Environment Agency

Environment Agency

We are the Environment Agency. It's our job to look after your environment and make it a better place – for you, and for future generations.

The Environment Agency. Out there, making your environment a better place.

Probabilistic Flood Forecasting

Mike Vaughan
Flood Forecasting Technical Specialist

85th European Study Group with Industry
UEA, Norwich, 16-20 April 2012

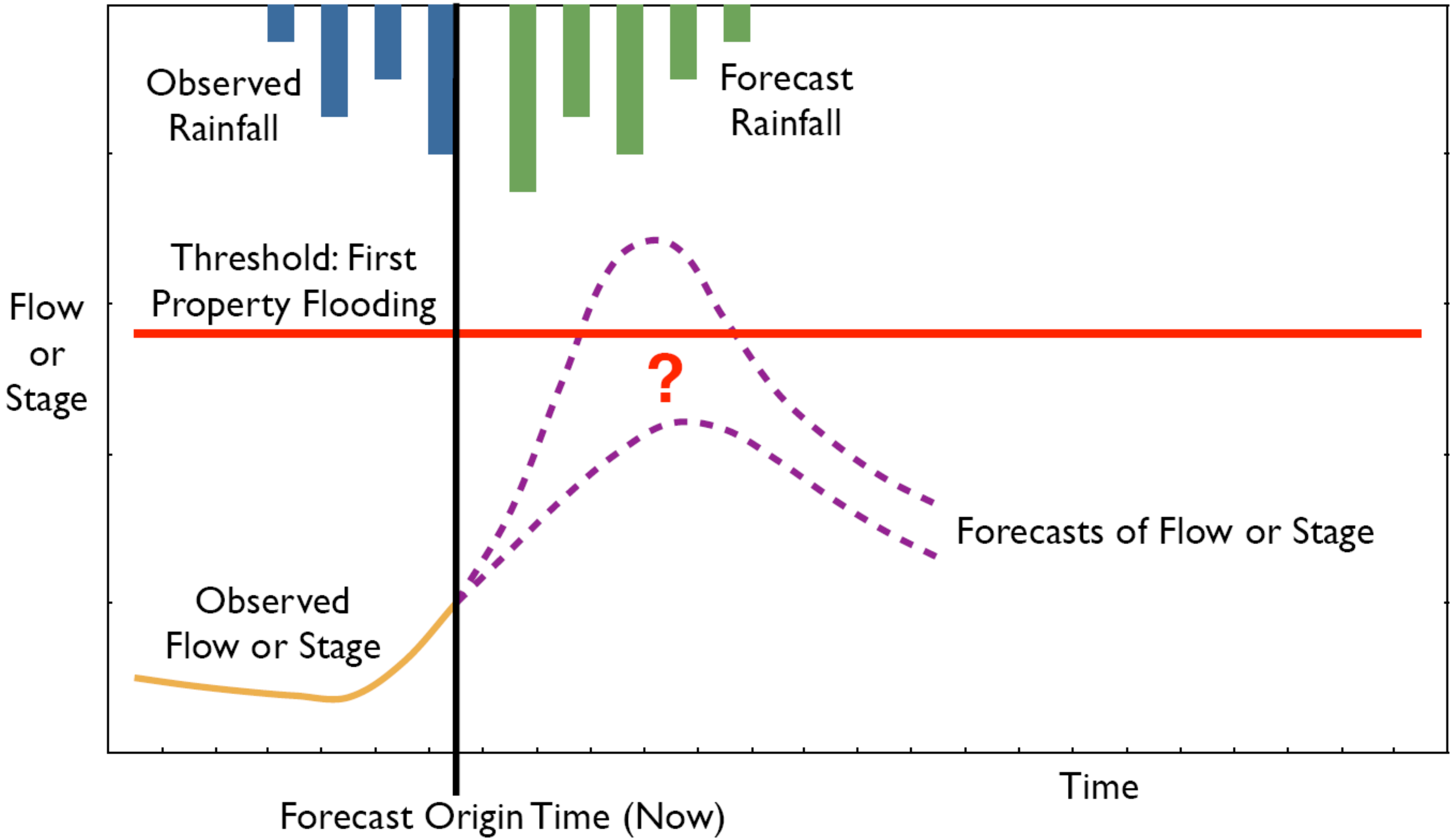
Acknowledgements

- Richard Cross
- Tim Harrison
- Stefan Laeger
- Paul Wass (JBA Consulting)
- Rob Lamb (JBA Consulting)
- … and others

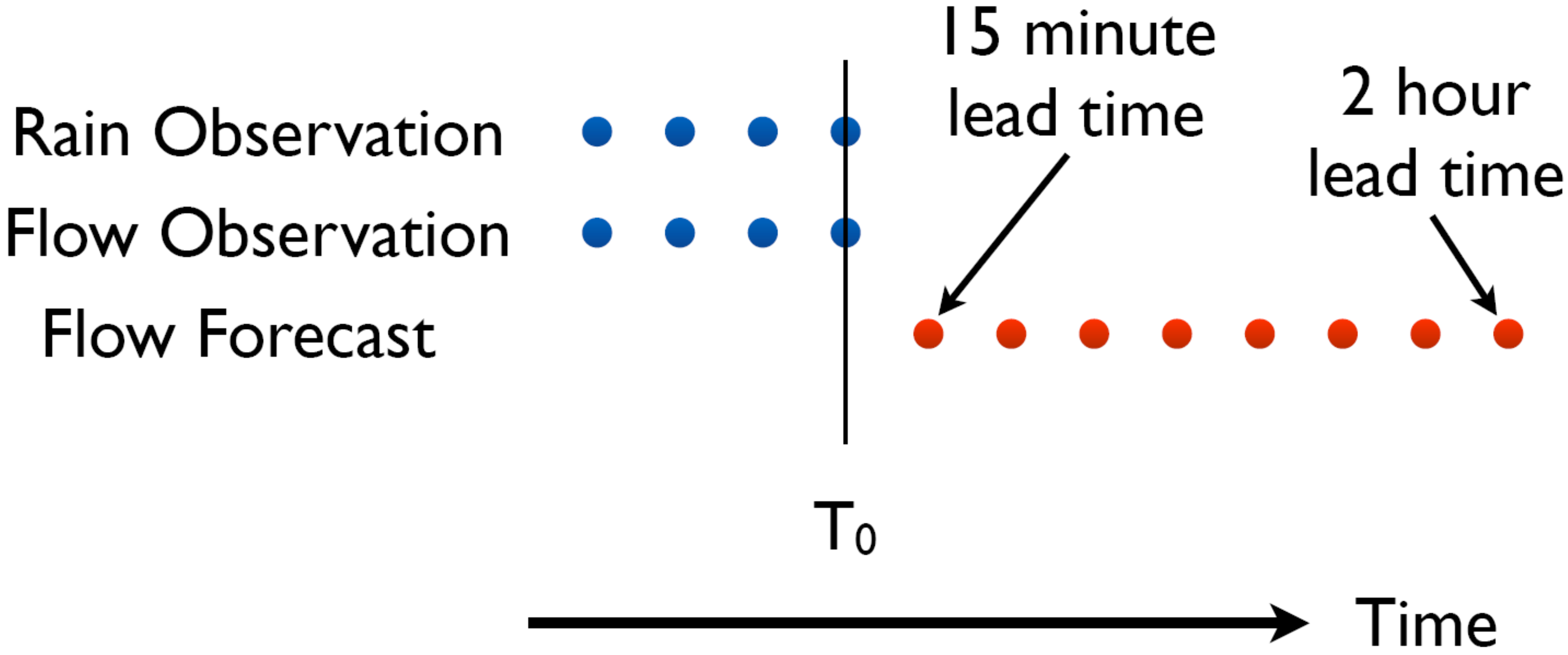
Environment Agency

What is real-time flood forecasting?

What do we forecast?



