UNIVERSITY OF SASKATCHEWAN

Prediction in ungauged basins

The challenge of catchment non-stationarity

Howard Wheater

CERC & Director, Global Institute for Water Security

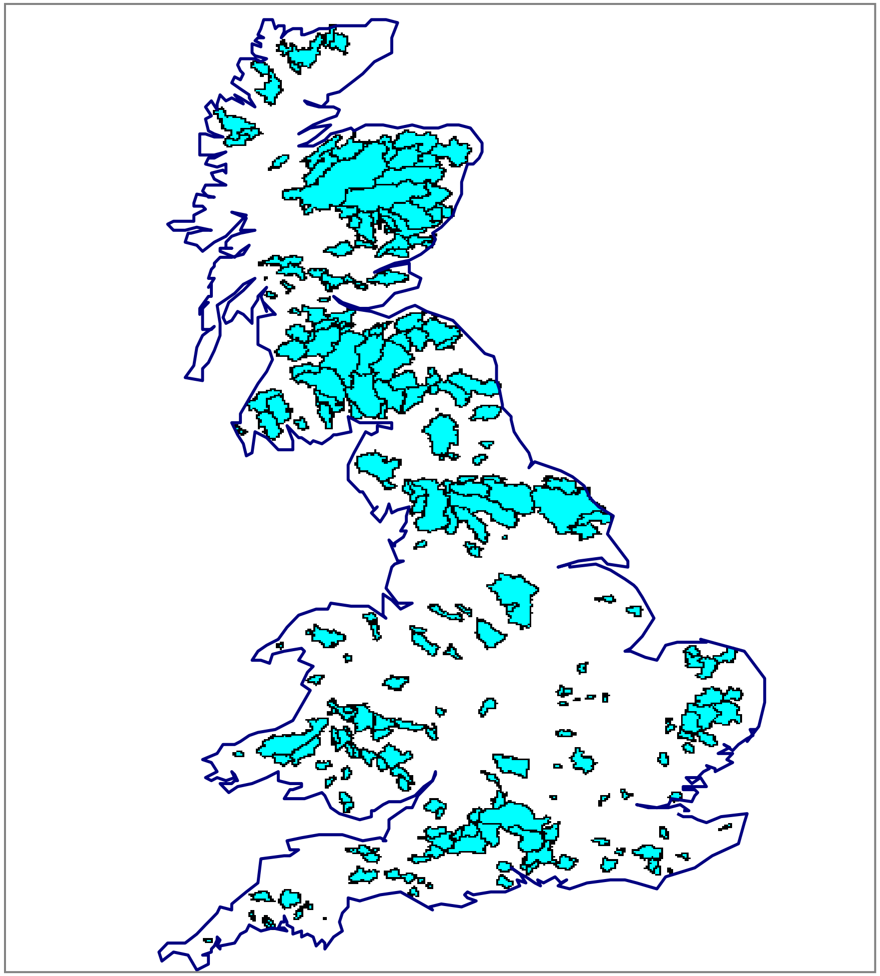
With acknowledgements to:

- Neil McIntyre (Imperial College London, UK)
- Natasha Bulygina (Imperial College London, UK)
- Caroline Ballard (Imperial College London, UK)
- Bethanna Jackson (Victoria University Wellington, NZ)

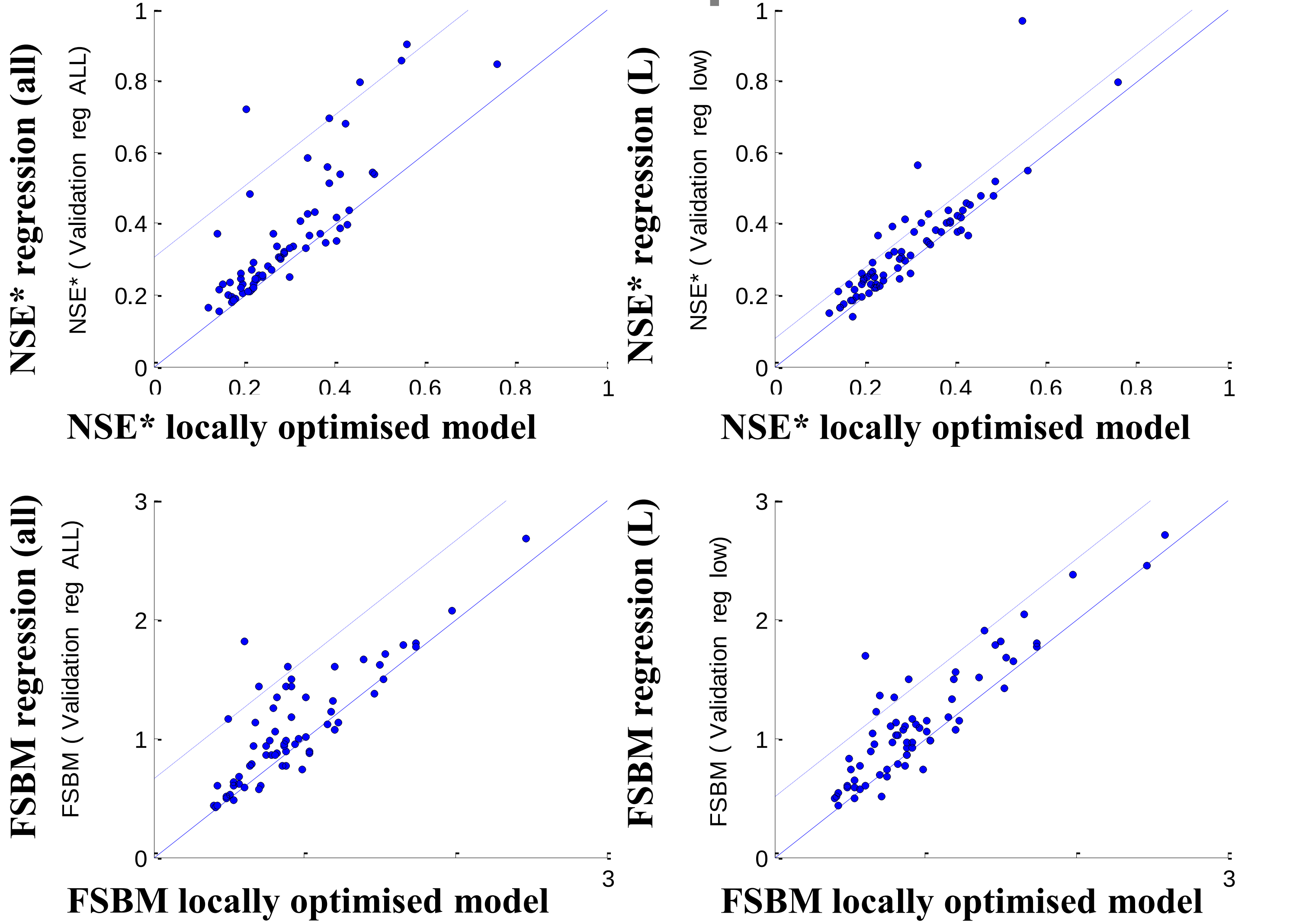
Regionalization of stationary systems

- Major progress has been made in methods to regionalize hydrological models
- Recognition of issues of parameter identifiability has led to use of parsimoneous conceptual models
- Alternative methods have been developed based on:
  a) Relationships between model parameters and catchment characteristics
  b) Transfer of ensembles of parameter sets from ‘donor’ catchments

Data set of 293 UK catchments
(daily data, > 15 years)



Comparison of locally optimised and regression model validation performance



Multiple parameter sets can be used from donor catchments, conditioned on:

a) Prior likelihoods based on calibration performance. A number of models N per gauged catchment may be used

$$P_i = \frac{(\mathrm{NSE}_i - \mathrm{NSE}_{\min})/(1 - \mathrm{NSE}_{\min})}{\sum_{i=1}^{N} (\mathrm{NSE}_i - \mathrm{NSE}_{\min})/(1 - \mathrm{NSE}_{\min})} \qquad \text{for } \mathrm{NSE}_i \geq \mathrm{NSE}_{\min}$$

b) Similarity weighting. Consider a number S of gauged catchments to be feasible 'donor' catchments; weight their influence by catchment similarity

$$B_j = \frac{(1 - E_j / E_{max})}{\sum_{j=1}^{S} (1 - E_j / E_{max})} \qquad \text{for } E_j \leq E_T$$

Posterior likelihoods combine prior likelihoods (P) and similarity weighting (B) of parameter sets from donor sites

$$W_{i,j} = \frac{P_{i,j} B_j}{\sum_{j=1}^{S} \sum_{i=1}^{N} P_{i,j} B_j}$$

Weighted average streamflow is thus derived

$$\overline{Q}(t) = \sum_{i=1}^{N \times S} Q_i(t) \times W_i$$

See e.g. McIntyre, N., H. Lee, H. Wheater, A. Young, and T. Wagener (2005), Ensemble predictions of runoff in ungauged catchments,
Water Resour. Res., 41, W12434, doi:10.1029/2005WR004289.

How do we represent non-stationarity e.g. land use/land management change?

