Verification for High Impact Weather

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Bureau of Meteorology, Australia

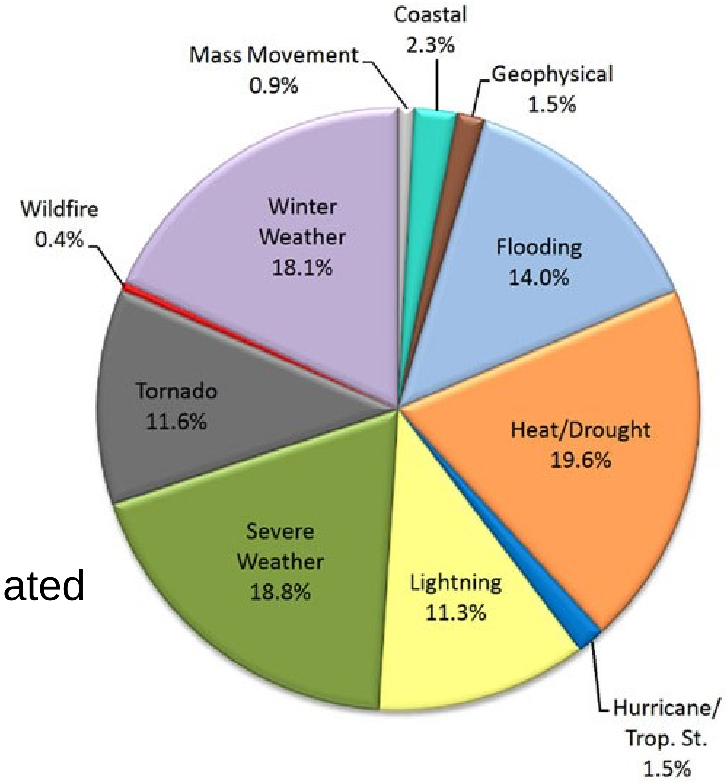
Acknowledgements: Barb Brown, Michael Sharpe, Manfred Dorninger, Helen Titley, Joanne Robbins, Lesley Allison, Brian Golding

Australian Government

Bureau of Meteorology

What is high impact weather?

- Affects people
- Involves making important decisions



Natural hazard related deaths in the US 1970-2004

Image: http://www.emergency-response-planning.com/news/bid/37452/INFOGRAPHIC-Natural-Disaster-Hotspots

High impact weather forecasts

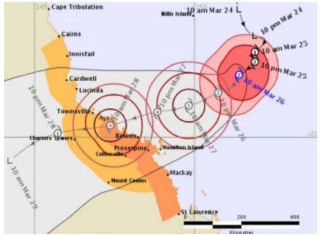
Warnings

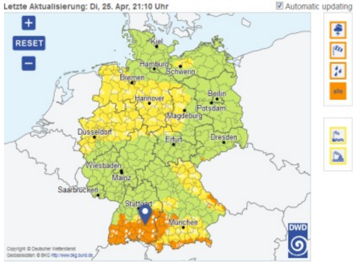
Outlooks

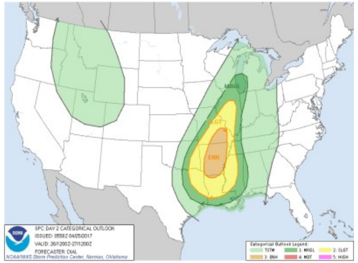
NWP

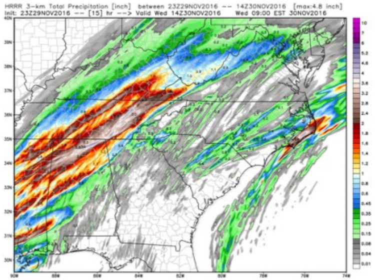
Fire Weather Warning
for the Northern Country, Wimmera, Mallee, North Central and Northeast forecast districts.
Issued at 04:05 pm EDT on Thursday 05 February 2009.

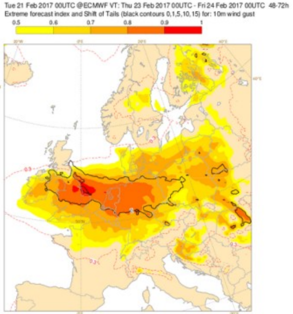
A fire weather warning for Friday is current in the Northern Country, Wimmera, Mallee, North Central and Northeast forecast districts. Temperatures up to 41 degrees, relative humidity down to 9% and winds to 25 km/h will cause extreme fire danger.
CFA advises people living in areas at risk of fire to activate their bush fire plan.
The next warning will be issued by 11:00 pm EDT Thursday.







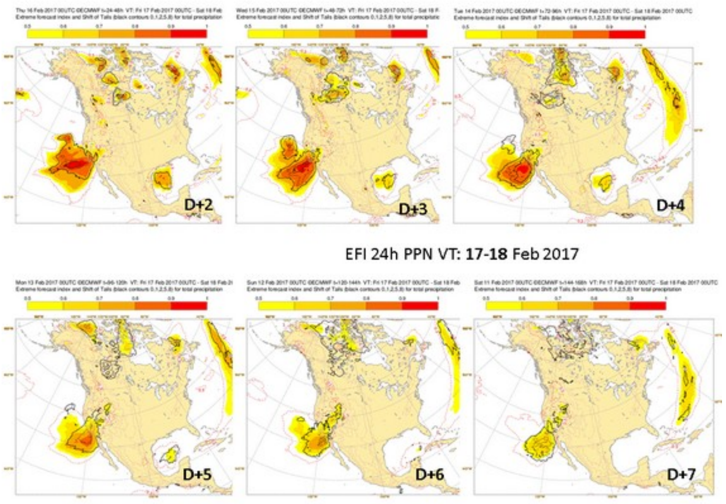




... Starting to link to hazard impact models

Challenges in modelling high impact weather

- Models may not capture the intensity of high impact events
  - Sub grid scale processes
  - Coarse resolution
  - Difficulty representing processes
- May be a mismatch between what models can provide and what warnings need to be made for
  - Lightning, hail, wind gusts, fog, …
- Large uncertainty with extreme events
  - Ensemble / probabilistic forecasts
  - Extreme forecast index (EFI) and anomaly forecasts (ANF) measure relative "extremeness"



Verification for high impact weather

- How should we do it?
- What recent research can assist?
- What are some of the challenges requiring further research?

Useful verification of HIW events

Guides users in making better decisions based on forecasts

- How reliable is the forecast at capturing events?
- What are typical errors in timing / location / intensity of events?
- Are the forecasts biased?

Informs modellers / forecast system developers on how to improve forecasts

- Do the forecasts show the right behaviour?
- What is the nature of the errors?

Assists managers in monitoring forecast performance

Historical perspective

TABLE NO. I.
Tornado Predictions and Verifications.

MONTH.	Predictions for	Total number.	Number of predictions "favorable for tornadoes."	Fully verified.	Number of predictions "unfavorable for tornadoes."	Fully verified.	Total number made.	Total number fully verified.
March	8 hours	771	43	6	728	721	771	727
April	8 hours	934	25	11	909	906	934	917
May	8 hours	558	10	8	548	542	558	550
May	16 hours	549						

Finley, J. P., 1884: Tornado prediction

MAY, 1917. **MONTHLY WEAT**

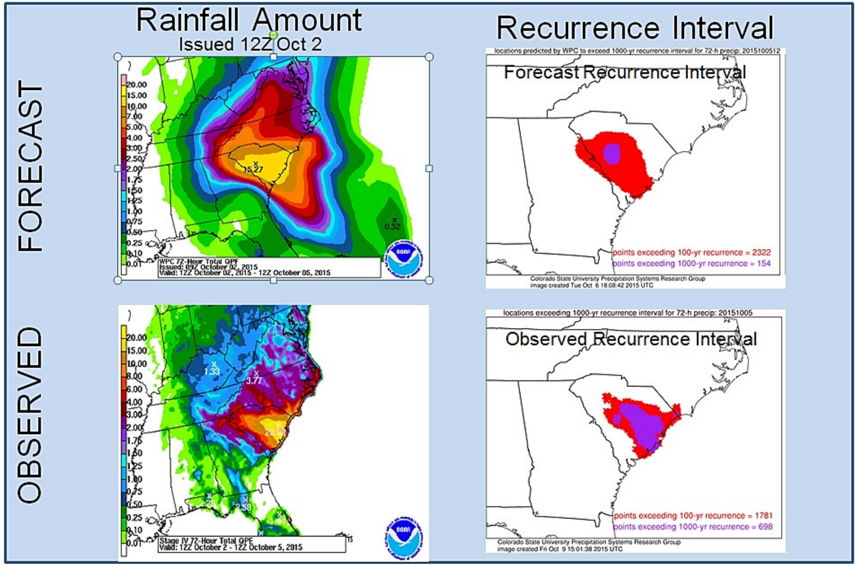
abnormally low temperature prevailed in the States to the west and north. Frost warnings were issued for Illinois, Missouri, Iowa, Wisconsin, and extreme eastern Kansas, and were generally verified. Warnings were issued each day from the 5th to 13th, inclusive, for some portion of the upper Mississippi Valley or western Lakes region, and were partially verified. No further warnings

