Assessing high resolution forecasts using fuzzy verification methods

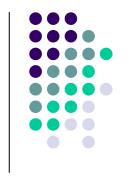
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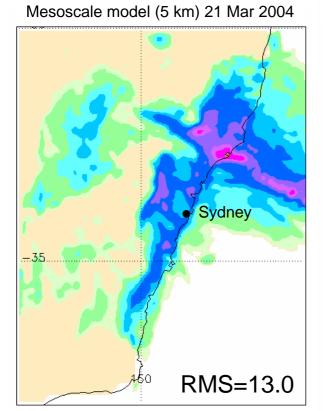


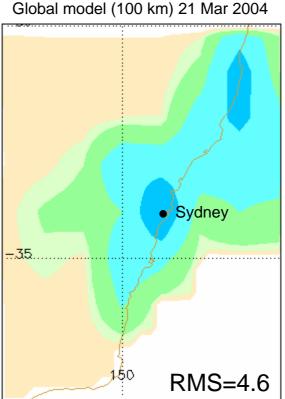
Thanks to Nigel Roberts, Barbara Casati, Frederic Atger, Felix Ament, Daniel Leuenberger, Urs Germann, Mike Kay, Susanne Theis, Ulrich Damrath, Daniela Rezacova

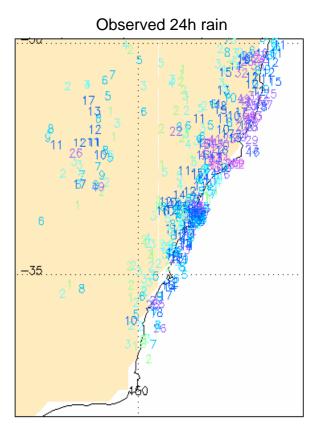




Which rain forecast would you rather use?









What makes a useful forecast?



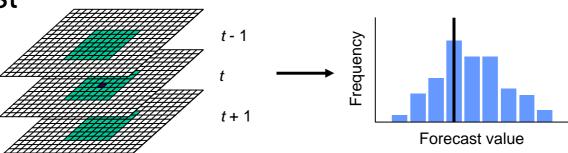
- Resembles the observations on the broader scale
- Predicts an event somewhere near where it was observed
- Predicts the event over the same area (i.e., with the same frequency) as observed
- Has a similar distribution of intensities as the observations
- Looks like what a forecaster would have predicted if she'd had knowledge of the observations







- Don't require an exact match between forecasts and observations
 - Unpredictable scales
 - Uncertainty in observations
- Look in a space / time neighborhood around the point of interest



 Evaluate using categorical, continuous, probabilistic scores / methods



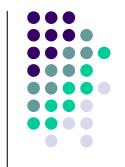




- First (?) suggested by H. Brooks at 1998 Mesoscale Verification workshop
 - Brooks et al. (1998)
 - Zepeda-Arce et al. (2000), Weygandt et al. (2004)
 - Atger (2001)
 - Damrath (2004)
 - Casati et al. (2004)
 - Germann and Zawadski (2004)
 - Theis et al. (2005)
 - Roberts (2005)
 - Rezacova et al. (2006)

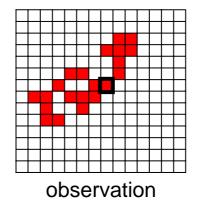


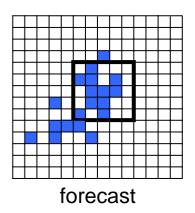




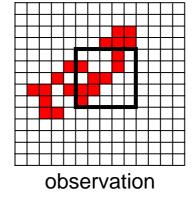
Fuzzy methods use one of two approaches to compare forecasts and observations:

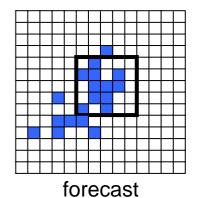
single observation – neighborhood forecast





neighborhood observation – neighborhood forecast







Fuzzy verification framework



Treatment of forecast data within a window:

- Mean value (upscaling)
- Occurrence of event* somewhere in window
- Frequency of event in window → probability
- Distribution of values within window

May apply to observations as well as forecasts (neighborhood observation-neighborhood forecast approach)

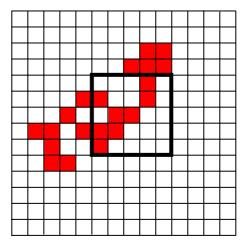
* Event defined here as a value exceeding a given threshold, for example, rain exceeding 1 mm/hr

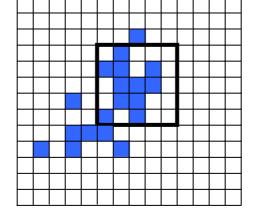


Example: Fractions skill score (Roberts and Lean 2005)



Compares fractional coverage in forecast with fractional coverage in observations





observation

forecast

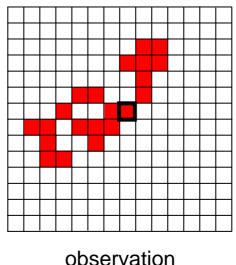
FSS = 1 -
$$\frac{\frac{1}{N} \sum_{i=1}^{N} (P_{fcst} - P_{obs})^{2}}{\frac{1}{N} \sum_{i=1}^{N} P_{fcst}^{2} + \frac{1}{N} \sum_{i=1}^{N} P_{obs}^{2}}$$

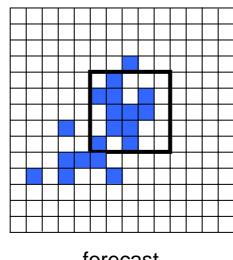


Example: Multi-category contingency table (Atger 2001)



Compares occurrence of event in forecast with observed occurrence of event





forecast

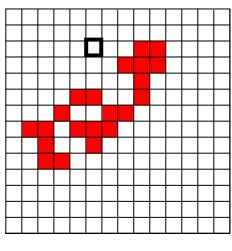
Hit = at least one forecast event in vicinity of observed event

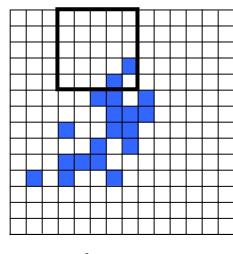






Accumulate scores as windows are moved through the domain





observation

forecast





Decision models

Fuzzy method	Matching strategy*	Decision model for useful forecast
Upscaling (Zepeda-Arce et al. 2000; Weygandt et al. 2004)	NO-NF	Resembles obs when averaged to coarser scales
Minimum coverage (Damrath 2004)	NO-NF	Predicts event over minimum fraction of region
Fuzzy logic (Damrath 2004), joint probability (Ebert 2002)	NO-NF	More correct than incorrect
Fractions skill score (Roberts 2005)	NO-NF	Similar frequency of forecast and observed events
Pragmatic (Theis et al. 2005)	SO-NF	Can distinguish events and non-events
CSRR (Germann and Zawadzki 2004)	SO-NF	High probability of matching observed value
Multi-event contingency table (Atger 2001)	SO-NF	Predicts at least one event close to observed event
Practically perfect hindcast (Brooks et al. 1998)	SO-NF	Resembles forecast based on perfect knowledge of observations
Intensity-scale (Casati et al. 2004)	NO-NF	Lower error than random arrangement of obs
Area-related RMSE (Rezacova et al. 2006)	NO-NF	Similar intensity distribution as observed

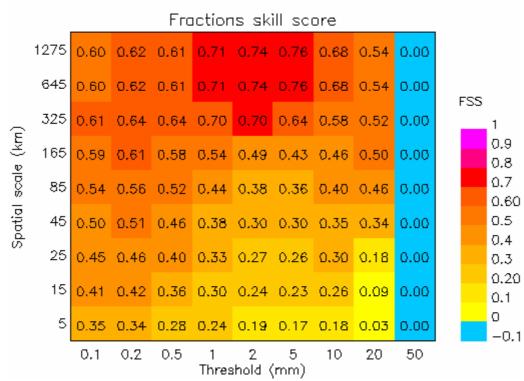


*NO-NF = neighborhood observation-neighborhood forecast, SO-NF = single observation-neighborhood forecast



