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Stochastic modelling approach for synthesising stream-flow

   

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Introduction

Mostly flood risk management project involves:

- Use of single 1:*N* years extreme flow/rainfall event

This approach does not accounts for:

- effect of flood clustering on channel cross-section
- effect of change in channel capacity on flood risk

Aim: To develop a modelling approach inclusive of…

- sediment transport processes & related flood risk
- multi-event simulation
- flood sequence/cluster risk-recovery processes

… we need sufficiently long time-series or possibly multiple series

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Motivation

- What effect has *N* years sediment transport on flood inundation?

Stochastic modelling of daily mean flow

- Generate multiple (e.g.100) flow sequences
- Hidden Markov Model + Generalised Pareto (HMM-GP)

1D sediment transport modelling of flow sequences

- 100 future channel configurations
- Define '*worst-case*' channel

1D/2D flood hazard modelling using '*worst-case*' channel

- Quantify change in inundation

Why do we need such a model?

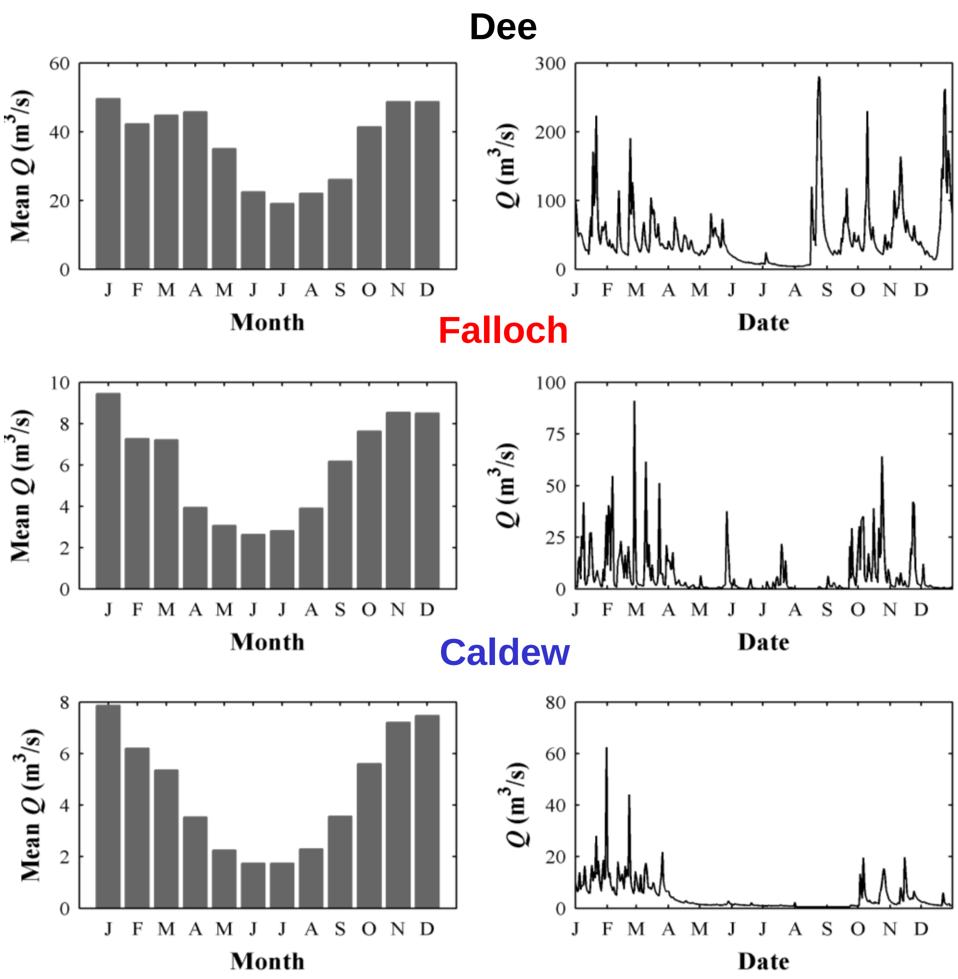
- Computationally efficient at generating multiple realisations for **uncertainty analysis**
- Provide **realistic realisations** of river flows
- Can be used for **long-term modelling**
- Allows estimation of **sediment transport** and loading on flood defences
- Ensure long-term **sustainability** of flood defence assets
- Easily applicable at **multiple sites**
- **Limits error** accumulation that occurs using rainfall and hydrological models

