

# Catchment-based precipitation ensemble forecast skill in the presence of observation uncertainty

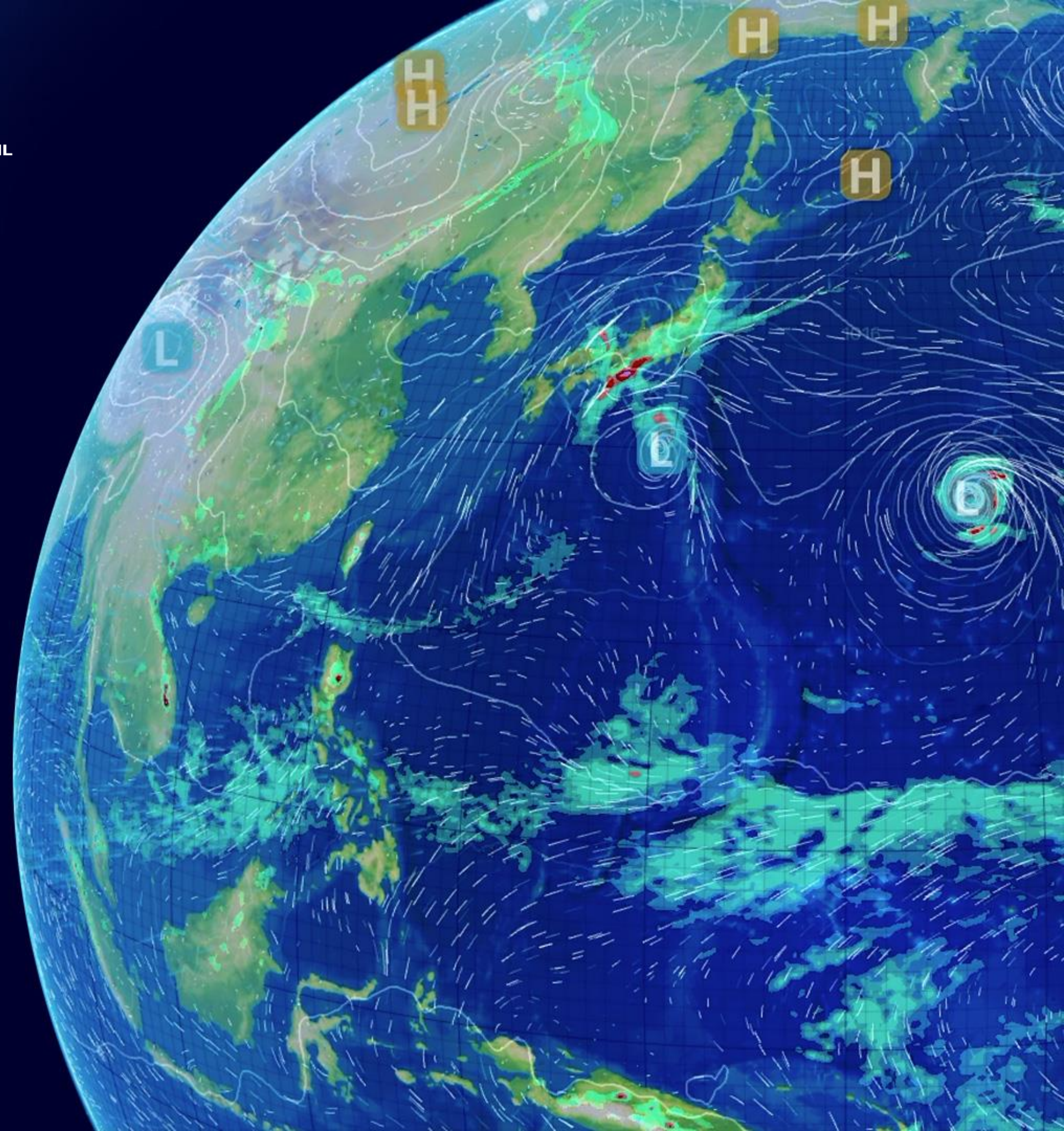
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*Met Office*

Seonaid Dey, Bob Moore and Steven Cole

*Centre for Ecology & Hydrology*

EMS 2018 – Budapest 6/9/2018





# Outline

- **Introduction of the project task**
- **Observation error**
  - **Mathematical background**
  - **Observation error estimation**
  - **Using the estimated observation error in the verification**
- **Summary**

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# “Rainfall and River Flow Ensemble Verification” project

- Commissioned by the **Flood Forecasting Centre** on behalf of the **Scottish Environment Agency, Environment Agency** and **Natural Resources Wales**
- Carried out jointly between **Centre for Ecology & Hydrology (CEH)** and the **Met Office**
- **Aim:** Develop a joint verification framework for catchment-scale precipitation and river flow ensembles
- **Using:** **deterministic** (e.g. ME, MAE, RMSE) and **probabilistic** (e.g. BS(S), CRPS(S), ROCSS, REV, Reliability & ROC diagram) **verification measures**

# Forecast chain

STEPS Nowcast  
(2km, t+7h)

MOGREPS-G  
(32km, ~t+144h)

MOGREPS-UK  
(2.2km, ~t+48h)

“Best medium-range  
blended ensemble”  
Res: 2km & 15 min

uses STEPS to combine nowcast, MOGREPS-UK and  
MOGREPS-G data together with stochastic noise

Grid-to-grid (G2G)  
hydrological model  
Res: 1km & 15 min  
developed by Centre for Ecology &  
Hydrology (CEH)

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Verification  
against:

Radar  
rainfall

Gridded  
rain-gauge

River flow observation

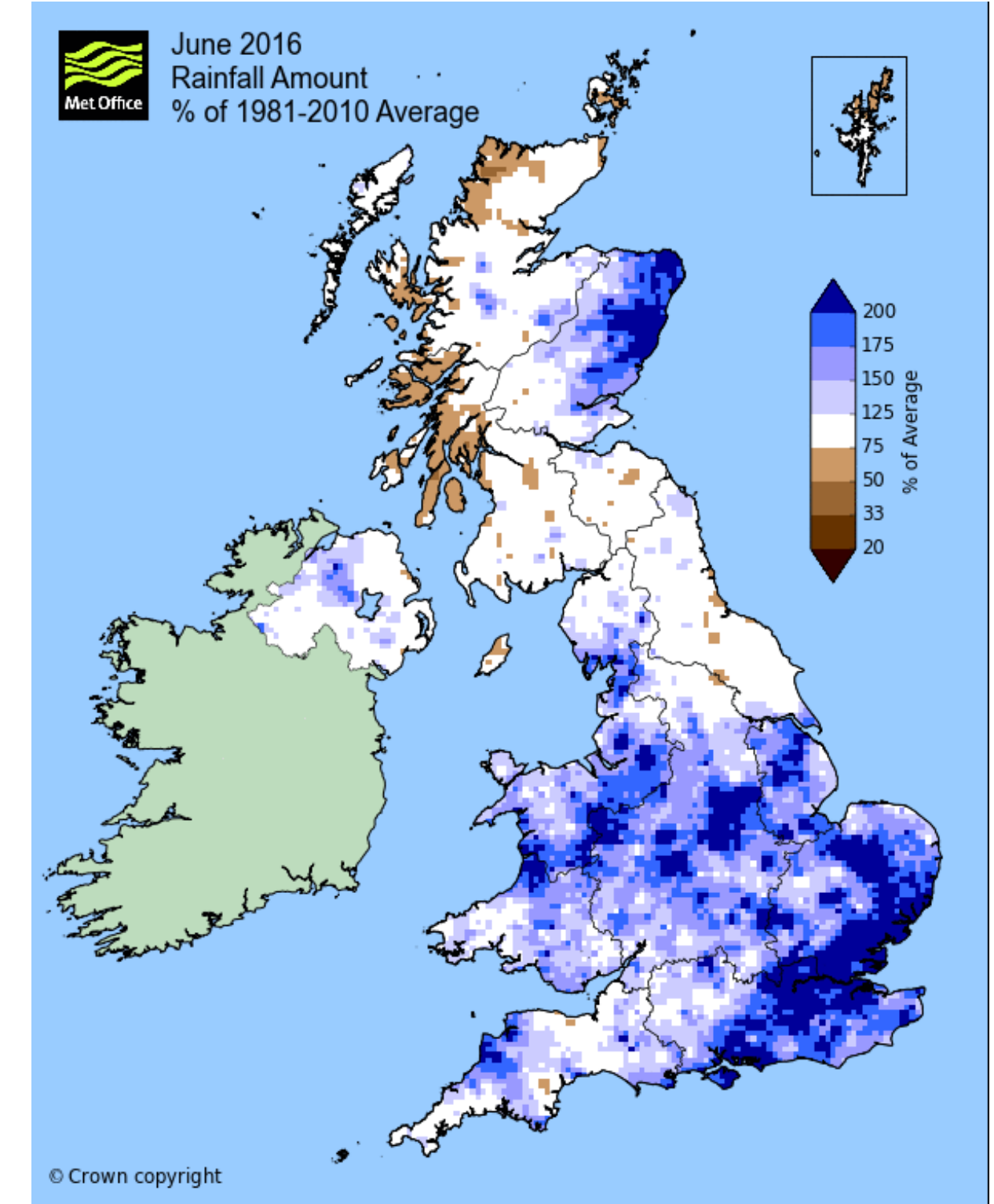
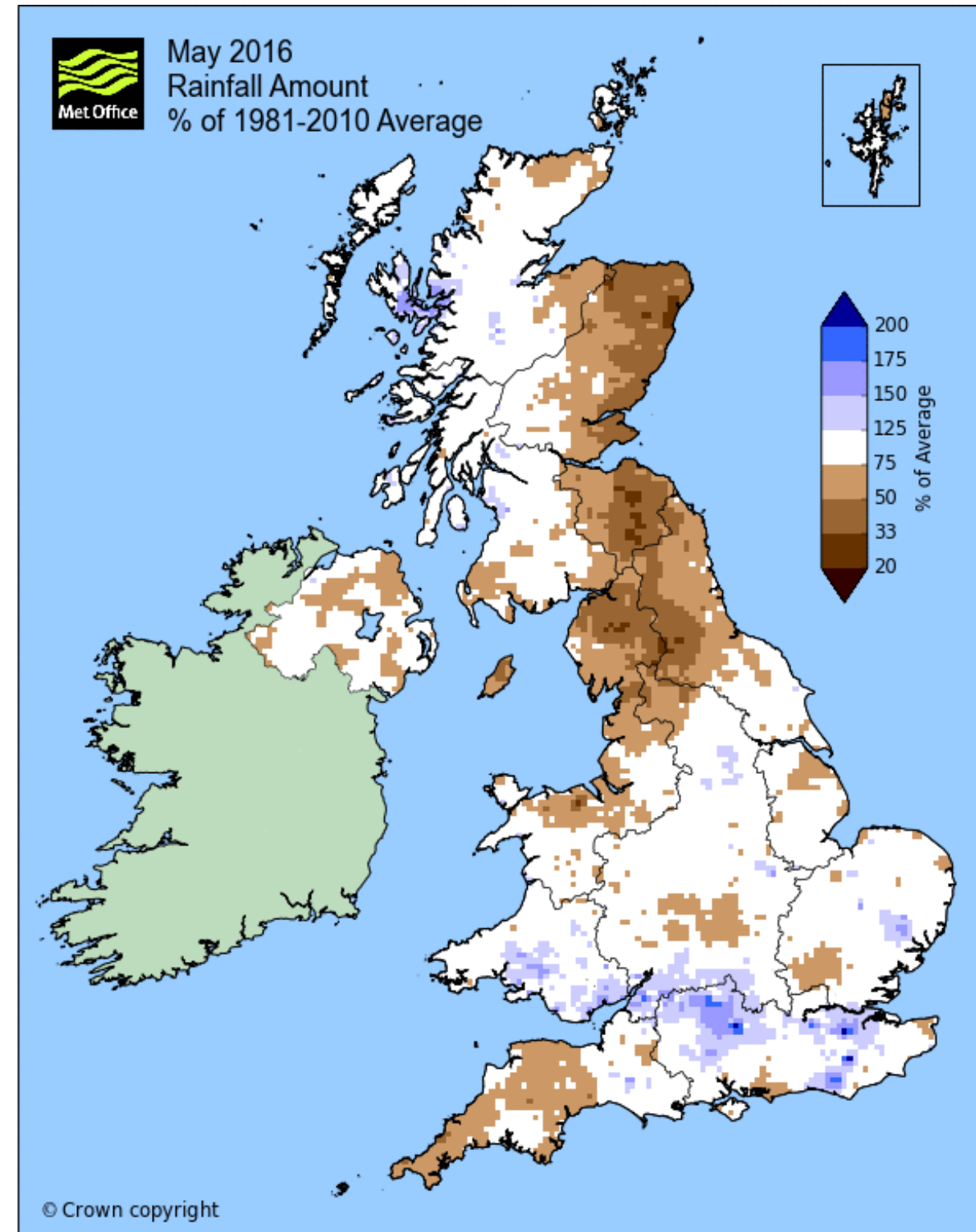
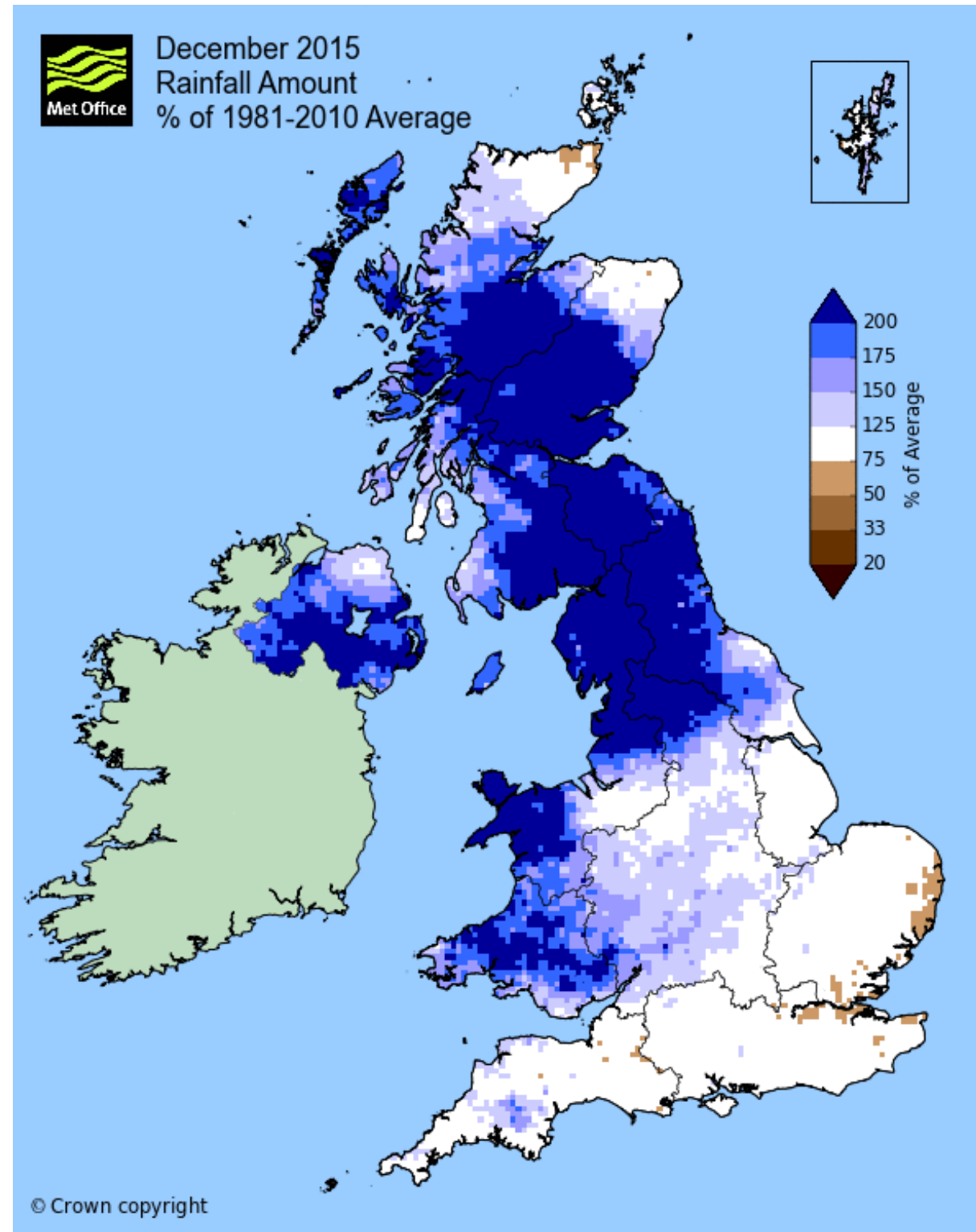