Lead time

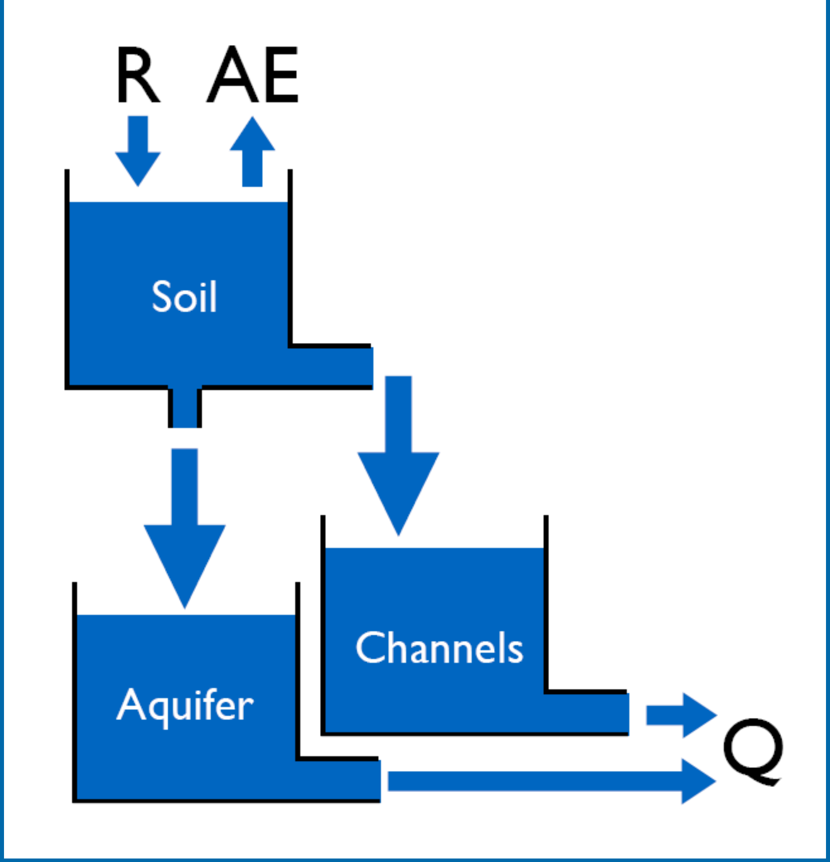


(Timestep = 15 minutes, for example)

Forecasting models

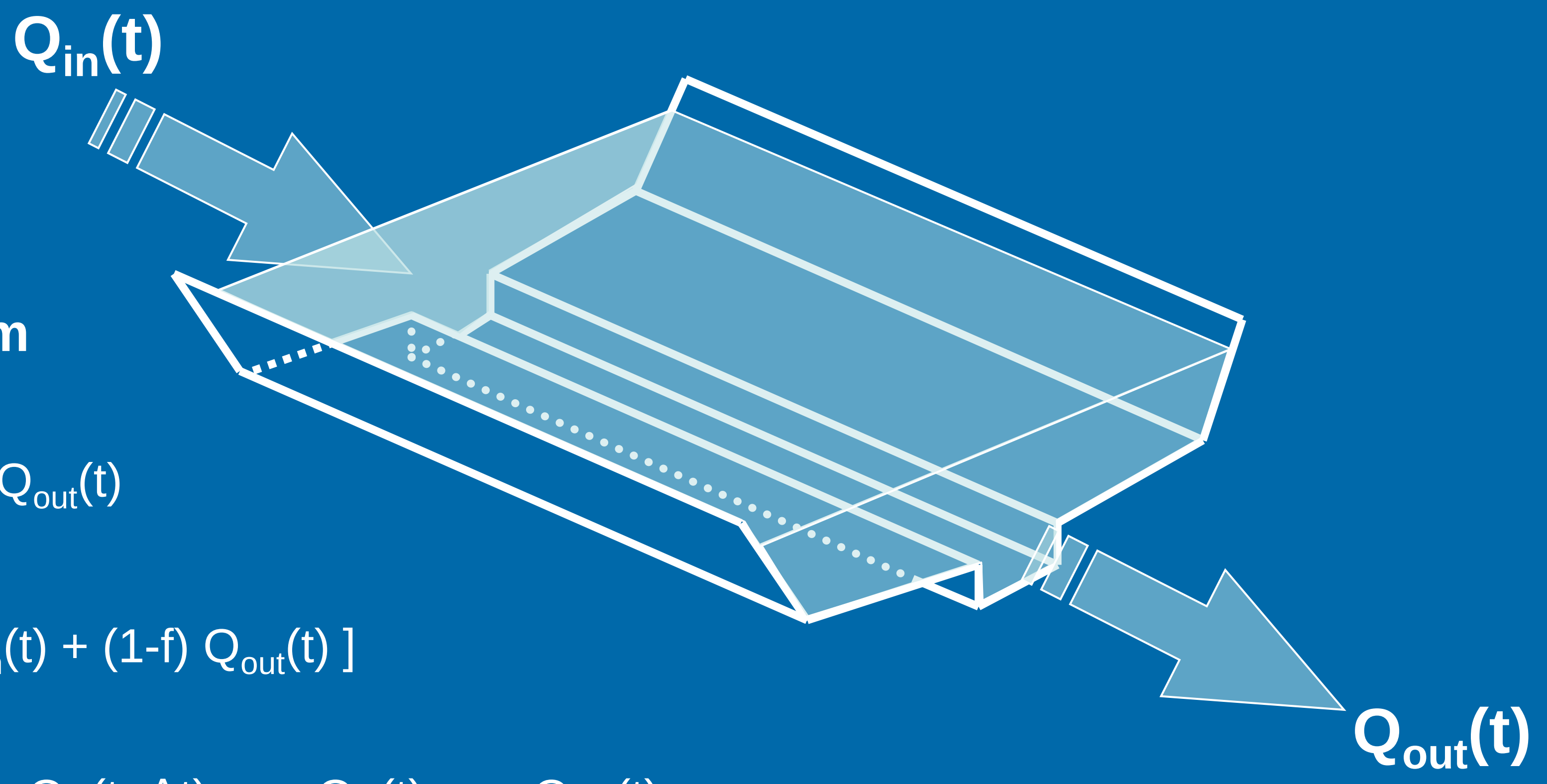
- Rainfall-runoff
- River routing
- Real-time updating
  - Error prediction / correction
  - Data assimilation
- Cascades of rainfall-runoff and routing models

Conceptual rainfall-runoff models



- Model structure
- Parameters
- Inputs
  - Rainfall
  - Potential evaporation
- Initial conditions
- Outputs
  - Discharge
  - Actual evaporation

River routing models



Muskingham

$$\frac{dS}{dt} = Q_{in}(t) - Q_{out}(t)$$

$$S(t) = k \left[f\, Q_{in}(t) + (1\text{-}f)\, Q_{out}(t) \right]$$

$$Q_{out}(t+\Delta t) = c_1\, Q_{in}(t+\Delta t) + c_2\, Q_{in}(t) + c_3\, Q_{out}(t)$$

Real-time updating

- State updating
- Error prediction / correction
- Parameter updating

Empirical State Updating

Prediction error

$$\epsilon_t = Q_t^{(sim)} - Q_t^{(obs)}$$

2 Parallel flow paths

$$Q_t^{(sim)} = q_{b,t} + q_{s,t}$$

Updated flows

$$q^*_{b,t} = q_{b,t} + \alpha g_b \epsilon_t$$

$$q^*_{s,t} = q_{s,t} + (1-\alpha) g_s \epsilon_t$$

$$\alpha = \frac{q_b}{(q_s + q_b)}$$

Moore, 2007 (Hyd. Earth. Sys. Sci.)

Error Prediction / Correction

$$\varepsilon_t = Q_t^{(sim)} - Q_t^{(obs)}$$

AR Model

$$\varepsilon_t = a_1 \varepsilon_{t-1} + a_2 \varepsilon_{t-2} + \cdots + a_n \varepsilon_{t-n} + \epsilon_t$$

Recursive Prediction

$$\hat{\varepsilon}_{t_0+k|t_0} = a_1 \hat{\varepsilon}_{t_0+k-1|t_0} + a_2 \hat{\varepsilon}_{t_0+k-2|t_0} + \cdots + a_n \hat{\varepsilon}_{t_0+k-n|t_0}$$

Stage (water level) forecasts

Rating curve used to convert flow forecasts from rainfall-runoff or simple river routing models

$$Q = \begin{cases} C_1(H - a_1)^{b_1} & H_1 \le H < H_2 \\ C_2(H - a_2)^{b_2} & H_2 \le H < H_3 \\ C_3(H - a_3)^{b_3} & H_3 \le H < H_4 \\ \quad \text{etc} & \end{cases}$$

Hydrodynamic model flow and stage are both model outputs

What is probabilistic flood forecasting?