Field site – Locations

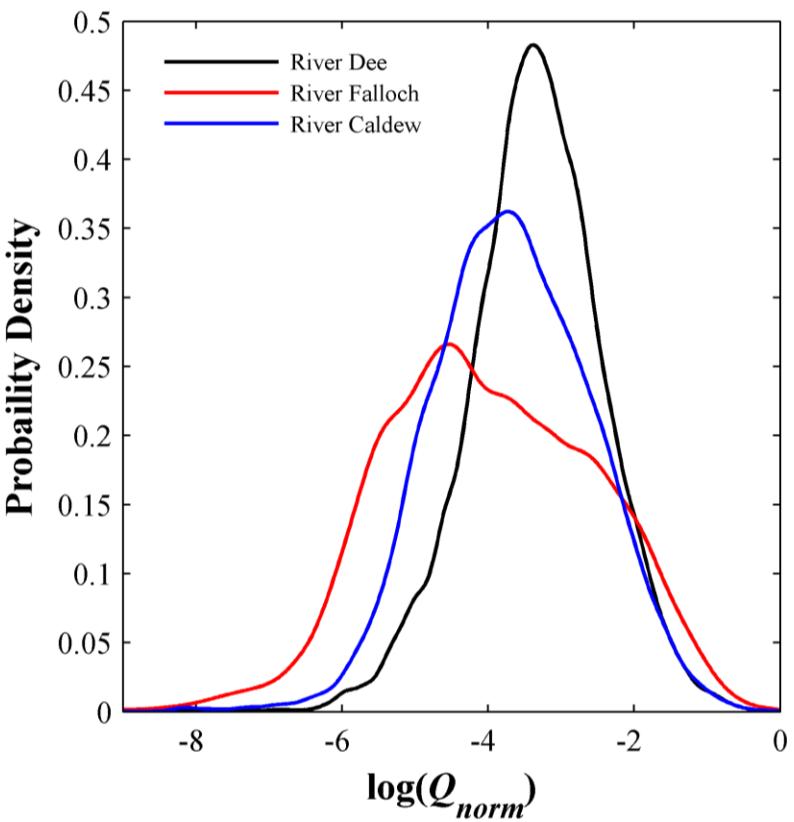
- **River Dee – Aberdeenshire**
  - Daily mean flow from 1929 – 2012
- **River Falloch – Stirlingshire**
  - Daily mean flow from 1970 – 2012
- **River Caldew – Cumbria**
  - Daily mean flow from 1968 – 2000

River	Record (yrs)	$Q_{5\%}$ (m^3/s)	$Q_{50\%}$ (m^3/s)	$Q_{100\%}$ (m^3/s)
Dee	83	8.29	26.52	648.50
Falloch	42	0.27	2.17	123.60
Caldew	32	0.75	2.69	96.39

Field site – Data



Mean monthly flows (Left panel) and 1995 hydrographs (Right panel)



Stochastic Modelling of stream flow

- to produce desired number of the synthetic flow-series our approach combines Hidden-Markov Model with extreme value distribution [Generalised Pareto (GP)].

Hidden Markov Model

- Based on the evolution of process/system in time from a given state to another state, i.e.
- Exploits the probability of the system to jump from one state to another
- Accounts for the transition of system through hidden states

Hidden Markov Model

A HMM model is comprised of five elements:

1. <u>Set of distinct observed states</u> - Percentile analysis of all observed values using increment of 10% to define eleven distinct observed states (A,B,C,D,E,F,G,H,I,J,K)

- State A – flow between the minimum and 10^{th} Percentile
- State B – flow between the10^{th} and 20^{th} percentile
- …
- …
- …
- So on.

Hidden Markov Model

2. <u>Set of unobserved (hidden) states within observed states</u> – account for all the discrete values with one decimal place within the range of each eleven distinct observed states.

<u>For example</u>:

➢if state A corresponds to values between 0 to 1 then set of unobserved states corresponding to state A will be 0.1, 0.2, 0.3, …, 0.9

➢if state B corresponds to values between 1 to 2 then set of unobserved states corresponding to state B will be 1.1, 1.2, 1.3, 1.4, …, 1.9

➢… so on

Hidden Markov Model

3. **State transitional probability matrix** – probability of transition between different observed states.

- Corresponding to eleven distinct states ⇒11 × 11 matrix

$$
\begin{array}{cc}
 & \begin{array}{ccccc} \mathbf{A} & \mathbf{B} & \dots & \dots & \mathbf{K} \end{array} \\
\begin{array}{c} \mathbf{A} \\ \mathbf{B} \\ \dots \\ \dots \\ \mathbf{K} \end{array} &
\begin{bmatrix}
m_{aa} & m_{ab} & \dots & \dots & m_{ak} \\
m_{ba} & m_{bb} & \dots & \dots & m_{bk} \\
\dots & \dots & \dots & \dots & \dots \\
\dots & \dots & \dots & \dots & \dots \\
m_{ka} & m_{kb} & \dots & \dots & m_{kk}
\end{bmatrix}
\end{array}
$$

Hidden Markov Model

4. **<u>Emission probability matrix</u>** – emission probability of underlying (hidden) states from discrete observed states.