# Time periods

Winter: 25/11/2015 – 26/12/2015

Summer: 15/05/2016 – 15/06/2016

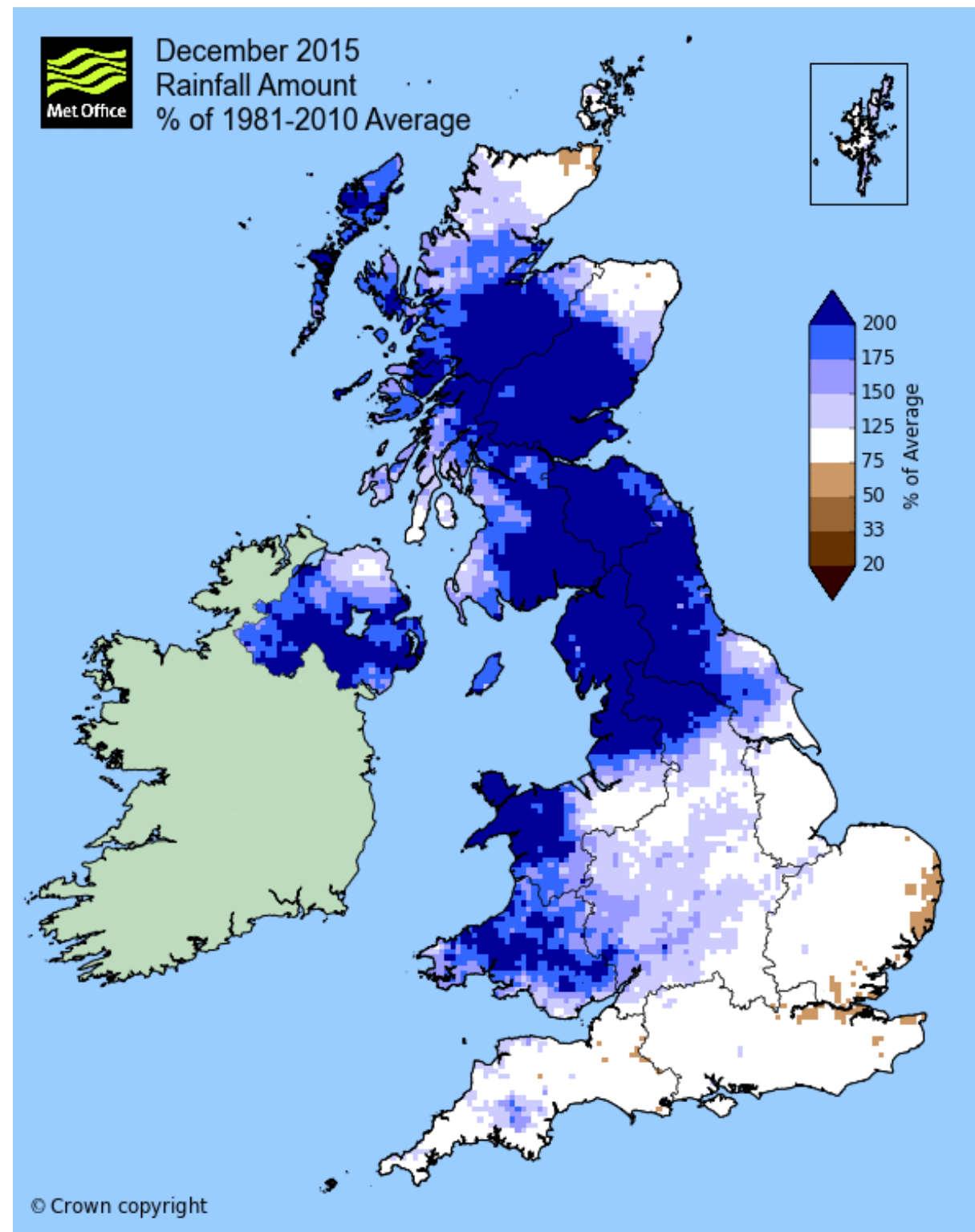
## Anomaly Rainfall maps



# Time periods

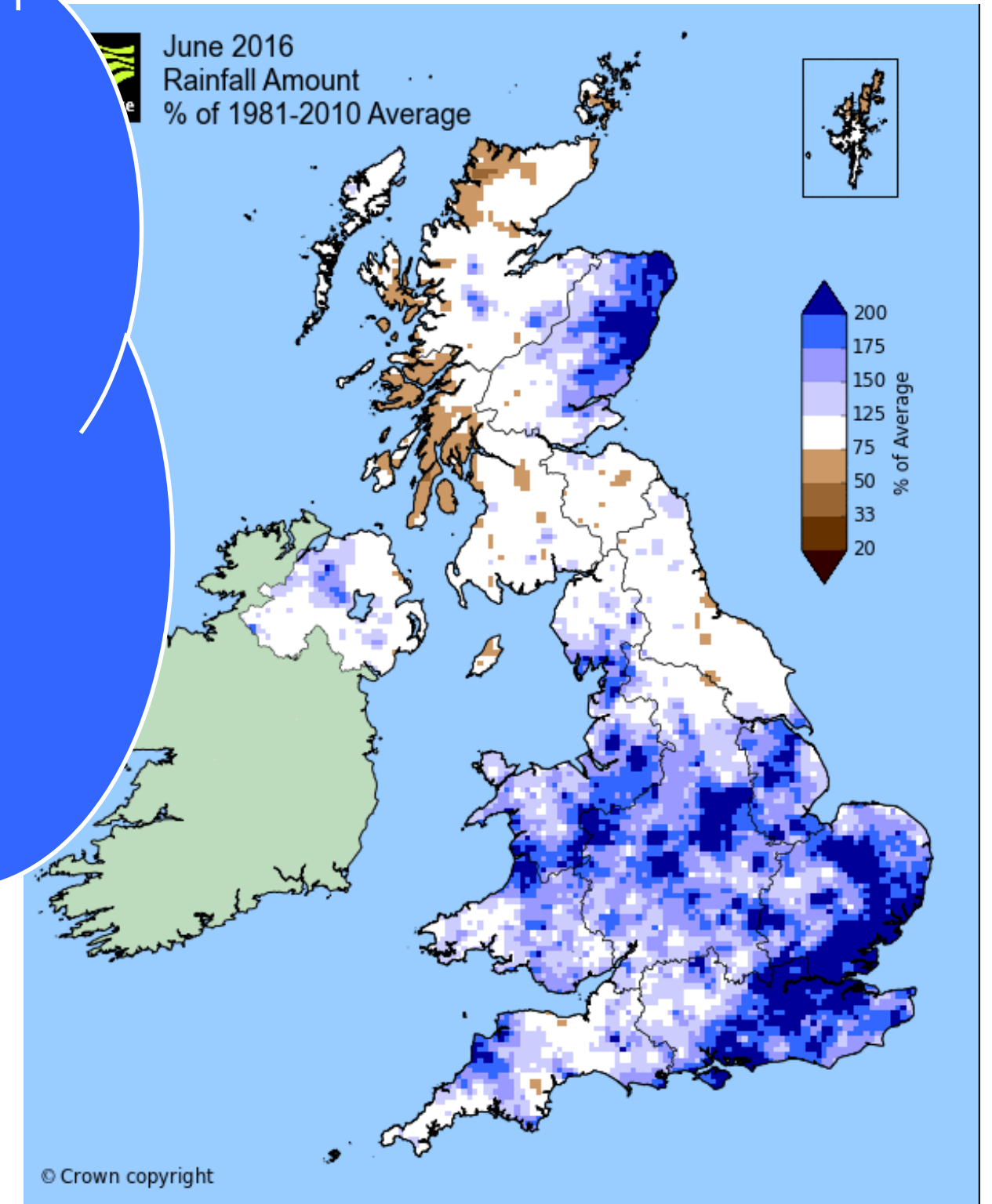
Winter: 25/11/2015 – 26/12/2015

Summer: 15/6/2016 – 15/06/2016



**Exceptionally wet and often windy**

**Storms: Desmond, Eva and Frank – with record-breaking rainfall over much of Scotland, Wales and northern England**

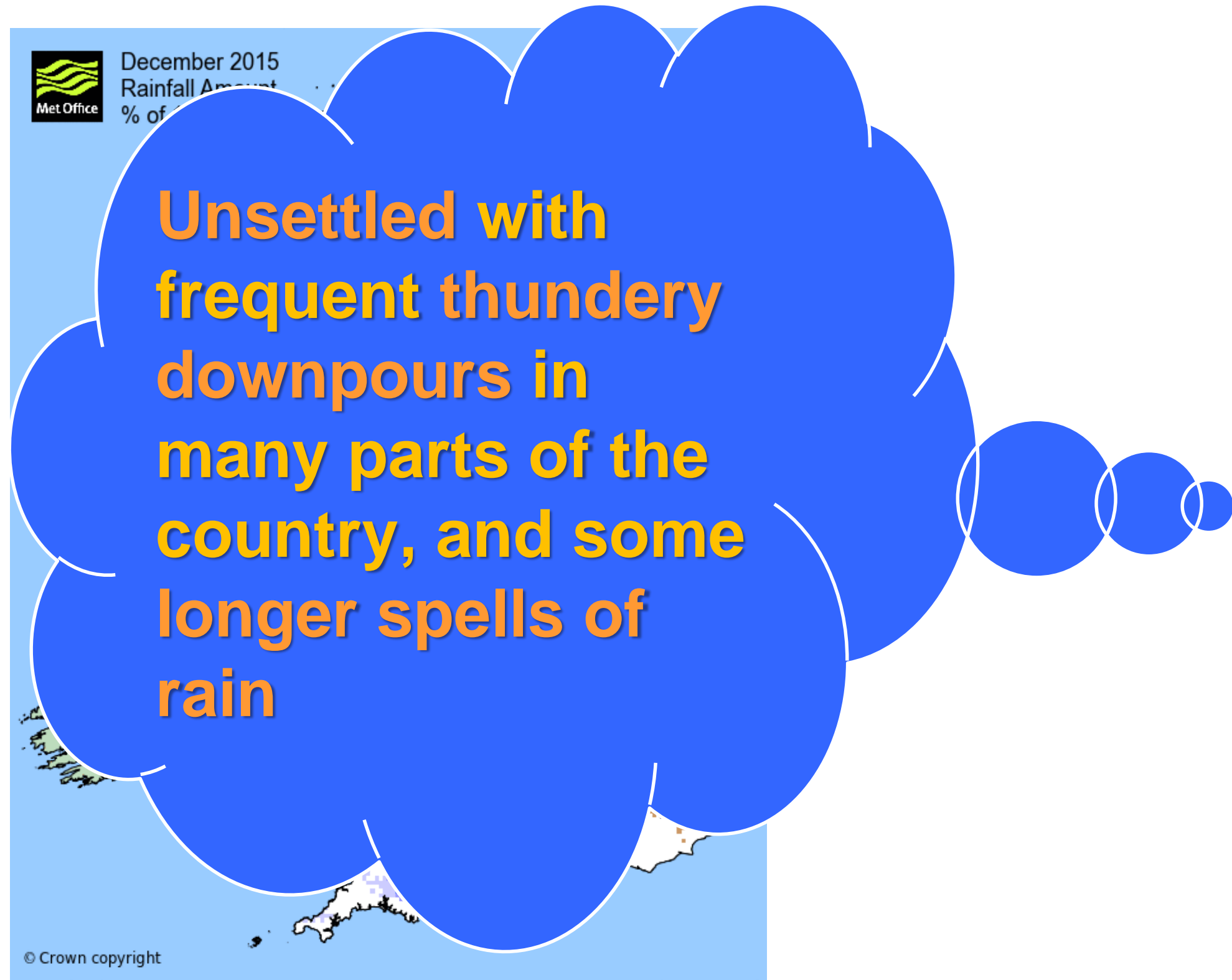




# Time periods

Winter: 25/11/2015 – 26/12/2015

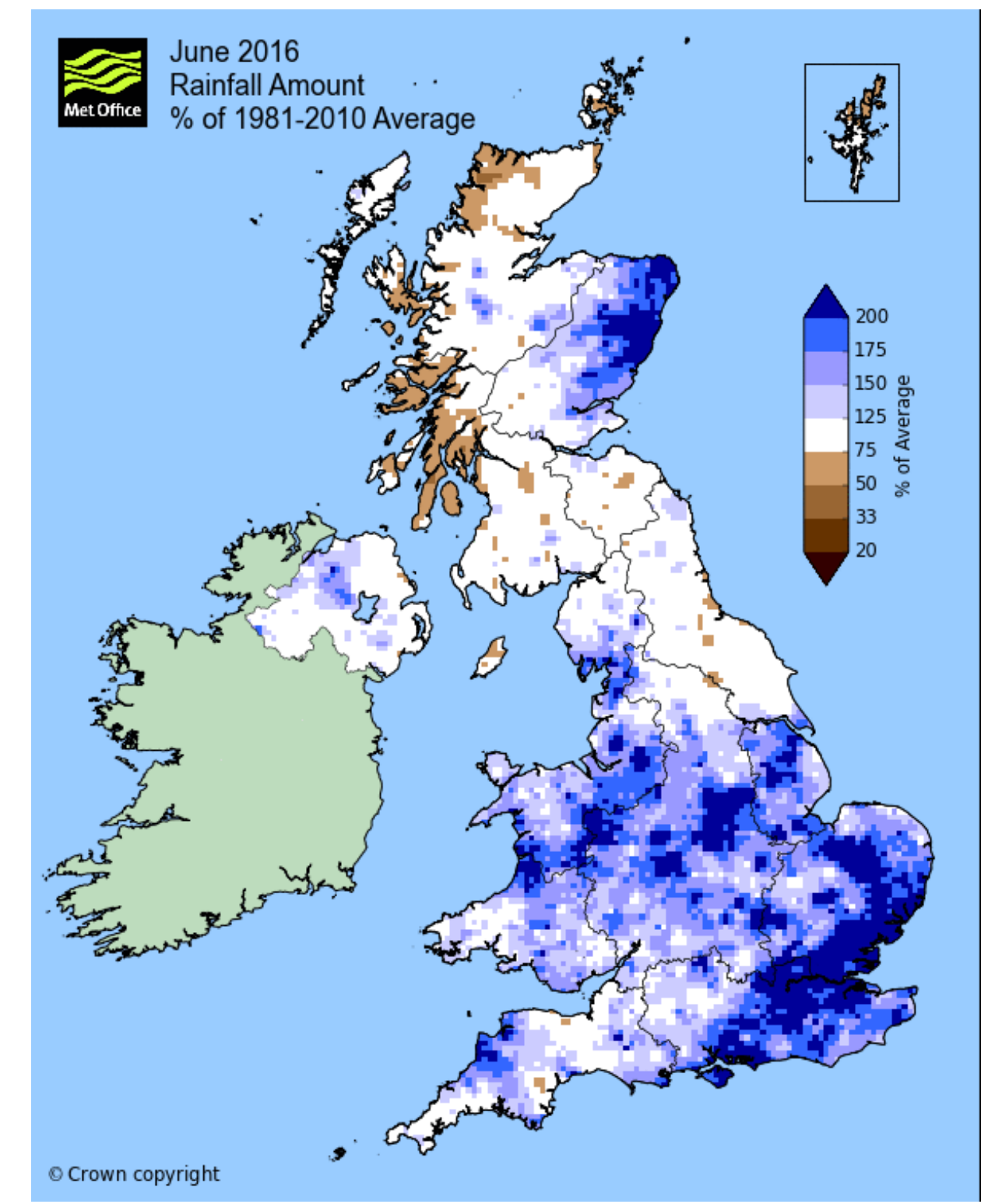
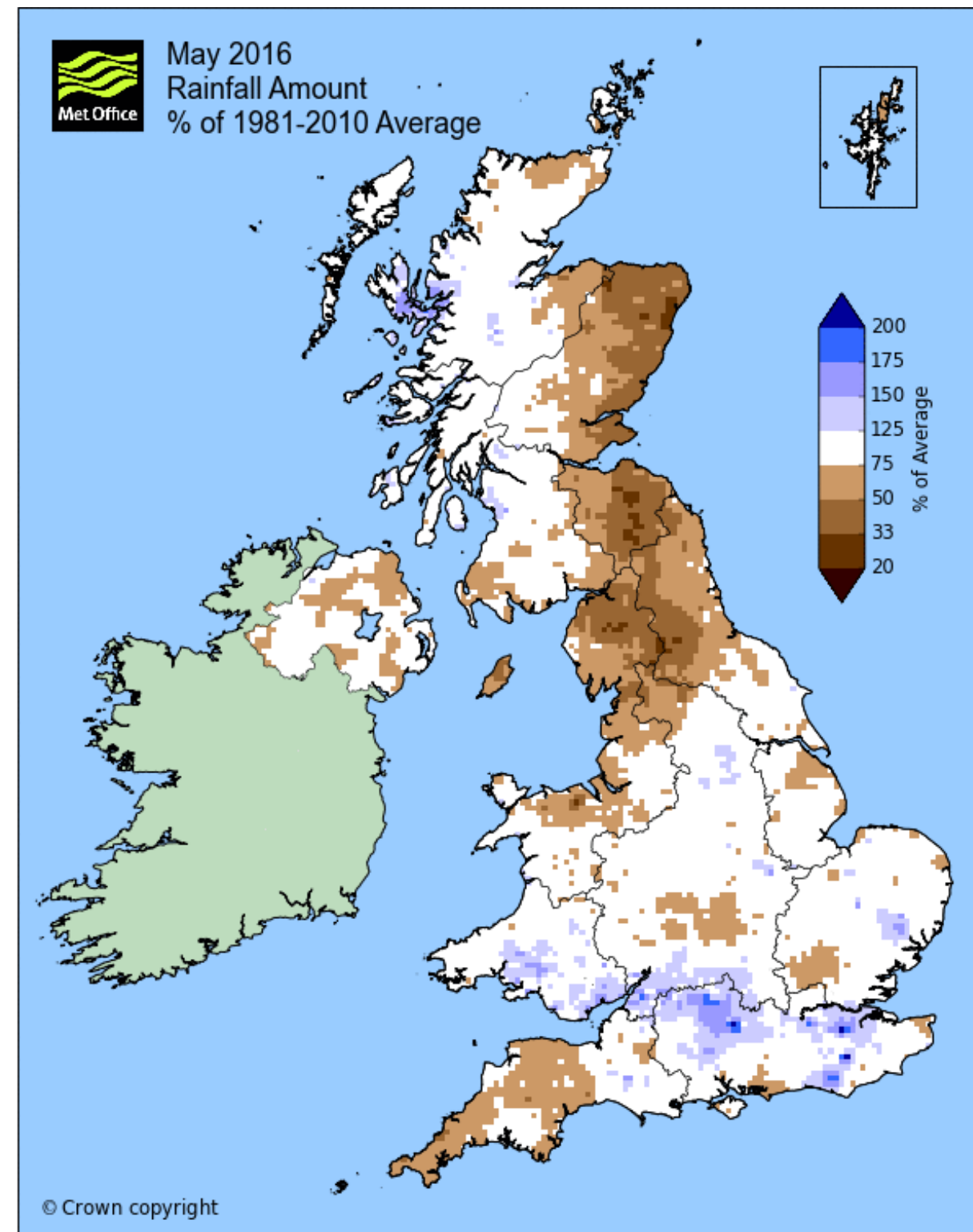
Summer: 15/05/2016 – 15/06/2016



