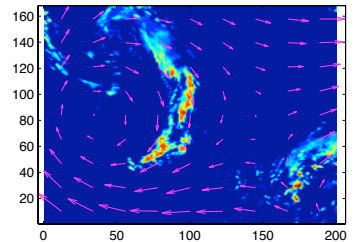
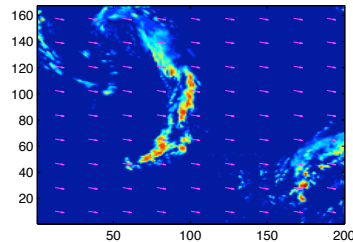
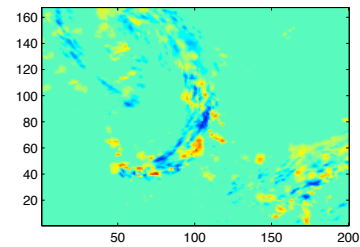
Test Cases



$$\theta = \text{MSE} = 17,508$$

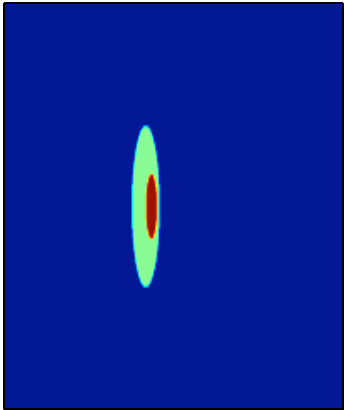


$$\theta_W = 9316$$

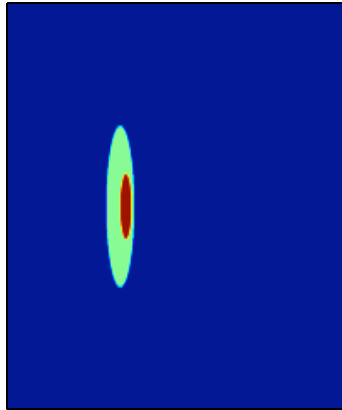


$$\eta_W = \frac{17,508 - 9316}{17,508} \approx 47\%$$

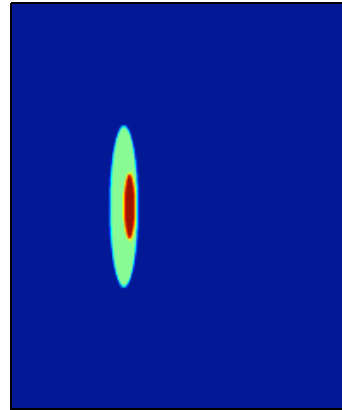
Forecast



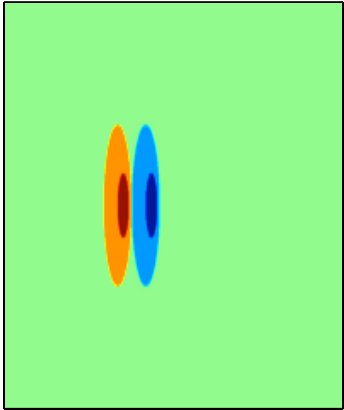
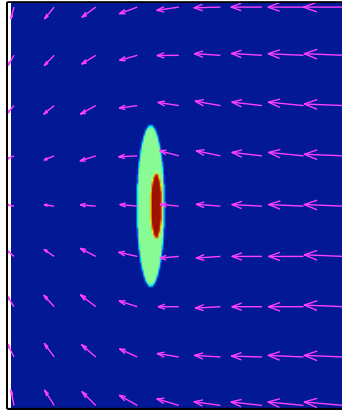
Observation



Deformed forecast

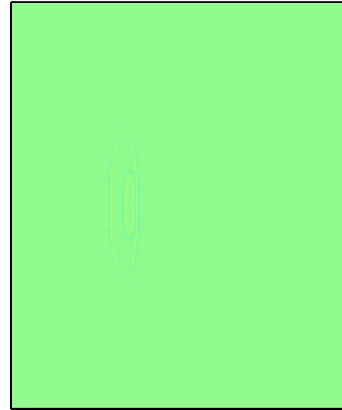


MSE 184.71

Warp $-3.64\text{e-}002$ 

$$\begin{array}{l} x: -16.0 \quad y: 0.0 \\ s_x: 0.848 \quad s_y: 0.949 \end{array}$$

