

An events-oriented verification

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Information content v.s. grid point verification

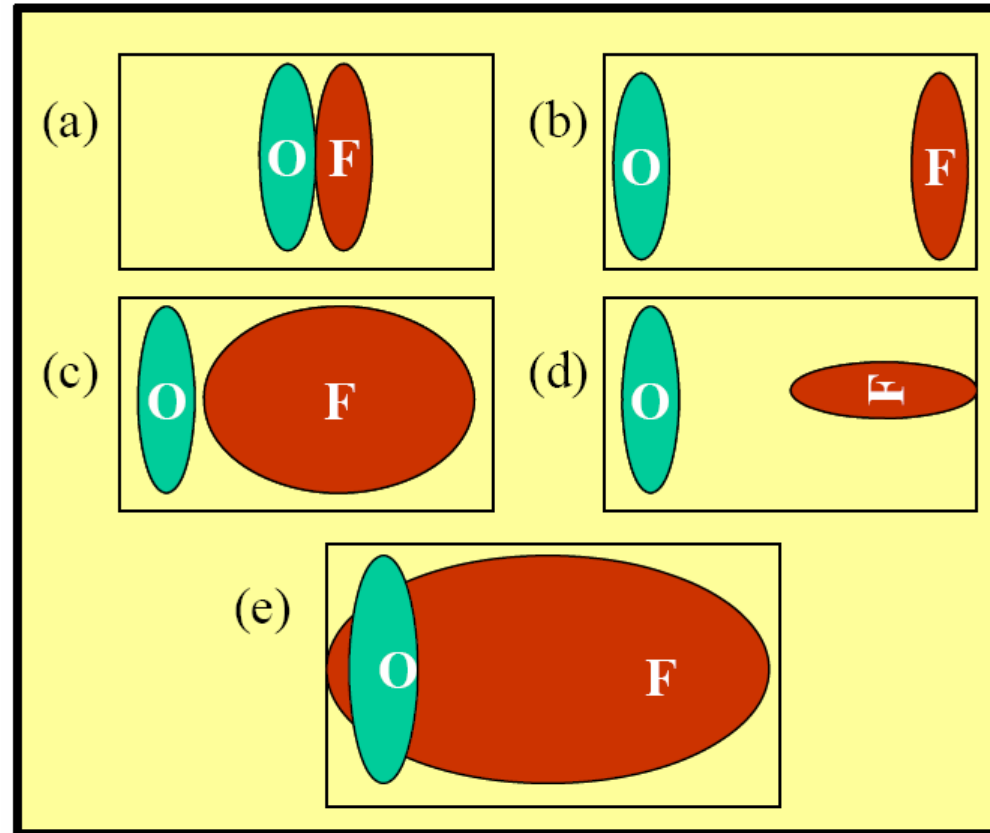
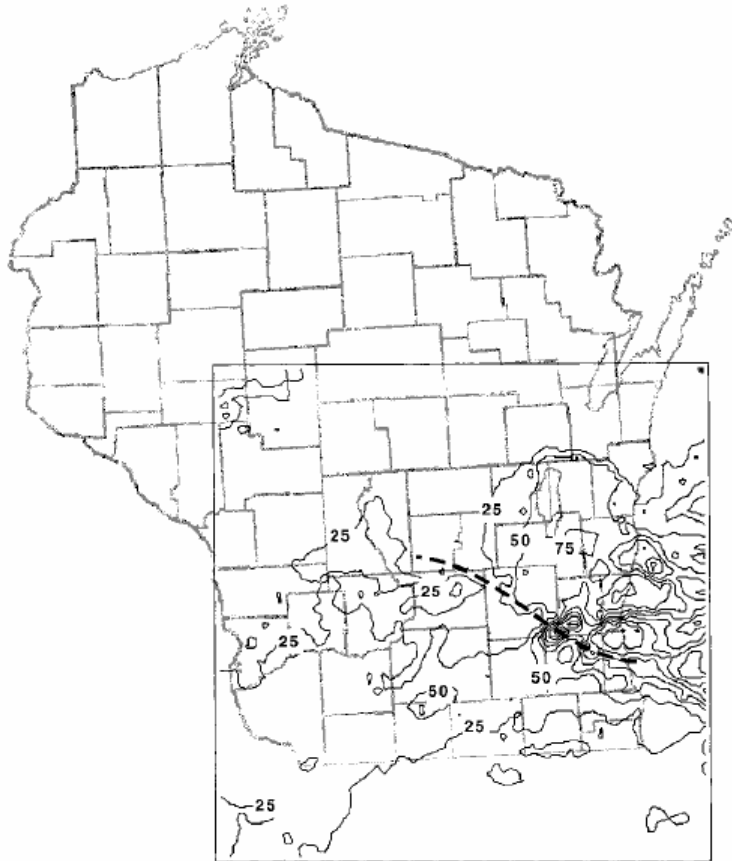
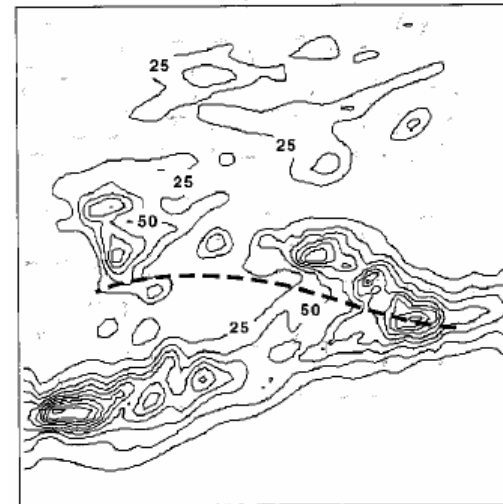