Environment Agency

Probabilistic forecasting

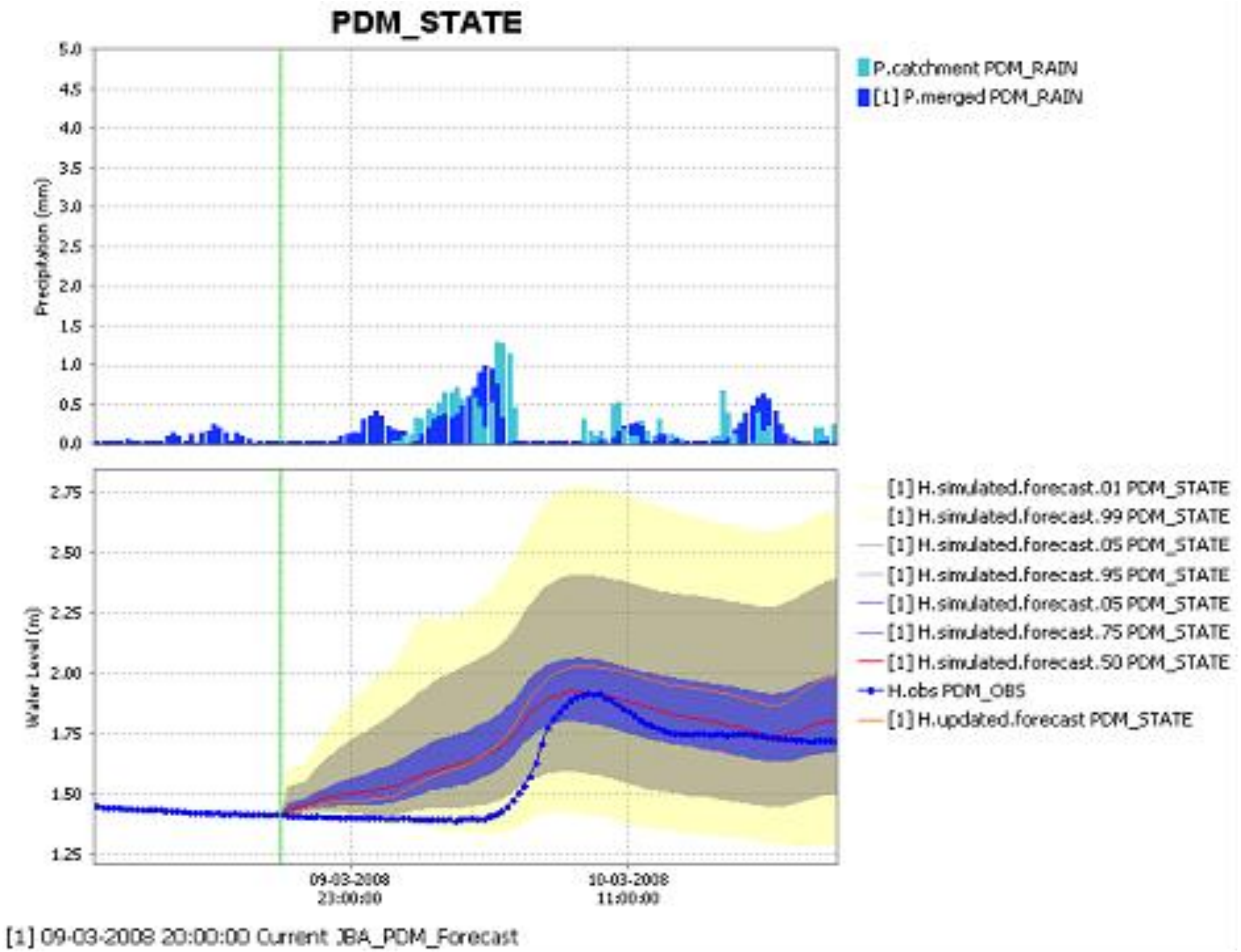
- Accept all forecasts are uncertain / in error
- Want objective way of indicating the uncertainty
- Particularly important for longer lead-times
  - But shorter lead-times too
- Forecasts of probability distributions
  - (or statistics thereof)
- Probabilistic not the only way
  - But may be useful for formal decision making

Approaches to probabilistic flood forecasting

- Forecast conditioning
  - Historic Forecast Performance Tool / Quantile Regression (HFPT / QR)
- Updating using a stochastic scheme
- Stochastic models
- Forward uncertainty propagation
  - Rainfall ensembles

Proposed method

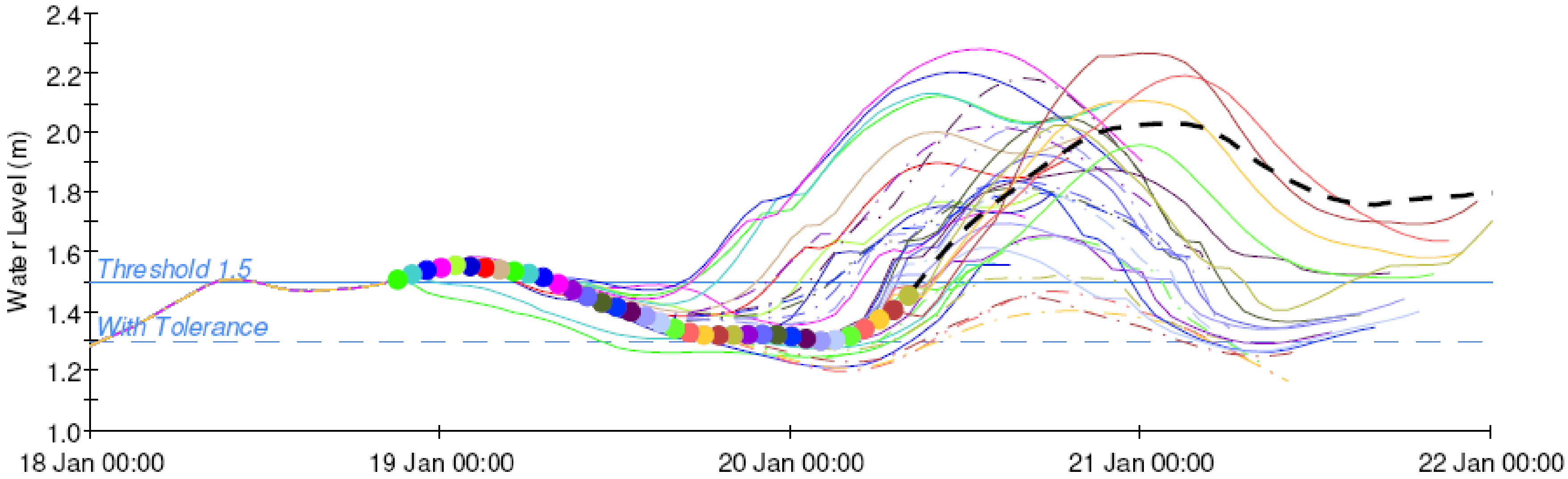
Example of HFPT in NFFS



How HFPT / QR works

- Analysis of historic forecasts
- Additive error
- Use QR to fit linear relationships between error quantiles (at a given lead-time) and forecast magnitude
  - NQT to transform to Gaussian domain
- Adjustment to prevent quantiles crossing
- Look-up table of error quantile as a function of forecast magnitude (for given lead-time)
  - NQT inverted
  - Intermediate lead-times interpollated