Modern perspective – case studies

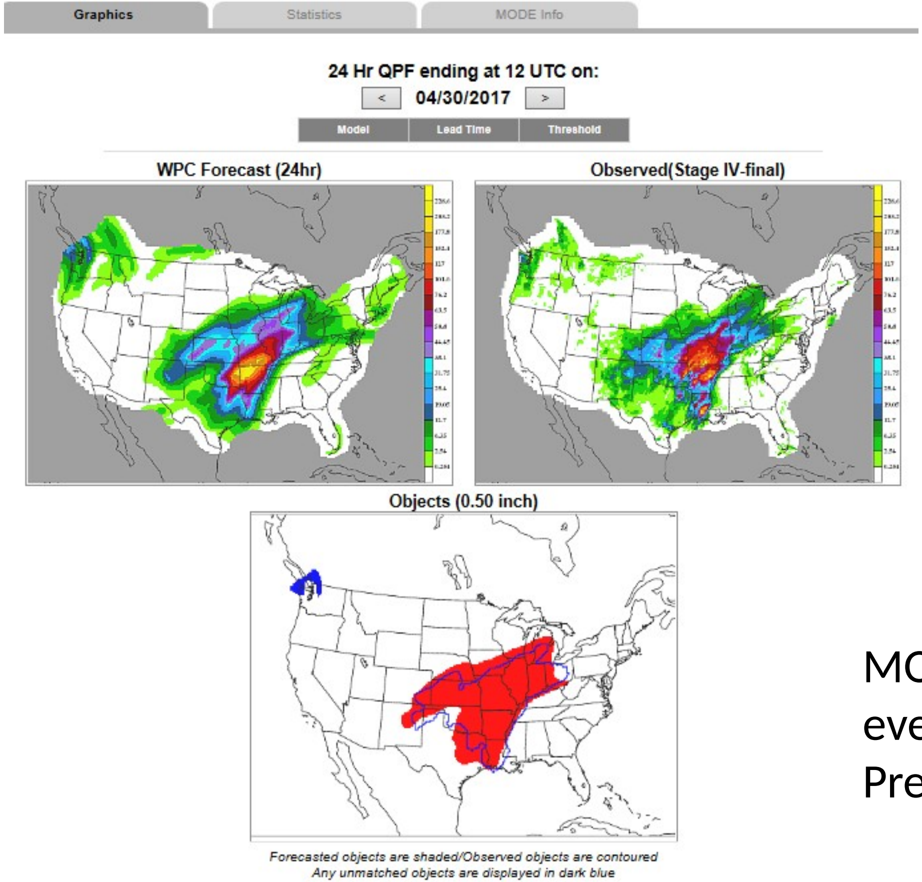
Service Assessment

The Historic South Carolina Floods of October 1–5, 2015

U.S. DEPARTMENT OF COMMERCE
National Oceanic and Atmospheric Administration
National Weather Service
Silver Spring, Maryland



Modern perspective – systematic verification



Top Performers
(ranked by interest value)

Observed Object Number	Model	Interest Value	Displacement Distance (km)
	WPC	0.993	49
1	GFS	0.990	54
	UKMET	0.982	68

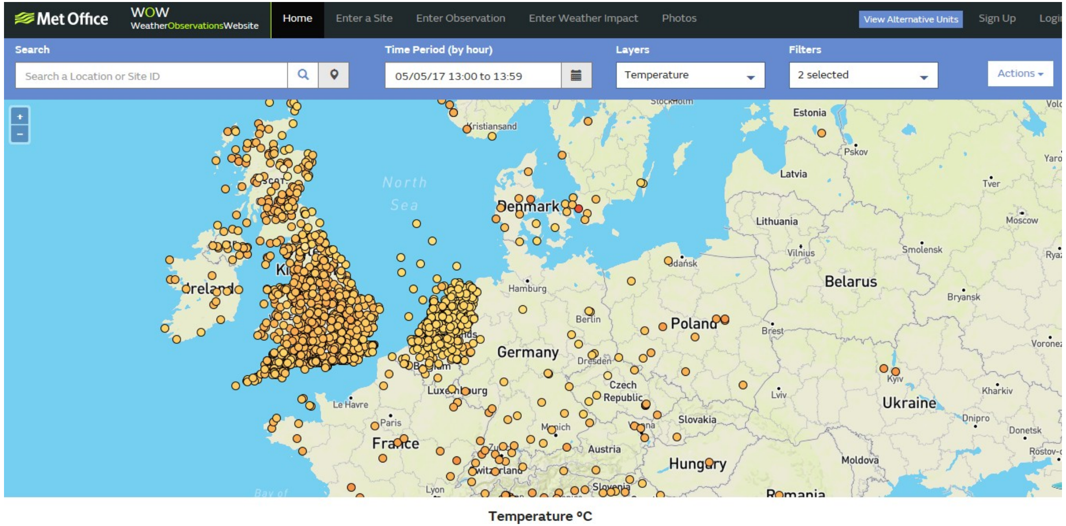
MODE verification performed every day at NWS Weather Prediction Center

Challenges in observing high impact weather

- Rare events
- Sampling error (timing, location, magnitude)
- Measurement error (gauge undercatch, radar attenuation, etc.)
- Non-reports
- May not match the forecast space & time scales (representativeness "error")

El Reno, TX, weather station post-tornado
Photo: Cliff Mass weather blog

3rd party observations and crowd sourcing



Weather Observations Website (WOW)

Mobile Precipitation Identification Near the Ground (mPING)

Observation uncertainty in verification

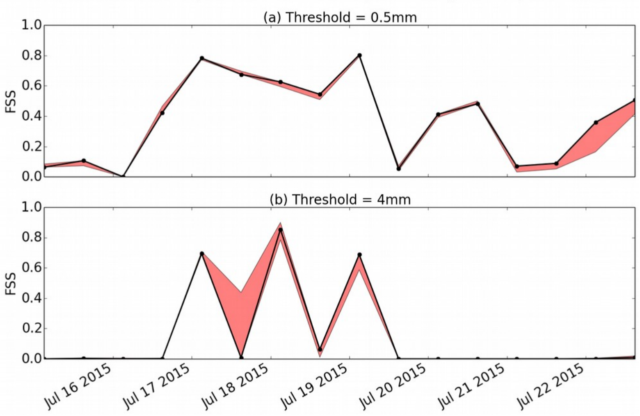
- As models improve, we can no longer ignore observation error!
- What are the effects of ignoring the observation error?
  - Forecasts may actually be better than they seem
  - Should users of verification results be advised?
- What are the effects of including the observation error?
  - "Noise" leads to poorer scores for deterministic forecasts
  - Probabilistic/ensemble forecasts have poorer reliability & ROC

➢ 7IVMW session on observation uncertainty

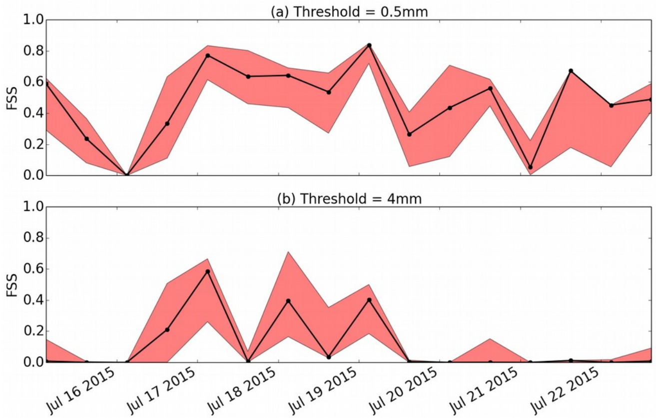
How does observation uncertainty compare to forecast uncertainty in verification?

- 6h forecasts of hourly precipitation, 11th June – 26th August 2015
- Observation (VPR) uncertainty – UKV vs radar ensemble (13 members)
- Forecast uncertainty – MOGREPS-UK ensemble (12 members) vs radar
- Fractions skill score for 51km neighbourhood

UKV against radar ensemble



MOGREPS-UK ensemble against unperturbed radar analysis



Courtesy Lesley Allison, Met Office

Dealing with observation uncertainty

- Strategies for reducing observation error
  - Quality control on measurements, correction of systematic errors
  - Averaging / analysis to larger space and time scales
  - Multiple observation sources

- Some approaches estimate the "true" verification scores, i.e., what would be computed if there were no observation error
  - Obs error distribution must be very well known **and** spatially uncorrelated

- "Tolerant" verification approaches
  - Distributions-based diagnostics including binning, quantiles, error bars
  - Object-based methods
  - Neighbourhood verification methods
  - Probabilistic observations probabilistic scores

Simple verification approaches suit some users

- Easy to understand
- Can guide decision making

Contingency table

Observed events

		yes	no	
Forecast events	**yes**	*hits*	*false alarms*	*forecast yes*
	no	*misses*	*correct negatives*	*forecast no*
		observed yes	*observed no*	*total number of fcsts*

Observed events

		yes	no	
Forecast events	**yes**	59	34	93
	no	22	674	696
		81	708	789

Q1: Given that an event is forecast, what is the chance that the event will actually occur?

59 / 93 (x 100) = 63%

Q2: When events occur, how often is the forecast correct?

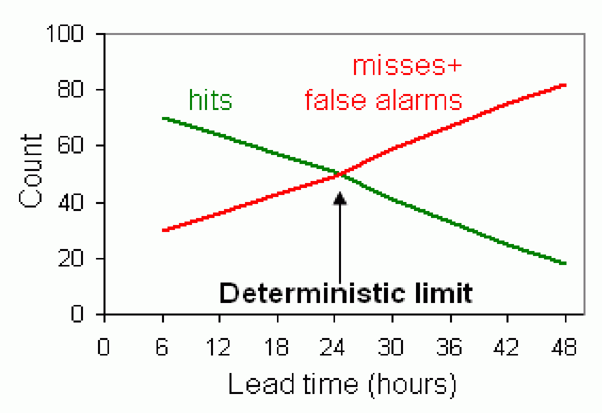
59 / 81 (x 100) = 73%

Q3: Do the forecasts predict events too often / not often enough?

(93-81) / 81 (x 100) = 15% (too frequent)

Simple verification approaches

Deterministic limit – how long does it take until the forecast is more wrong than right?