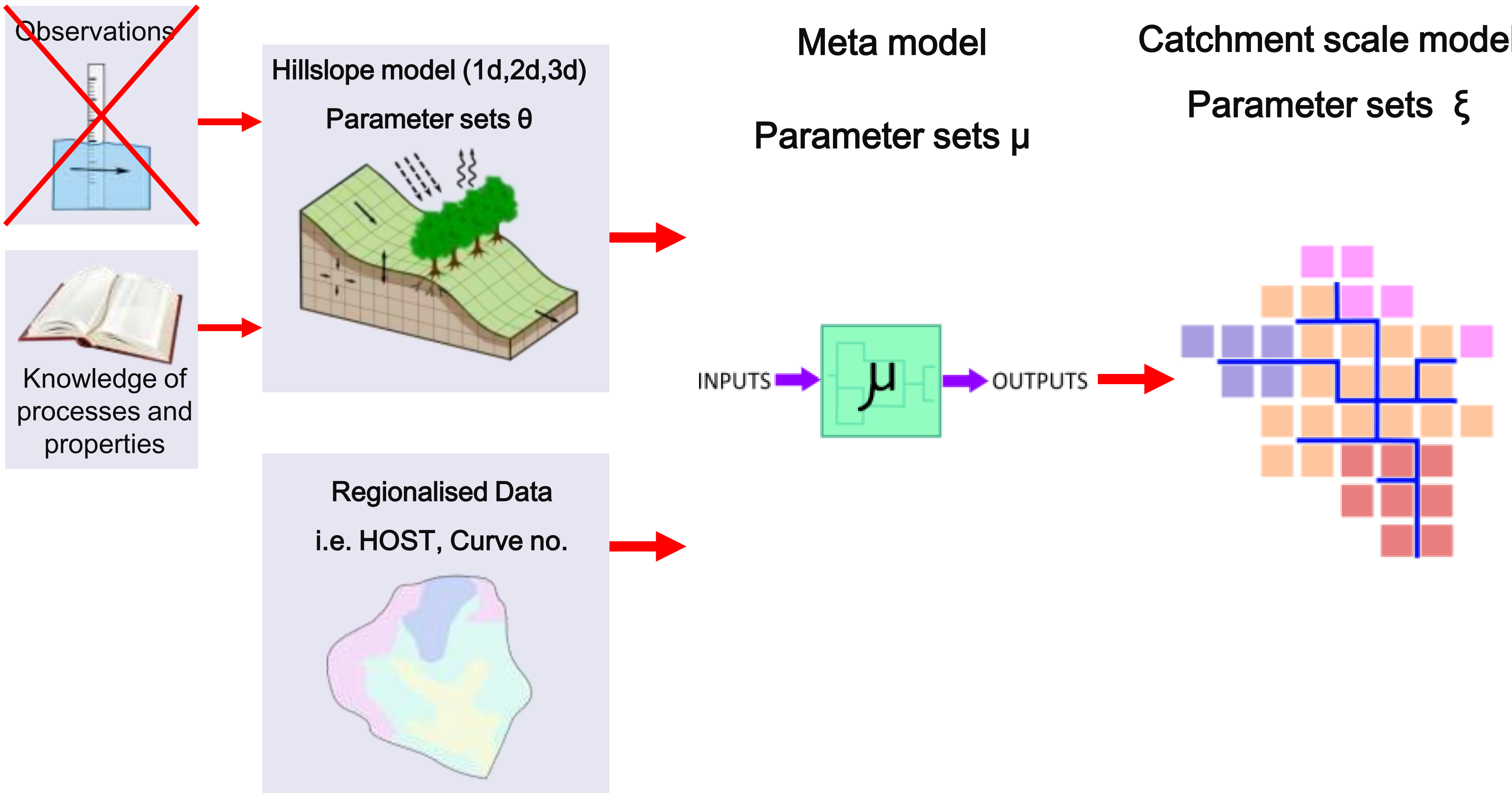
A major UK programme (FRMRC) has been examining effects of agricultural intensification on flood risk

- Analysis of national catchment scale data was unable to identify effects
- Process-based modelling has been needed to evaluate effects of field-scale management interventions
- Extension to ungauged sites has been investigated using process-based and conceptual modelling approaches

Upscaling Strategy

- The case for data-poor sites

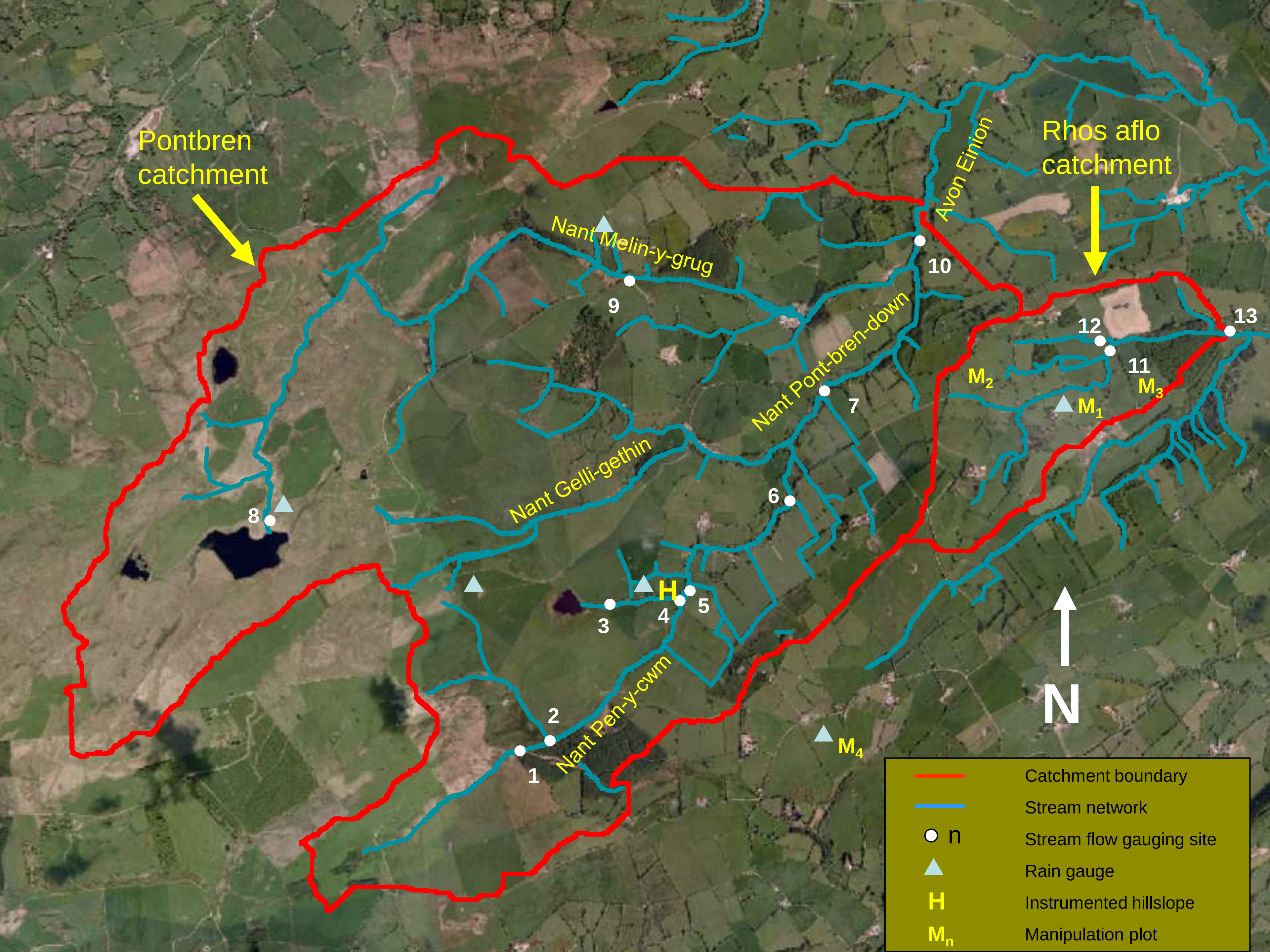
Information about local response



Model structure and process mappings

Data-rich site

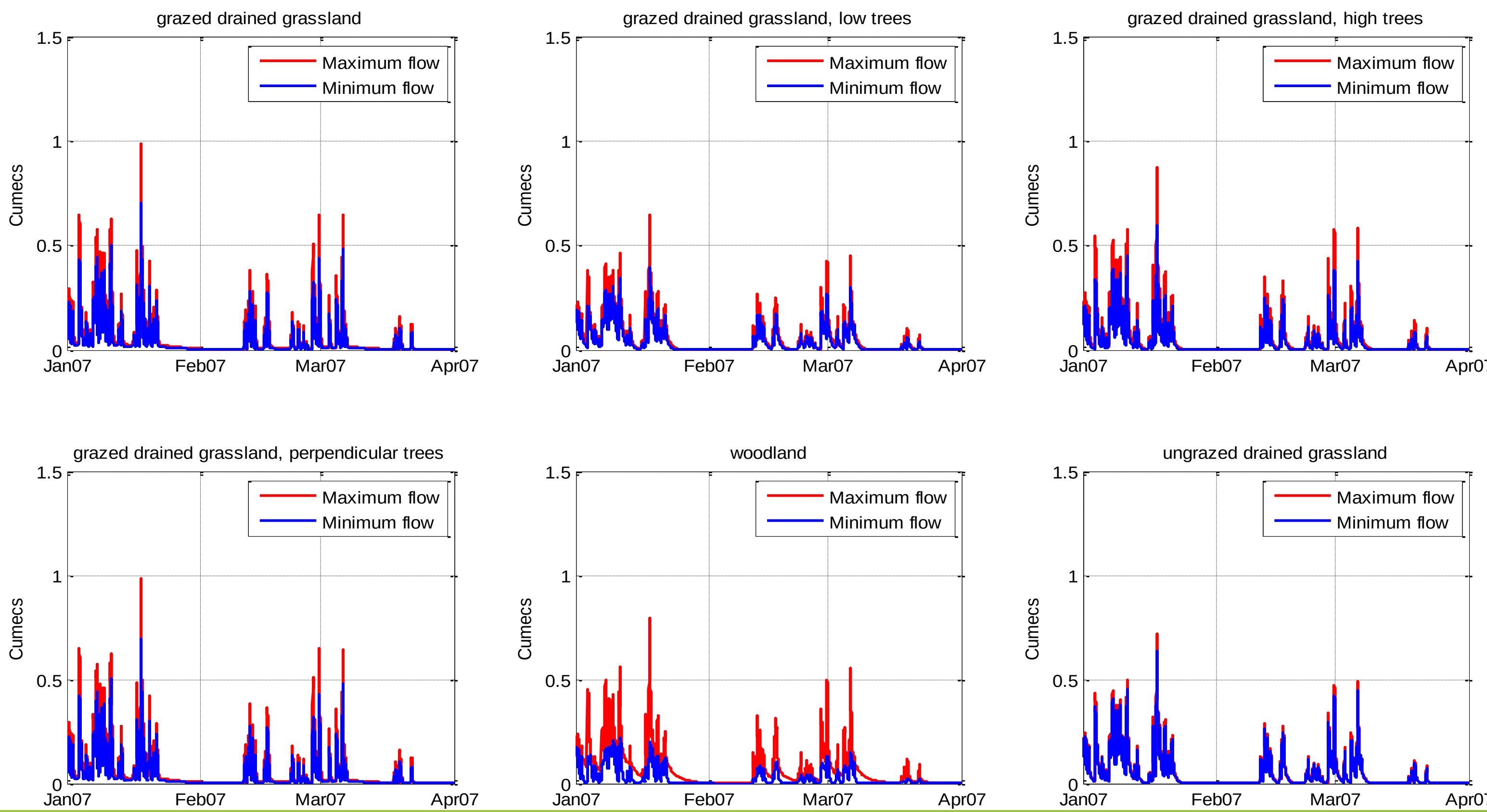
The Pontbren multi-scale experiment, Wales, UK