MSE 0.31

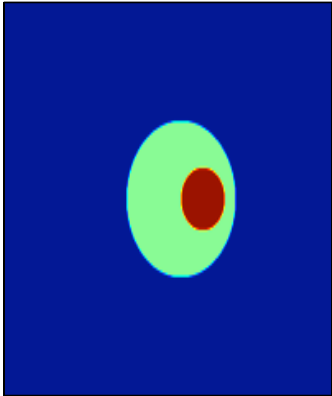


$$\eta_W \approx 99.8\%$$

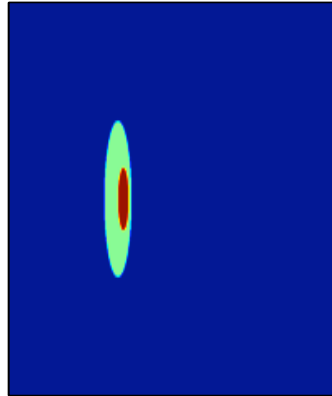
Geometric 1; 50 pts too far to the east

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

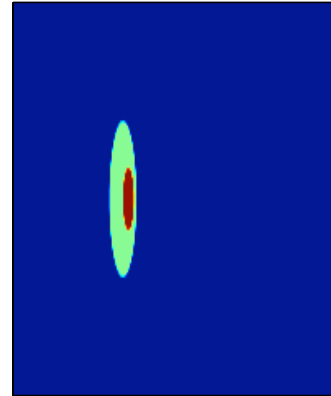
Forecast



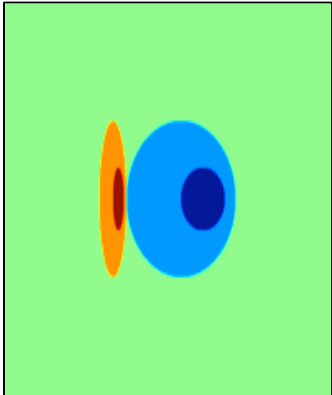
Observation



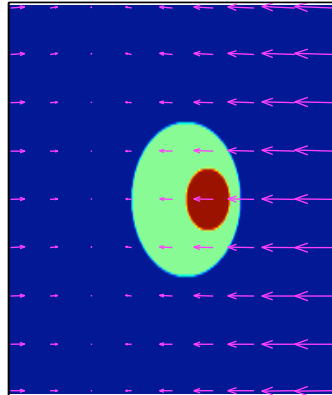
Deformed forecast



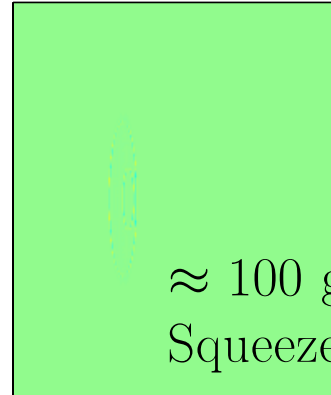
MSE 471.32



Warp $-3.39e-003$



MSE 0.27

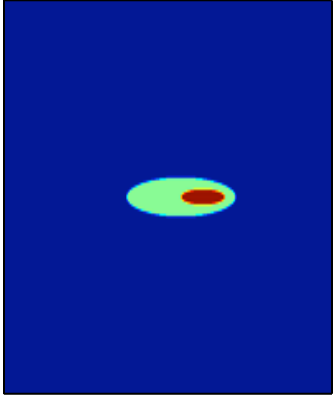


≈ 100 grid points west
Squeezes horizontally.