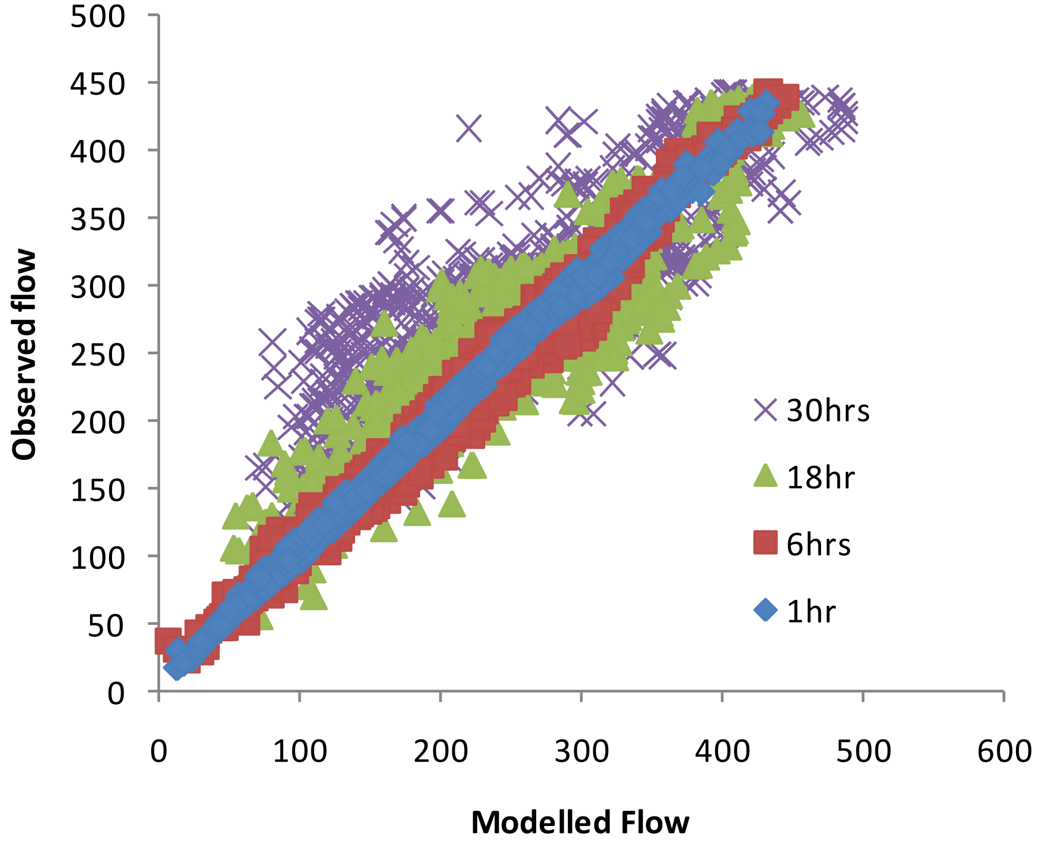
Example forecasts for a single event



Pairs of forecasts and observations at lead times

Figure Error! No text of specified style in document.**-1 : Pairs of observed and modelled values extracted from performance evaluation study at four lead times (River Ouse at Viking)**

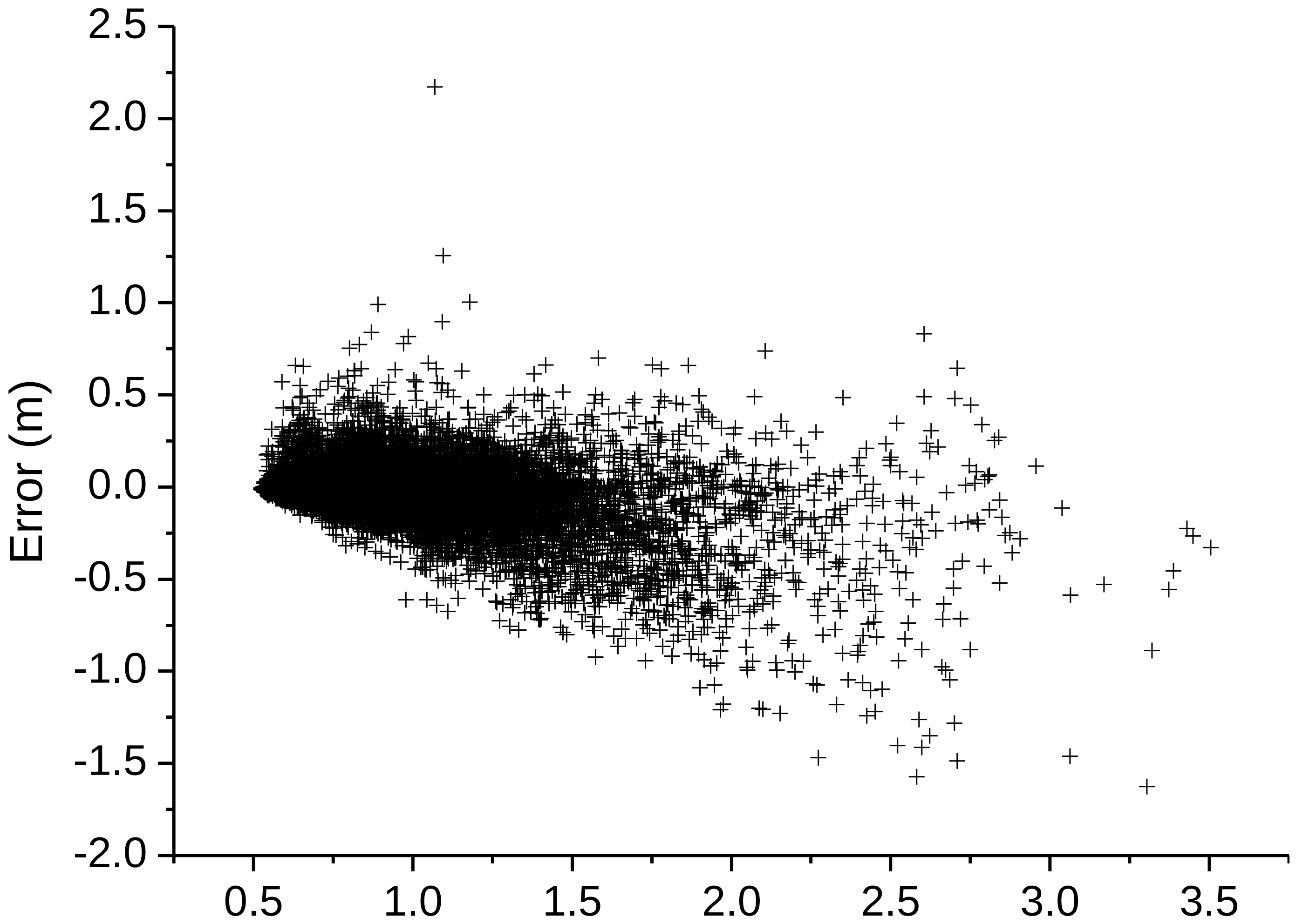
$s(t)$



$\hat{s}(t)$

Forecast errors related to magnitude for a lead time

$$e(t) = s(t) - \hat{s}(t)$$



$\hat{s}(t)$ Forecast magnitude (m)

Normal Quantile Transform (NQT)