December 2015  
Rainfall Amount  
% of 1981-2010 Average

**Unsettled with frequent thundery downpours in many parts of the country, and some longer spells of rain**

© Crown copyright



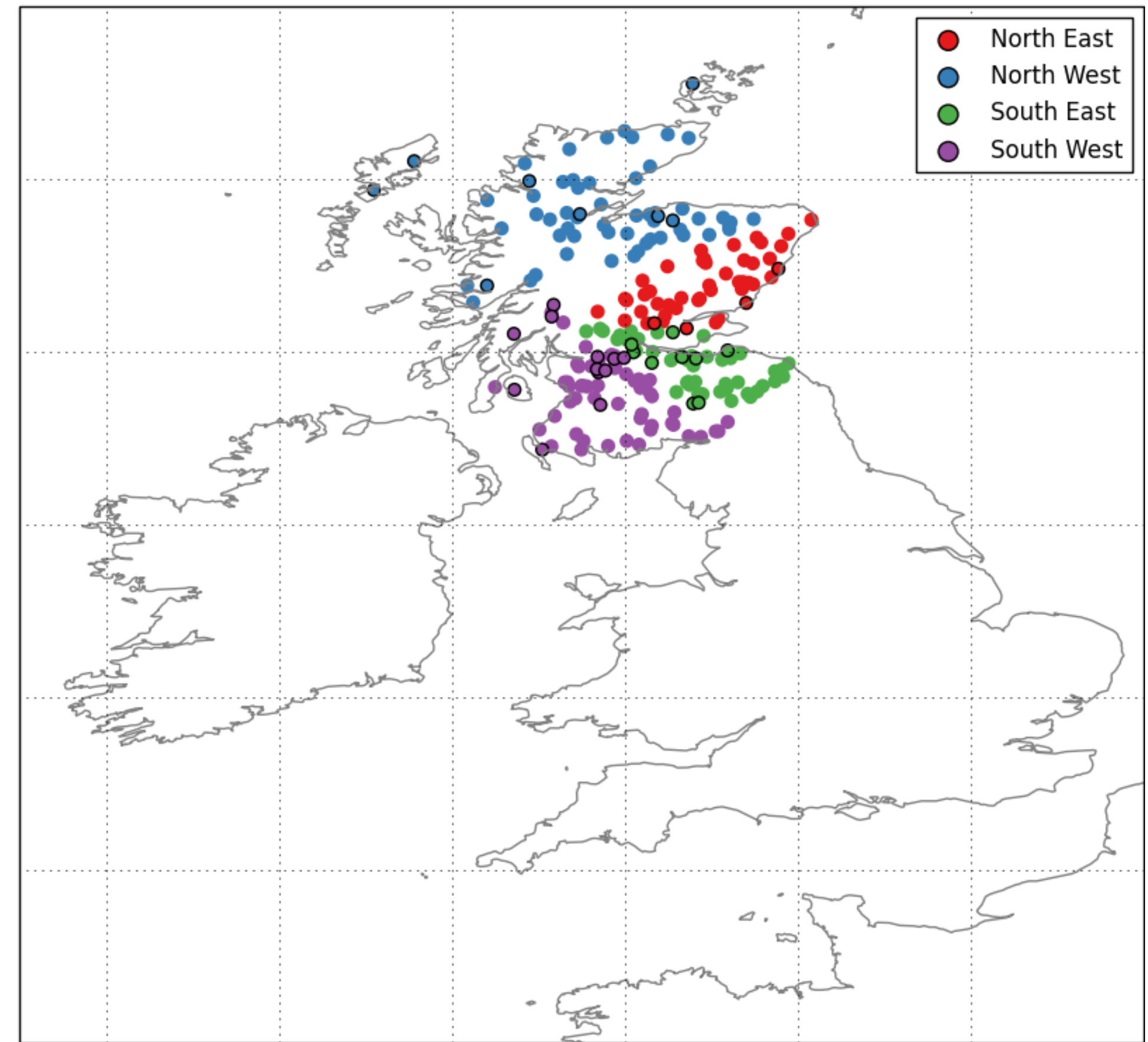
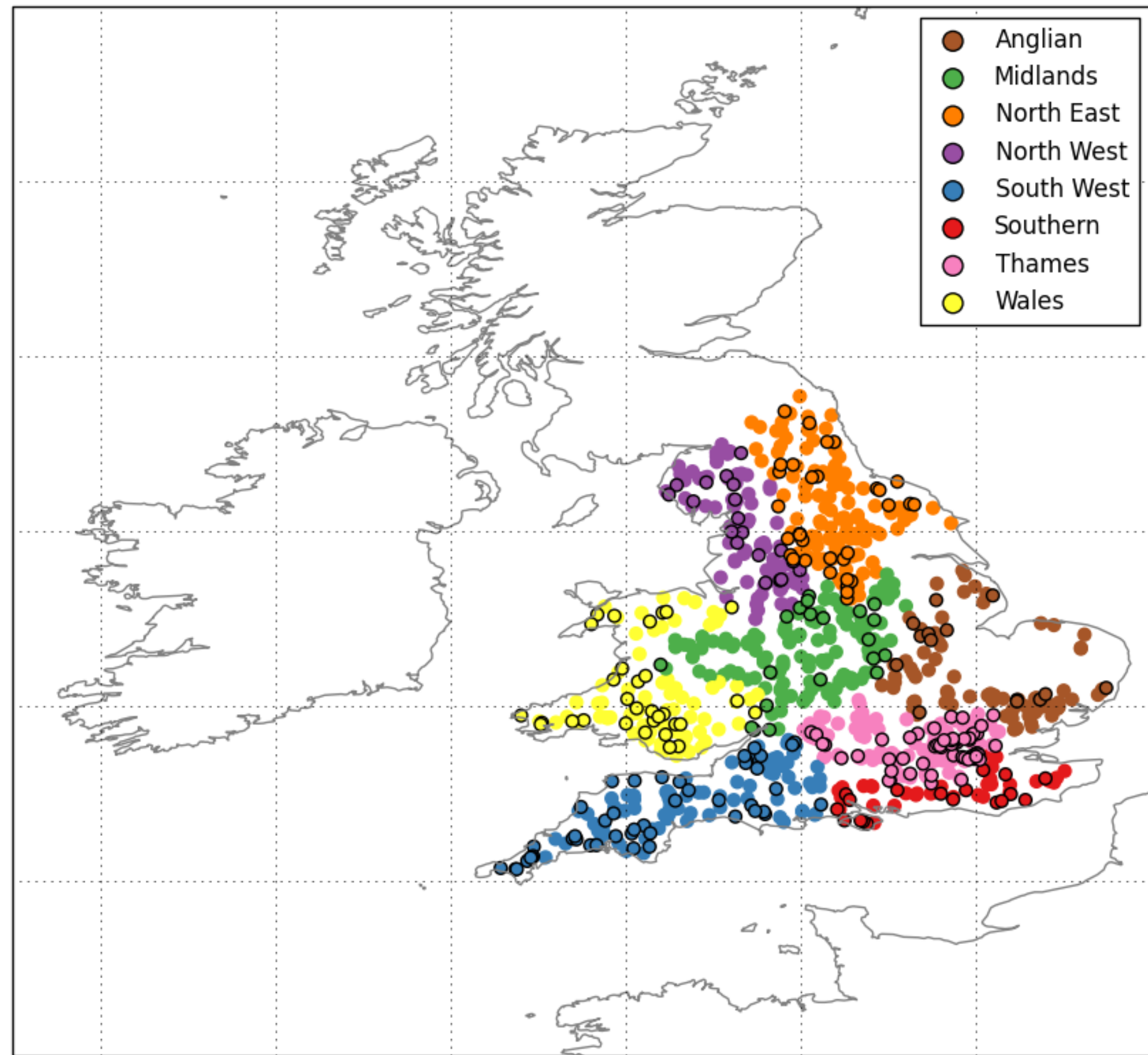


# Catchments, Regions and Countries

Used the *catchment averages* as the forecast and observation dataset

## England & Wales (E&W)

## Scotland





# Examined parameters in different attributes in the project work and in the observation error calculations

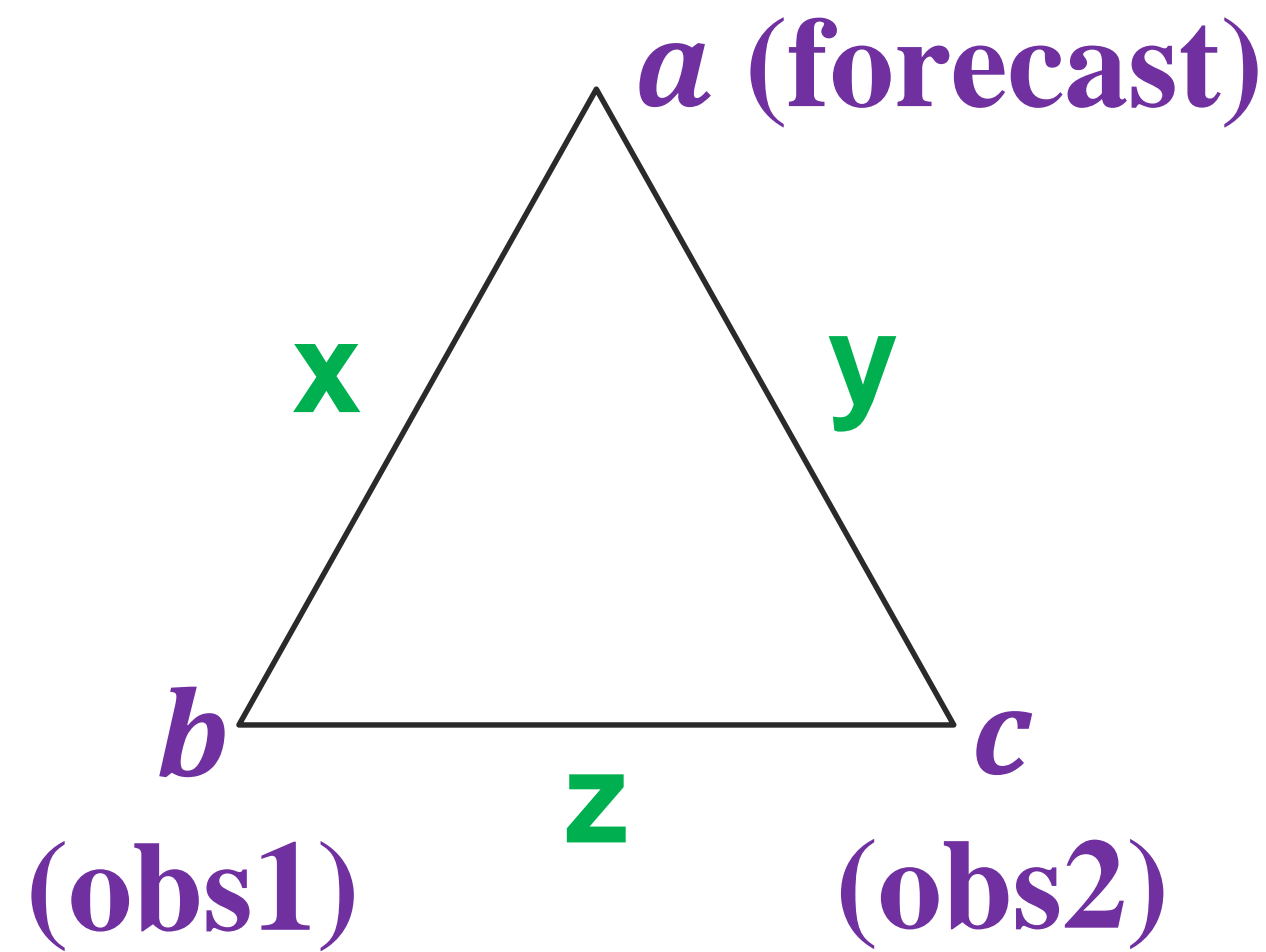
- **Countries:** England&Wales and Scotland
- **Time resolutions:** daily, hourly, 15-min
- **Time periods:** winter and summer
- **Observation types:** radar and gauge
- **Aggregating lead times:** Day1, Day2-3, Day4-6



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$f_a$  : actual values of forecast

$f_b$  : actual values of obs1

$f_c$  : actual values of obs2

$t$  : true values

$x$ : MSE of the forecast & obs1

$y$ : MSE of the forecast & obs2

$z$ : MSE of the obs1 & obs2

$x = E(f_a - f_b)^2 = E[(f_a - t) - (f_b - t)]^2 = E(\delta_a^2) + E(\delta_b^2) - 2E(\delta_a \delta_b)$  **Assumption: the two errors are not correlated**

$E(f_a - f_b)^2 = x = E(\delta_a^2) + E(\delta_b^2)$

$E(f_a - f_c)^2 = y = E(\delta_a^2) + E(\delta_c^2)$

$E(f_b - f_c)^2 = z = E(\delta_b^2) + E(\delta_c^2)$

$E(\delta_a^2) = \frac{x + y - z}{2}$  **forecast error**

$E(\delta_b^2) = \frac{x - y + z}{2}$  **obs1 error**

$E(\delta_c^2) = \frac{-x + y + z}{2}$  **obs2 error**

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# Observation error estimation

- Determined an adjacent bin series:

BIN1: [0,0.1)

BIN2: [0.1,1)

BIN3: [1, 2)

BIN4: [2, 4)

BIN5: [4, ∞)

The distribution of the forecast (ensemble mean & control) and the observations based on the bins

%	BIN 1	BIN 2	BIN 3	BIN 4	BIN 5
Ensemble mean	59.4	31.4	6.3	2.7	0.2
Radar	74.5	17.8	4.3	2.6	0.8
Gauge	71.1	21.4	4.3	2.5	0.7
Control forecast	72.1	17.7	5.5	3.7	1.0