(Hewson 2007)

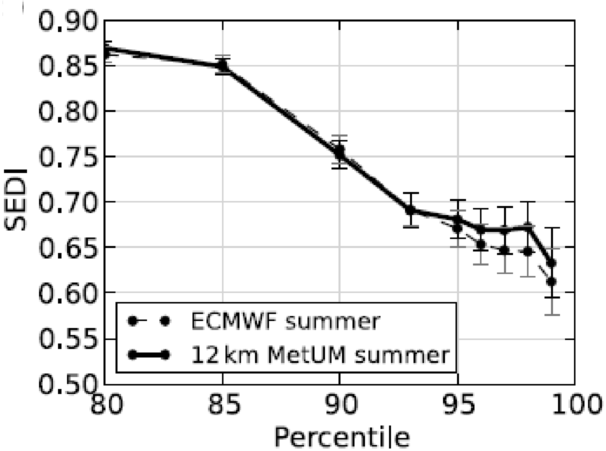
- Can be used to set appropriate targets for warning provision
- Provides guidance on when to switch from deterministic forecasts to probabilistic ones

Verifying rare extreme values

Scoring categorical forecasts

- Metrics should reward hits, penalise misses and false alarms
- For rare events, traditional categorical scores like ETS□ 0
- Symmetric extremal dependency index:

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

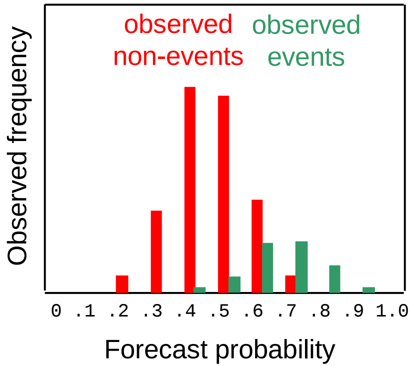


North, *Met. Apps.*, 2013

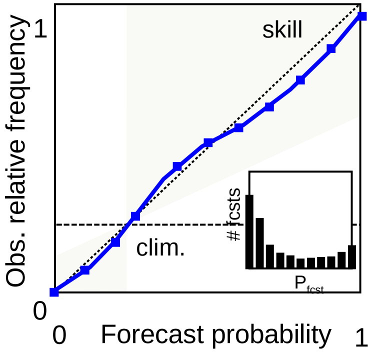
Verifying probability forecasts

- Cannot verify an individual probability forecast
- Probabilistic verification requires a large sample of forecasts
- Difficult to explain to many people
- Continuous Ranked Probability Score (CRPS) emerging as score of choice for model verification

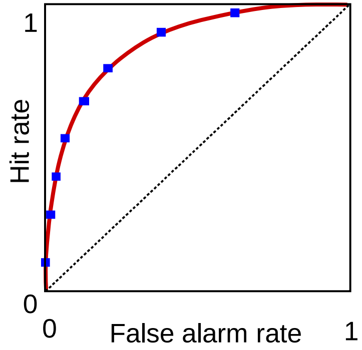
Likelihood diagram



Reliability diagram



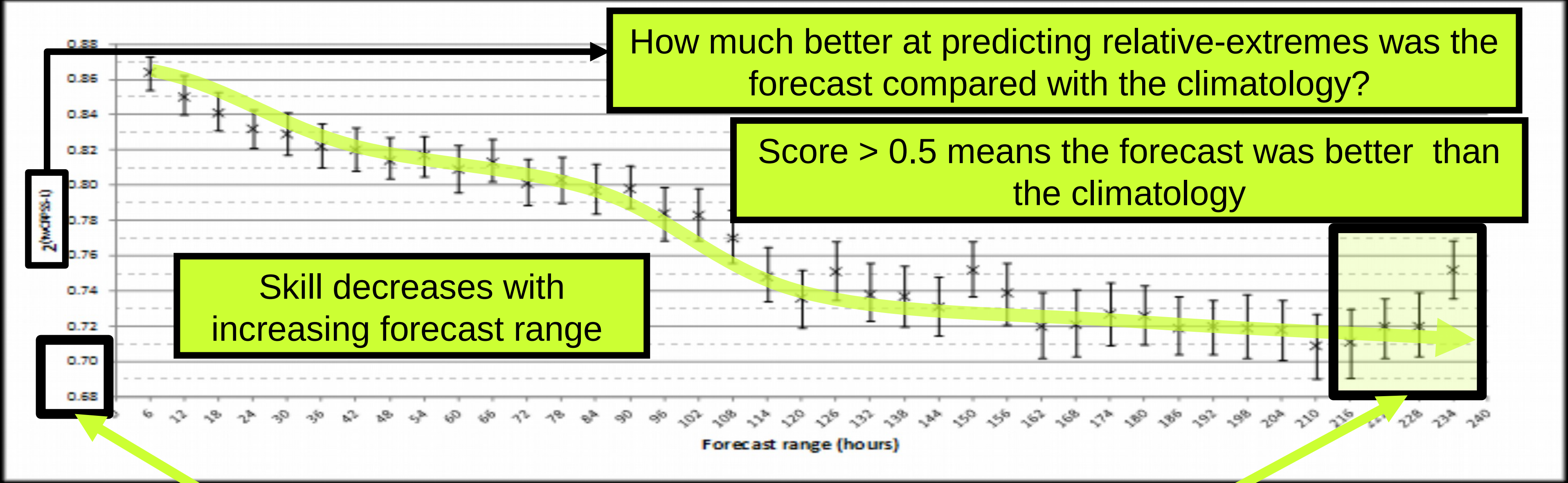
Relative Operating Characteristic



simple → complex

Verification of extreme events

Summary day-time max temperatures over UK, 2014-2015



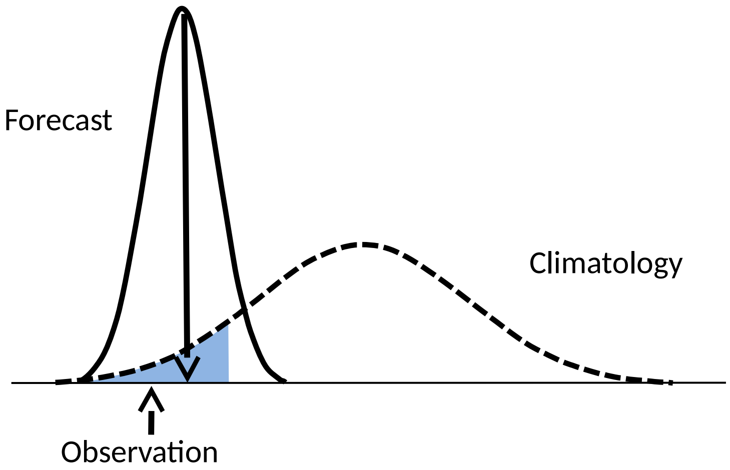
Even the forecast on day 9 is better than the climatology

Courtesy Michael Sharpe, Met Office

Other modifications of CRPS

- Rare/extreme values are in the tails of the climatological distribution
- Possible strategies
  - Weighted scoring rules
  - Extreme value theory
  - Quantile verification

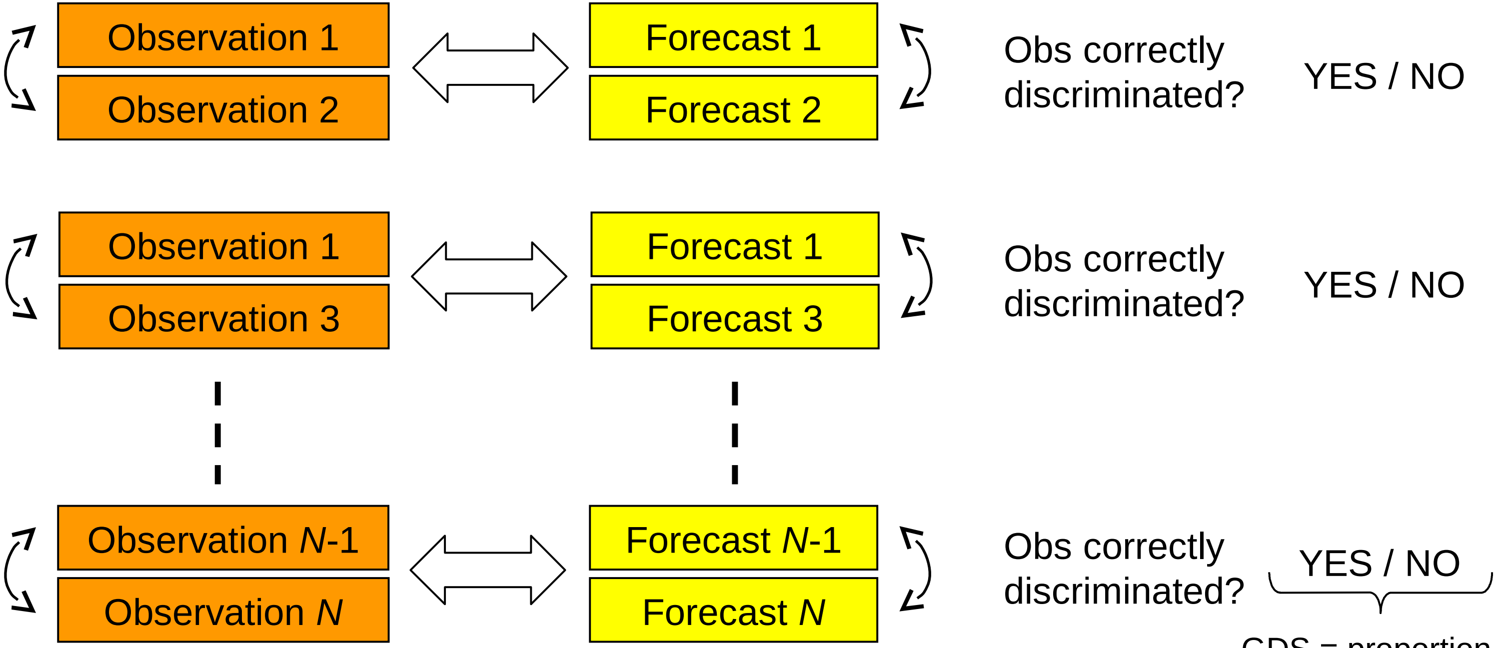
➢ Talks this session by
Petra Friederichs,
Maxime Taillardat,
Sebastian Lerch, Hong Guan