1. Sort the sample X from the smallest to the largest observation, $x_{(1)}, \ldots, x_{(n)}$.

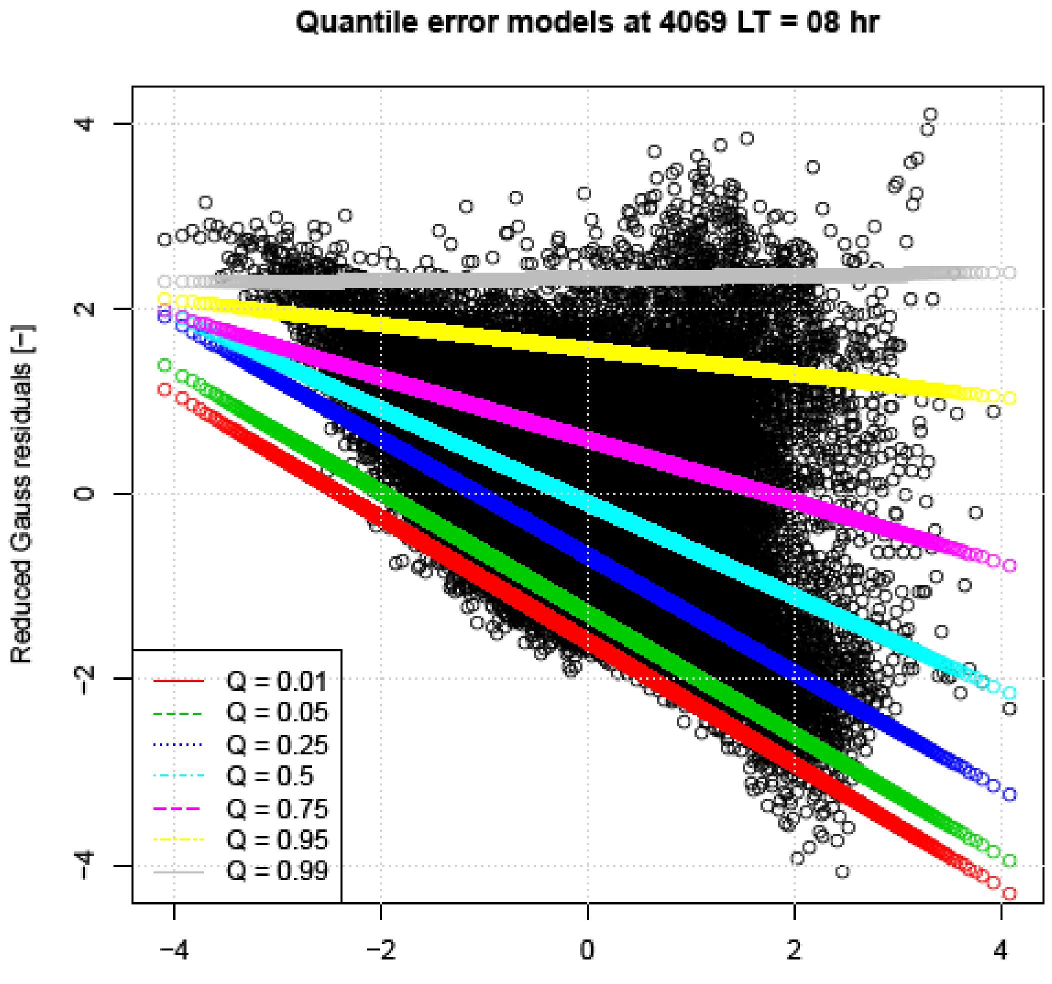
2. Estimate the cumulative probabilities, $p_{(1)}, \ldots, p_{(n)}$, such that $p_{(i)} = Pr(X \leq x_{(i)})$

3. Transform each $x_{(i)}$ of X into $y_{(i)} = Q^{-1}(p_{(i)})$ of the standard normal variate Y.

(e.g. Bogner et al. 2012, Hydrol. Earth Syst. Sci.)