Figure 2. Simple example of the impacts of different types of errors on verification results. Each of the forecasts in (a) through (e) has 0 skill according to traditional verification approaches, whereas the forecast in (e) has positive skill. From Davis et al. (2006a).

Information content v.s. grid point verification



Analysis



Forecast

Events orientation: Synoptic “forcing” of precipitation

- **(laplacian of) warm air advection**
- **(differential) cyclonic vorticity advection**
- **frontal circulations**
- **jet streak circulations**

Procedure

- 1) Identify contiguous precip areas from gridded observational (NPA, 4 km) and DWFE datasets**
 - 24 hour accumulated (synoptic)**
 - agglomerative hierarchical cluster analysis (Euclidean distance, shortest distance metric)**

- 2) Subjective identification of precip classes for 15 Jan – 31 March 2001-05**
 - artificial neural network is trained on 2001-04 to classify forcing**

Procedure (continued)

3) Precipitation clusters are “processed” as objects following Davis et al. (2006):

- precipitation centroid**
- length of major and minor axes**
- major axis orientation**

4) Objects are “matched” between forecast and observations as a function of precipitation forcing class: (this is ongoing)

- translation and rotational errors**
- areal coverage errors**
- intensity errors**

Results (Observed 24-h precipitation)

	25th Percentile	50th Percentile	75th Percentile
Sqr. Root Area (km)	176	418	716
Aspect Ratio	0.31	0.44	0.60
474 objects			

Results (Observed 24-h precipitation)

NOT surprisingly (but good news) ...

- **Warm air advection objects are larger and more circular**
- **Frontal circulation objects are larger and more elongated**

