# Quantifying the quality of forecasts and forecasting systems

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Meteorology Meets Social Science UK Met Office / 8 June 2007

#### **Outline**

#### Overview of verification

Aspects of forecast quality Uncertainty in verification

#### Verification for extreme events

A probability model Application to rainfall forecasts

Conclusion

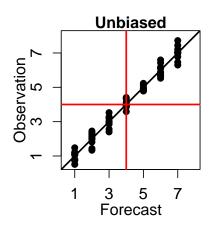
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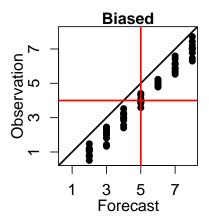
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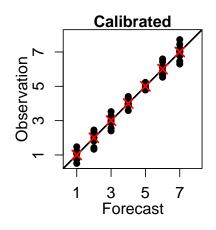
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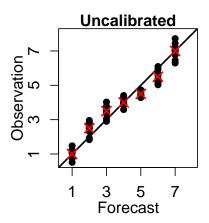
## Aspects of forecast quality: bias



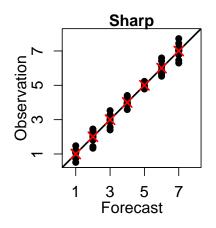


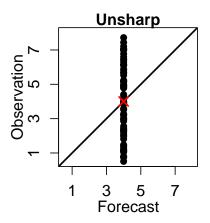
## Aspects of forecast quality: calibration





## Aspects of forecast quality: sharpness

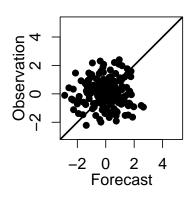


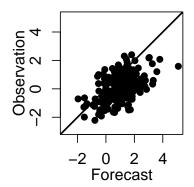


## Mean squared error (MSE)

MSE = variance of observations + variance of forecasts- 2 x covariance + squared bias

= calibration - resolution + variance of observations





## Signal detection theory: ROC analysis

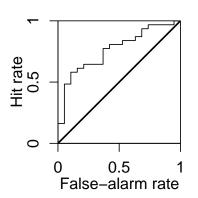
Forecast event if decision variable exceeds threshold.

	Observed	Not Obs.	
Forecasted	а	b	a+b
Not Forecasted	С	d	c + d
	a + c	b+d	n

Form table and compute

Hit rate 
$$= \frac{a}{a+c}$$
  
False-alarm rate  $= \frac{b}{b+d}$ 

for each possible threshold.



#### Properties of verification scores

**Proper** Expected score is optimised by forecasting true, probabilistic belief: discourages hedging.

**Consistent** Proper, for scores of deterministic forecasts derived from probabilistic forecasts via a rule.

**Equitable** Expected score is identical for all constant or random forecasts.

**Sufficient** Forecasts, from which others with equal quality to mine can be derived, score better than mine.

**Regular** Contours of score on ROC diagram are convex, complete, and pass through (0,0) and (1,1).

Score depends on the forecasted probability of the observation only.

#### How should/do we use verification measures?

#### Forecast producers

- Systematic assessment can reveal deficiencies...
  - ... and possible remedies.
- Prevent hedging: what, why, how?

#### Forecast users

- Some measures can relate directly to value...
  - ... perhaps more links can be established.
- ▶ How are decisions influenced by overall forecast quality?

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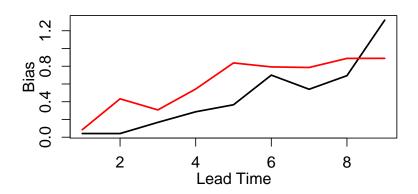
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## Uncertainty in verification

#### Incomplete information

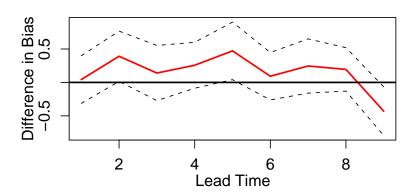
- Assume the sample represents the population
- ► Compute confidence intervals etc. for the 'true' quality
- Avoid using the same data to form and assess forecasts



## Uncertainty in verification

#### Incomplete information

- Assume the sample represents the population
- Compute confidence intervals etc. for the 'true' quality
- Avoid using the same data to form and assess forecasts



## Uncertainty in verification

#### Incomplete information

- Better methods for quantifying uncertainty
- What if forecast quality is not stationary?

Observation error

Quality of untried forecasting systems

Quality of systems in untried situations

Other sources of uncertainty?