Environment Agency

Transformed data and fitted quantiles

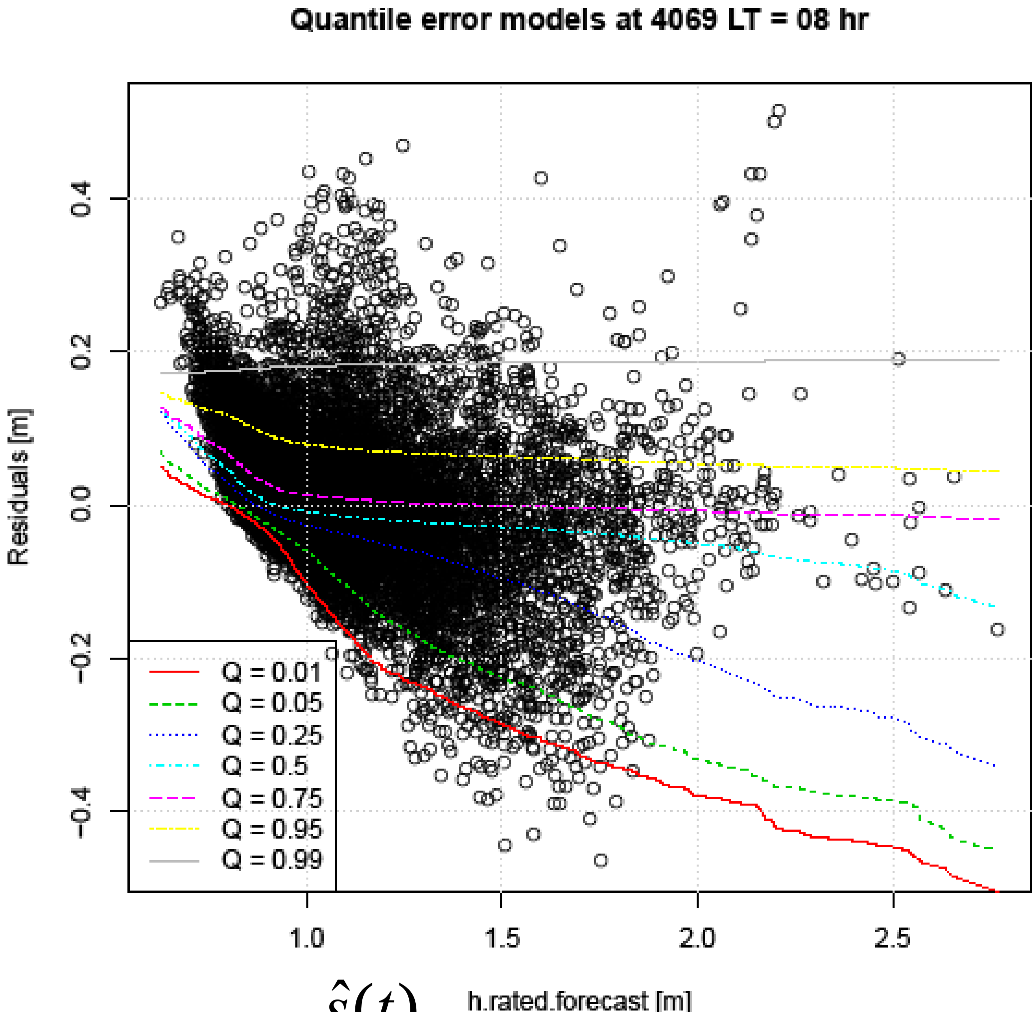


$e_{NQT}(t)$

$\hat{s}_{NQT}(t)$

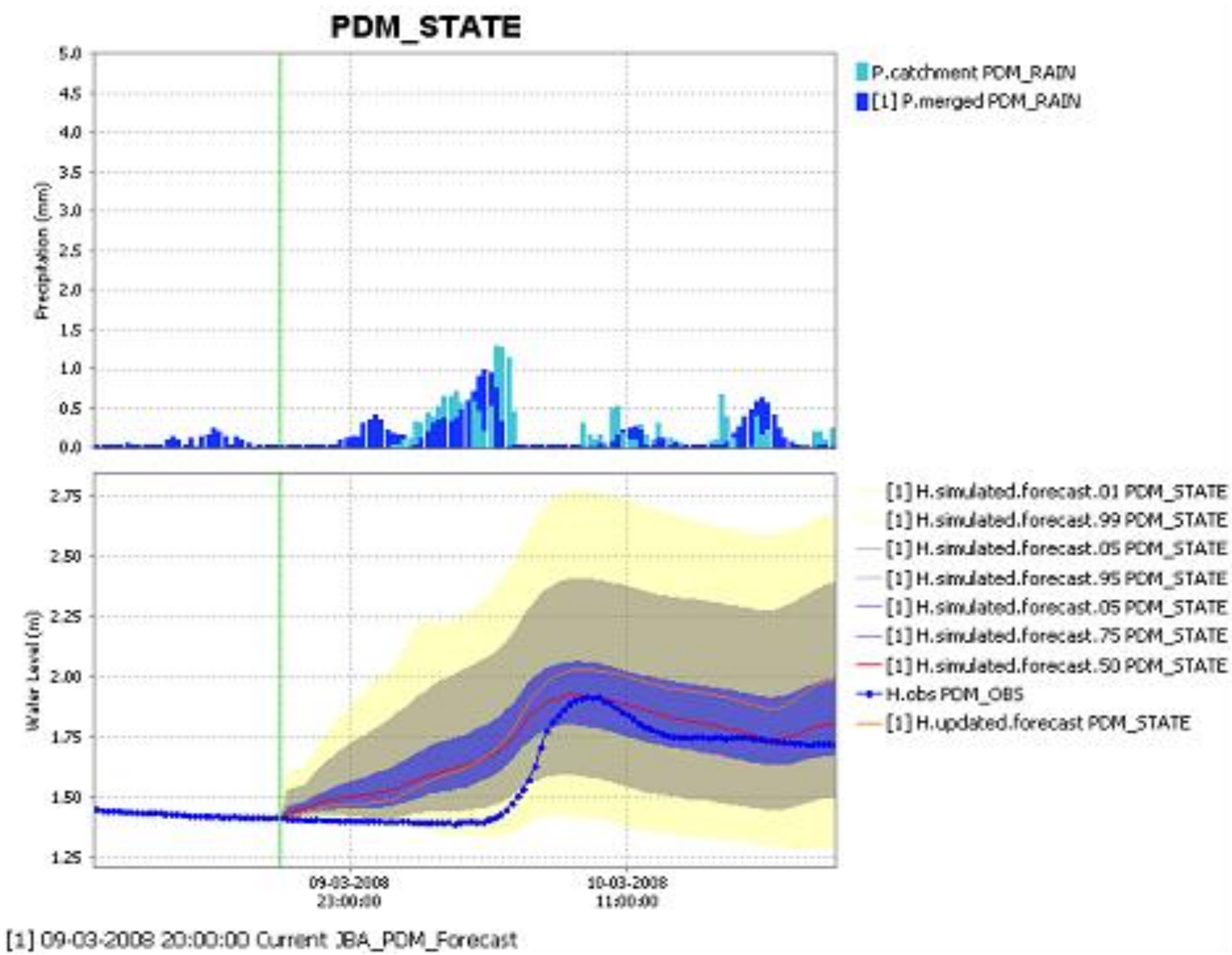
Back transformed data and quantiles

$e(t)$



$\hat{s}(t)$

Example of HFPT in NFFS (again)



Problems found

HFPT – what works

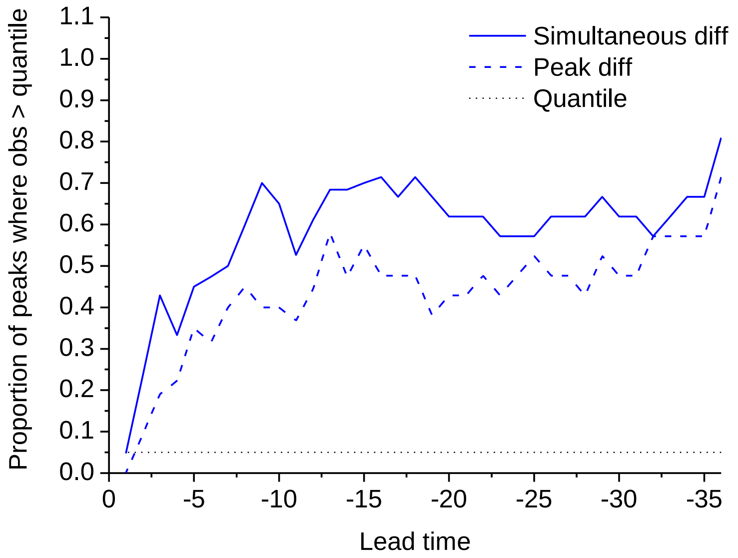
- Weerts et al. (2011) and R&D project
  - Approx 20 sites
  - 2 years calibration (forecast origins every 2(?) hours)
  - 2 years validation – predicted quantiles contained (roughly) the right proportion of observations (for most sites)
- JBA consulting carried out a similar analysis
  - 10 sites / range of catchment types
  - Much longer period of record
  - Same conclusion

HFPT – what doesn’t work

- Events & peaks of most interest
- Further analysis looked at peak and event behaviour
- High proportion of peaks exceeding the highest quantile (95%)

Peak exceedence

- More peaks exceed the upper quantiles than expected



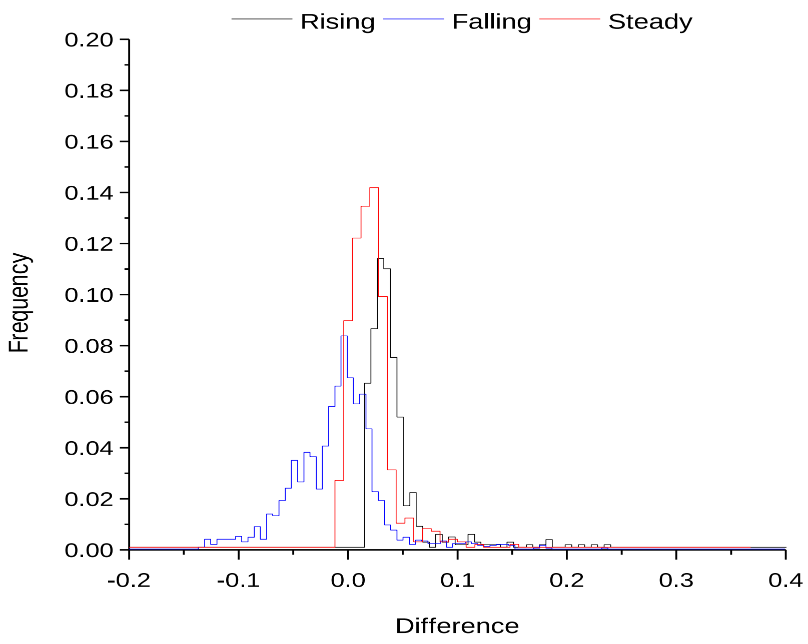
What does this mean?

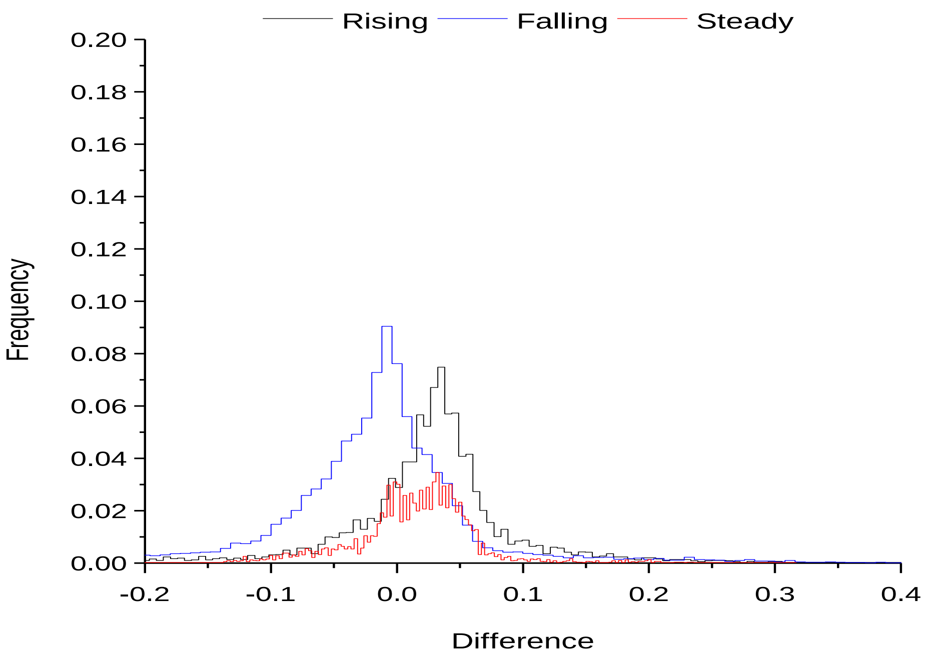
- Plume is not representative of behaviour at the peak
- It DOES mean:
- "over all forecasts made, there is a 5% probability that any one observation will fall above the 95% quantile"
- It does NOT mean that:
- "there is a 95% probability that the observed line will sit below the quantile for this forecast"