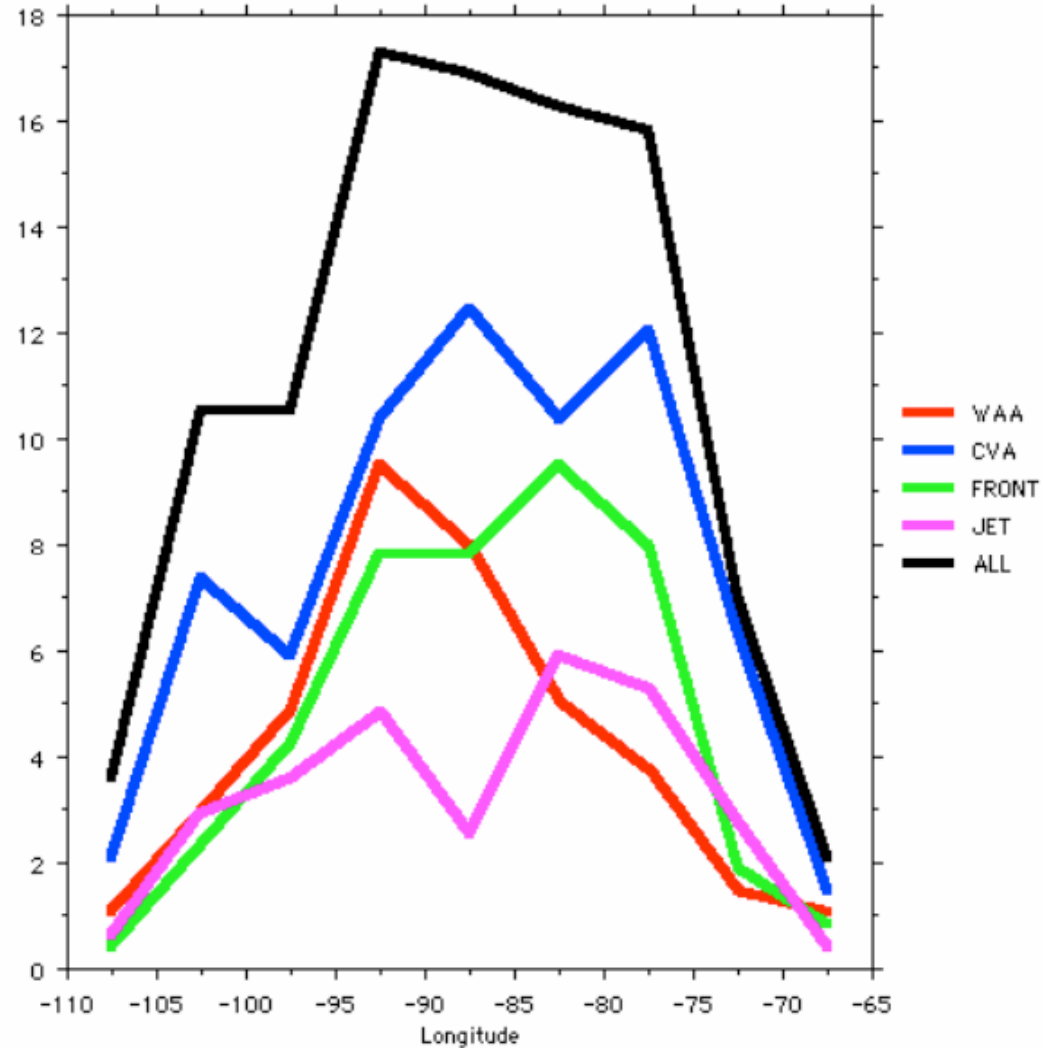
Results (Observed 24-h precipitation)

Process (WAA, CVA, FNT, JET)	Frequency (%)
CVA	24.1
CVA + WAA	12.0
CVA + FNT	9.7
CVA + WAA + FNT	8.2
FNT	7.4
JET	7.0
CVA + JET	6.3
WAA	5.3
WAA + FNT	4.4
FNT + JET	4.4
CVA + FNT + JET	3.4
WAA + CVA + FNT + JET	3.4
WAA + FNT + JET	1.9
WAA + JET	1.3
WAA + CVA + JET	1.3
ALL PROCESSES	100.0

**Multiple “forcing”
in 56% of events**

- CVA 68%**
- FNT 43%**
- WAA 38%**
- JET 29%**

Results (Observed 24-h precipitation)



Can we train an ANN to classify like me?

- **Used the 2001-04 data for training + cross-validation**
- **Used the 2005 data for independent testing**
- **Two hidden layer MLP with “schematic” inputs:**

**lat/lon of surface lows, 500 hPa vorticity maxima,
300 hpa wind speed maxima**

- **These inputs provide a “pattern” which the ANN tries to map to the desired output (which “forcing”)**

Can we train an ANN to classify like me?

Class	Pct Correct	POD	FAR	CSI
WAA	65%	0.65	0.40	0.45
CVA	68%	0.68	0.10	0.63
FRONT	70%	0.80	0.29	0.60
JET	57%	0.68	0.56	0.36

Can we train a student to classify like me?

- **Percent agreement with student is about 60%.**
- **Certain degree of subjectivity to these classes beyond this level, so can't expect network to perform much better.**
- **Note: could “define” what constitutes a particular forcing, but there would be inevitable subjective determinations as to what constitutes a particular class or set of classes.**
- **Still useful as a means for organizing our thinking regarding model errors (yet to be determined).**

What remains to be done:

- 1) Match the precipitation objects to the observed objects (cluster analysis for both is complete, still need to quantify the DWFE precip objects)**

- 2) Perform the verification and break down the results as previously described: for each “forcing”:**
 - location errors (translation and rotation)**
 - size errors**
 - intensity errors**

How can this be of value to community?

- 1) Precip cluster analysis protocol and code (courtesy of Caren Marzban)**
- 2) Protocol and code for obtaining schematic synoptic “elements” from reanalysis/model data**
- 3) Protocol and code for neural network classification of synoptic forcing – could be extended to other scales and elements**
- 4) Code (following Davis et al. 2006) that produces precipitation objects from cluster data**
- 5) How does model performance vary as a function of synoptic forcing – can quantify this, using synoptic classification combined with precip objects**