➢Corresponding to eleven distinct states and nine underlying (hidden) state $\Rightarrow$11 × 9 matrix

$$\begin{array}{c} A \\ B \\ .. \\ .. \\ K \end{array} \begin{bmatrix} m_{a1} & m_{a2} & \cdots & m_{a9} \\ m_{b1} & m_{b2} & \cdots & m_{b9} \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ m_{k1} & m_{k2} & \cdots & m_{k9} \end{bmatrix}$$

5. **<u>Set of eleven initial probability of observed states</u>** – obtained from the analysis of time series data

Extreme Value Distribution

Generalized Pareto (GP) distribution has been fitted to the data > 99th percentile to sample extreme values

Why Extreme Value Distribution?

- With pure HMM upper extreme values were controlled by measured data, e.g.

  For example, if original data has n discrete extreme values $x_1, x_2, \dots, x_n$; then all synthetic series will have extreme values sampled from these n values.

- Application of extreme value distribution provide an opportunity to sample extreme values from a continuous distribution rather than few discrete values.

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Results

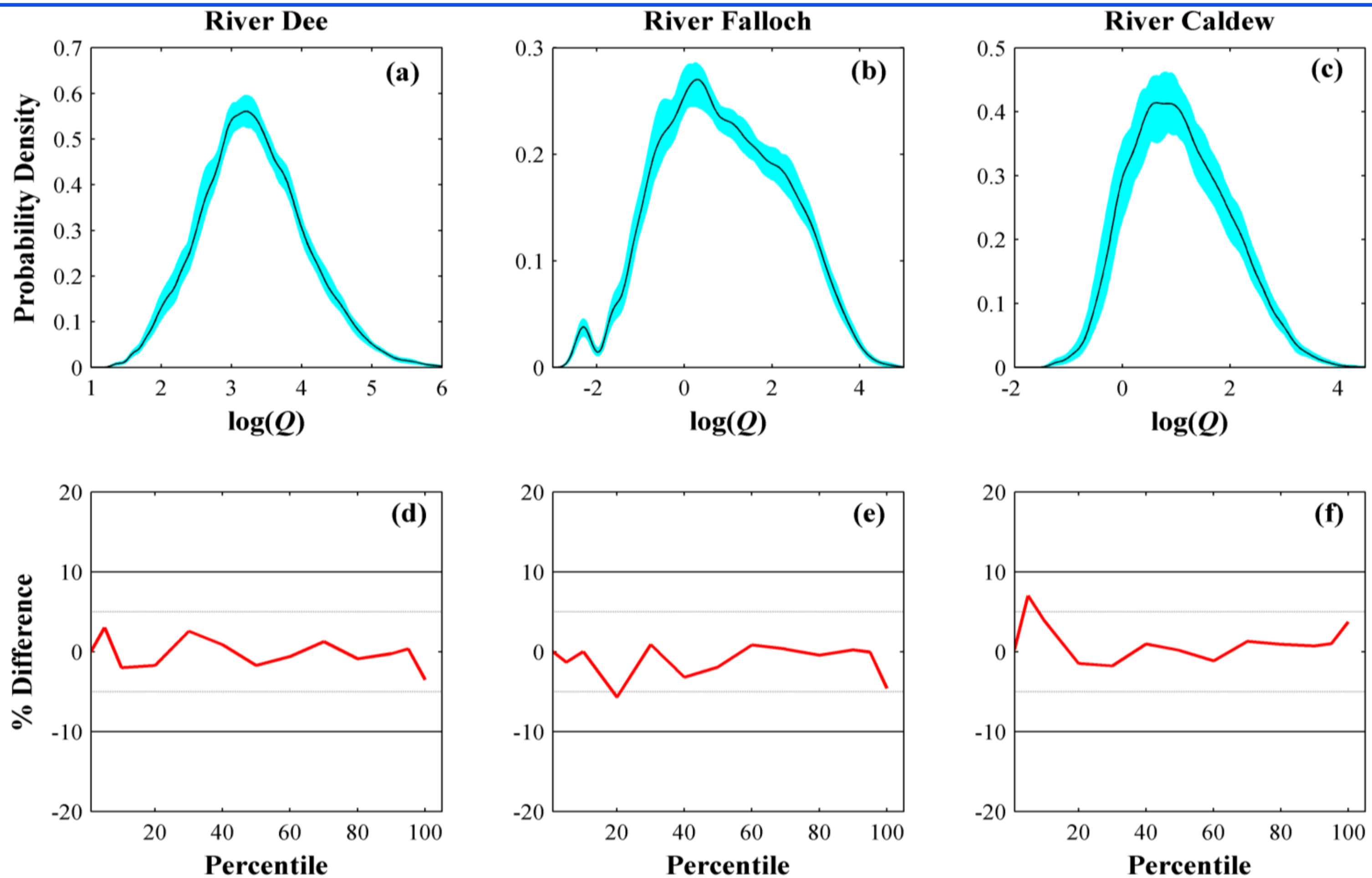
- 100 sequences the same length as the historic record are generated
- Comparison of probability densities
- More detailed comparison at a range of percentiles
  - Percentage difference between historic and mean of the 100 sequences