Possible explanations

Heteroscedacity

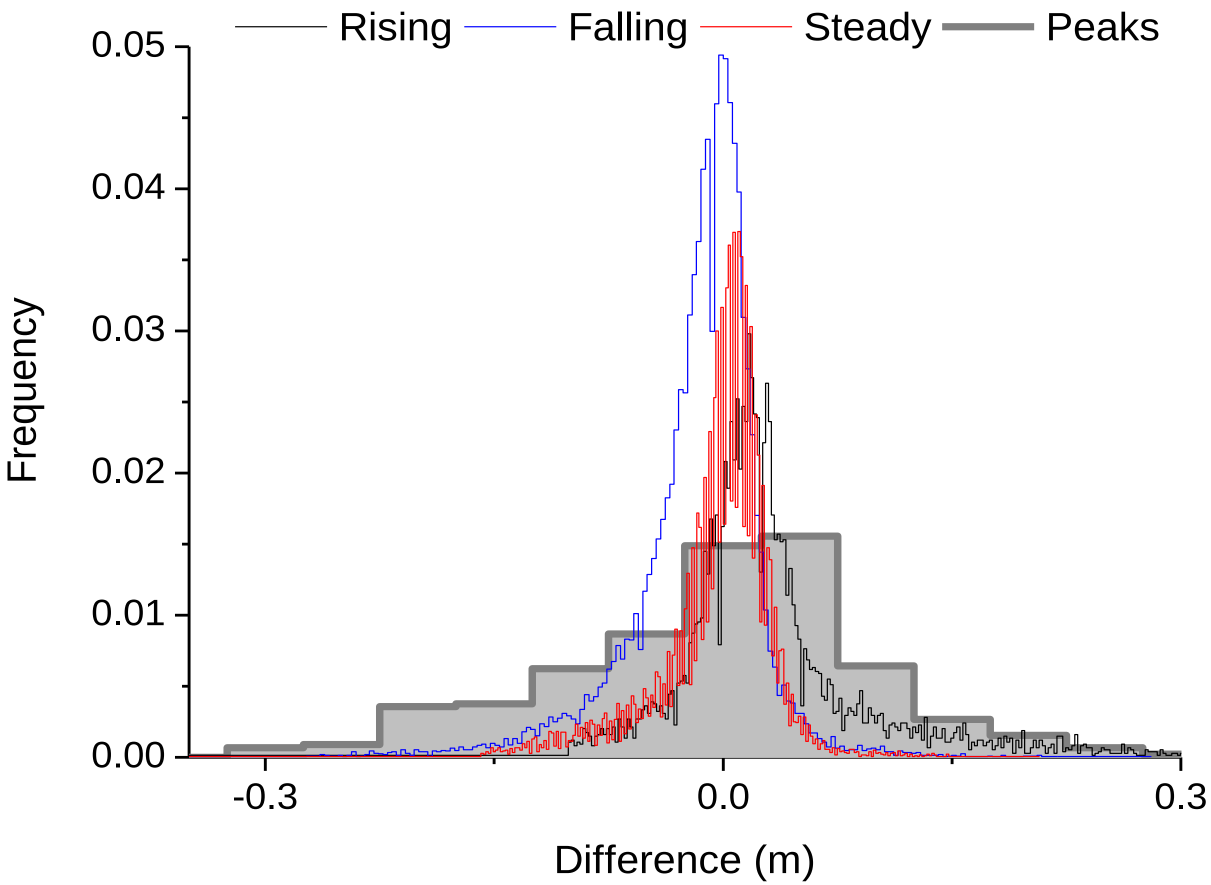
- Errors are different for different parts of a flood event
- Frequency distribution at a lead time for forecast & observed rain (single lead time)





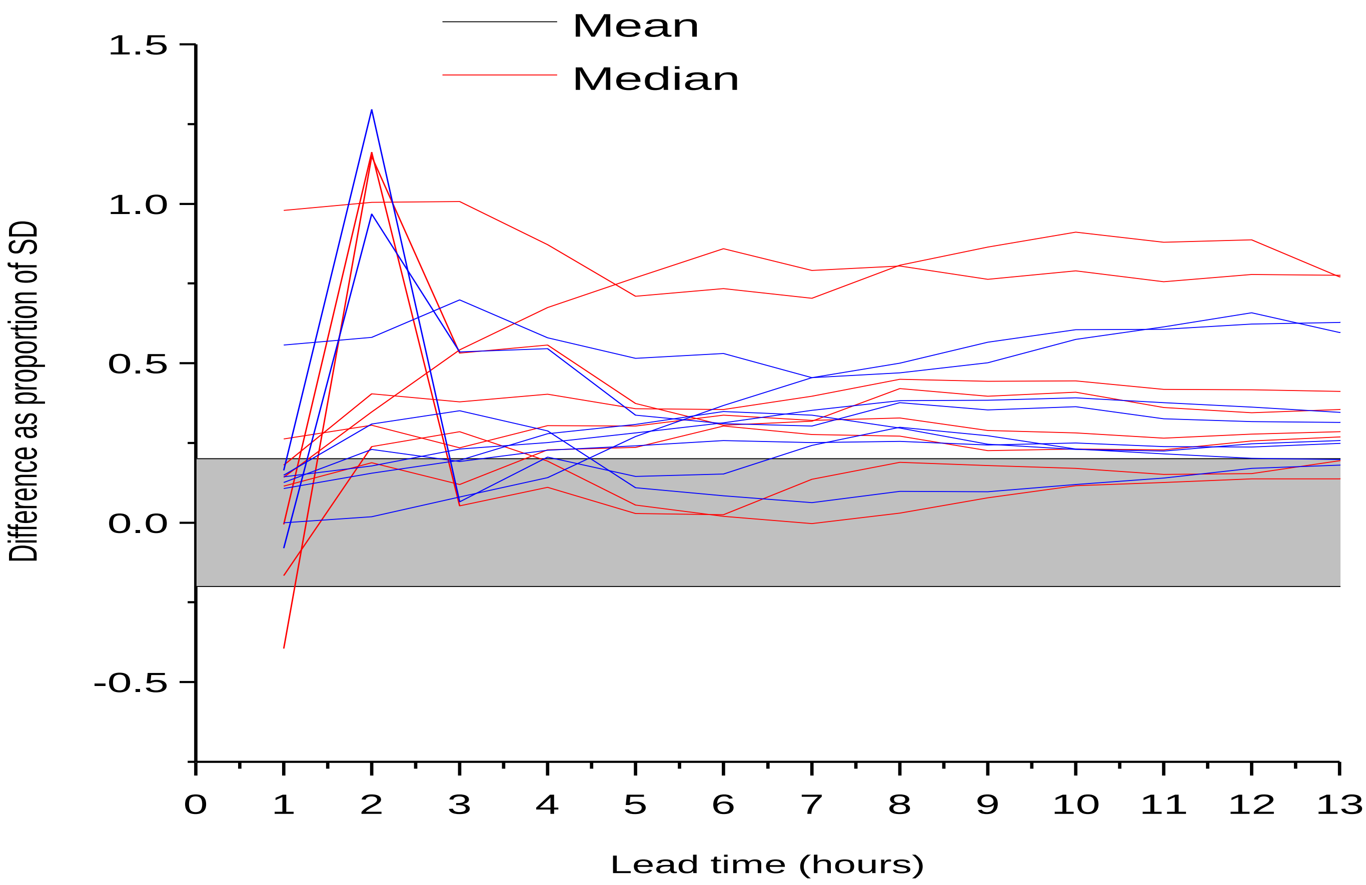
Heteroscedacity

- Including errors in peaks as well (single lead time)



All Tame forecast locations

- Forecast rain



Reasons

- Errors smallest when river receeding (no rain)
- Recession over represented in sample (longer than rise)
- Observed/forecast rainfall errors more prominent at/before peak
- Error correction more problematic on the rise
- Timing errors more of a problem on the rise/peak
- Data heavily autocorrelated – all pairs are not equal (but are treated as such)