Generalized Discrimination Score (GDS)

Mason & Weigel, *MWR*, 2009

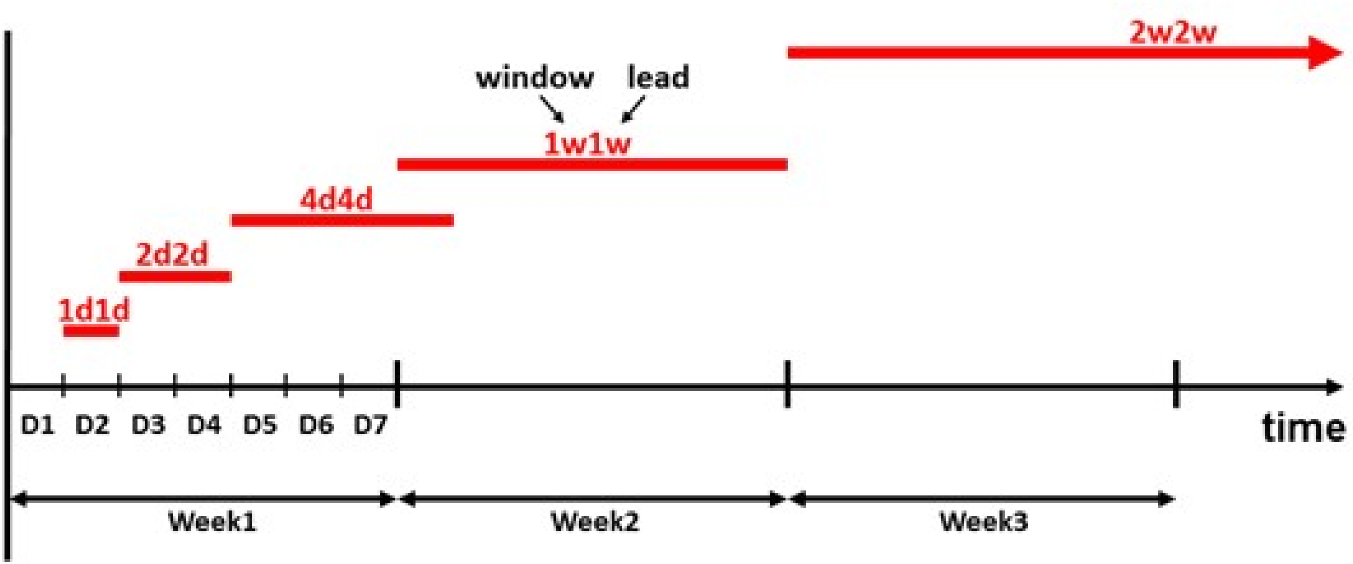
Two-alternative forced choice:



GDS = proportion of successful rankings (no skill = 50%)

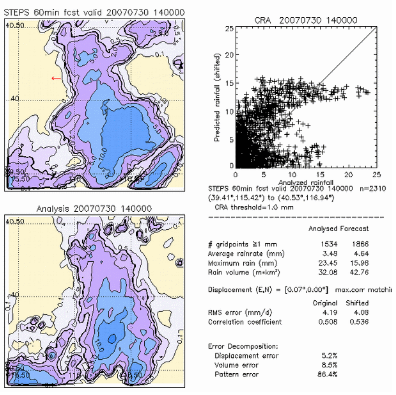
- Talks by Roger Harbord, Alexander Jordan

Seamless verification to span scales

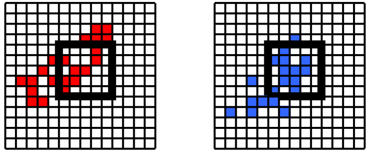


Zhu et al. 2014

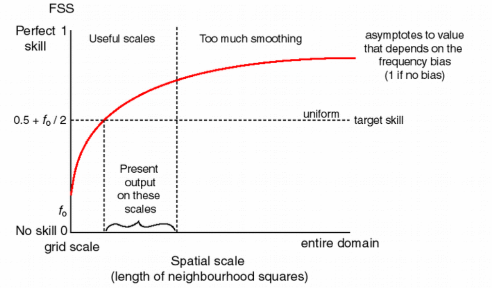
Spatial verification



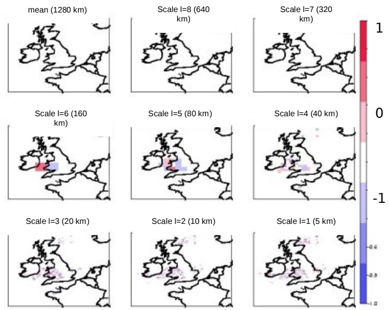
Object-oriented



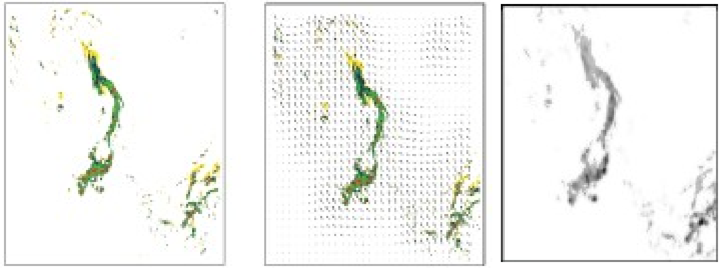
observation forecast



Neighborhood



Scale separation



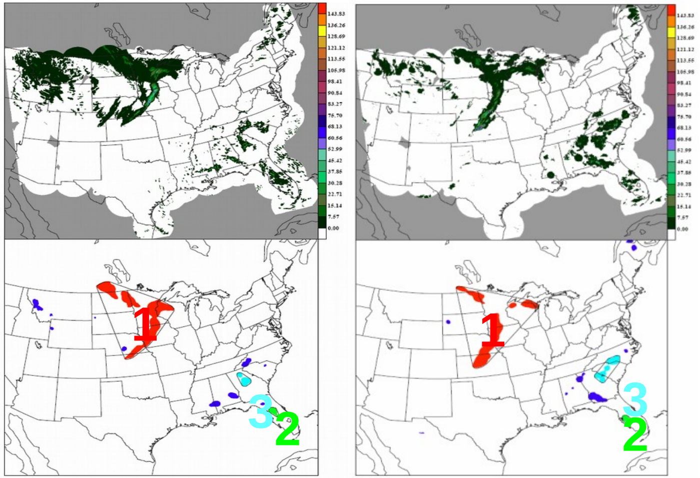
Field distortion

Distance metrics – watch this space…

Object-based vs. traditional verification

TRADITIONAL SCORES	
POD	0.22
FAR	0.86
CSI	0.09
GILBERT (ETS)	0.08
BIAS	1.6

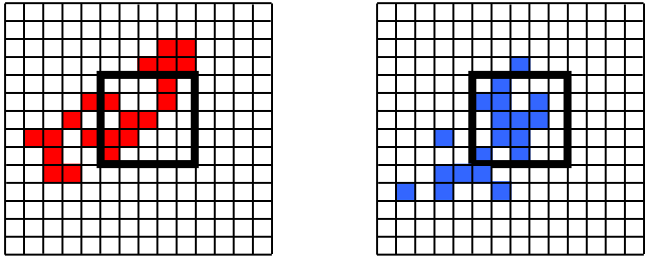
Forecast Observed



- Traditional scores suggest the forecast was very poor
- MODE provides much more information about performance than traditional scores
- MODE defines and quantifies the flaws and good qualities of the forecast:
  - Many misses and false alarms (small objects/areas)
  - Significant storm area somewhat too large and too intense, but placed well
  - Less significant storm area (SE) too small and not intense enough

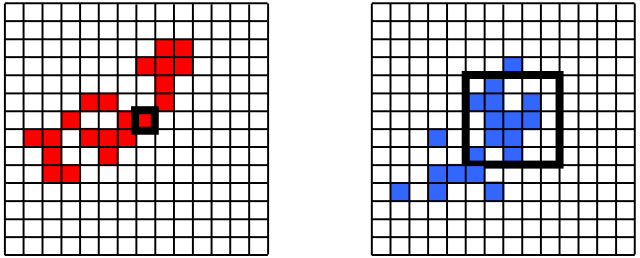
Neighborhood verification credits "close" forecasts

Fractions skill score compares forecast and observed fractional coverage (Roberts and Lean 2008)

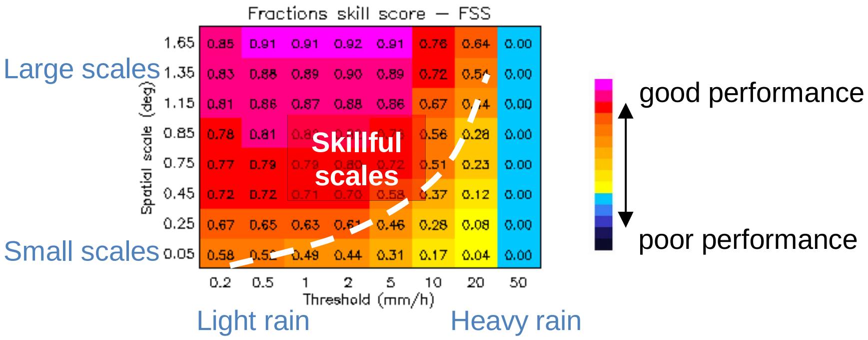


observation forecast

Multi-event contingency table measures whether a forecast event is close to an observed event (Atger 2001)