Pontbren catchment
Rhos aflo catchment
Avon Einion
Nant Melin-y-grug
Nant Pont-bren-down
Nant Gelli-gethin
Nant Pen-y-cwm
H
M_1
M_2
M_3
M_4
1
2
3
4
5
6
7
8
9
10
11
12
13
N
Catchment boundary
Stream network
n
Stream flow gauging site
Rain gauge
H
Instrumented hillslope
M_n
Manipulation plot

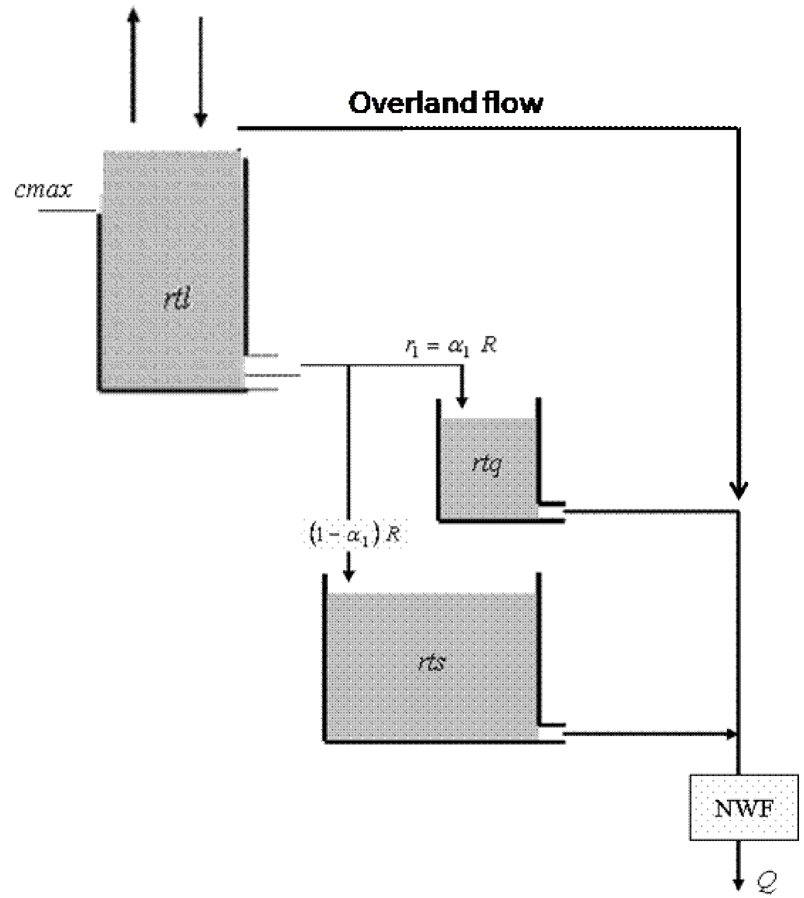
Physics-based Modelling Strategy

- Reproduce experimental observations at the plot and hillslope scales using detailed physically-based models
- Explore *local* effects of management strategies
- Capture detailed model response with meta-model structure at the scale of fields and hillslopes
- Develop semi-distributed catchment scale model, using meta-model for individual elements
- Investigate catchment-scale effects of land-use change

Physics-based model: Field-scale runoff for different land use types, with uncertainty bounds

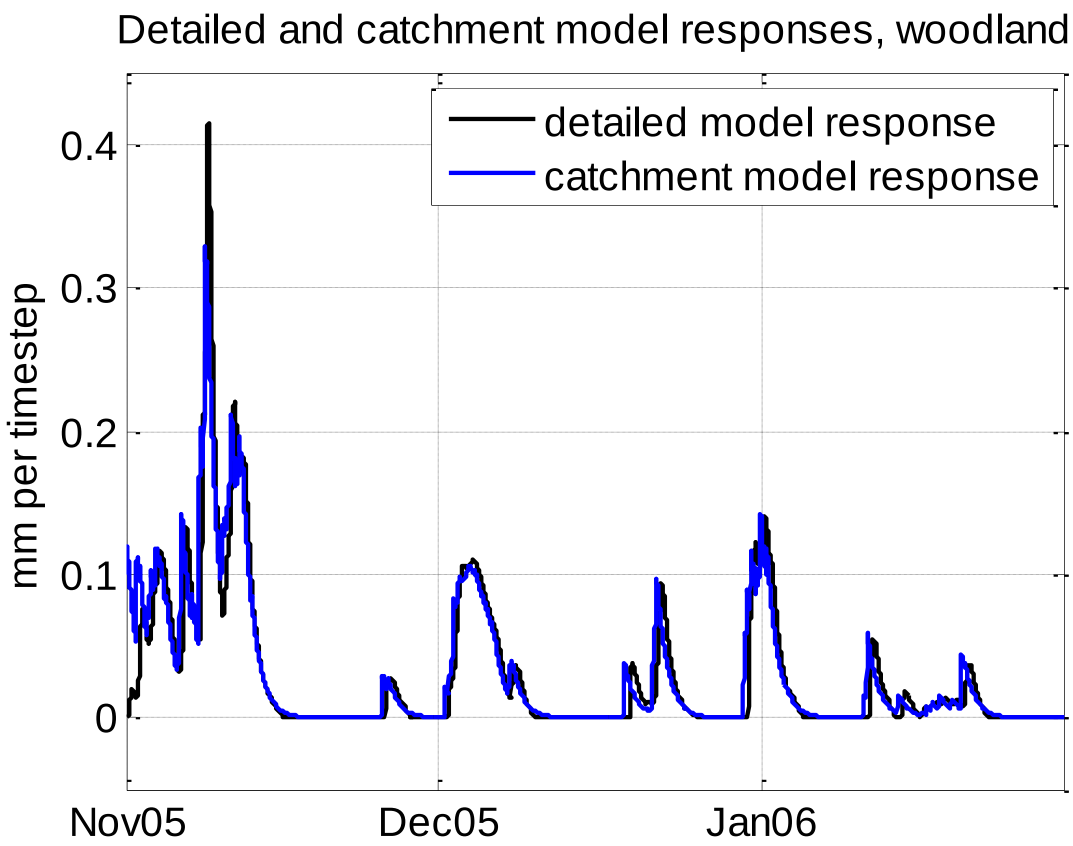


Meta-model structure



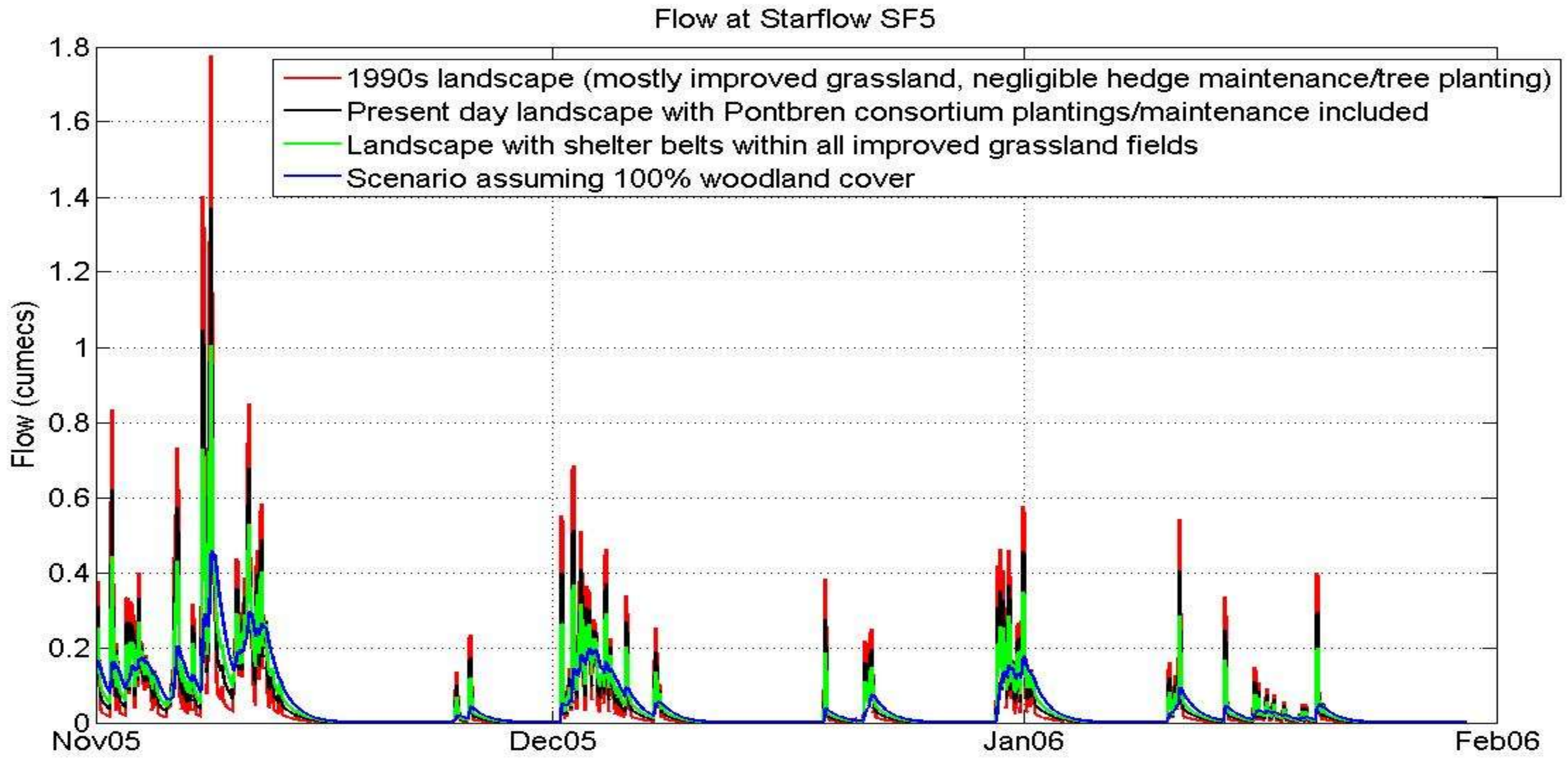
Meta-model performance (woodland response)