$$\%\,\text{Difference} = \frac{\text{mean}(Q_{p,synthetic}) - Q_{p,recorded}}{Q_{p,recorded}}$$

  - Overall Relative Mean Absolute Difference (RMAD) across the range of percentiles

$$\text{RMAD} = \sum_{p=1}^{n} \left| \frac{Q_{p,synthetic} - Q_{p,recorded}}{Q_{p,recorded}} \right| \times \frac{100\,\%}{n}$$

Results



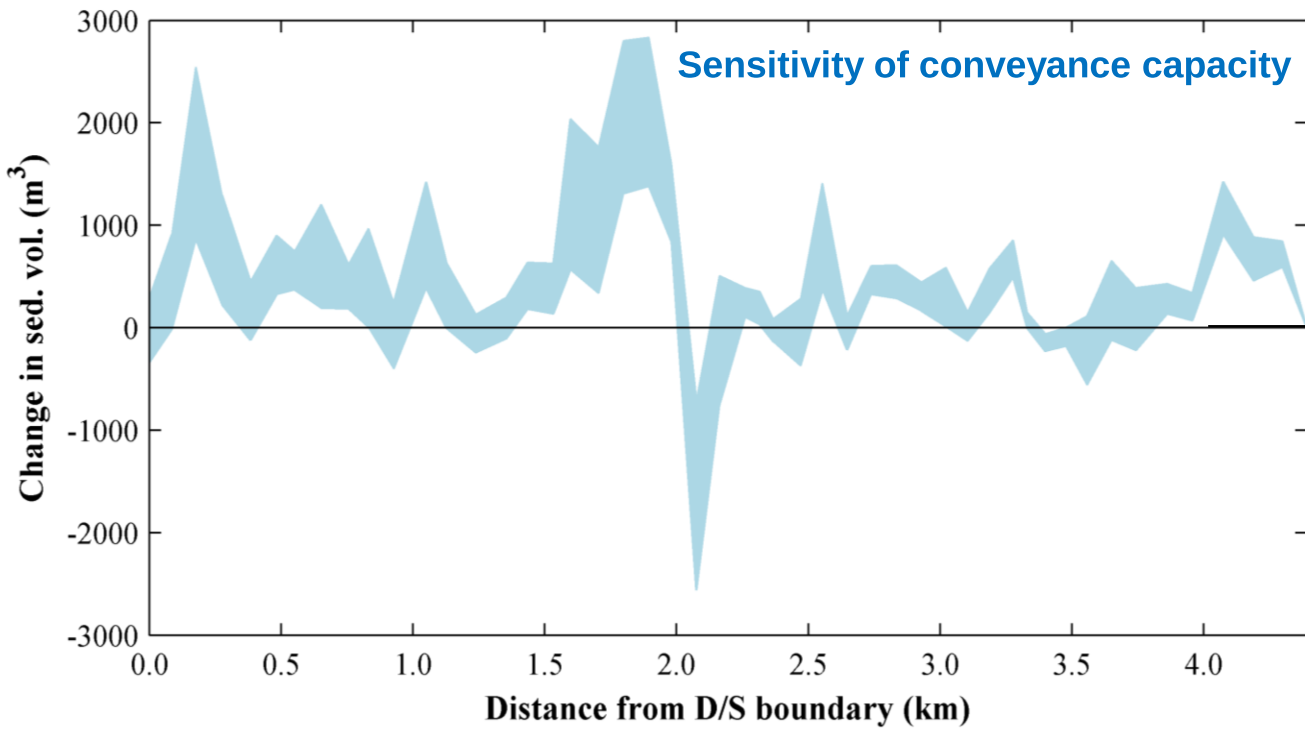
RMAD = 1.4%　RMAD = 1.5%　RMAD = 1.9%

Pender, D., Patidar, S., Pender, G. & Haynes, H. (2016) *Stochastic simulation of daily streamflow sequences using a hidden Markov model.* Hydrology Research, Vol. 47, no. 1, pp. 75-88.