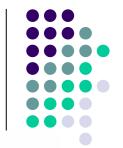


 Forecast performance depends on the scale and intensity of the event

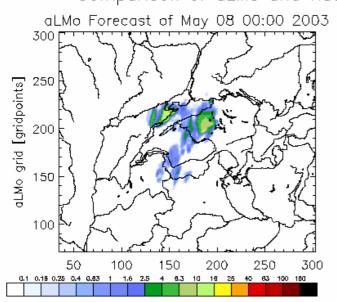


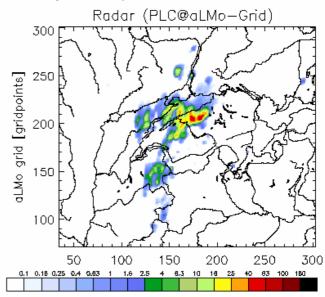


Case study









 Verification of 2 km resolution precipitation forecast of 1 hr rainfall in Switzerland using MeteoSwiss Alpine Model (aLMo)

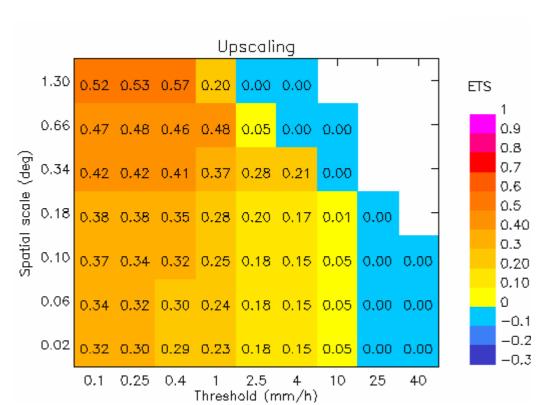
(data courtesy of Daniel Leuenberger, MeteoSwiss)

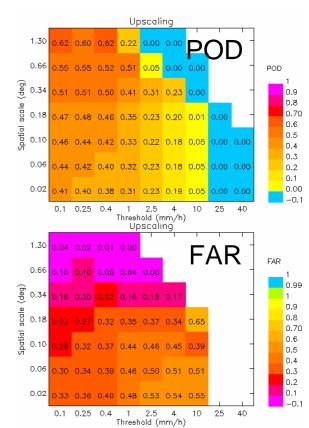






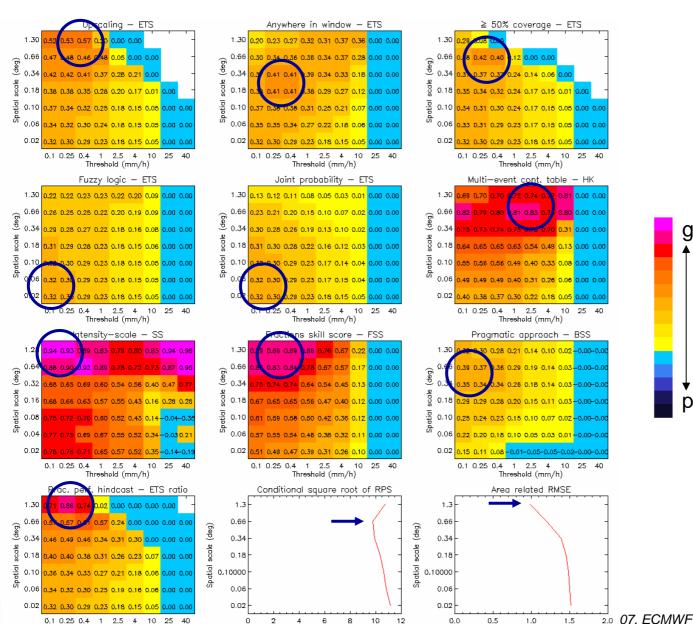
Decision model – Useful forecast resembles observations when averaged to coarser scales