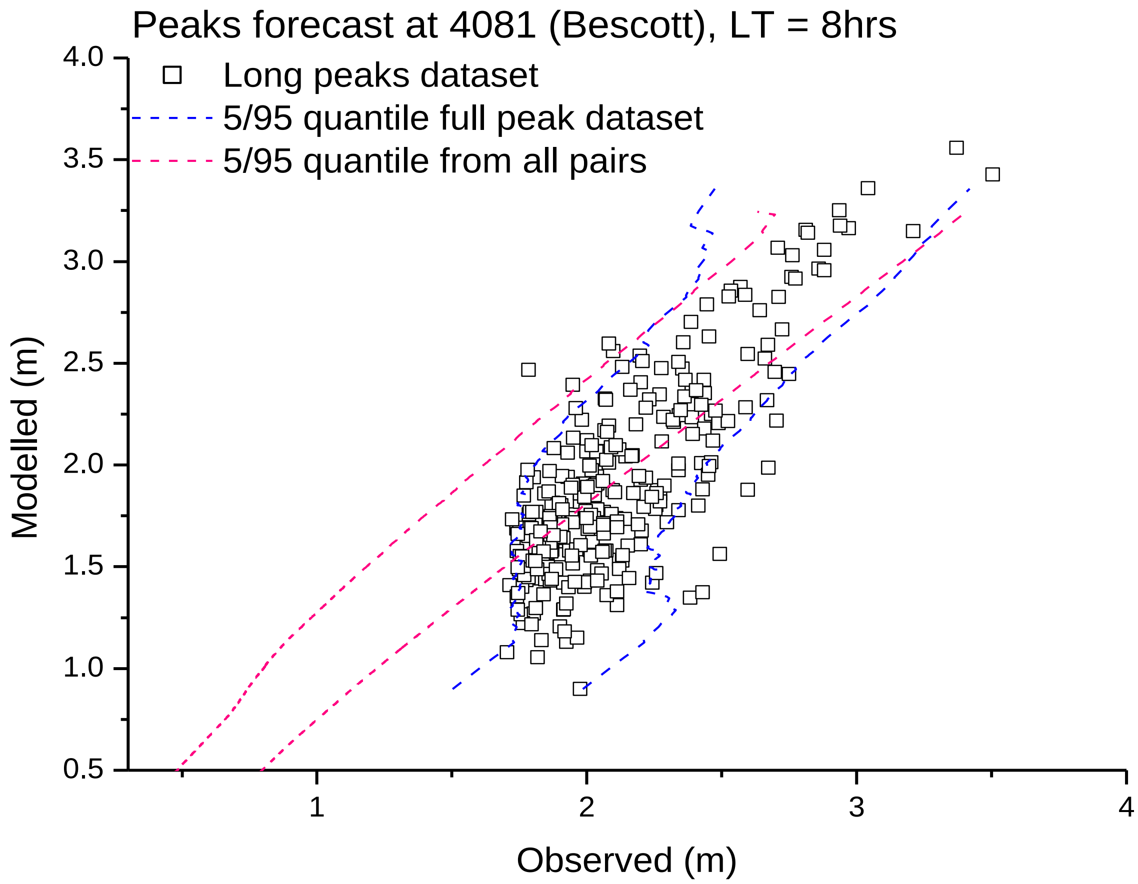
Possible solutions

Alternative QR datasets

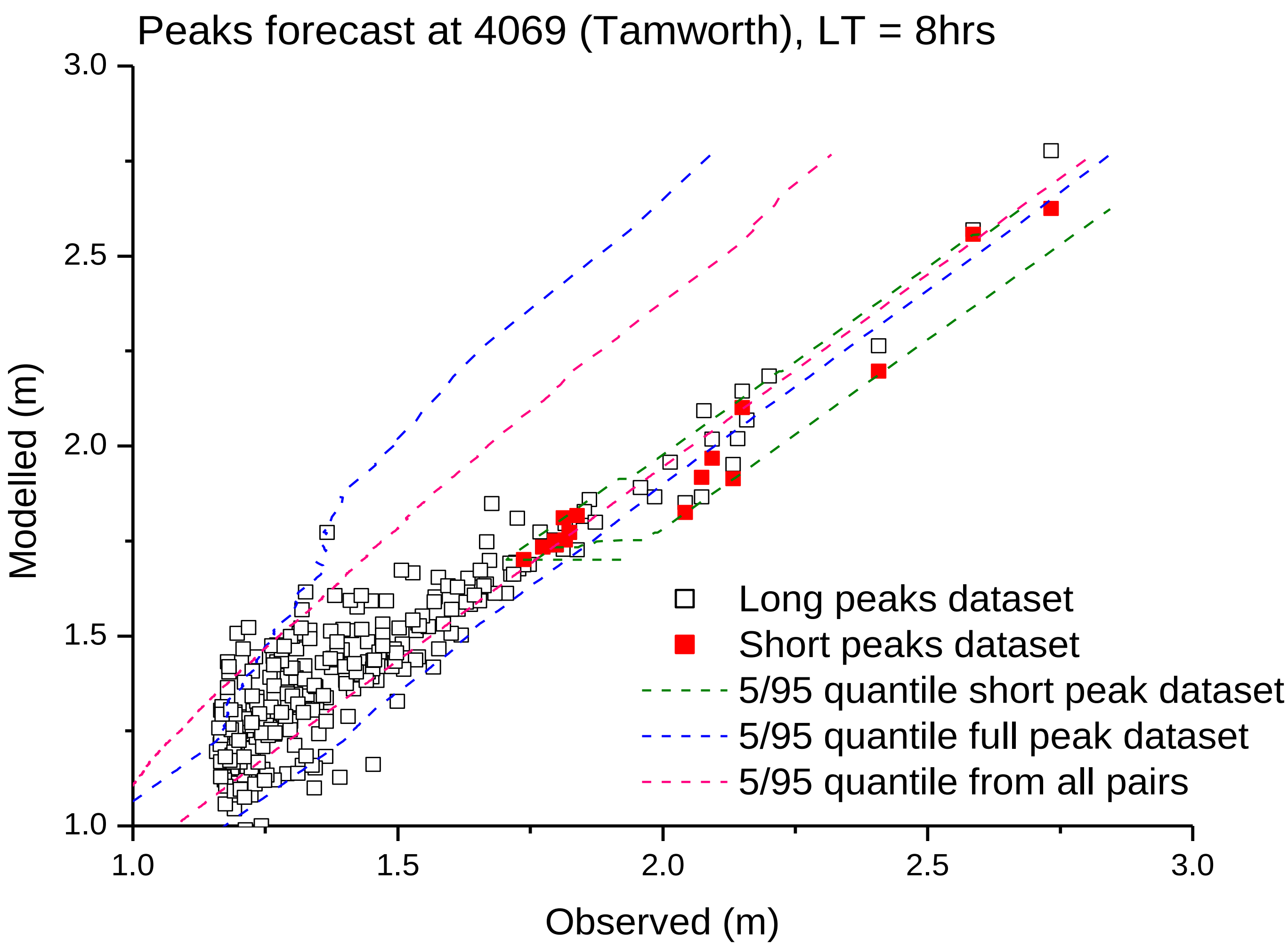
- Peaks – magnitude of difference, ignoring timing error
- One point per event, per lead time for a specific, crucial, point in the forecast
- May enable a probabilistic interpretation of the forecast <u>peak and its timing</u>
- <u>Potential problems:</u>
- Small dataset
- Still sensitive to sampling approach and assumptions about linearity
- Only (truly) applies to forecast peak (no plume)
- --
- Pairs from rising limb

Sampling just the peaks

- Pairs of peak modelled/observed data for single lead time



Linear model a potential problem?



Summary

Environment Agency

Conclusions

- Appears that HFPT / QR, in it’s current form, doesn’t deliver what users expect
  - Non-stationarity
  - QR assumptions
- Modifications possible, but further investigation needed
- Users interested in derived quantities, rather than the whole hydrograph

Questions

- Can the HFPT approach be adapted to give us what we need?
- If so, what needs to be done?

The Test Dataset

- Observed and forecast stage data for one site
  - Time series
  - Pairs for given lead-times & (by rising / falling)
- R script for creating quantile look-up tables
- Quantile fit plots
- Look-up tables
- Metadata
- Catchment map
- Presentation / problem statement