- meta-models work!



Catchment modelling: Pontbren

Scenario comparisons



Data sparse site
The Hodder Catchment, N.W. England

Peat models presented in today's talk

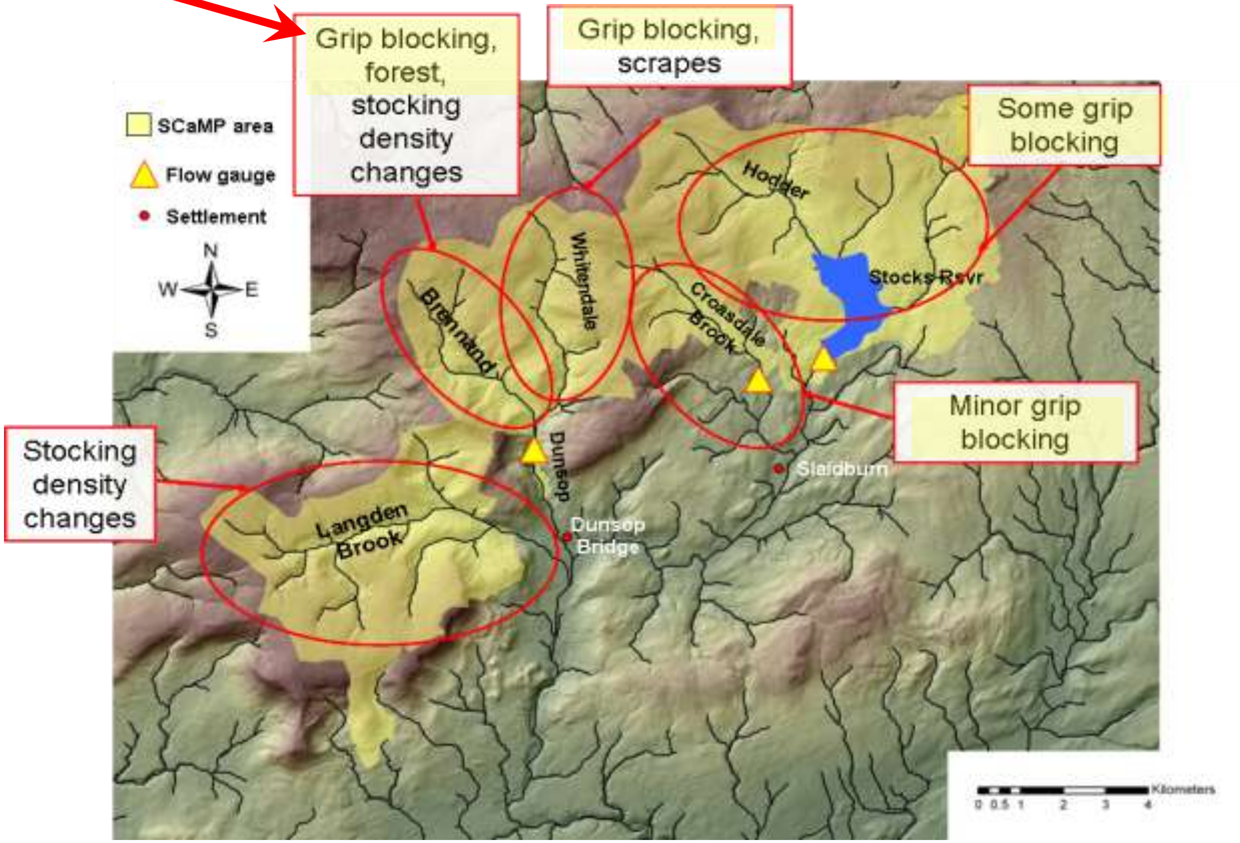
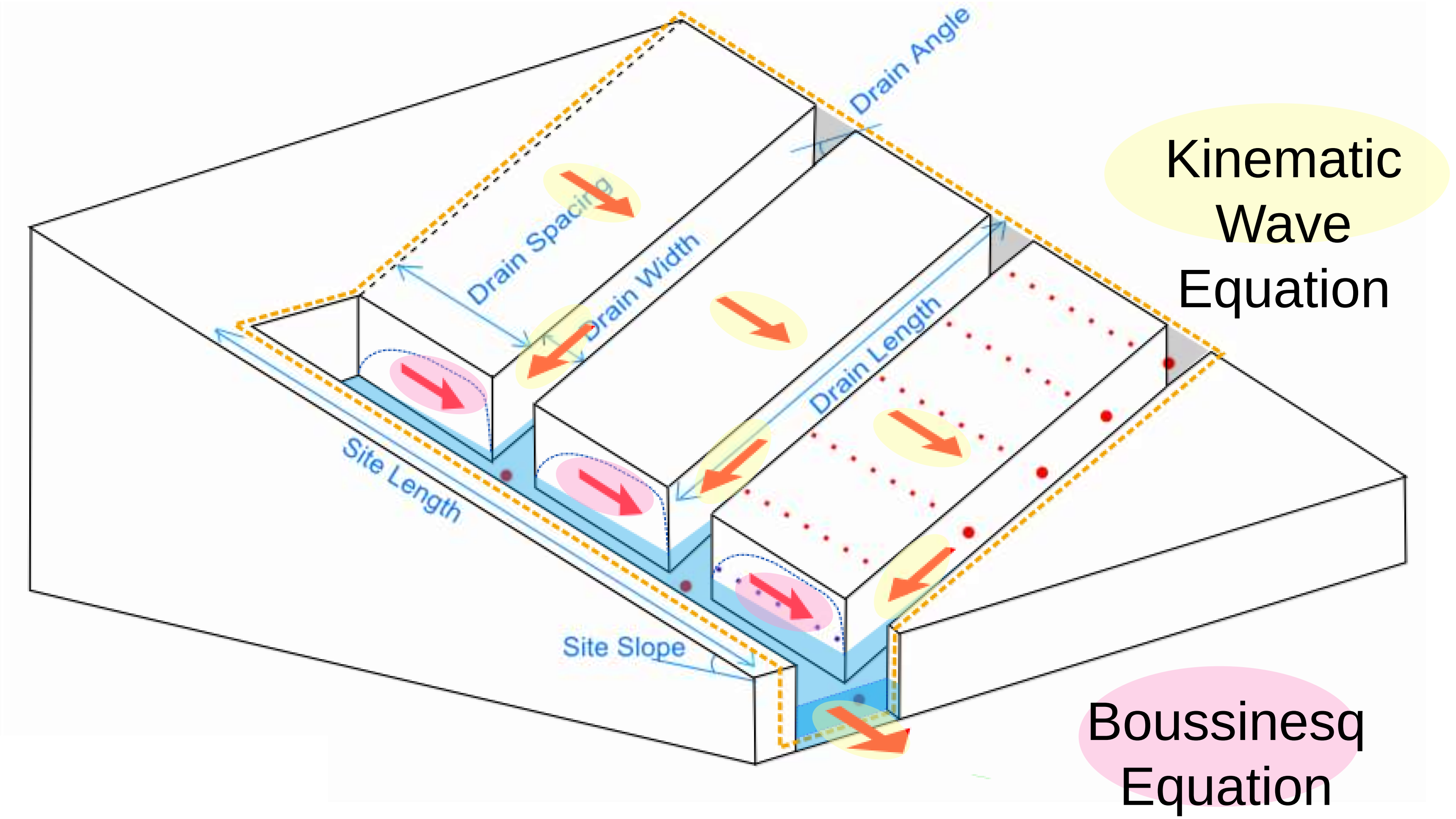