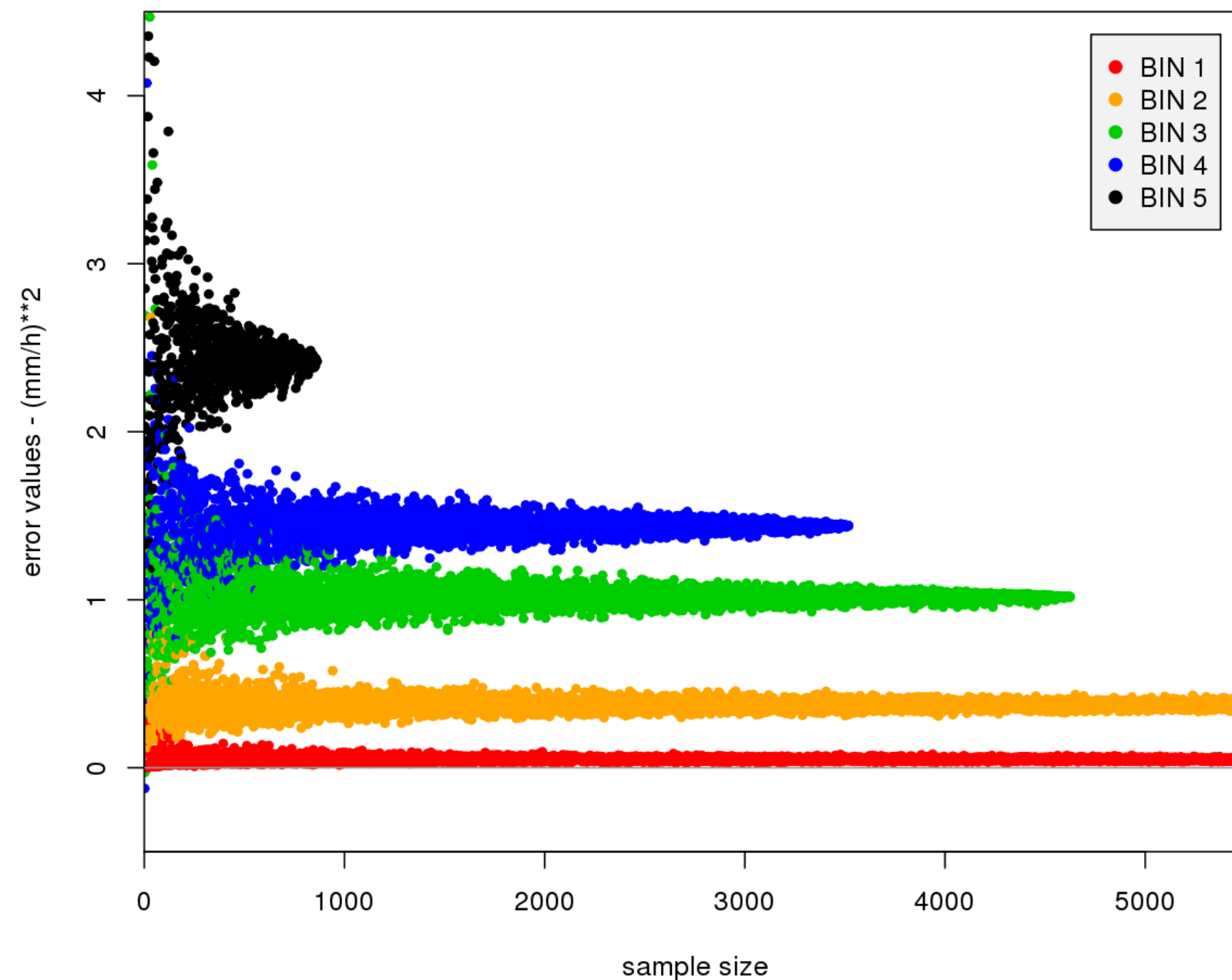


# Observation error estimation

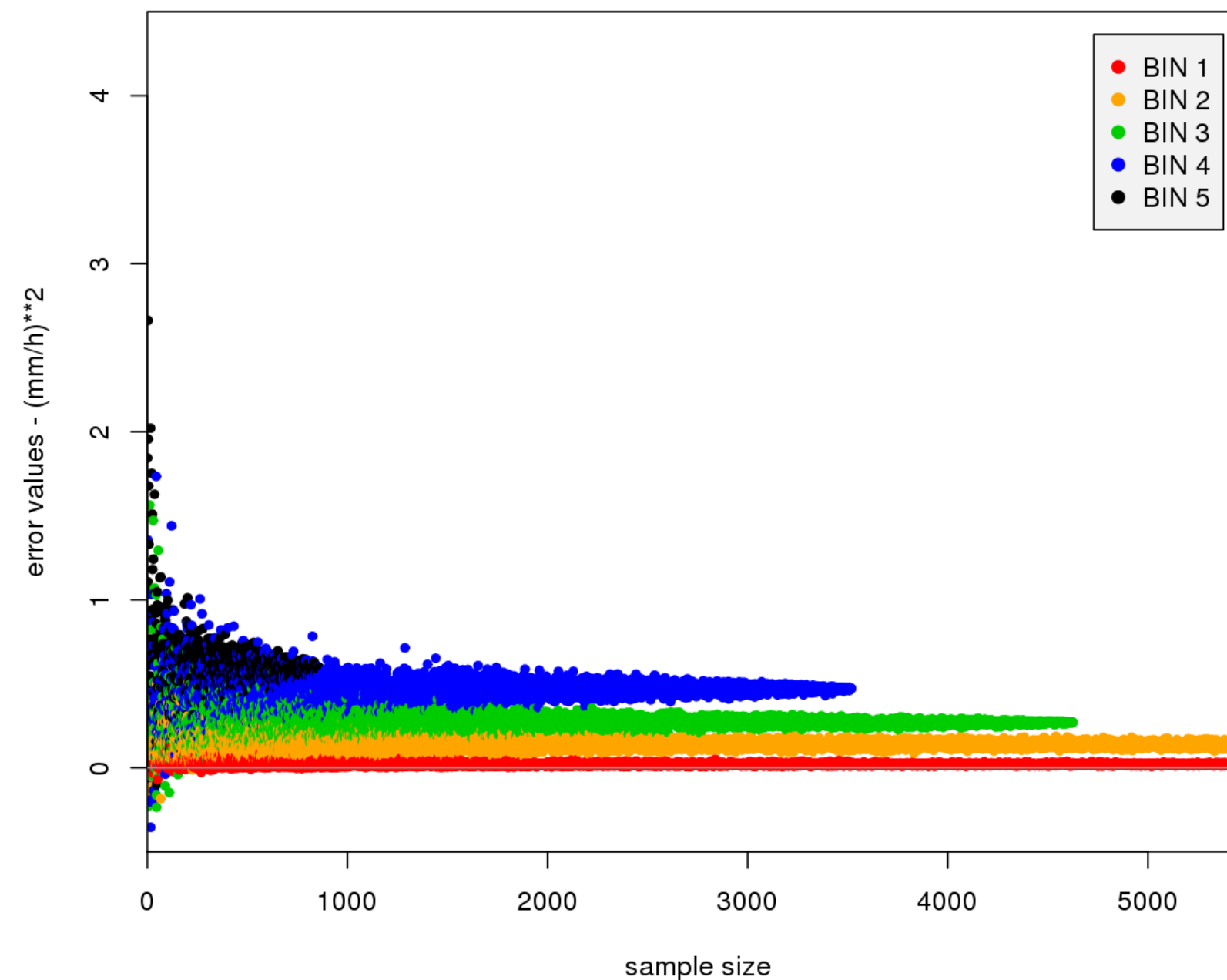
## Squared error plots as a function of the sample size

- Binning based on the **Control**
- Forecast error were calculated from **Ensemble mean**

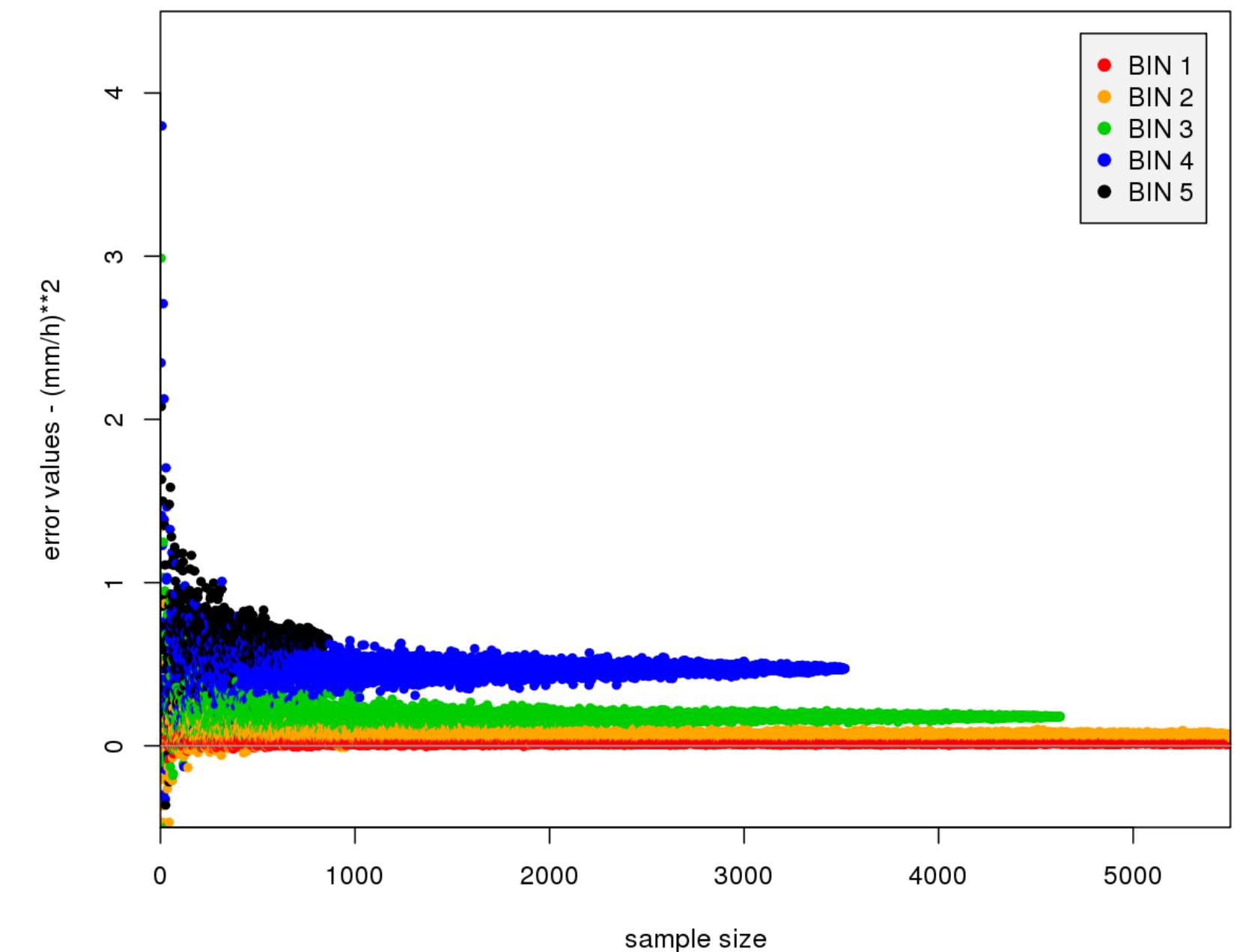
EnsMean squared error  
LT = T+12; England&Wales; Winter  
Bins based on: Control