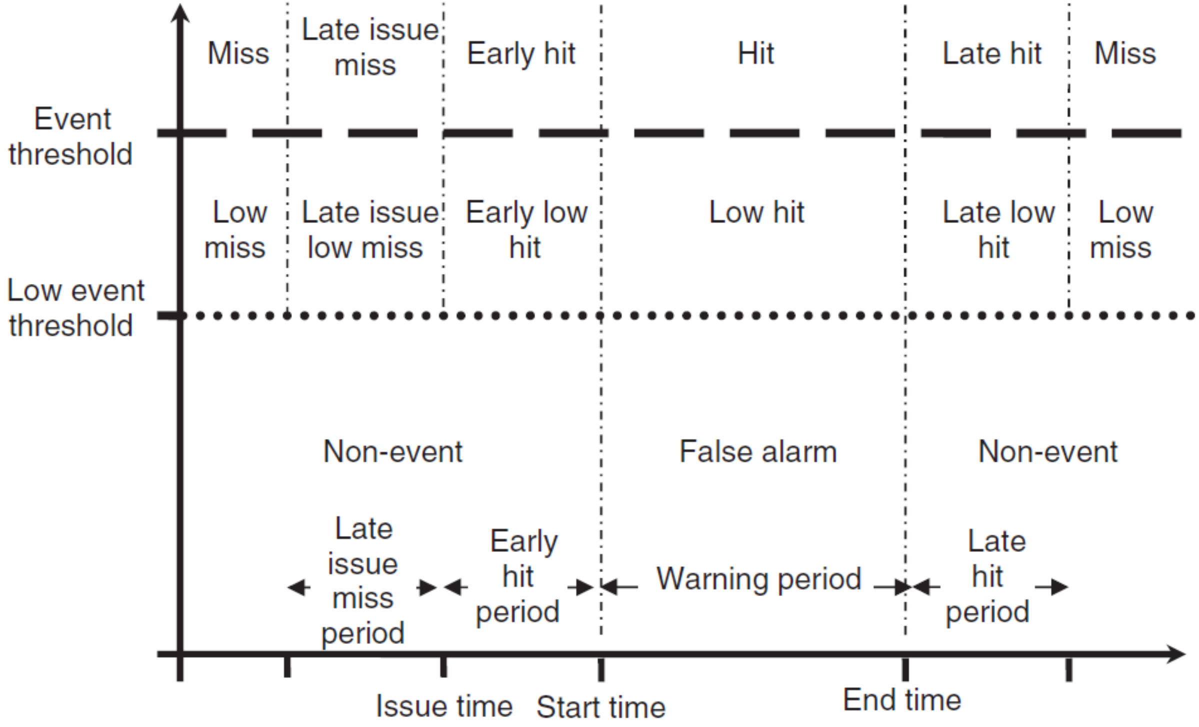


observation forecast



Knowing which scales have skill suggests the scales at which the forecast should be presented and trusted

Flexible verification of warnings



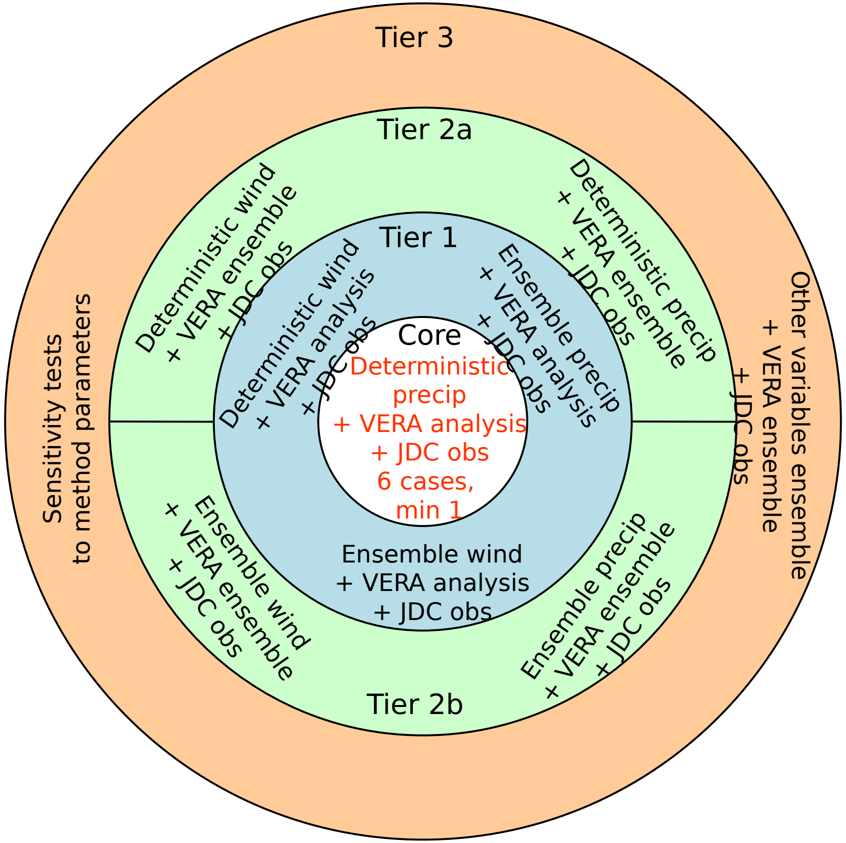
Sharpe, *Met Apps* 2016

MesoVICT: Mesoscale Verification Intercomparison over Complex Terrain

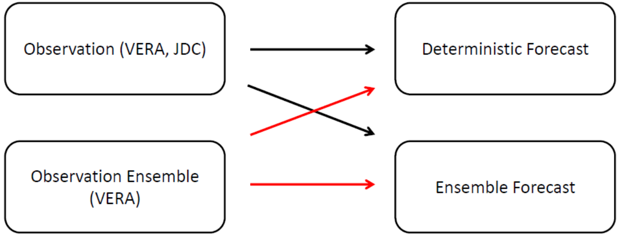
- How well do spatial verification methods work in complex terrain?
- Can they be used effectively to verify other parameters besides precipitation, e.g., wind?
- Can spatial verification methods be applied to ensemble forecasts?
- Can they account for uncertainty in observations?

http://www.ral.ucar.edu/projects/icp/

MesoVICT experiment design



- Ensemble forecasts
- Ensemble analyses to explore observation uncertainty



Spatial verification and ensembles

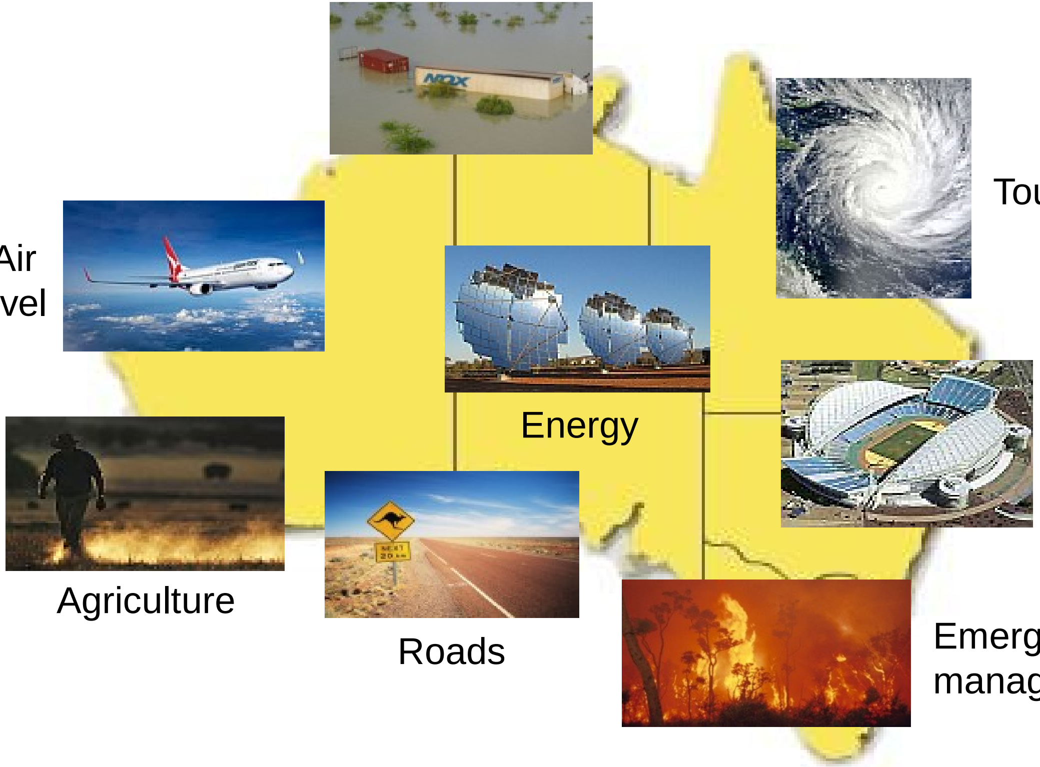
- Neighborhood verification is easily extended to ensembles
- Adapting existing scores for comparing probabilistic forecasts and probabilistic observations