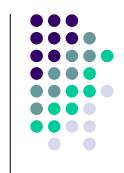


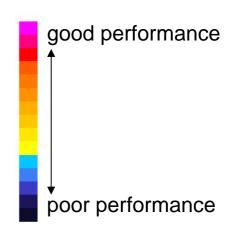
Fuzzy verification framework



CSRR

RMSE







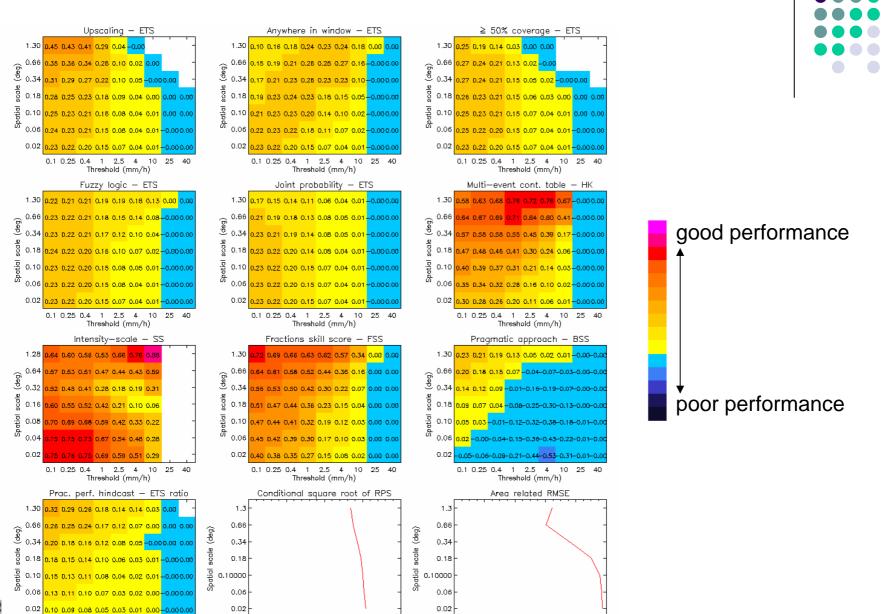
Threshold (mm/h)

Aggregate results for 24 h period

15

CSRR

20





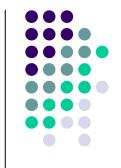
0.1 0.25 0.4 1 2.5 4 10 25 40

Threshold (mm/h)

1.0)7. ECMWF

0.6

Advantages of fuzzy verification



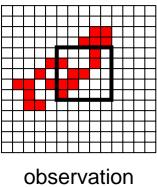
- *
 - Knowing which scales have skill suggests the scales at which the forecast should be presented and trusted
 - Suitable for discontinuous fields like precipitation
 - Can give good results for forecasts that verify poorly using exact-match approach
 - Results match with our intuition
 - Can be used to compare forecasts at different resolutions
 - Multiple decision models and metrics
 - Direct approach → verification of intensities
 - Categorical approach → verification of binary events
 - Probabilistic approach -> verification of event frequency

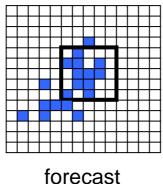


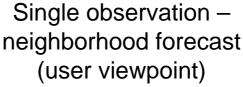
Many verification possibilities

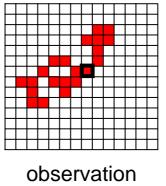


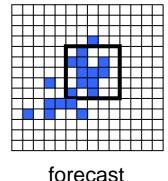
Neighborhood observation – neighborhood forecast (modeler viewpoint)











- categorical scores
 - POD, FAR, ETS, etc.
- probabilistic methods
 - BS, RPS, reliability, ROC, etc.
- continuous scores
 - RMSE, MAE, etc.

- categorical scores
 - POD, FAR, ETS, etc.
- probabilistic methods
 - BS, RPS, reliability, ROC, relative value, etc.