Current uses within flood risk studies

Sediment transport modelling

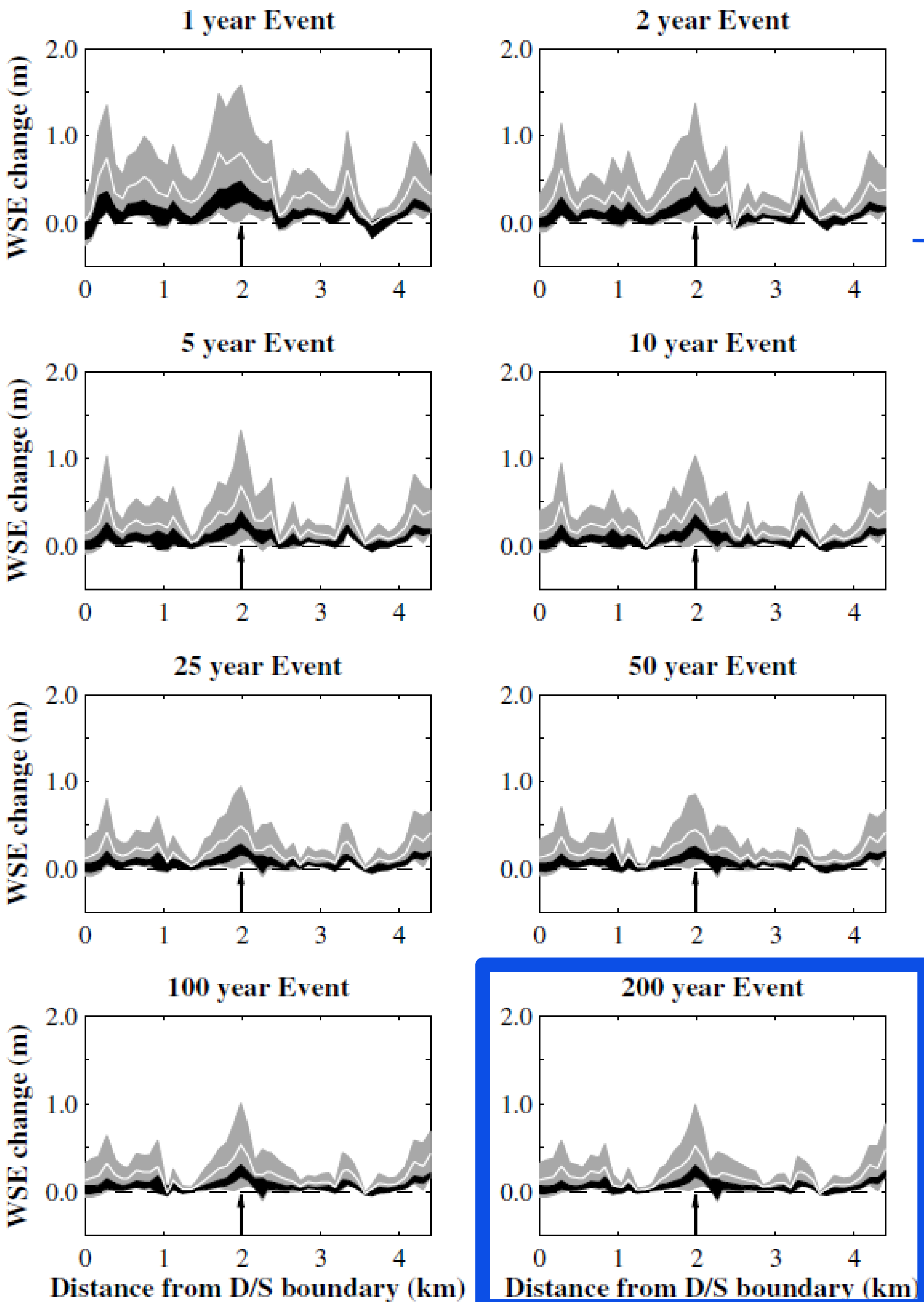
- Generate 100 × 50 years of flow data
- Simulate sediment transport and morphological changes
- Determine best and worst case future channel and future flood risk



Aggradation = ↑ Hazard

Degradation = ↓ Hazard

Changes to cross-section sediment volume for the 50 year period…



Sediment Transport modelling

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Figure: The change in Water Surface Elevation (WSE), along the reach, for the Min/Max; and All methods for new channel geometries are provided by the grey and black envelopes respectively. The average WSE along the reach using the Min/Max channels is indicated by the white line

1 in 200yr RP

- Conservative approach:

  WSE ↑ 0.3 - 0.5m

- Extreme approach
  - WSE ↑ 0.3 – 0.4m (mean)
  - WSE ↑ 0.5 - 0.8m (max)

Future R&D…

✓Finer resolution time step (15min)

✓Constrain run time (POT; clusters)

✓Supply

✓2D

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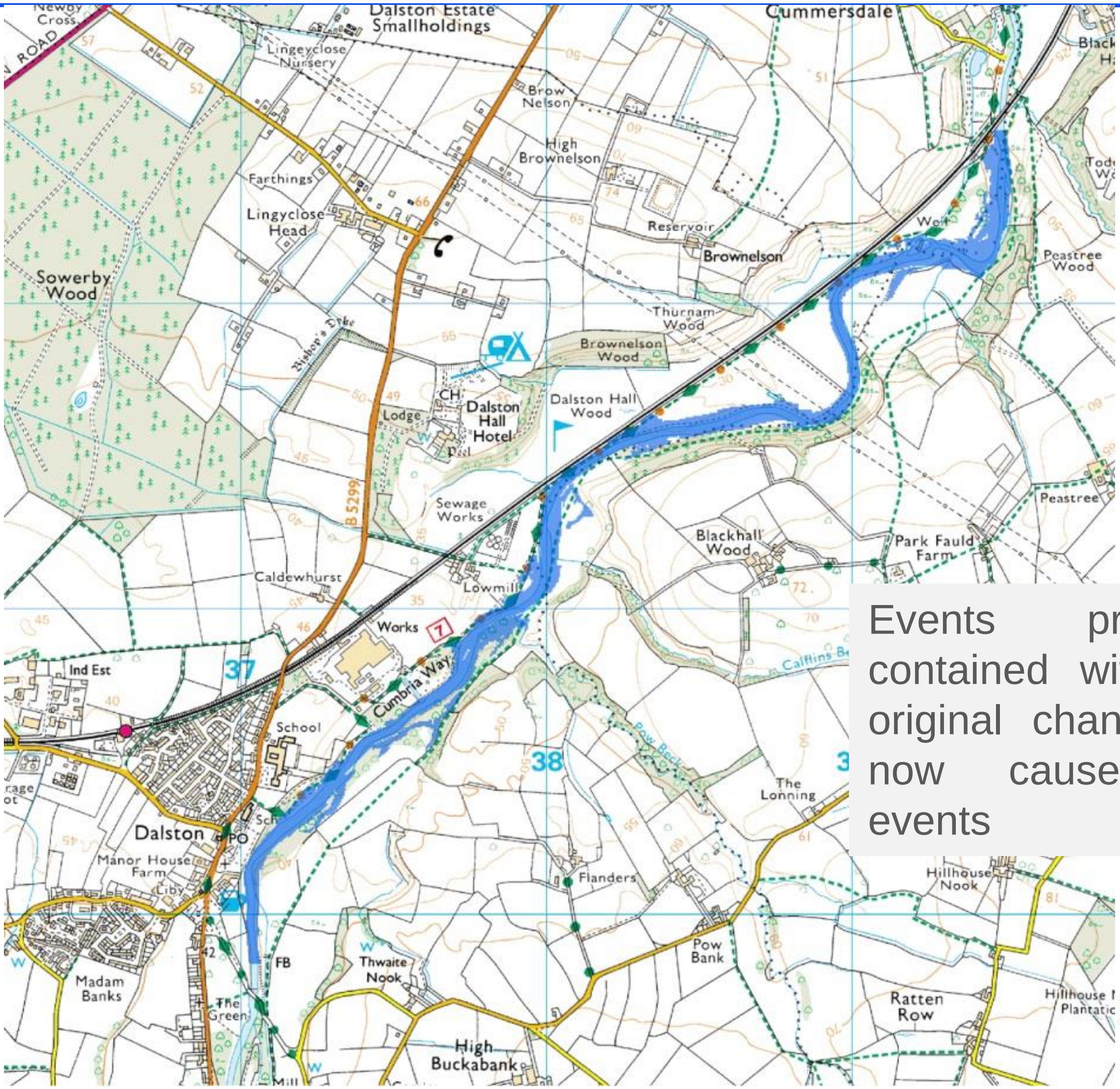
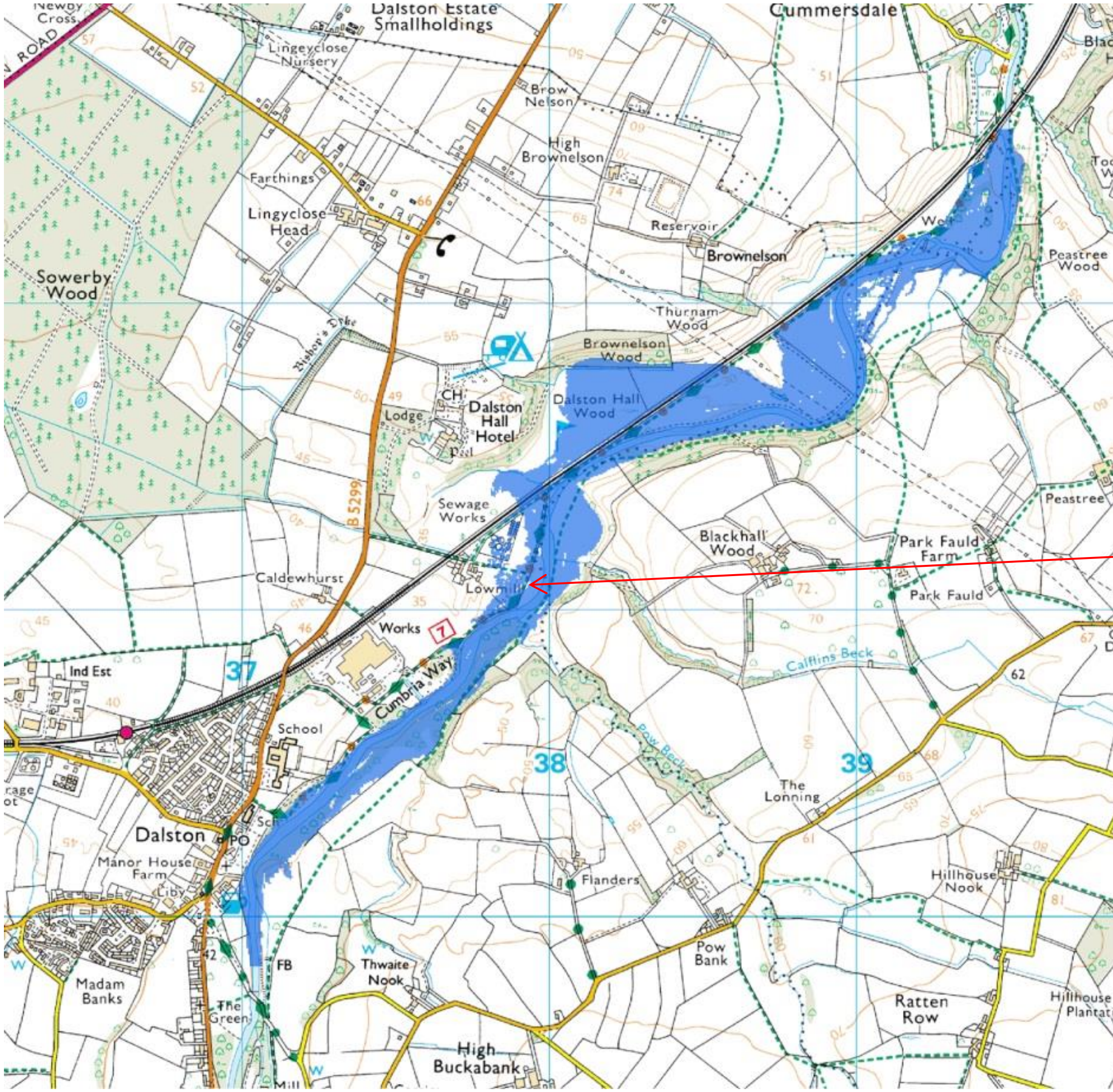
Inundation modelling