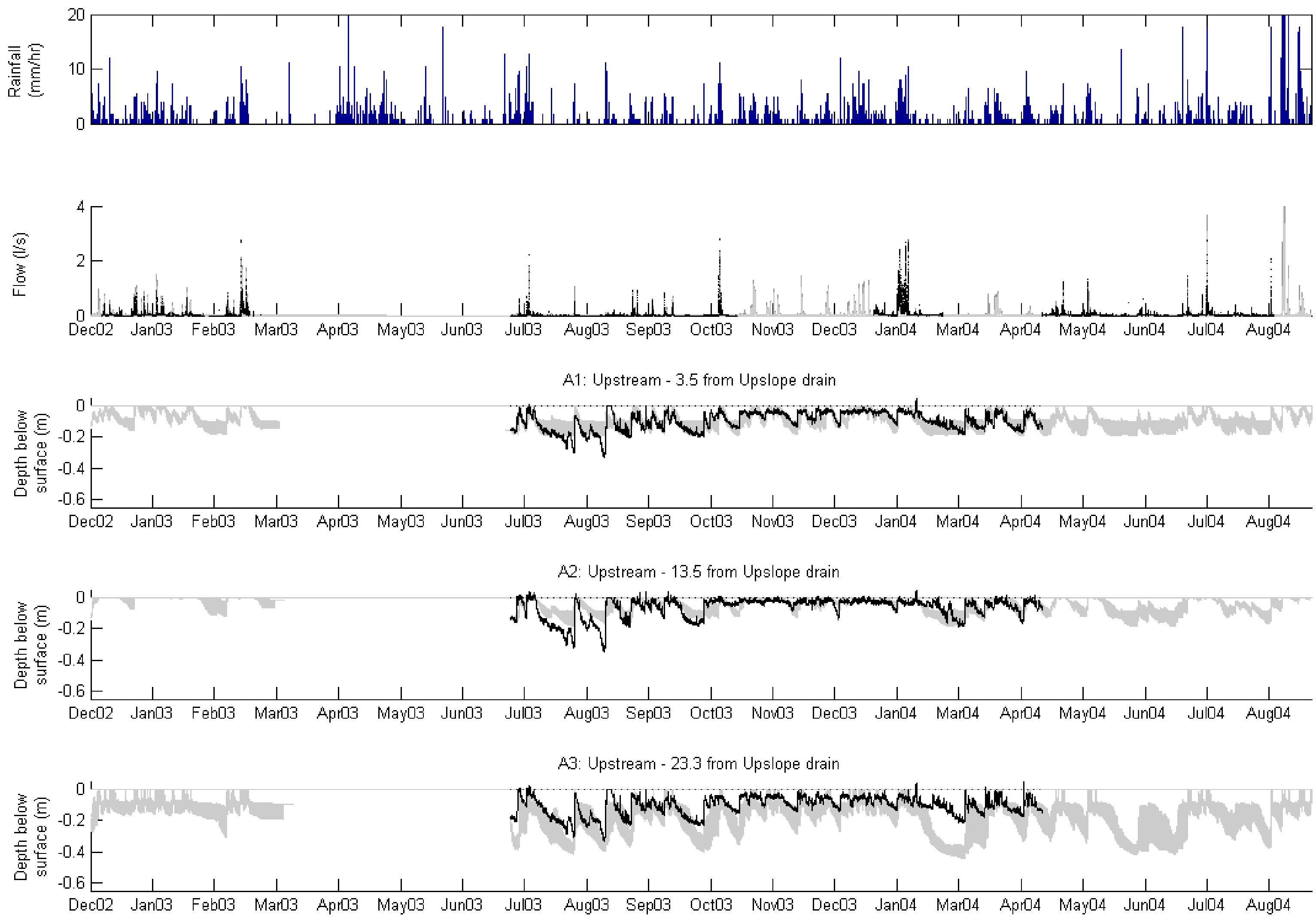
Image from "Multiscale Experimentation, Monitoring and Analysis of Long-term Land Use Changes and Flood Risk (EA Project SC060092): Experimental Design, Monitoring Design, and Project Record", J. Ewen, G. O'Donnell, W. Mayes, J. Geris and E. O'Connell

Drained Peatland Detailed Model

General Model Setup

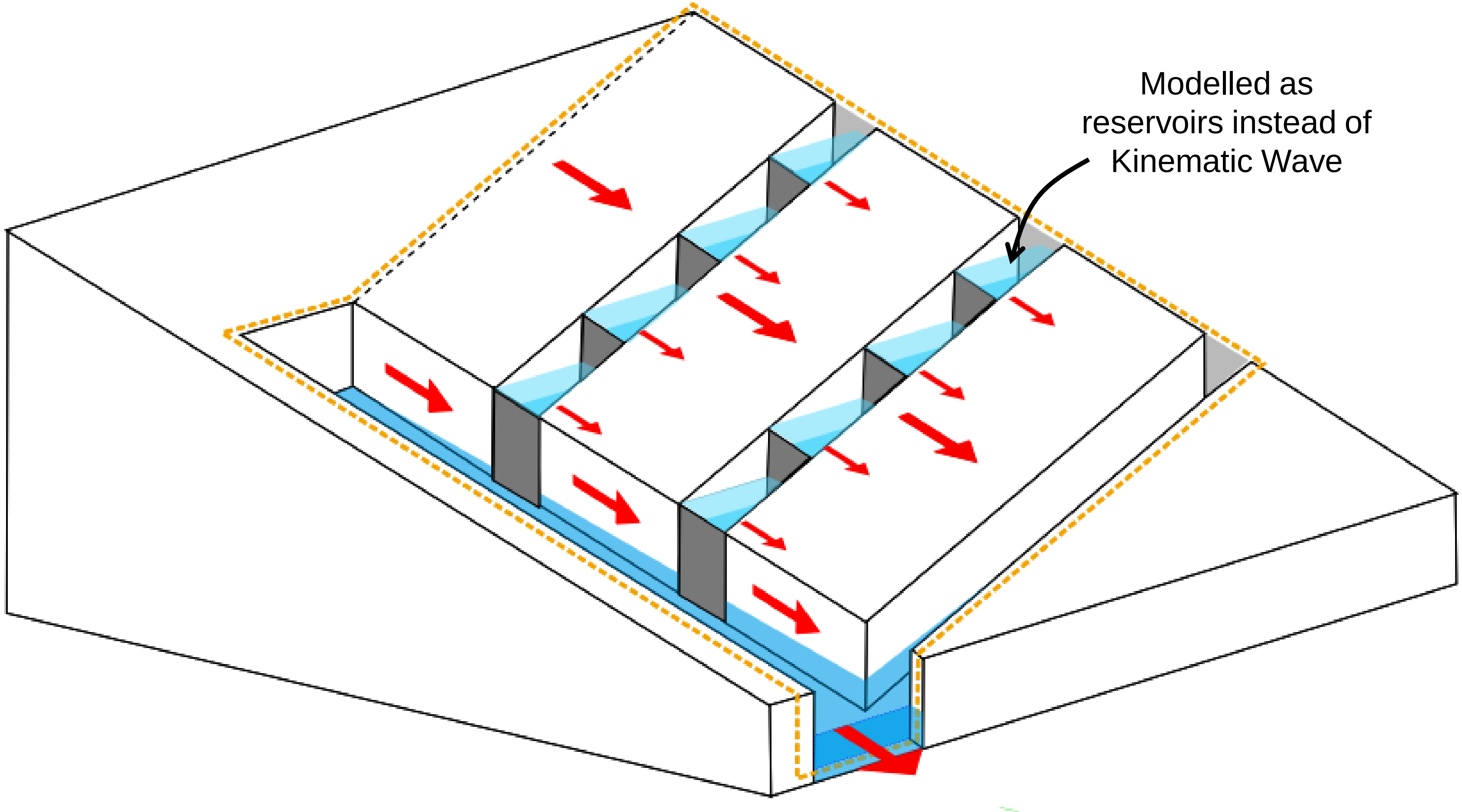


Water Table Results

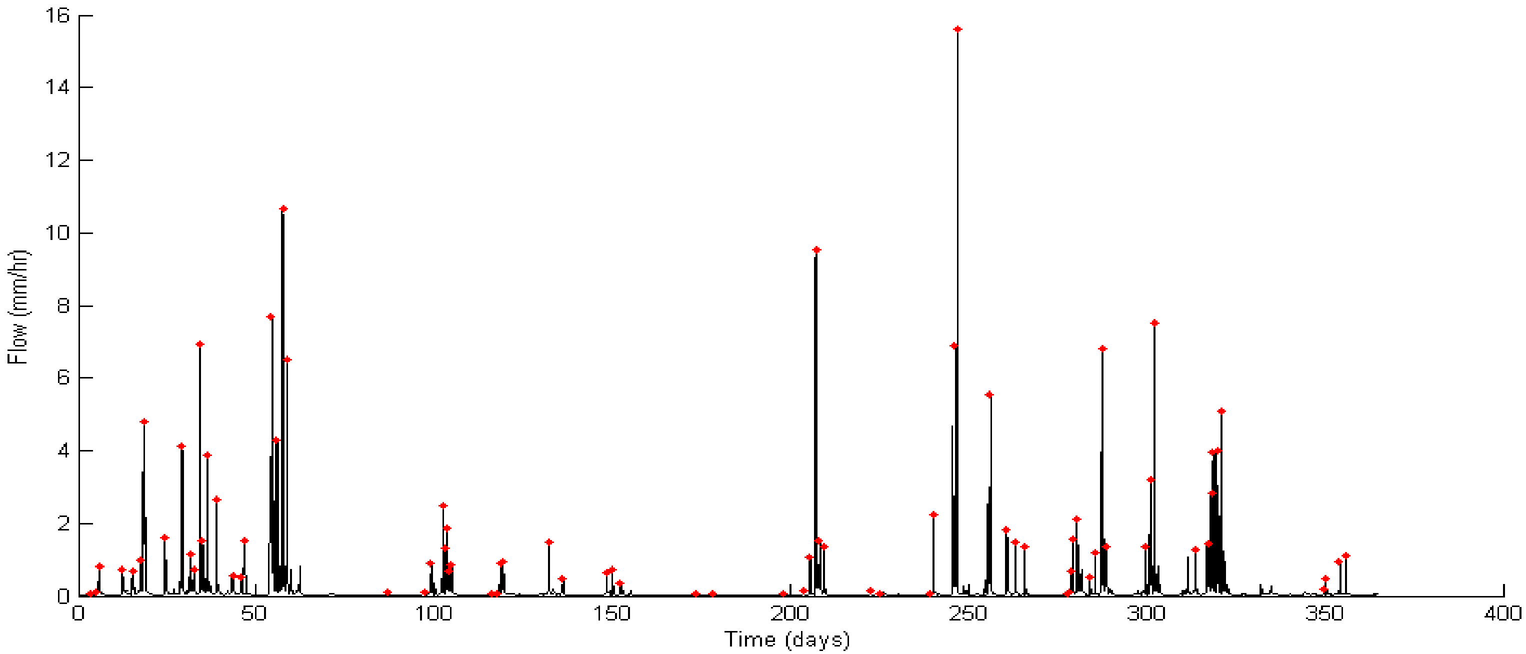


Data from a surrogate site in Upper Wharfedale, provided courtesy of Professor Joe Holden, Leeds University