Radar squared error  
LT = T+12; England&Wales; Winter  
Bins based on: Control



Gauge squared error  
LT = T+12; England&Wales; Winter  
Bins based on: Control



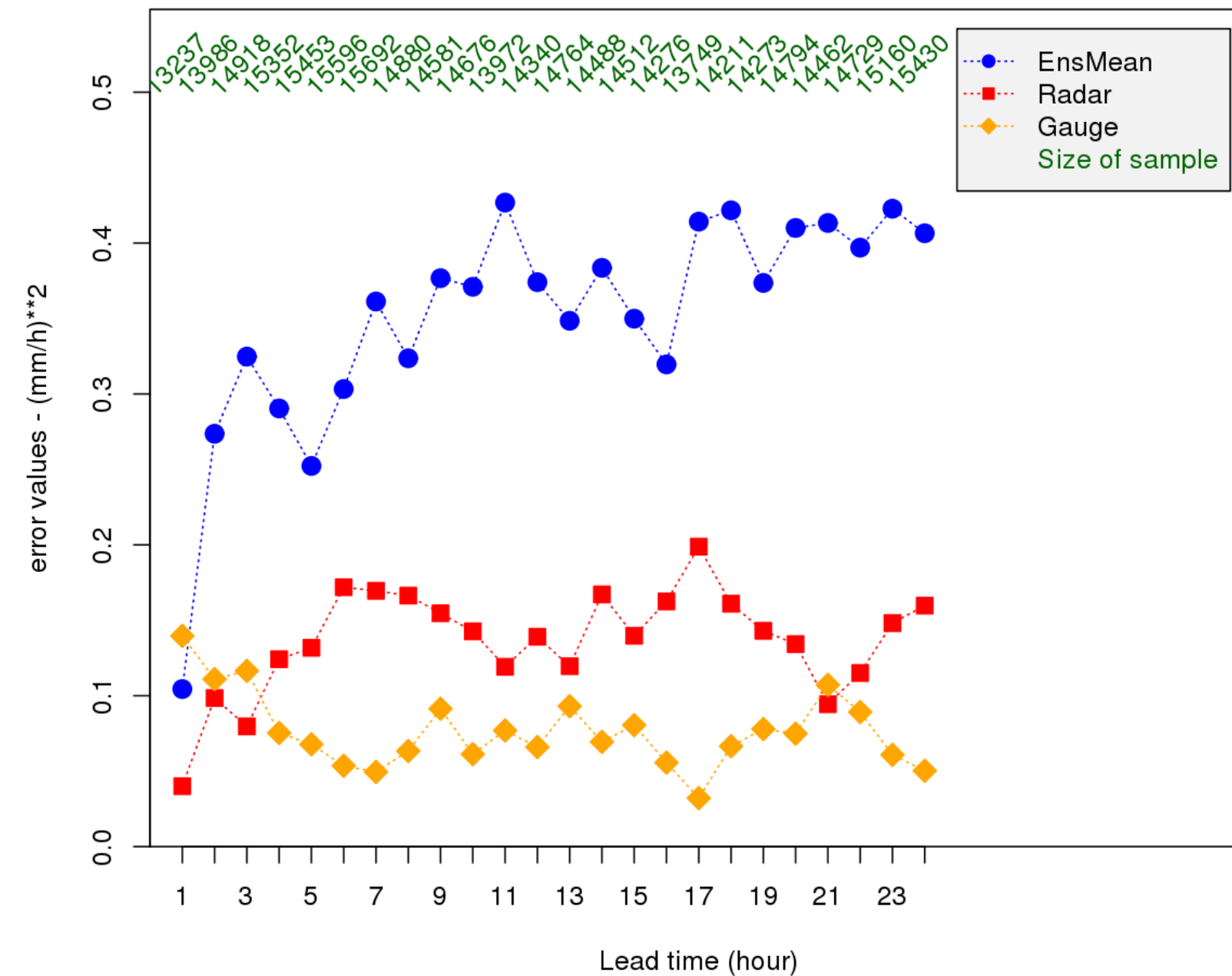


# Observation error estimation

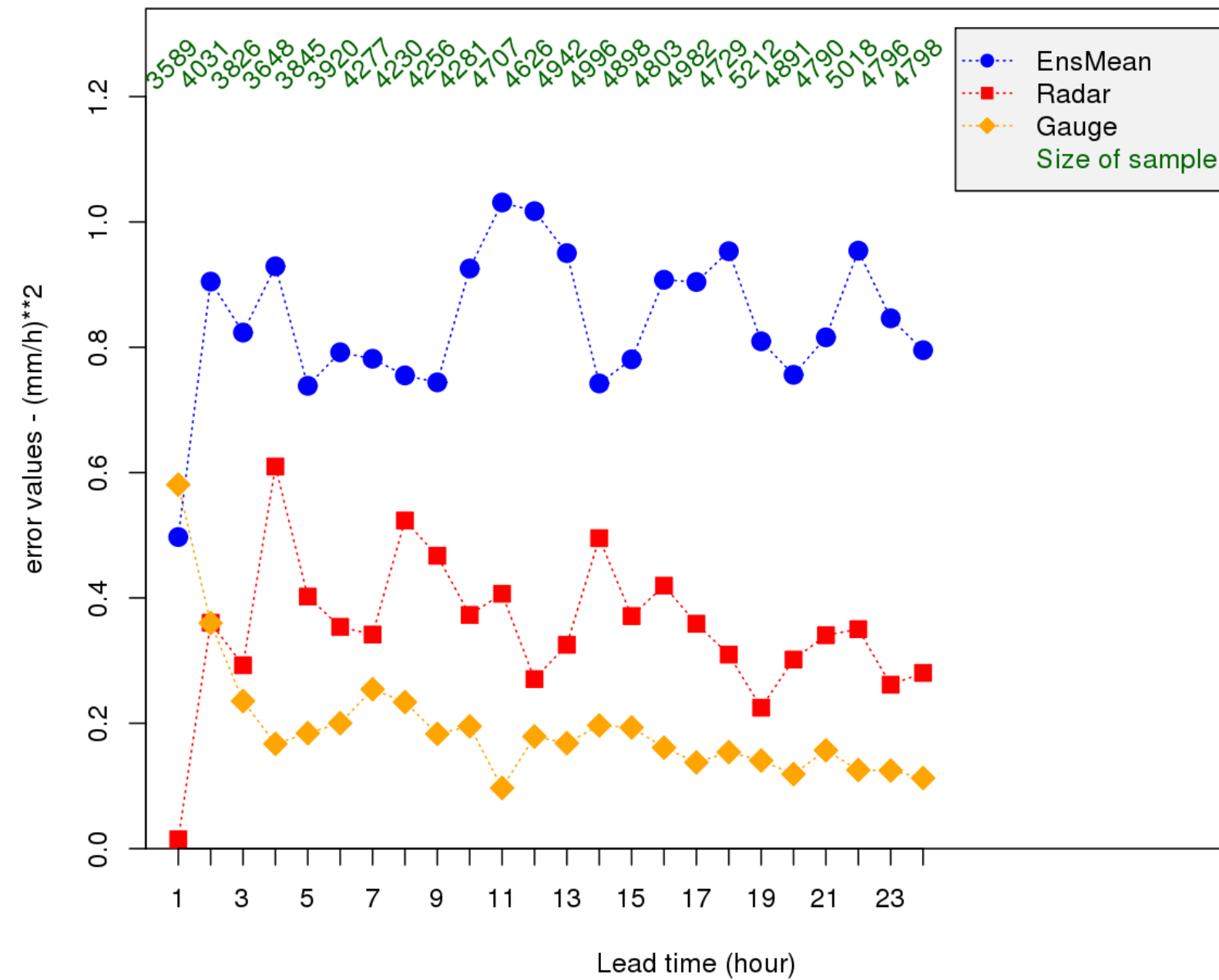
## Squared error plots as a function of the lead time

- Observation errors are **not changing** with the lead time
- The forecast error is **increasing** with the lead time

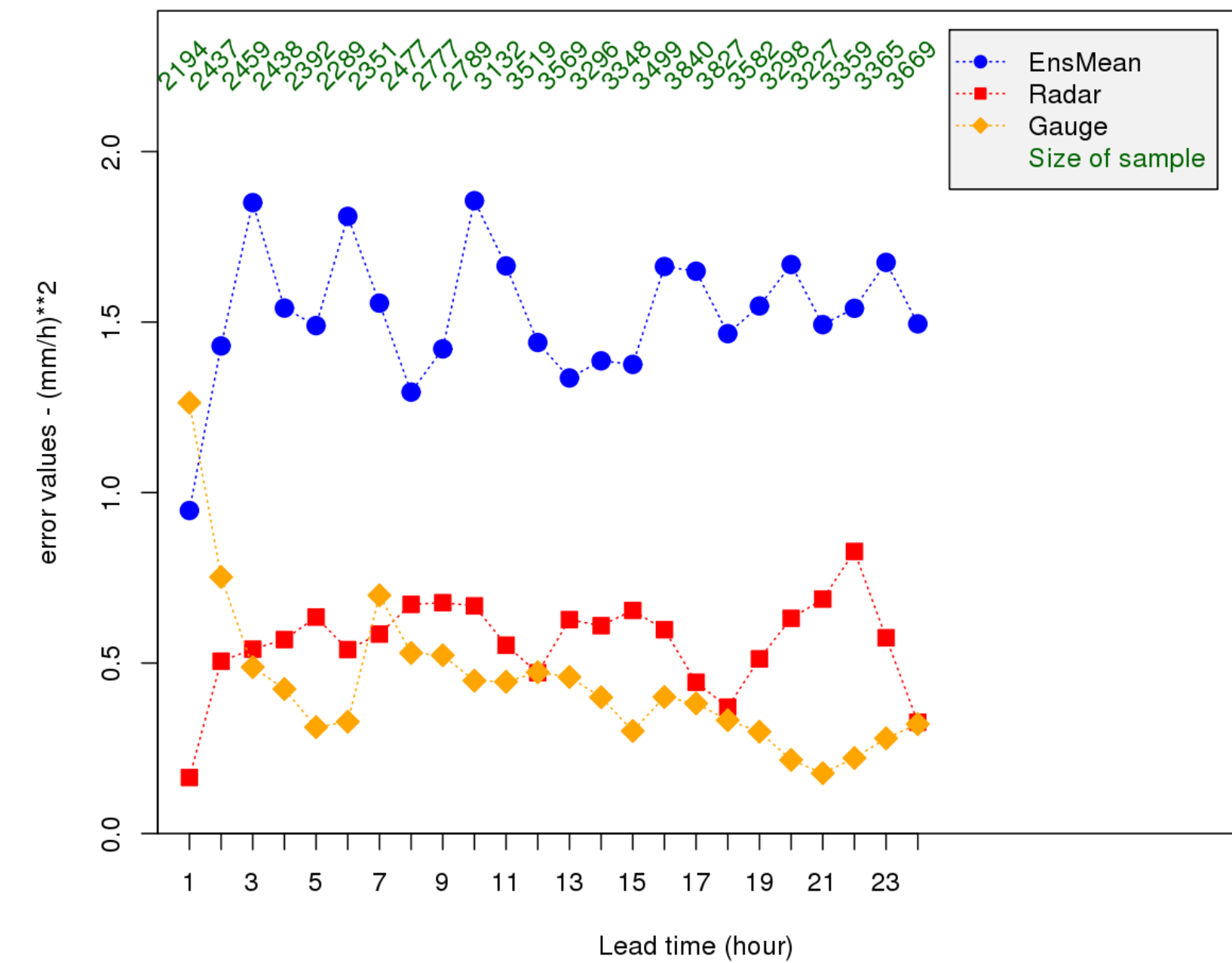
Squared errors for the different lead times  
BIN: 2; England&Wales; Winter  
Bins based on: Control



