# Verification of numerical models – what are the biggest challenges?



#### OZEWEX 2014, 28-29 OCTOBER 2014, CANBERRA



Australian Government

**Bureau of Meteorology** 

The Centre for Australian Weather and Climate Research A partnership between CSIRO and the Bureau of Meteorology



### Validation and Verification







#### Does my model do the right thing?

Process studies Field experiments Special observations

#### Did my model get the right answer?

Systematic verification Diagnostic verification Routine observations

### Trends in numerical prediction



#### Higher resolution

• Focus on surface weather



#### Coupled extended range

• Focus on longer range



#### Ensembles

• Focus on uncertainty



#### Impact models

• Focus on user decisions



### High resolution NWP



#### **Benefits**

- Surface weather
- Greater realism
- Extreme values

#### Verification challenges

- Observations
- Double penalty
- Rare extreme values



### Verifying rare extreme values

- Hard to observe
- Categorical scores more robust
  - Metrics should reward hits, penalise misses and false alarms
  - For rare events, usual summary scores (e.g., CSI, ETS, HSS, ...)  $\rightarrow$  0
  - New extremal dependence scores:

$$EDI = \frac{\log F - \log H}{\log F + \log H} \qquad SEDI = \frac{\log F - \log H - \log(1 - F) + \log(1 - H)}{\log F + \log H + \log(1 - F) + \log(1 - H)}$$

Ferro & Stephenson, Weather and Forecasting, 2011



### Spatial verification methods





Scaledependent error

Phase and amplitude errors

Gilleland et al., Bulletin of the American Meteorological Society, 2010

### Neighbourhood verification



- 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

### Feature-based verification



#### Compare attributes:

- centroid location
- intensity distribution
- area
- orientation
- etc.

#### When objects not matched:

- false alarms
- missed events
- rain volume
- etc.

#### Method for Object-based Diagnostic Evaluation (MODE)

StageII



#### WRF



24h forecast of 1h rainfall on 1 June 2005

### Spatial Verification Methods Intercomparison



Category	Scales with skill	Location errors	Intensity errors	Structure errors	Occurrence (hits, misses, false alarms)
Traditional (gridpoint)	×	×	$\checkmark$	×	$\checkmark$
Neighbourhood	$\checkmark$	×	$\checkmark$	×	$\checkmark$
Scale separation	$\checkmark$	×	$\checkmark$	×	$\checkmark$
Features based	×	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Deformation	×	$\checkmark$	$\checkmark$	×	×

#### • Conclusions from 1<sup>st</sup> phase

- Different methods have different strengths
- All address bias
- 2<sup>nd</sup> phase
  - Wind and precipitation in complex terrain
  - Ensemble forecasts
  - Point observations, ensemble observations

### Neighbourhood ensemble verification





#### Feature-based ensemble verification





Possible strategies for verifying an ensemble of "objects"

- 1. Verify objects in probability maps
- 2. Verify "ensemble mean"
- 3. Verify distributions of object properties

### Interacting weather & climate processes



Moncrieff et al., WMO Bulletin, 2007



Seamless prediction: How to verify across time scales?

### Generalized Discrimination Score (GDS)

Two-alternative forced choice:



13 Mason & Weigel, *Monthly Weather Review*, 2009

#### Multi-temporal verification



- Compute skill for a large range of lead times.
- As lead time is increased, also increase the time-averaging window for a seamless transition from weather to climate.



DJF

### Transpose AMIP



#### Run climate models in NWP mode

• Verification against observations  $\rightarrow$  evaluation of processes



### Weather modelling $\rightarrow$ impact modelling





#### Flight time error (FTE) = flight\_time<sub>obs</sub> - flight\_time<sub>fcst</sub>

- Accurate measure of wind forecast accuracy directly relevant to airlines
- Calculated using the track that the aircraft actually took
- Uses AMDAR observations from real flights rather than model analyses or radiosondes



### Uncertainty in observations

- As models improve, we can no longer ignore observation error!
- Remove observation bias errors where possible
- Effects of random obs error on verification
  - "Noise" leads to poorer scores for deterministic forecasts
  - Ensemble forecasts have poorer reliability & ROC
- What can we do?
  - Error bars in scatter plots
  - · Quantitative reference to "gold standard"
    - Correct for systematic error in observations
    - RMSE Ciach & Krajewski (Adv. Water Res., 1999)
    - Categorical scores Briggs et al. (MWR, 2005), Bowler (MWR, 2006)
  - Multiple observation sources / analysis methods



### Verification against own model analyses



• Pros

- Convenient
  - · Available in-house
  - Matched grid
- Spatially complete

 Temp and diff averaged from 2008020100 to 2008043000

 (a) Center Mean, 500mb
 (b) NCEP-Mean, 500mb



#### Cons

- Analysis contains bias
  - Inherited from model first guess
  - Different satellite processing
  - Different observations assimilated
  - Poor models of error covariance
- → Misleading model skill





-1 -0.8 -0.6 -0.4 -0.2 -0.1 D.1 D.2 D.4 D.6 D.8 1

(e) CMC-Mean, 500mb



(f) FNO-Mean, 500mb



Wei et al., AMOJ, 2010

### Observations quantity and quality

### Verification in "obs" space

- Satellite
  - A-Train
  - Himawari-8/9
  - GPM
  - etc.
- Radar
  - National & int'l networks
  - Polarimetric & phased array
- GPS
- 3<sup>rd</sup> party data
  - Mobile phone technology
- Multi-sensor analyses





Model reflectivity

Obs reflectivity Melick *et al.*, *NWA*, 2012





#### Progress and challenges in model verification

- Spatial verification becoming mainstream
- New scores for extreme events
- Evaluating ensembles
- Verification across time scales
- Relevant metrics for weather impacts
- Observation quality/quantity
- Verification and data assimilation

### Thank you!



## More slides

#### Fractions skill score

Compare forecast fractions with observed fractions (radar) *probabilistically* over different sized neighbourhoods







All FC+6, all UTC, 1 mm/h



Roberts & Lean, Monthly Weather Review, 2008

### Spread and skill for location forecasts



Spread = average distance to ensemble median location

Skill = distance between ensemble median and observed location

Contiguous rain areas with max rain ≥ 20 mm d<sup>-1</sup> Warm season, southern Australia

#### Mean values for 112 events



Ebert, IVMW4, 2009

#### Uncertainty in reference data