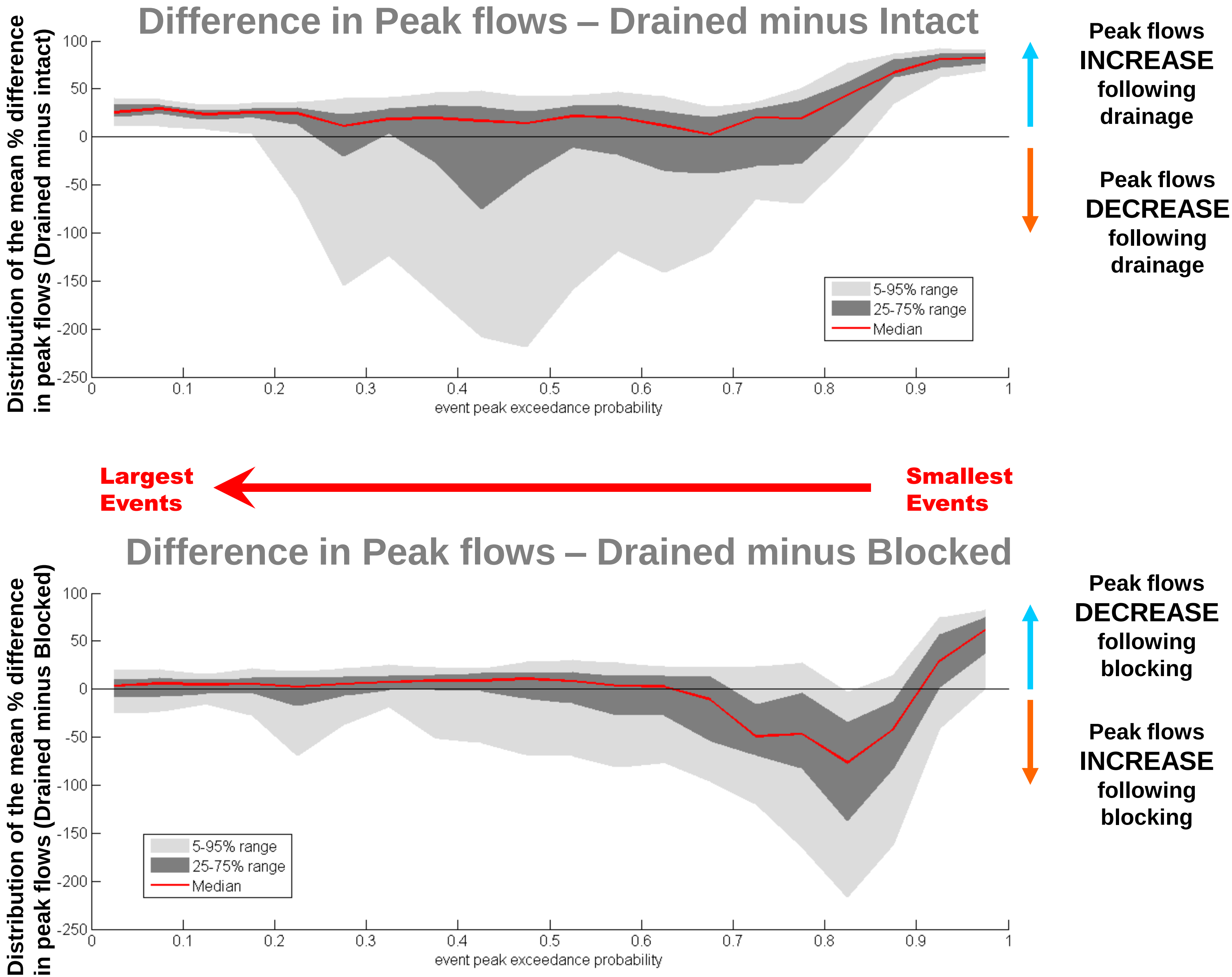
Grip Blocking



Simulations with scenarios



- Events analysis - 79 events for the year.
- 100 parameter sets – used for Drained, Blocked and Intact simulations of a 1 year period



Difference in Peak flows – Drained minus Intact
Distribution of the mean % difference in peak flows (Drained minus intact)
100
50
0
-50
-100
-150
-200
-250
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
event peak exceedance probability
5-95% range
25-75% range
Median
Peak flows INCREASE following drainage
Peak flows DECREASE following drainage
Largest Events
Smallest Events
Difference in Peak flows – Drained minus Blocked
Distribution of the mean % difference in peak flows (Drained minus Blocked)
Peak flows DECREASE following blocking
Peak flows INCREASE following blocking

Peatland summary

- Physics-based modelling conditioned on surrogate data has been used to explore impacts of management interventions
- Drainage of peatlands leads to an increase in the largest and smallest flows
- The effect of drain blocking on flooding is dependent on local conditions, increasing and decreasing flow peaks
- The model can be used to prioritise drain blocking activities to provide the greatest benefit in terms of peak flow reduction
- The model has been applied at catchment scale using the meta-modelling strategy defined above

Bayesian conditioning of hydrological models using regionalised indices

- Model parameters are sampled from the feasible parameter space
- Regionalised indices are available as a function of soils (BFI HOST) and land management (CN)
- Parameter sets are weighted according to the consistency of model performance with the predicted indices

Bayesian parameter conditioning: data

In regionalisation

D = areal physical properties, *not* direct response observations

Here, we consider

D = {soil hydrological type (HOST), land use}

$$L(\vartheta / D) \text{ -?}$$

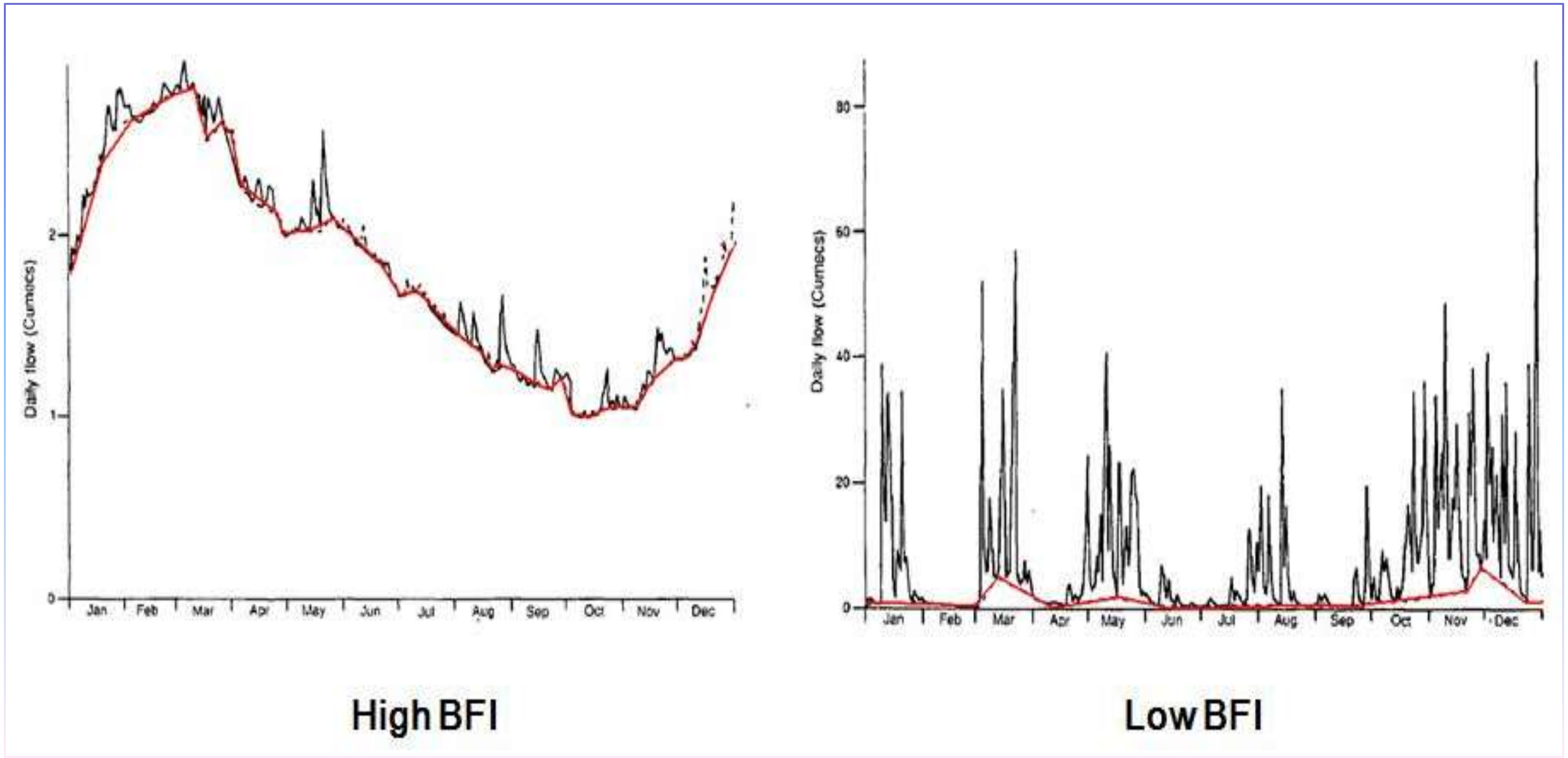
Bayesian parameter conditioning: likelihood