Squared errors for the different lead times  
BIN: 3; England&Wales; Winter  
Bins based on: Control

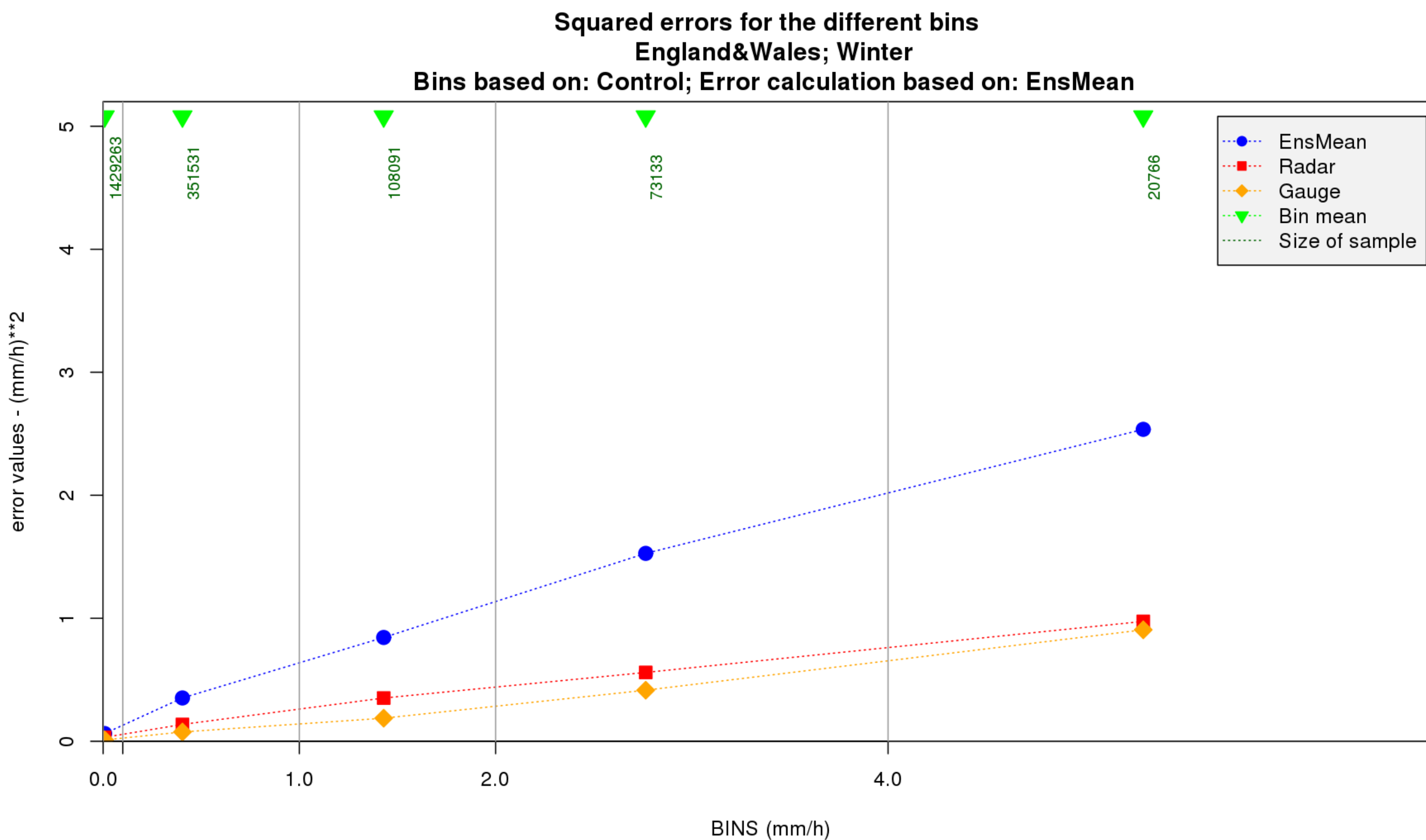


Squared errors for the different lead times  
BIN: 4; England&Wales; Winter  
Bins based on: Control



# Observation error estimation

## Squared error values as a function of the bin-mean values of the forecast



The functions are roughly log linear

=>

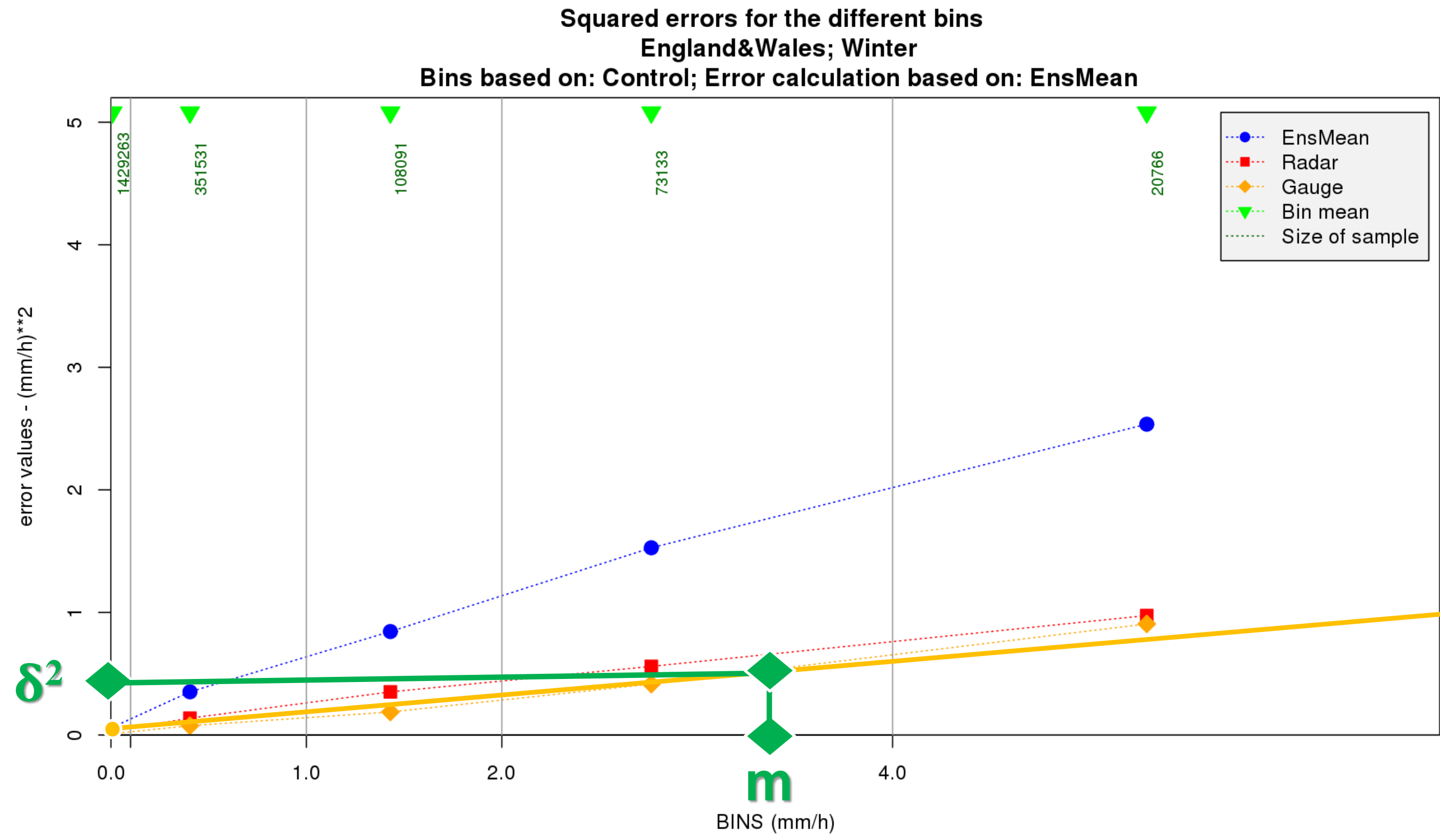
Can fit linear models to them



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# Using the estimated observation error in the verification