## Summary

- Various aspects of forecast quality
- Careful use of appropriate measures
- Faithful description of uncertainty

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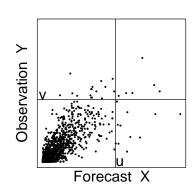
## Direct approach

	Observed	Not Obs.	
Forecasted	а	b	a + b
Not Forecasted	С	d	c+d
	a + c	b+d	n

Hit rate = 
$$\frac{a}{a+c}$$

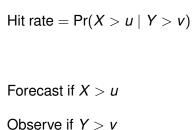
Forecast if X > u

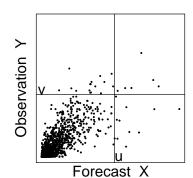
Observe if Y > v



## Probability approach

	Observed	Not Obs.	
Forecasted	Pr(X > u, Y > v)	*	Pr(X > u)
Not Forecasted	*	*	*
	Pr(Y > v)	*	1





# Probability model

Imagine choosing *u* so that

$$Pr(X > u) = Pr(Y > v) =: p$$
 (base rate)

Extreme-value theory implies

$$Pr(X > u, Y > v) = \kappa p^{1/\eta}$$
 for small  $p$ 

under weak conditions.

Ledford & Tawn (1996, Biometrika)



#### Interpretation

	Observed	Not Observed	
Forecasted	$\kappa oldsymbol{ ho}^{1/\eta}$	*	р
Not Forecasted	*	$1-2p+\kappa p^{1/\eta}$	*
	р	*	1

Superior Superior Hit rate  $= \kappa p^{1/\eta - 1}$ for  $p > p^*$ for all p  $\kappa_1$  $\kappa_2$ Superior Inferior for  $p < p^*$ for all p  $\eta_1$  $\eta_2$ 

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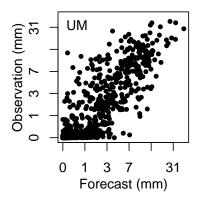
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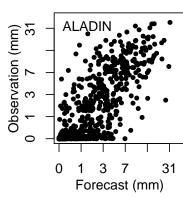
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## Daily rainfall: mid-Wales, 1 Jan 05 – 11 Nov 06

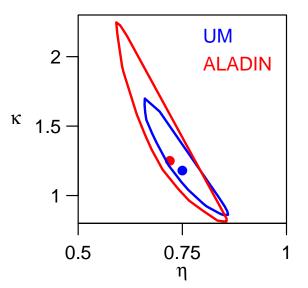




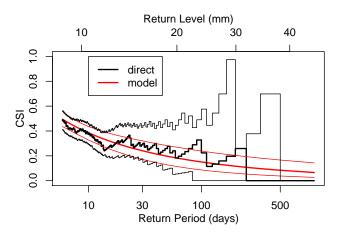


- ▶ Maximum-likelihood estimates of  $\eta$  and  $\kappa$  based on ranks
- ▶ Threshold choice and model assumptions

#### Parameter estimates



#### Verification measures



- Direct estimates degenerate for rare events
- Model estimates change smoothly and are more precise

## Summary

- Deterministic forecasts of rare, extreme events
- Only two parameters needed to describe how quality or value of calibrated forecasts changes with base rate
- The model gives more precise estimates of forecast quality

#### Conclusion

- Statistical models help to identify and measure aspects of forecast quality, their changes and associated uncertainty.
- Why/how should/do producers/users use/do verification?
- Are current methods and procedures adequate?
- Can we verify the quality of decisions?

Papers, code and slides available at

www.secam.ex.ac.uk/people/staff/ferro

c.a.t.ferro@exeter.ac.uk



**Appendix** 

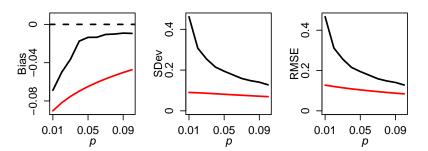
Simulation study

Model theory

Limiting behaviour of verification measures

# Simulation study

- Bivariate Normal data: correlation 0.8
- Direct and model estimates of hit rate



## Model theory - 1

Imagine choosing *u* so that

$$\Pr(X > u) = \Pr(Y > v) =: p \qquad \text{(base rate)}.$$
 Define  $\tilde{X} = -\log[1 - F(X)] \quad \text{where} \quad F(x) = \Pr(X \le x)$  
$$\tilde{Y} = -\log[1 - G(Y)] \qquad \qquad G(y) = \Pr(Y < y)$$