Each soil type and land use are represented via *behavioural indices*:

- Base flow index (BFI_{HOST})
- Curve number (CN_{SCS})

$$L(\vartheta |\ D) = L(\vartheta |\ BFI_{HOST}, CN_{SCS})$$

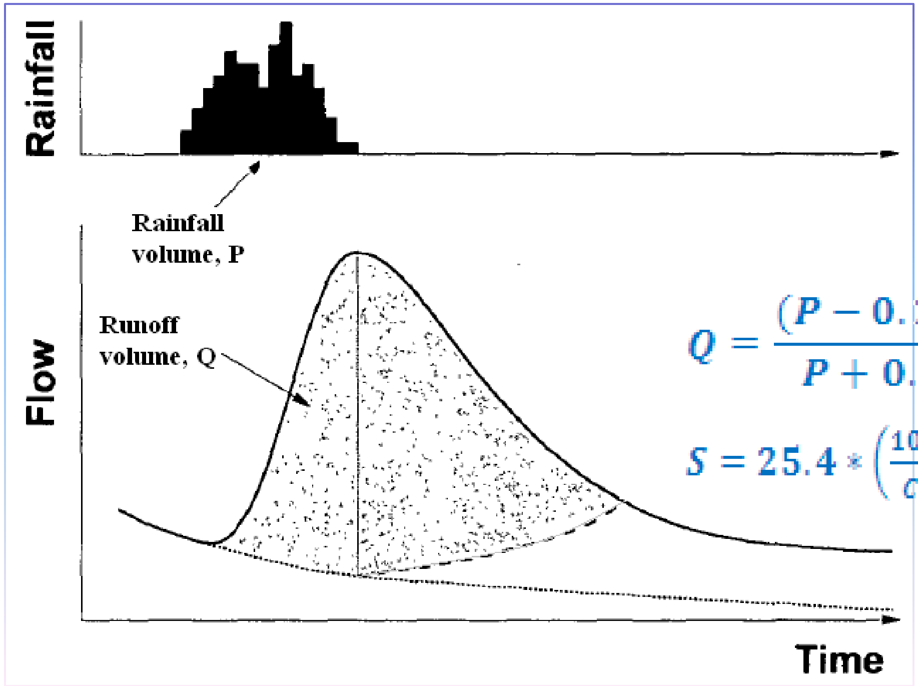
Behavioural indices: Base Flow Index (BFI)



Proportion of baseflow (BFI) can be estimated from soil type (HOST) using a UK regional relationship

Behavioural indices: SCS Curve Number (CN)

Curve Number relates rainfall volume to direct surface runoff amount



$$Q = \frac{(P - 0.2S)^2}{P + 0.8S}$$

$$S = 25.4 * \left(\frac{1000}{CN} - 10\right)$$

CN is available as a function of soil type and land management

Selected curve numbers

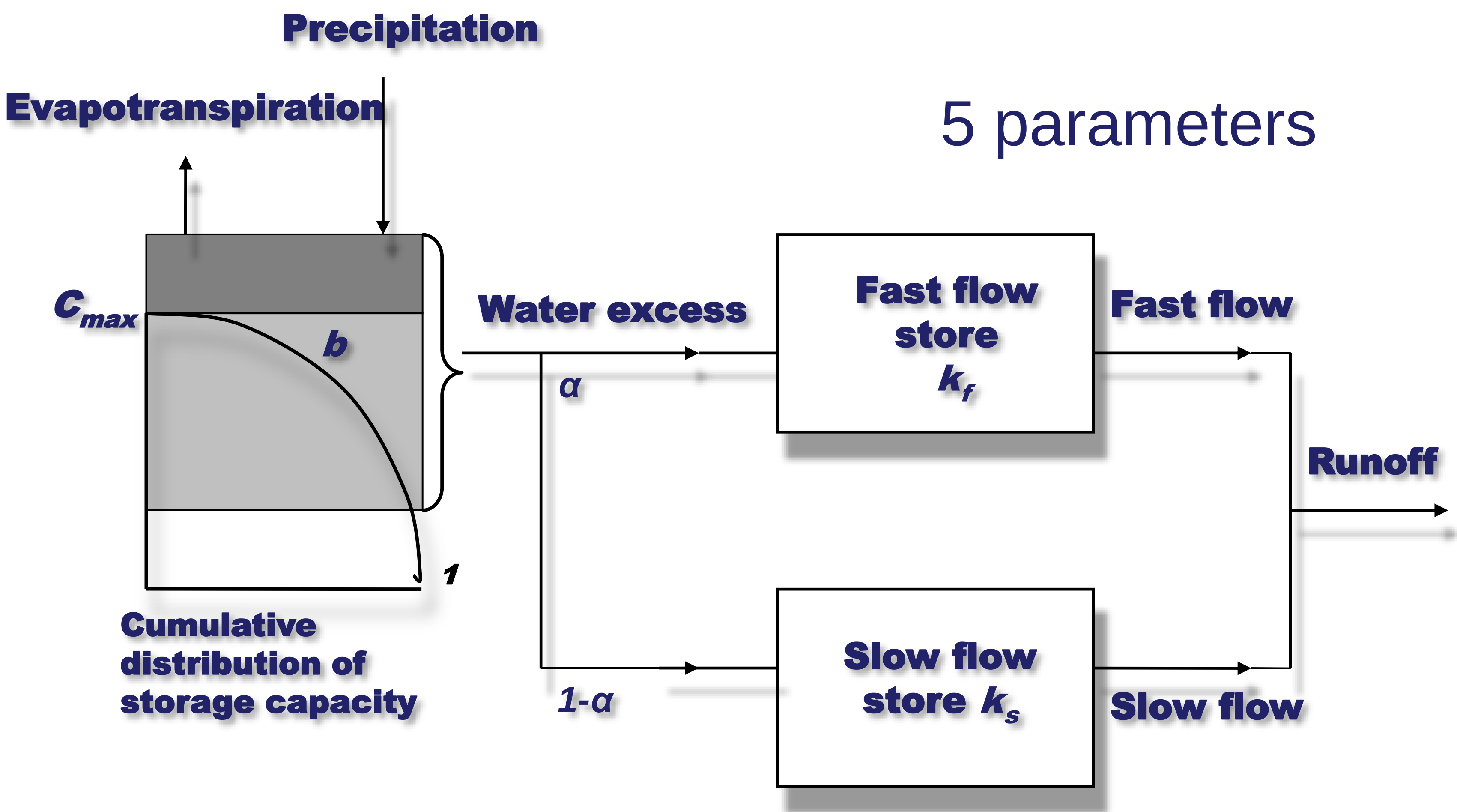
Land use	Hydrological soil group			
	A	B	C	D
Pasture[1]				
Poor	68	79	86	89
Fair	49	69	79	84
Good	39	61	74	80
Woods[2]				
Poor	45	65	77	83
Fair	36	60	73	79
Good	30	55	70	77

[1] *Poor*: heavily grazed with no mulch.
Fair: not heavily grazed.
Good: lightly or only occasionally grazed.

[2] *Poor*: forest litter, small trees, and brush are destroyed by heavy grazing or regular burning.
Fair: woods are grazed but not burned, and some forest litter covers the soil.
Good: woods are protected from grazing, and litter and brush adequately cover the soil.