$$CRPS = \int_{-\infty}^{\infty} (P_{fcst}(x) - P_{obs}(x))^2 \, dx$$

- SAL also applies well to ensembles

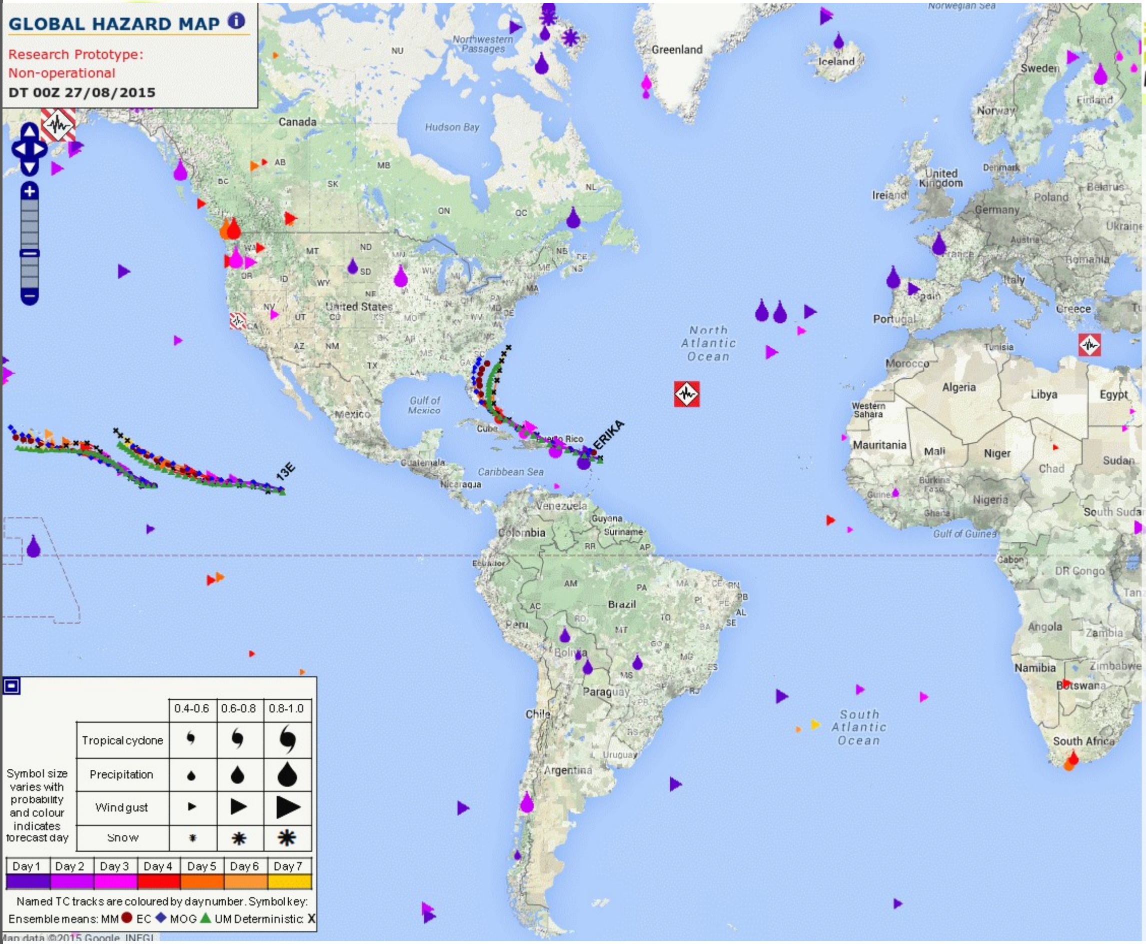
➢ Talks by Craig Schwartz, Marion Mittermaier, Helge Goessling, Sabine Radanovics

Weather forecasts *impact forecasts*



Met Office

Global Hazard Map



- Summarise risk of high-impact weather across the globe in the next 7 days using global multi-model ensemble forecasts
  - Precipitation / wind / snow
  - Tropical cyclones
  - Heatwave and coldwave
- Web Map Service
- Symbol-based summary map
- Drill down to particular variables / days / models / areas of interest
- Overlay vulnerability and exposure layers
  - Population density
  - Fragile State Index
  - Soil moisture
  - Recent earthquakes

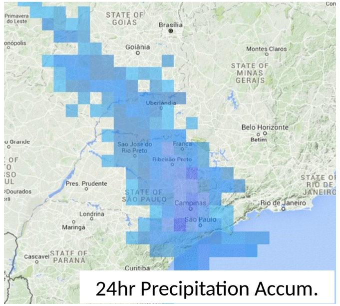
GHM forecast layers and identifying high-impact weather events

Met Office

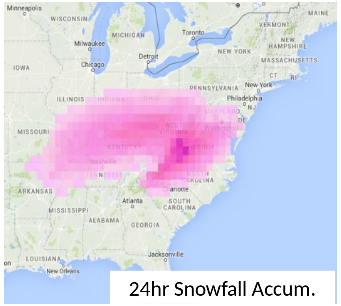
ECMWF ENS; MOGREPS-UK; Multi-Model

ECMWF ENS only

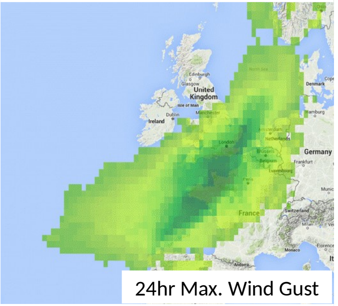
Day 3 forecast from 00Z 09/03/2016



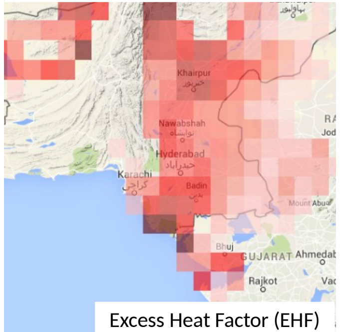
Day 4 forecast from 00Z 19/01/2016



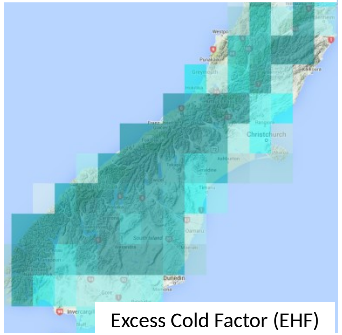
Day 4 forecast from 00Z 25/03/2016



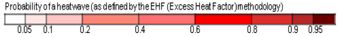
Day 5 forecast from 12Z 15/06/2015

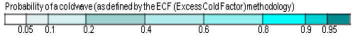


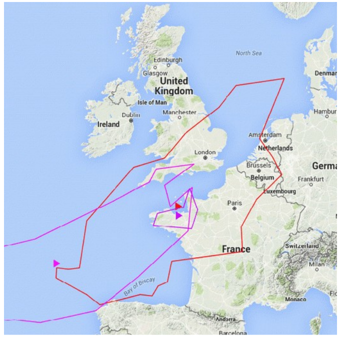
Day 6 forecast from 00Z 15/06/2015

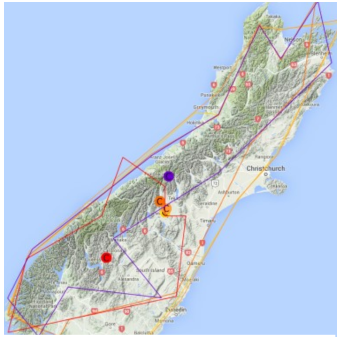


Probability of exceeding the 99th centile of forecast climatology









Summary polygons, coloured by lead time, show areas where probabilities are significant (≥0.4) for that lead time and hazard

Global Hazard Map: evaluation of precipitation forecasts

How does GHM perform in meeting its key aim “to summarise the risk of high-impact weather for the week ahead”?

(1) Did the forecast weather at a certain level of severity occur?

Traditional ensemble-based verification against weather observations

Comparing gridded hazard forecasts against station-based weather observations to create contingency based verification statistics as to whether or not the weather event occurred

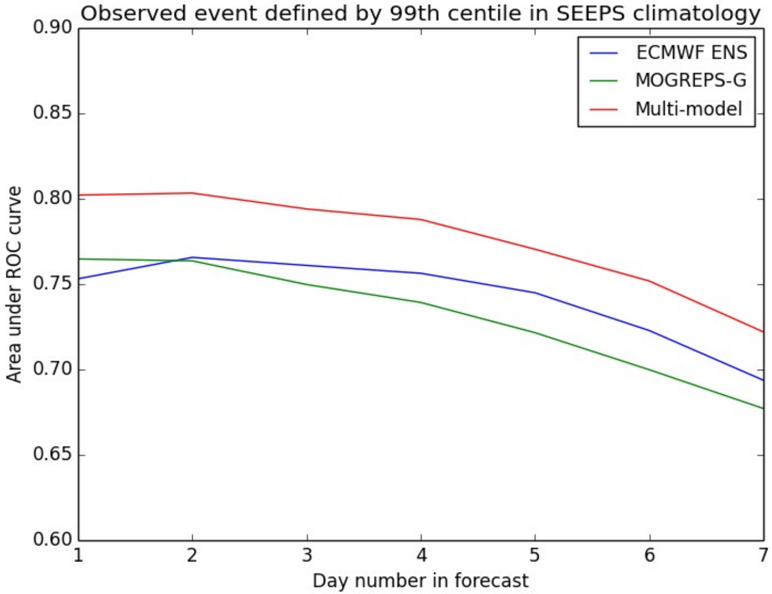
(2) Did the forecast weather result in a high-impact event?