Then  $\tilde{X}$  and  $\tilde{Y}$  are Exponential with unit means and

$$Pr(X > u, Y > v) = Pr(\tilde{X} > -\log p, \tilde{Y} > -\log p)$$
  
=  $Pr(Z > -\log p)$ 

where  $Z = \min\{\tilde{X}, \, \tilde{Y}\}.$ 

## Model theory – 2

For  $\tilde{X}$  and  $\tilde{Y}$  Exponential with unit means and  $Z = \min\{\tilde{X}, \tilde{Y}\},\$ 

$$\Pr(Z > z) = \left\{ egin{array}{ll} \exp(-z) & ext{if } \tilde{X} \equiv \tilde{Y} \\ \exp(-2z) & ext{if } \tilde{X} \perp \tilde{Y} \end{array} 
ight.$$

**Assume** 

$$\Pr(Z > z) \sim \mathcal{L}(e^z) \exp(-z/\eta)$$
 as  $z \to \infty$ ,

where  $0 < \eta \le 1$  and  $\mathcal{L}(rt)/\mathcal{L}(r) \to 1$  as  $r \to \infty$  for all t > 0.

e.g. 
$$(X, Y) \sim \text{Normal has } \eta = [1 + \text{cor}(X, Y)]/2.$$

Ledford & Tawn (1996, Biometrika)

## Model theory – 3

$$\Pr(Z>z) \sim \mathcal{L}(e^z) \exp(-z/\eta)$$
 where  $\mathcal{L}(rt)/\mathcal{L}(r) \to 1$  as  $r \to \infty$ .

For a high threshold  $w_0$ ,

$$\Pr(Z > w_0 + z) \approx \mathcal{L}(e^{w_0 + z}) \exp[-(w_0 + z)/\eta]$$
  
 
$$\approx \mathcal{L}(e^{w_0}) \exp[-(w_0 + z)/\eta]$$

so model

$$Pr(Z > z) = \kappa \exp(-z/\eta)$$
 for all  $z > w_0$ 

i.e.

$$\Pr(Z > -\log p) = \kappa p^{1/\eta}$$
 for all  $p < \exp(-w_0)$ .



# Limiting behaviour of measures

Hit rate 
$$= \frac{a}{a+c} \sim \kappa p^{1/\eta-1} \rightarrow \left\{ egin{array}{ll} 0 & \mbox{if } \eta < 1 \\ \kappa & \mbox{if } \eta = 1 \end{array} 
ight.$$

$$PC = \frac{a+d}{n}, \qquad PSS = \frac{ad-bC}{(a+c)(b+d)}, \qquad OR = \frac{ad}{bc}$$

$$\frac{\eta < \frac{1}{2}}{C} \qquad \frac{\eta = \frac{1}{2}}{1 - 2p \uparrow 1} \qquad \frac{\eta = 1}{1 - 2\bar{\kappa}p \uparrow 1}$$

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where  $\delta = 1/\eta$  and  $\bar{\kappa} = 1 - \kappa$ 

## Limiting behaviour of measures

Hit rate 
$$=\frac{a}{a+c}\sim \kappa p^{1/\eta-1} \to \left\{ egin{array}{ll} 0 & \mbox{if } \eta<1 \ \kappa & \mbox{if } \eta=1 \end{array} 
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$$PC = \frac{a+d}{n}$$
,  $PSS = \frac{ad-bc}{(a+c)(b+d)}$ ,  $OR = \frac{ad}{bc}$ 

where  $\delta = 1/\eta$  and  $\bar{\kappa} = 1 - \kappa$ 

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$$\begin{aligned} & \text{PC} = \frac{a+d}{n}, & \text{PSS} = \frac{ad-bc}{(a+c)(b+d)}, & \text{OR} = \frac{ad}{bc} \\ & \frac{\eta < \frac{1}{2}}{\text{PC}} & \frac{\eta = \frac{1}{2}}{1-2\rho \uparrow 1} & \frac{\eta > \frac{1}{2}}{1-2\bar{\kappa}\rho \uparrow 1} & \frac{\eta = 1}{1-2\bar{\kappa}\rho \uparrow 1} \\ & \text{PSS} & -\rho \uparrow 0 & -\bar{\kappa}\rho \uparrow 0 & \kappa\rho^{\delta-1} \downarrow 0 & \kappa-\bar{\kappa}\rho \uparrow \kappa \\ & \text{OR} & \kappa\rho^{\delta-2} \downarrow 0 & \kappa-2\kappa\bar{\kappa}\rho \uparrow \kappa & \kappa\rho^{\delta-2} \uparrow \infty & \kappa/(\bar{\kappa}^2\rho) \uparrow \infty \end{aligned}$$

where  $\delta = 1/\eta$  and  $\bar{\kappa} = 1 - \kappa$ 

## Contradictory skill scores?

ERA-40 daily rainfall forecasts:  $\eta = 0.81, \kappa = 1.16$ 