For each forecast case:

1. Based on the forecast magnitude ( $m$ ) and the linear model  $\Rightarrow$  estimate the observation error ( $\delta$ )
2. Random sample from  $N(0, \delta^2)$
3. Add the random sample to given forecast case magnitude



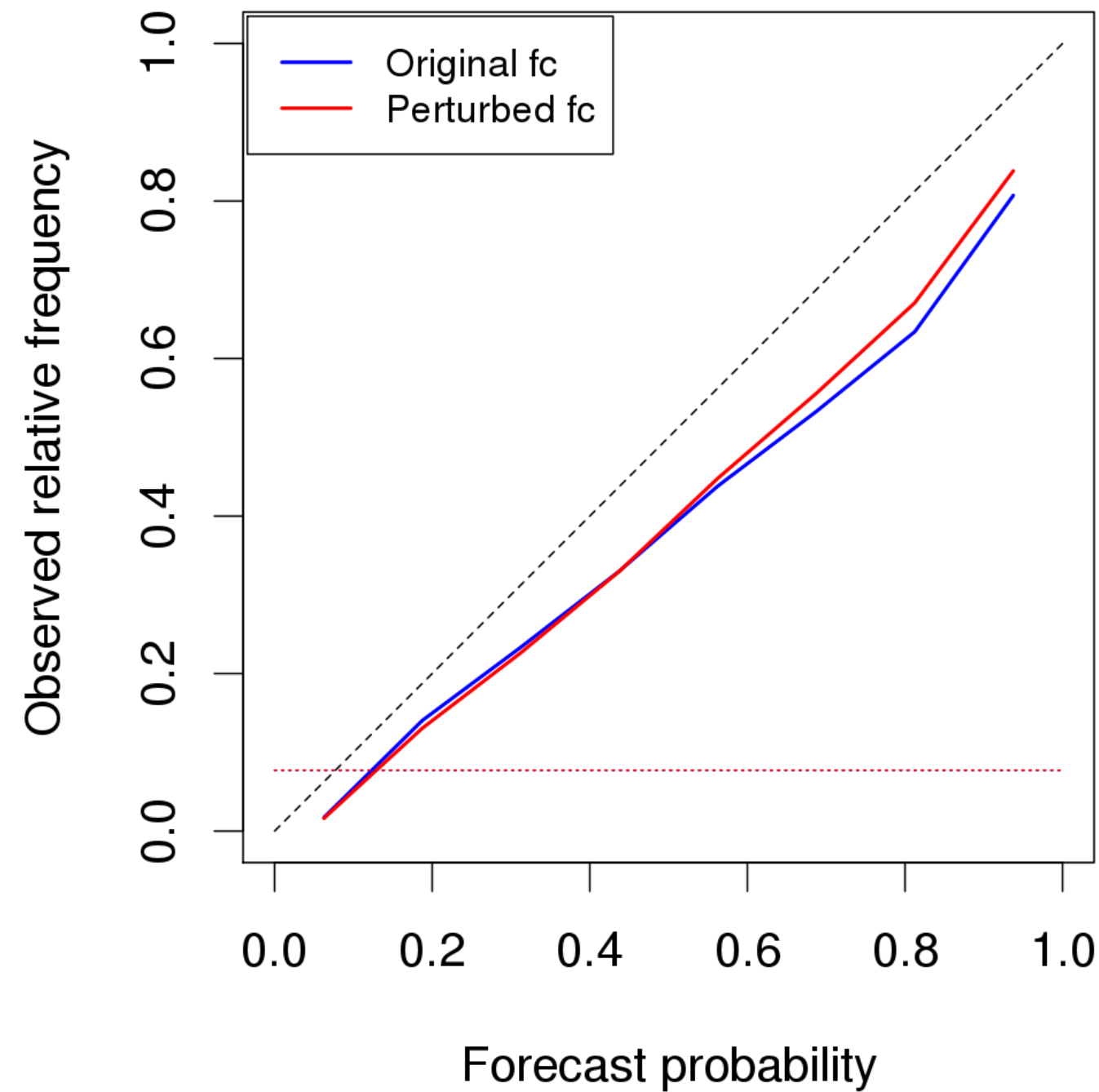
# Using the estimated observation error in the verification

## Reliability diagrams

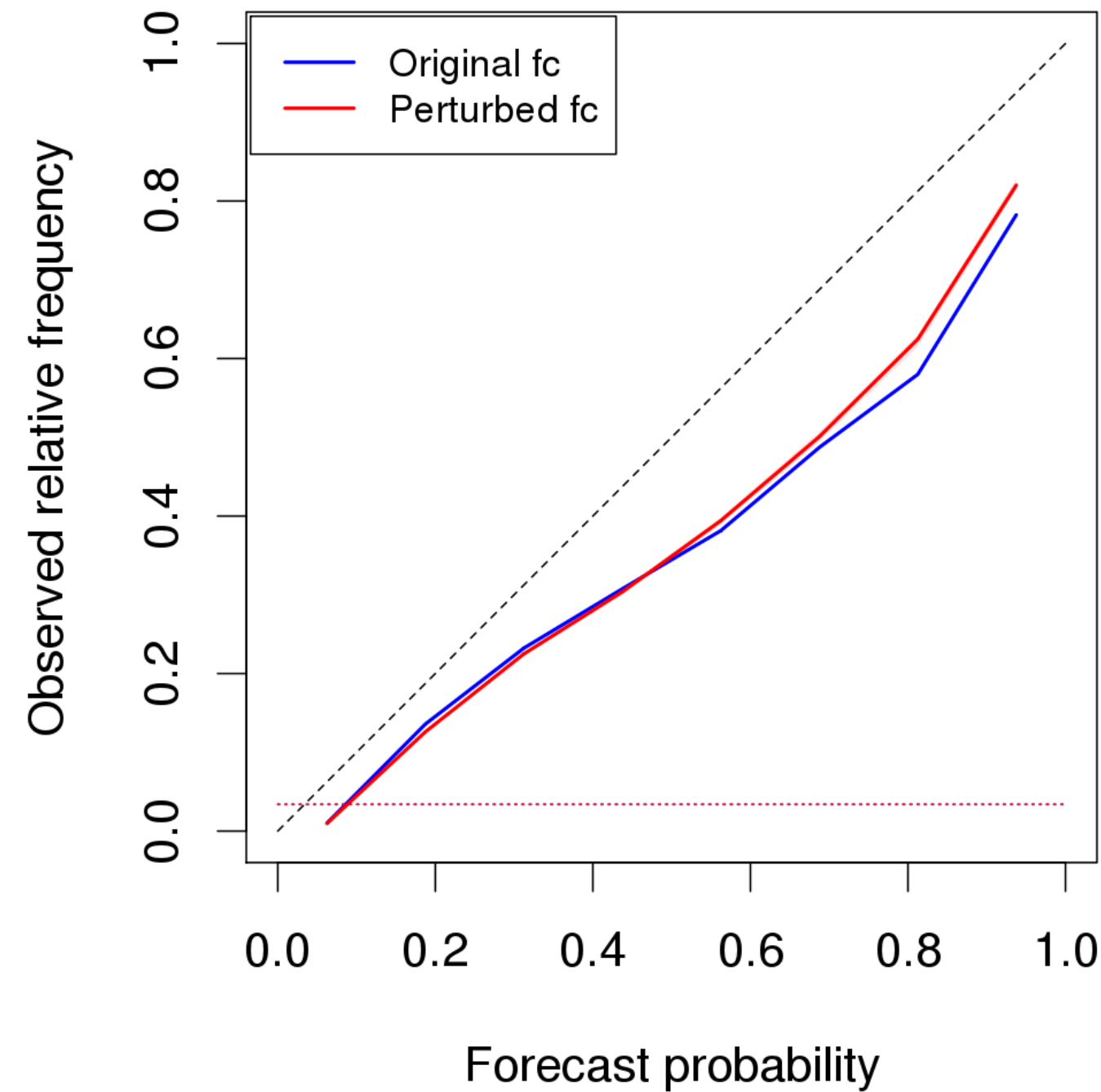
### Radar

Thresholds: 1, 2, 4 mm/h

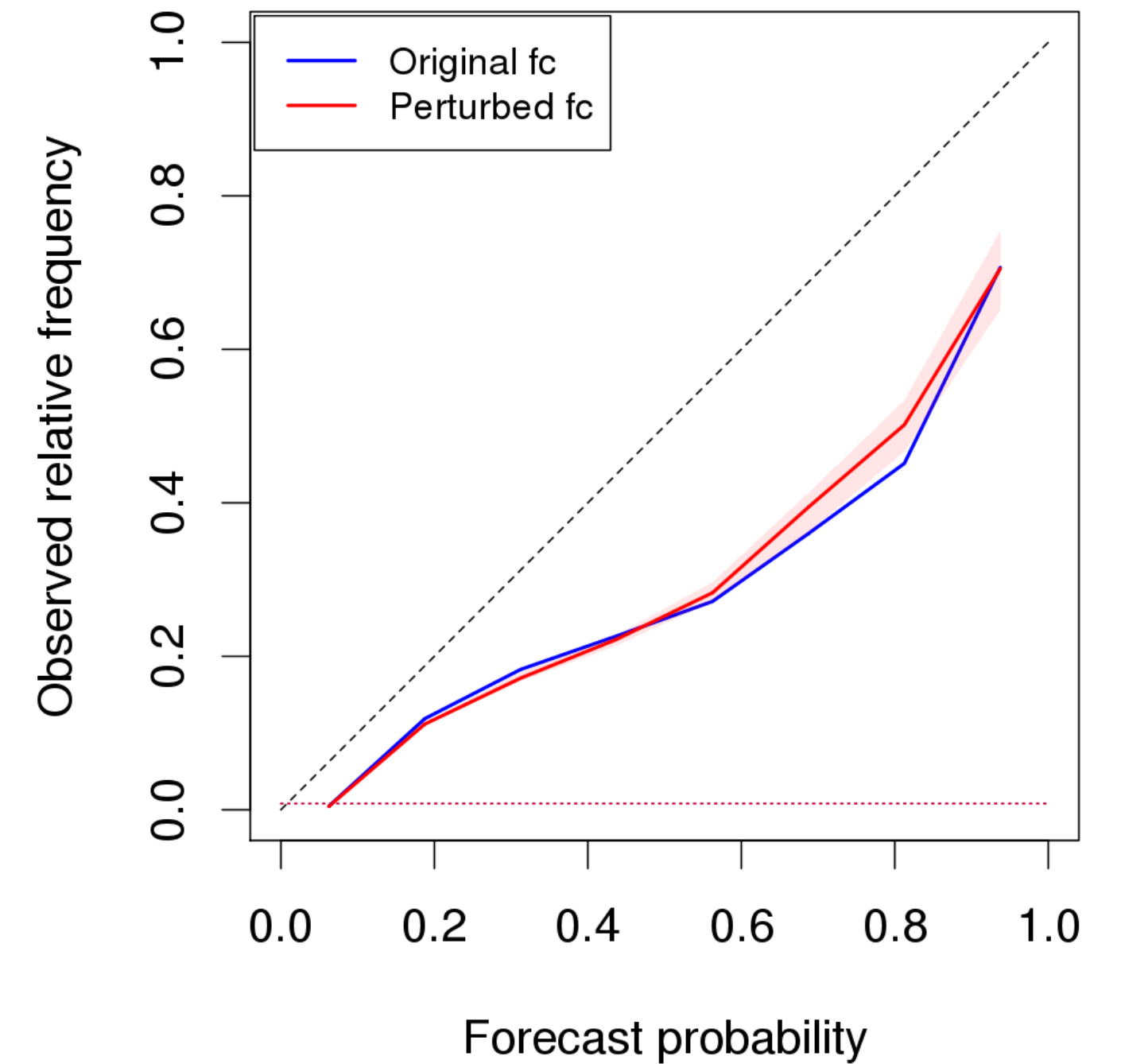
Reliability diagram  
England&Wales, Winter, Day1,  
Threshold: 1 mm/h, Truth: Radar