Newly developed impact-based evaluation method

Aims to evaluate how well the Global Hazard Map summary polygons relate to records of community impacts (e.g. fatalities, injuries, displacement, evacuation, receipt of aid, disruption, denial of access, hardship)

GHM: (1) Verification against precipitation observations

- Verification against global station-based observations (3315 sites) from Feb-Dec 2015
- **Forecast event**: probability of 24-hour precipitation exceeding the 99th percentile in the forecast climatology
- **Observed event**: 24-hour precipitation exceeding the 99th percentile in the observed climatology at that site
- Calculated contingency based statistics (reliability, ROC diagram, Brier skill score, etc.) for each of the three model precipitation layers (ECMWF ENS, MOGREPS-G and the multi-model ensemble)



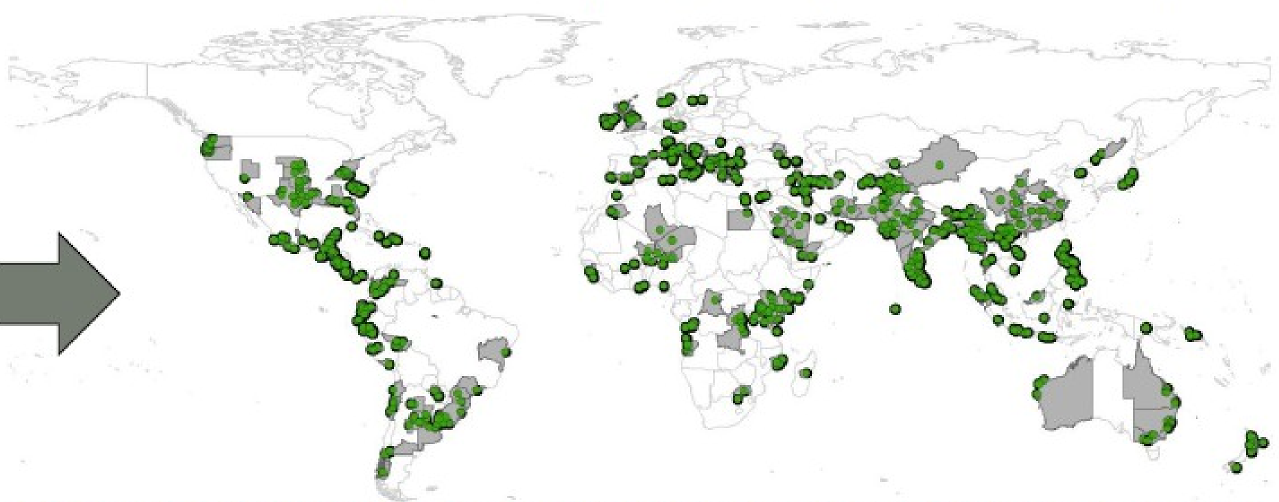
- Skill (area under ROC curve) greatest for multi-model at all lead times
- Good skill shown throughout forecast period

Socio-economic Impact Databases

Met Office

Heavy Rainfall Database
Spatial_ID (entry ID)
Event_ID (hazard event ID)
Record Date
Start Date
End Date
Hazard Type ('Heavy rainfall')
Trigger/Cause
Secondary Hazards
Hazard Notes
Country Name
Region/State/Province Name
Region/State/Province Latitude
Region/State/Province Longitude
Settlement Name
Settlement Latitude
Settlement Longitude
Impact Information
Impact Categorisation
References

Location of heavy rainfall impacts (February – December 2015)



Between February 8th and December 31st 2015 a total of 261 heavy rainfall events were recorded, resulting in 853 database entries

Public Health England

Global hazards weekly bulletin

Swiss Re

chrome

FloodList

reliefweb

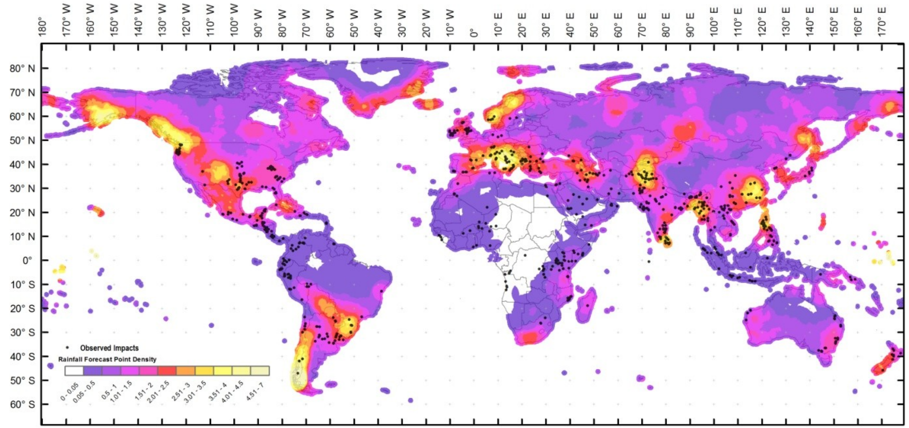
EM-DAT

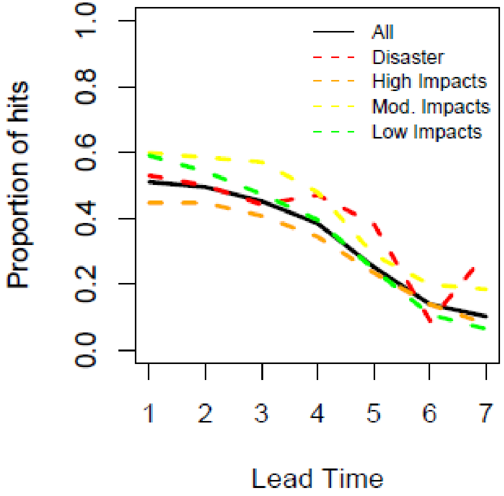
The International Disaster Database

Centre for Research on the Epidemiology of Disasters - CRED

GHM: (2) Evaluation against rainfall impact observations

- Forecast heavy rainfall events compared to heavy rainfall impacts, Feb-Dec 2015
- **Forecast event**: GHM summary polygon features from multi-model ensemble representing the area where forecast probabilities exceed 0.4.
- **Observed event**: polygon features representing the location of observed community impacts. Heavy rainfall impact database contains 853 entries, split into impact severity categories (low, moderate, high and disastrous)