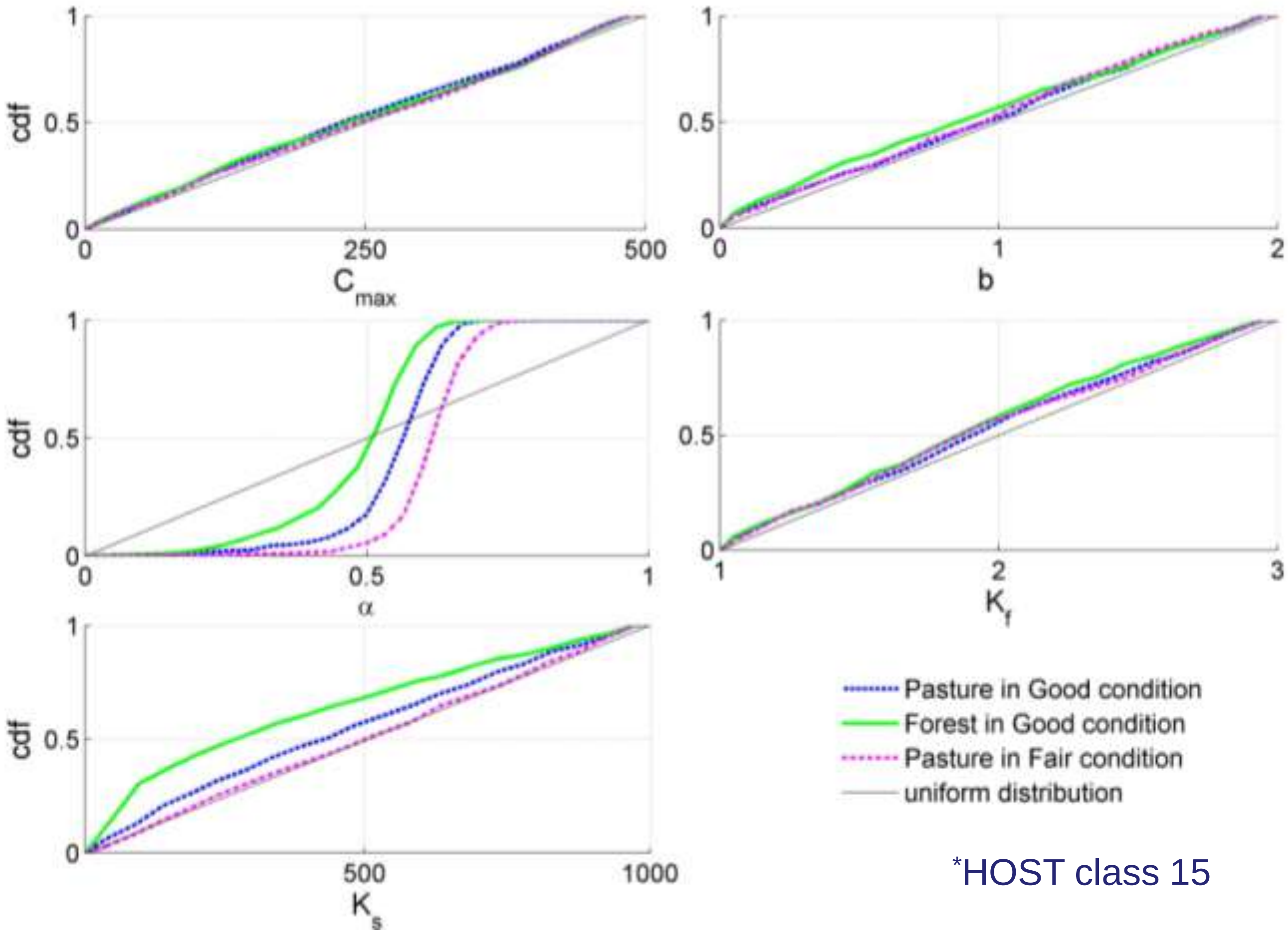
Model structure - PDM

5 parameters



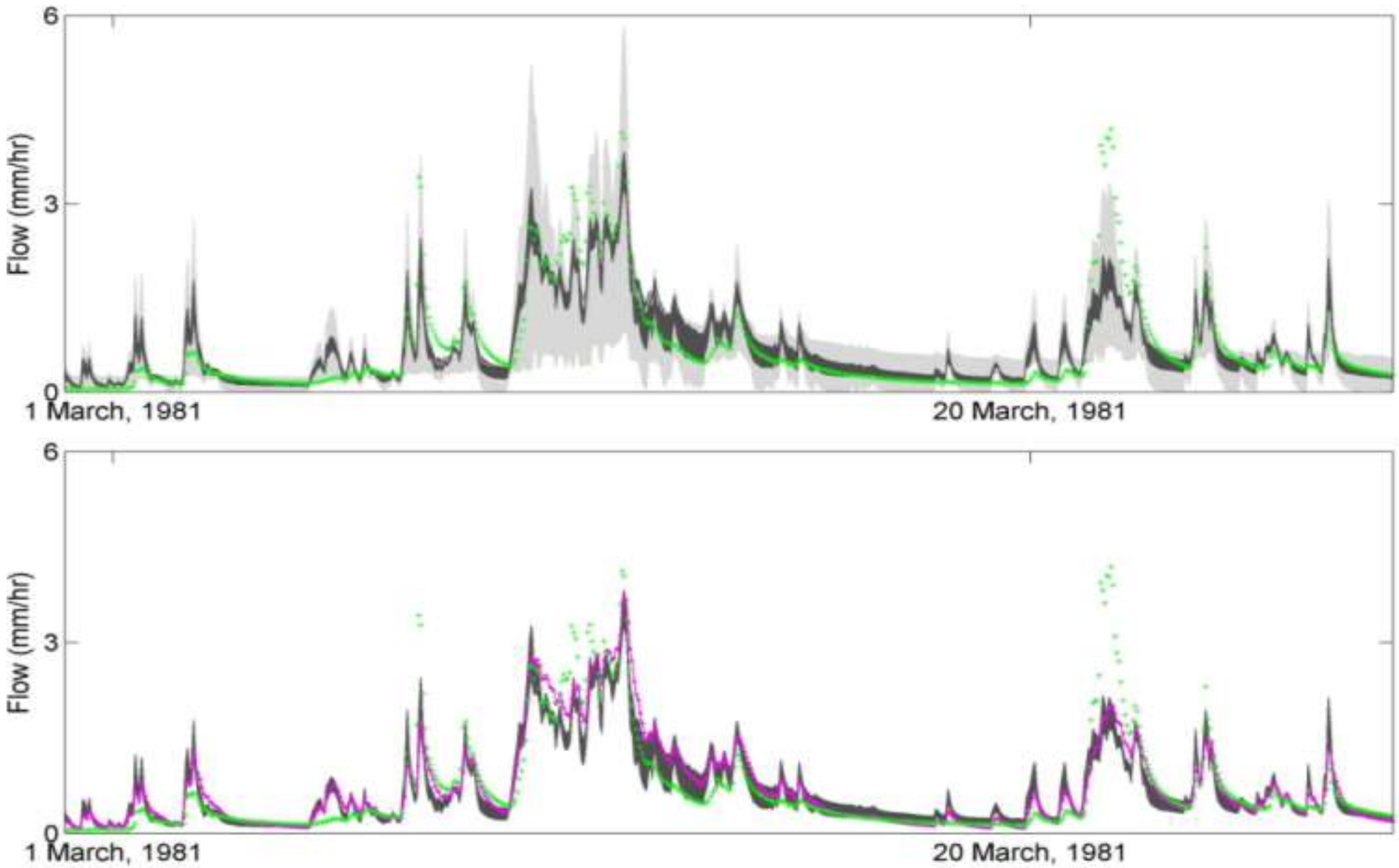
Plynlimon paired catchments, Wales, UK

Parameter restrictions*



*HOST class 15

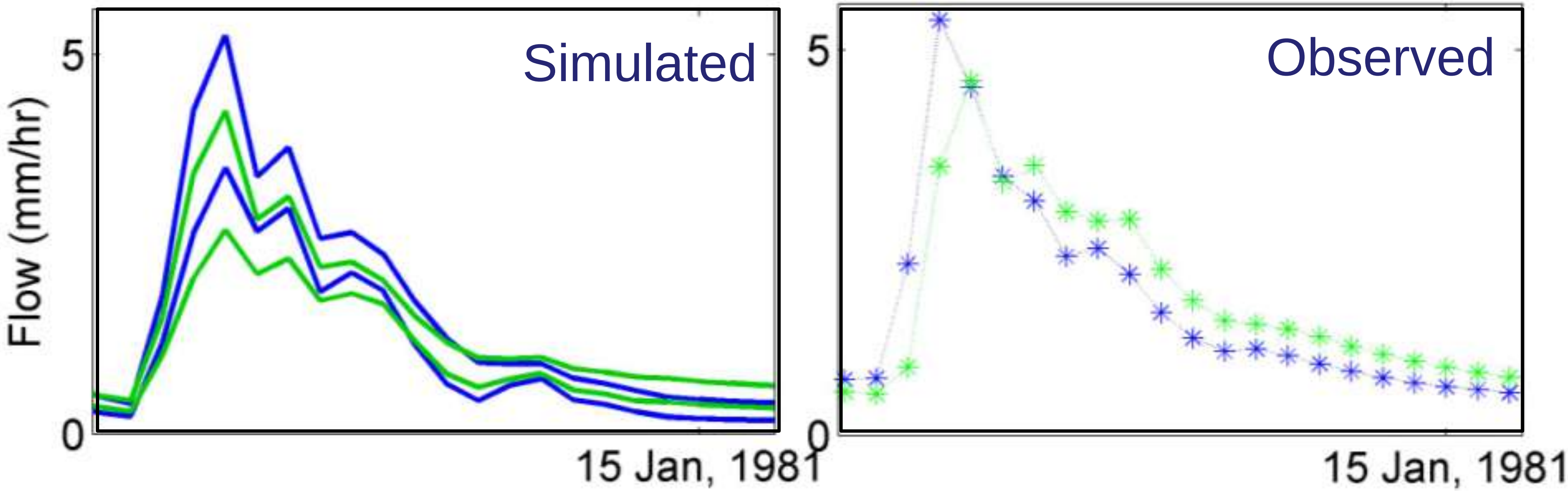
Flow predictions



Nash-Sutcliffe efficiency

Parameter estimation	Severn				Wye			
	Severn	Tanllwyth	Hafren	Hore	Wye	Gwy	Cyff	Iago
Regionalisation	0.74	0.70	0.73	0.73	0.76	0.77	0.8	0.76
Calibration	0.78	0.74	0.75	0.76	0.85	0.81	0.88	0.83

Land use effects can be simulated



green = Severn
blue = Wye

Conclusions from regionalisation study

- *Soil type* and *land use* are used to restrict model parameter space via regionalised *BFI* and C*N*
- *BFI* and *CN* are only *partially* informative for parameters
- *Other* regionalised behavioural indices are needed
- The proposed regionalisation:
  - significantly reduced prediction uncertainty
  - was comparable with calibrated model predictions
  - allows *land use effects* estimation

Modelling changing land use - conclusions

- Physics-based models can provide important insights into non-stationary responses, but uncertainty must be recognised and much work remains to be done to explore the limits of predictability

- New meta-modelling methods provide a computationally efficient way to represent local scale complexity in large scale models

- Use of hydrological indices to condition conceptual models has proved surprisingly effective

- The CN method has potential for use in conditioning models to represent land management effects – but without more research to demonstrate local (UK) validity, results are speculative