Scale separation in verification measures

B. Casati

Talk outline:
- Motivations
- Review of some of the key approaches
  2. Casati et al. (2004)
  3. Denis et al. (2003), De Elia et al. (2001)
- Discussion
Motivations

1. Different scale phenomena, different physics, different aspects of the model

2. Compare different spatial scale resolutions
Briggs and Levine (1997)
“Wavelets and field forecast verification”

Verification of different spatial scale components obtained from a 2D wavelet decomposition of the forecast and analysis field

1. 2D discrete wavelet decomposition of the forecast and analysis fields
2. Noise removal by wavelet coefficient thresholding
3. Reconstruction of each spatial scale component.
4. Verification of each spatial scale component by:
   • RMSE, corr. coeff., energy (variance) ratio
   • % MSE, % corr. coeff. (wavelet components orthogonality)
500 mb geop. Height, 9 Dec 1992, 12:00 UTC, over N. America
De-noising preserving extremes

Wavelet decomposition:

- large scale coefficients
- small scale coefficients
# Summary

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Casati, Ross, Stephenson (2004)

"A new intensity-scale approach for the verification of spatial precipitation forecasts" Met. App., vol. 11, pp. 141-154

Evaluate the forecast skill as a function of the precipitation intensity and the spatial scale of the error
Threshold $\rightarrow$ Binary Images

Binary Analysis

Binary Rec. Forecast

Binary Error Image

$u = 1\text{mm/h}$

$$E_u = I_{Y'>u} - I_{X'>u}$$
Wavelet decomposition of the binary error $E_u = \sum_{l=1}^{L} E_{u,l}$

mean (1280 km)  Scale l=8 (640 km)  Scale l=7 (320 km)

Scale l=6 (160 km)  Scale l=5 (80 km)  Scale l=4 (40 km)

Scale l=3 (20 km)  Scale l=2 (10 km)  Scale l=1 (5 km)
Intensity-scale MSE decomposition

\[ E_u = \sum_{l=1}^{L} E_{u,l} \]

\[ MSE_u = \sum_{l=1}^{L} MSE_{u,l} \]

Wavelet decomposition of Binary Error Image

Wavelets orthogonality
MSE additive properties

Case C: intense storm displaced

<table>
<thead>
<tr>
<th>MSE(_{u,l})</th>
<th>0.014</th>
<th>0.012</th>
<th>0.010</th>
<th>0.008</th>
<th>0.006</th>
<th>0.004</th>
<th>0.002</th>
<th>0.000</th>
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<tr>
<td>threshold (mm/h)</td>
<td>0</td>
<td>1/32</td>
<td>1/16</td>
<td>1/8</td>
<td>1/4</td>
<td>1/2</td>
<td>1</td>
<td>2</td>
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</table>
MSE skill score

\[ SS_u = \frac{MSE_u - MSE_{u,\text{random}}}{MSE_{u,\text{best}} - MSE_{u,\text{random}}} = 1 - \frac{MSE_u}{2\varepsilon(1-\varepsilon)} \]

\[ SS_{u,l} = 1 - \frac{MSE_{u,l}}{2\varepsilon(1-\varepsilon)/L} \]

\[ \varepsilon = \frac{a+c}{n} = P(X > u) \]

Case C: intense storm displaced
$MSE_u$ versus $SS_u$

- Front slightly displaced: $\varepsilon = 0.5$, $SS_u = 0.92$
- Shower displaced: $\varepsilon = 0.02$, $SS_u = -0.02$
- Binary error: $MSE_u = 0.04$

$SS_u$ takes into account the base rate $\varepsilon$
Links with categorical verification