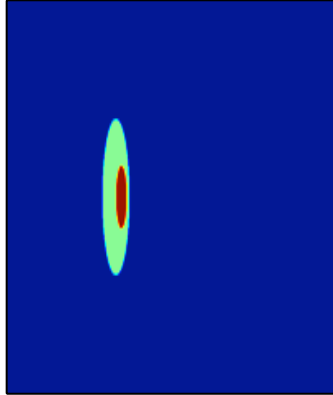
x: -33.3 y: -0.1
s_x: 0.252 s_y: 1.029

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

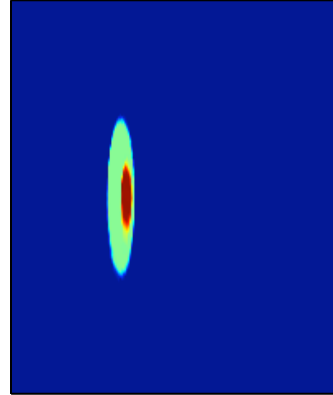
Forecast



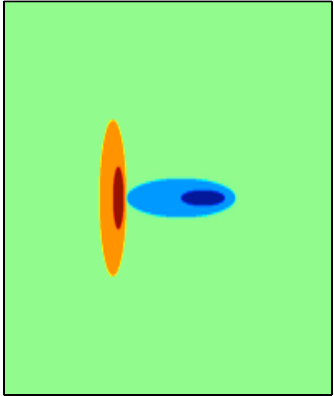
Observation



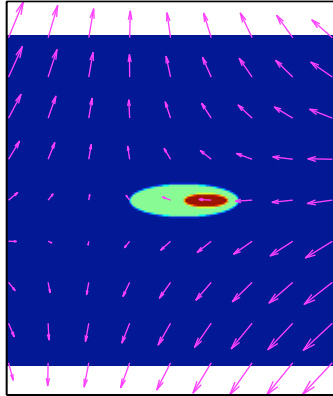
Deformed forecast



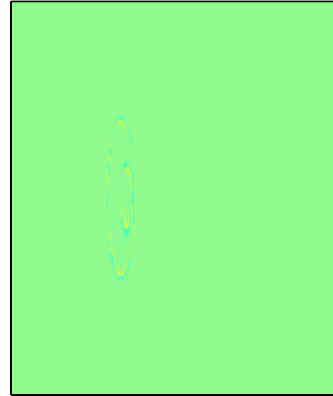
MSE 184.93



Warp $-1.88e-001$



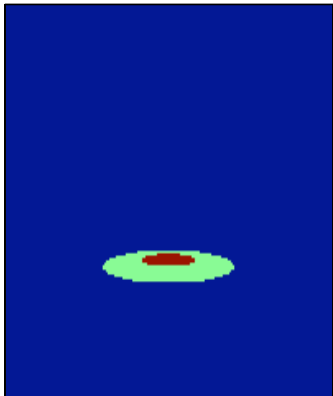
MSE 0.47



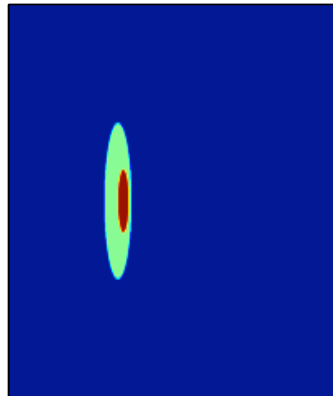
x: -31.2 y: 20.5
s_x: 0.267 s_y: 2.524

Geometric 4; 125 pts too far east and incorrect orientation

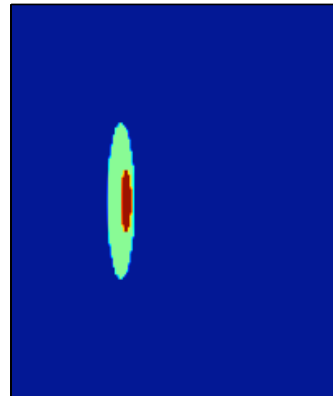
Forecast



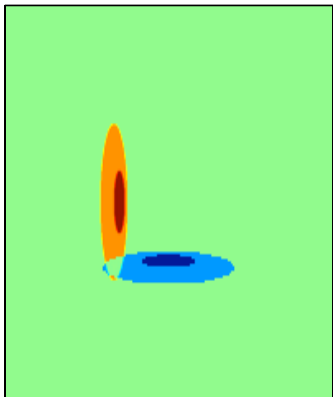
Observation



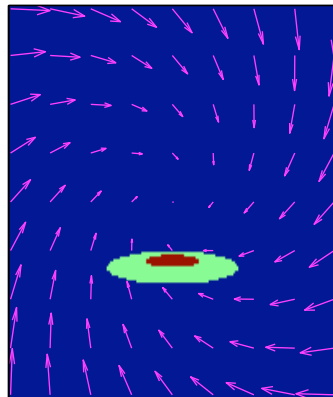
Deformed forecast



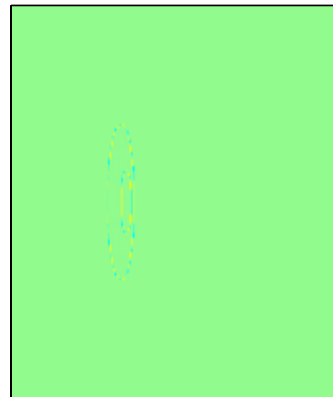
RMS 176.75



Warp $-4.35e-002$



RMS 0.82



x: -10.1 y: 0.9
s_x: 1.116 s_y: 0.781

True Rotation

Discussion, Ongoing and Future Work

- Rotations vs. Re-scaling is tricky!
- Control points (fewer mean faster computation, but less intricate warps).
- Statistical model will allow for confidence intervals.
- Works well on binary images as well as real cases.
- Potentially can be used on most any field (e.g., wind vector fields, temperature, etc.)
- Extendable to multiple dimensions (time, vertical, etc.)
- Gives information about types of error.
- thin-plate splines move pixels globally, better to use B-splines?

References

- Åberg, S., Lindgren, F., Malmberg, A., Holst, J., Holst, U., 2005. An image warping approach to spatio-temporal modelling. *Environmetrics* 16 (8), 833–848.
- Alexander, G., Weinman, J., Karyampudi, V., Olson, W., A.C.L., L., 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.
- Glasbey, C., Mardia, K., 2001. A penalized likelihood approach to image warping. *Journal of the Royal Statistical Society. Series B (Methodology)* 63 (3), 465–514.
- Keil, C., Craig, G., 2007. A displacement-based error measure applied in a regional ensemble forecasting system. *Mon. Wea. Rev.* 135, 3248–3259.
- Sampson, P. D., Guttorp, P., 1992. Nonparametric estimation of nonstationary spatial covariance structure. *Journal of the American Statistical Association* 87 (417), 108–119.