Reliability diagram  
England&Wales, Winter, Day1,  
Threshold: 2 mm/h, Truth: Radar



Reliability diagram  
England&Wales, Winter, Day1,  
Threshold: 4 mm/h, Truth: Radar

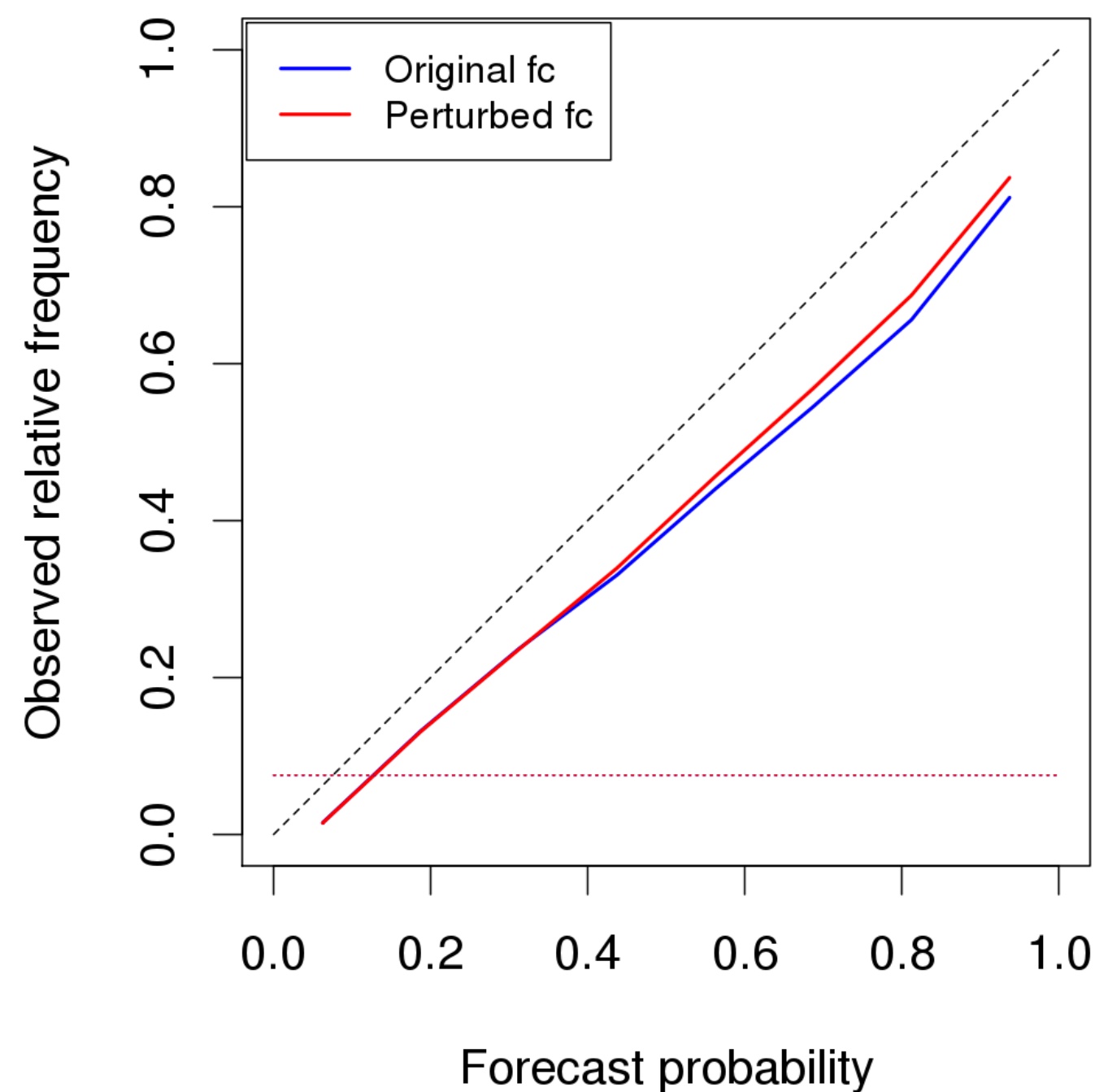


# Using the estimated observation error in the verification

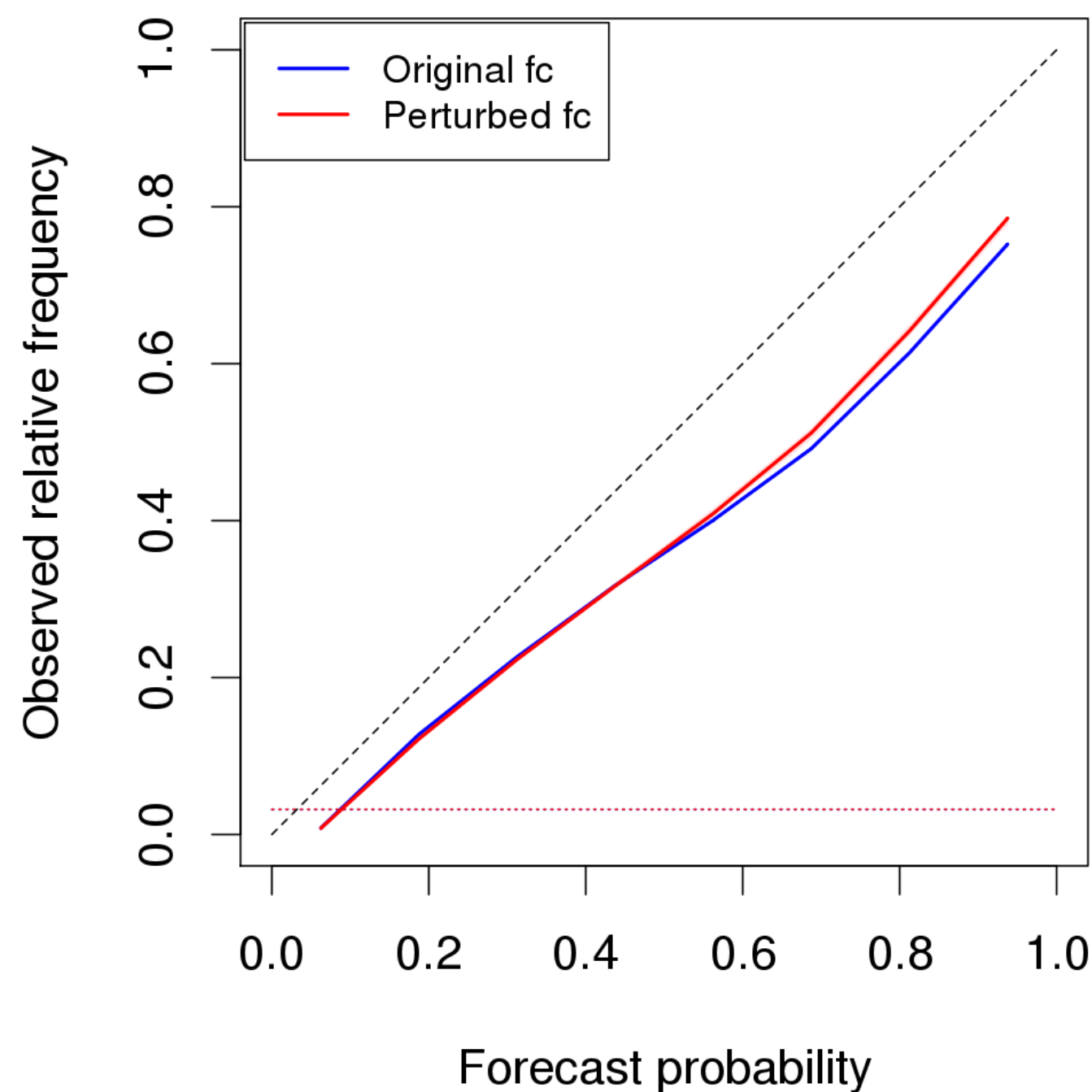
## Reliability diagrams

Rain gauges  
Thresholds: 1, 2, 4 mm/h

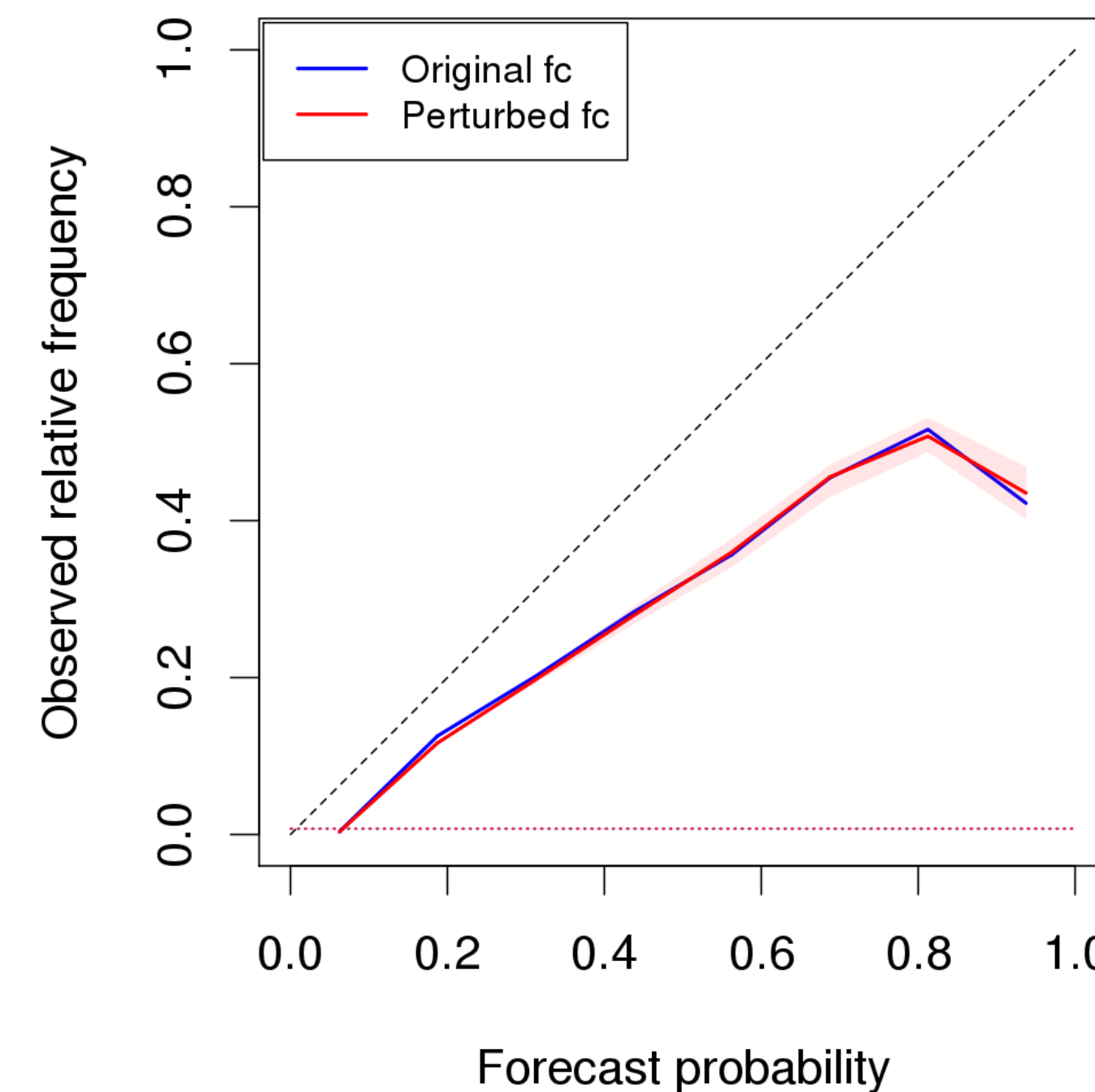
Reliability diagram  
England&Wales, Winter, Day1,  
Threshold: 1 mm/h, Truth: Gauge



Reliability diagram  
England&Wales, Winter, Day1,  
Threshold: 2 mm/h, Truth: Gauge



Reliability diagram  
England&Wales, Winter, Day1,  
Threshold: 4 mm/h, Truth: Gauge





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# Summary

- **Need to count with observation- and representativity errors**
- **Two different kinds of observation style =>**
  - **errors have been estimated**
  - **perturbed the ensemble forecast with estimated error values**
- **The preliminary results are encouraging**





Cumbria, Dec, 2015



Budapest, June, 2013

# Thank you for your attention!

## Questions?

A special thank you to **Jonathan Flowerdew (Met Office)** for helping in the mathematical aspects of the observation error handling.