### Binary Analysis

- **MSE_u** = \( \frac{b + c}{n} \)
- **SS_u** = HSS

### Binary Rec. Forecast

<table>
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<th>( X &gt; u )</th>
<th>( X &lt; u )</th>
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<tr>
<td><strong>Y &gt; u</strong></td>
<td><strong>Hits</strong> a</td>
<td><strong>False Alarms</strong> b</td>
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<tr>
<td><strong>Y &lt; u</strong></td>
<td><strong>Misses</strong> c</td>
<td><strong>Correct Rejections</strong> d</td>
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Denis, Laprise, Caya (2003)  

“Sensitivity of a regional climate model to the resolution of the lateral boundary conditions”, Climate Dynamics, vol. 20, pp. 107-126

Aims:
- test ability of RCM to (re)generate small-scale features
- test sensitivity to different resolution lateral boundary condition
Experiment set up

RCM on large domain at high resolution → Big Brother

BB filtered to GCM resolution → RCM on small domain at high resolution → Little Brother

LBC at different resolution

Verify Little Brother vs Big Brother
(on small domain at high resolution)
Discrete Cosine Transform filtering of a 925-hPa specific humidity field
Taylor diagram for precipitation

Small scales only
De Elia, Laprise, Denis (2001)

850-hPa vorticity fields

Predictability: perturbed vs control run

Filtered lateral boundary condition
850-hPa vorticity fields

Predictability: perturbed vs control run

Temporal shift of forecast
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Zepeda-Arce et al. (2000)
“Space-time rainfall organization and its role in validating quantitative precipitation forecasts” JGR vol. 105 (D8) pp. 10,129-10,146

- Assess ability of reproducing multi-scale spatial structure and space-time dynamics of ppn fields
- Different scales are obtained by spatial averaging

1. TS on different scales
2. Depth-Area-Duration curves

![Graph of TS vs Scale](image1)

![Graph of DA curve](image2)
3. **Scale-to-scale variability:**

\[ \xi_L = \text{fluctuation on scale } L \]

\[ \sigma_{\xi,L} = L^H \]

4. **Spatio-temporal organization:**

\[ \Delta \ln I(t,L) \text{ constant,} \]

then \[ t = L^z \]
Harris et al. (2001)

“Multiscale statistical properties of a high-resolution precipitation forecast” J. of Hydromet., Vol 2, pp. 406-418

1. Fourier analysis
2. Structure function
3. Moment-scale analysis

1. variability

2. Smoothness, spatial correlation

3. Intermittency, sparseness + peaks
Tustison et al. (2003)
“Scale Recursive Estimation (SRE) for multisensor QPF verification: a preliminary assessment” JGR vol. 108 (D8)

COARSE TO FINE
\[ X(\lambda) = A(\lambda) \ X(\lambda-1) + B(\lambda) \ W(\lambda) \]
\[ P_X(\lambda) = A^2(\lambda) P_X(\lambda-1) + B^2(\lambda) \]

FINE TO COARSE
\[ X(\lambda-1) = F(\lambda) \ X(\lambda) + W^*(\lambda) \]
\[ P_X(\lambda-1) = F^2(\lambda) P_X(\lambda) + Q(\lambda) \]

- \( X(\lambda) = \) field
- \( P_X(\lambda) = \) field variance
- \( A(\lambda), B(\lambda) \) parameters estimated by model of ppn multiscale variability structure
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Concluding remarks

- **Wavelets** for discontinuous sparse fields, no Fourier!
- **Categorical approaches** are robust and resistant; they enable to verify for different intensities
- **De-noising preserving extremes**
- **Skill** measures; error relative to presence of features at each scale; account for **predictability** at different scales
- Error decomposition (displacement, amount) at different scales
- Error in spectral representation
Wavelets are locally defined real functions characterised by a **location** and a **spatial scale**.

- Any real function can be expressed as a linear combination of wavelets, i.e. as a sum of components with different spatial scales.

- Wavelet transforms deal with discontinuous and sparse fields better than Fourier transforms do.
Haar Wavelet filter

mean value

deviation from mean value

mean value on all the domain
De-noising preserving extremes

Wavelet decomposition:

large scale coefficients

small scale coefficients