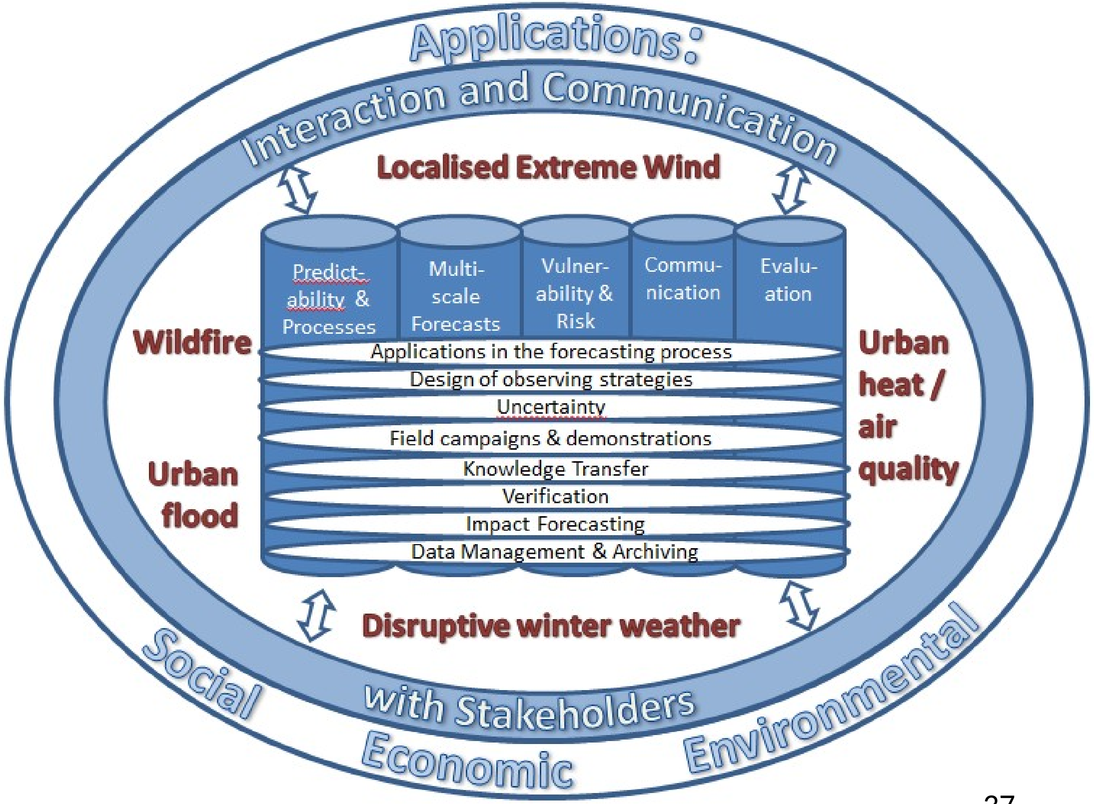




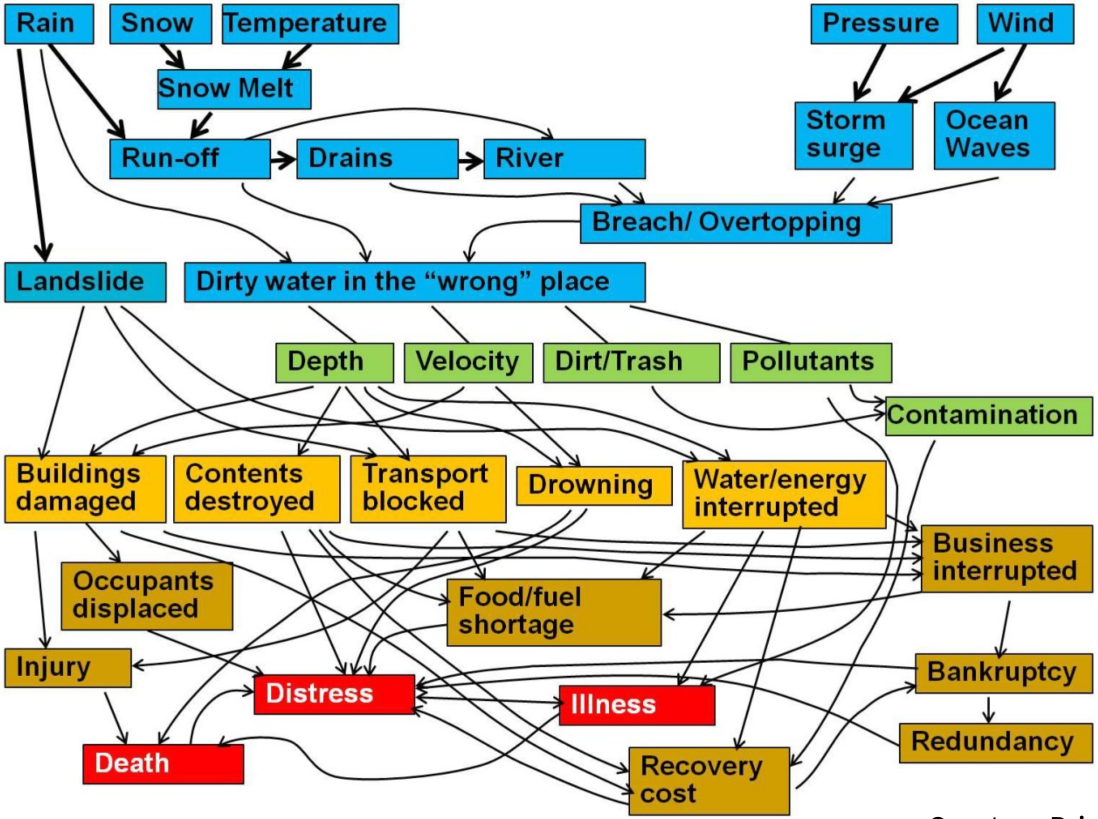
Measures intersects between impact polygons and GHM forecast summary polygons

WWRP High Impact Weather Project

Aim: Improve forecasts on timescales of minutes to weeks and enhance their utility in social, economic and environmental applications

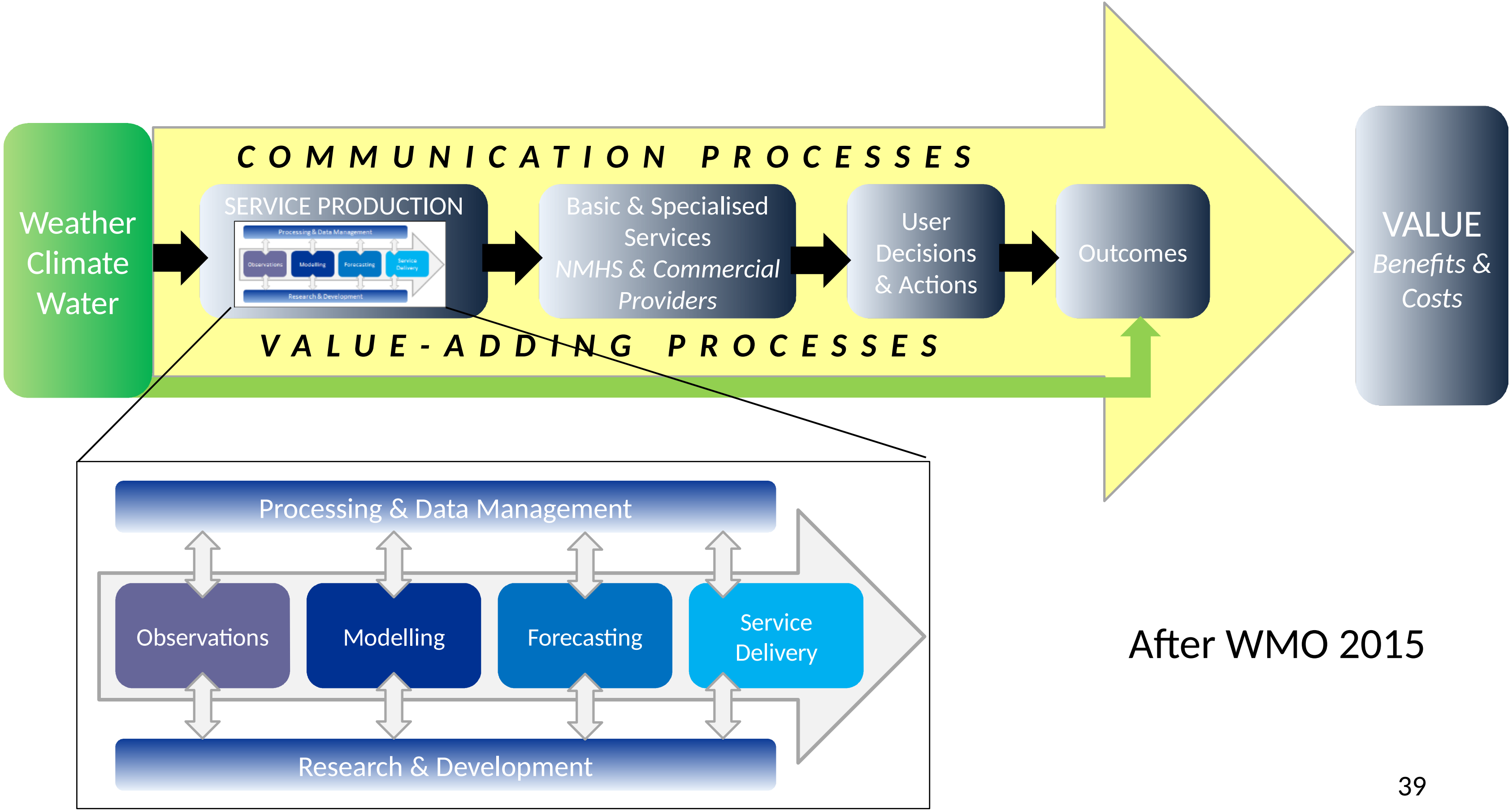


Example: Flood hazard and its impacts



Courtesy Brian Golding

Weather information value chain



After WMO 2015

HIWeather challenges for user-oriented evaluation

- Appropriate verification methods for temporal and spatial high impact weather forecasts (high resolution ensembles, extremes, nowcasts, warnings, downstream hazards, etc.)
- Use social media and non-standard data to evaluate hazards, impact, response
- Build users' trust by informing about good and bad forecasts, and user-focused verification approaches
- Entrain social scientists to help understand the decisions made in response to high impact weather and associated hazards
- Evaluation of the weather information value chain
- Quantify the socio-economic benefits of high impact weather forecasts, including identifying avoided losses

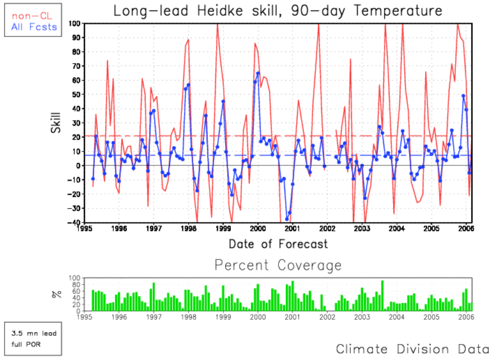
Final remarks

- Enormous progress in recent years in improving methods for verifying high impact weather
  - Spatial / diagnostic verification approaches now mainstream
  - New methods for verifying rare extreme events
  - Simple approaches appropriate for communicating with some users
  - Need more work on timing verification
- Observations of high impact weather remains a challenge
  - Unconventional observations getting more uses
  - Methods for dealing with observation uncertainty are in development
- WWRP High Impact Weather project is encouraging user-oriented evaluation of impacts and whole value chain

Levels of user focus

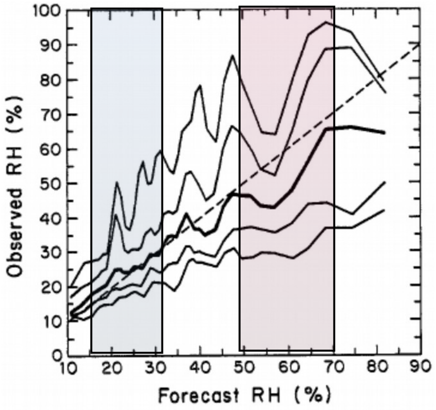
Level 0: Conventional *measures-based approaches*

- Best for administrative purposes



Level 1: Broad *diagnostic approaches*

- Evaluate variables of interest to users
- User-selectable information (stratifications, thresholds)
- Often graphical
- Confidence intervals



Courtesy Barb Brown

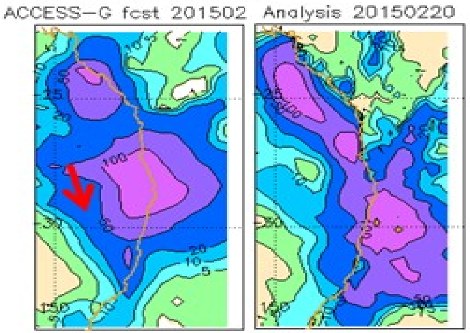
Levels of user focus

Level 2: *Features-based and enhanced diagnostic* approaches applied

- Evaluation of **multiple attributes** of broad interest to users

Level 3: *User-specific* approaches and measures

- Interact closely with users to determine meaningful approaches and measures
- May include specialized datasets that are user-specific



Level 4: *Forecast value* estimated, making use of user-focused verification information

- Close interaction with users
- Deep understanding of users' decision-making and applications of forecasts

Courtesy Barb Brown