Events previously contained within the original channel can now cause flood events

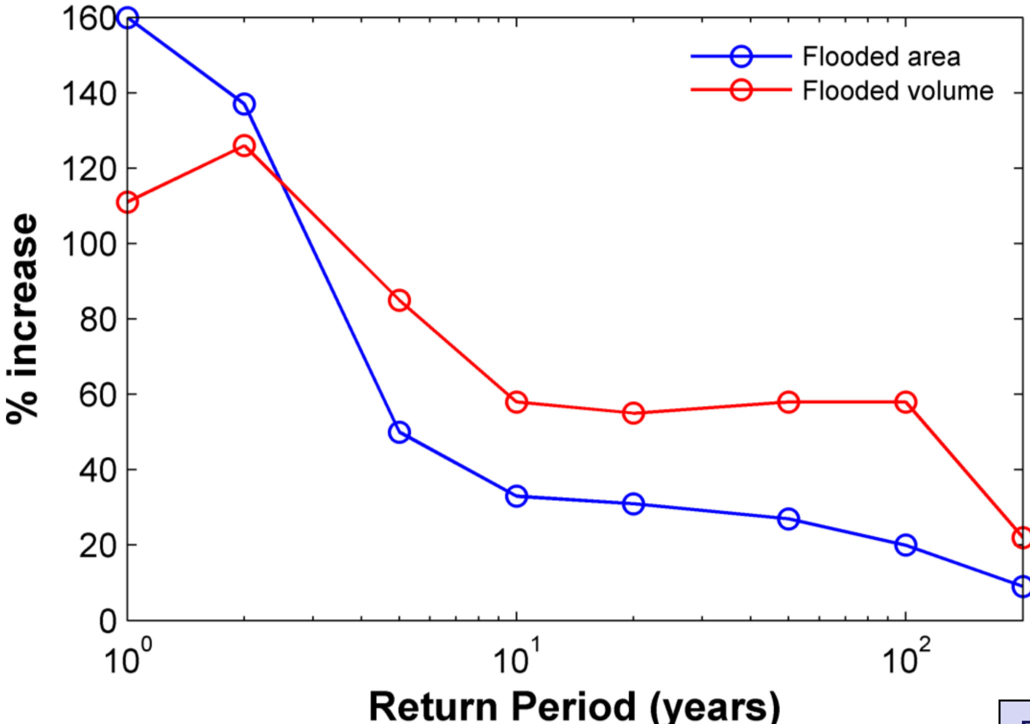
Inundation modelling



An increase in the 200 year inundation extent will have consequences for FRAs and planning applications

Identified risk to homes & STW at Lowmill

Inundation modelling



- Increase in inundation area & volume due to sequence & morphology
- As RP increases % change decreases
- Floods of 5-200yr RPs show 5-50% increase in flooded area
- Even small change to hazard carries extra hazard

Pender, D., Patidar, S., Hassan, K. & Haynes, H. (2016). *Method for Incorporating Morphological Sensitivity into Flood Inundation Modeling*. Journal of Hydraulic Engineering, Vol. 142, Issue 6.

Future R&D…

- Extent sensitivity probability maps
- Soft couple to cluster-from-benchmark?
- More case study sites

…since FloodMEMORY…

FloodMEMORY concludes (May 2016) that:

Single design-event flood risk assessment methodology should be revised towards multi-event simulation, including channel morphodynamics affecting floodwater conveyance capacity.

Aim to improve & constrain methods towards practitioner needs …

- Climate change within the HMM-GP
- Refine DMF time step → 15 minute gauge data
- Constrain sequence → clusters of influence
- Move from single gauge → downstream translation of sensitivity

…so, we have made a start…

Integrating precipitation with HMM-GP model for synthesising flows sequences

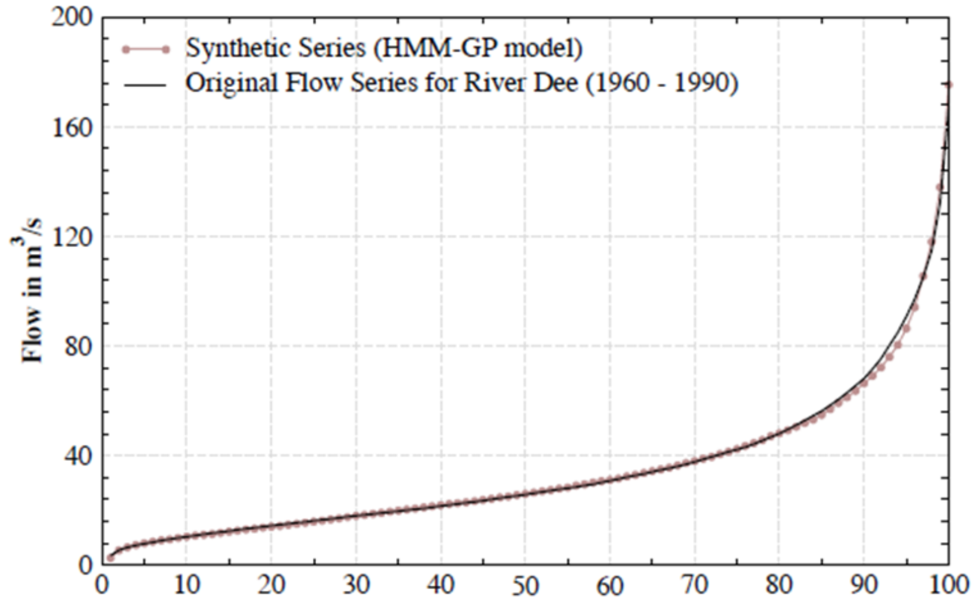
Percentile Distribution Model (PDM) to integrate precipitation information with the synthetic river flow series (generated by HMM-GP)

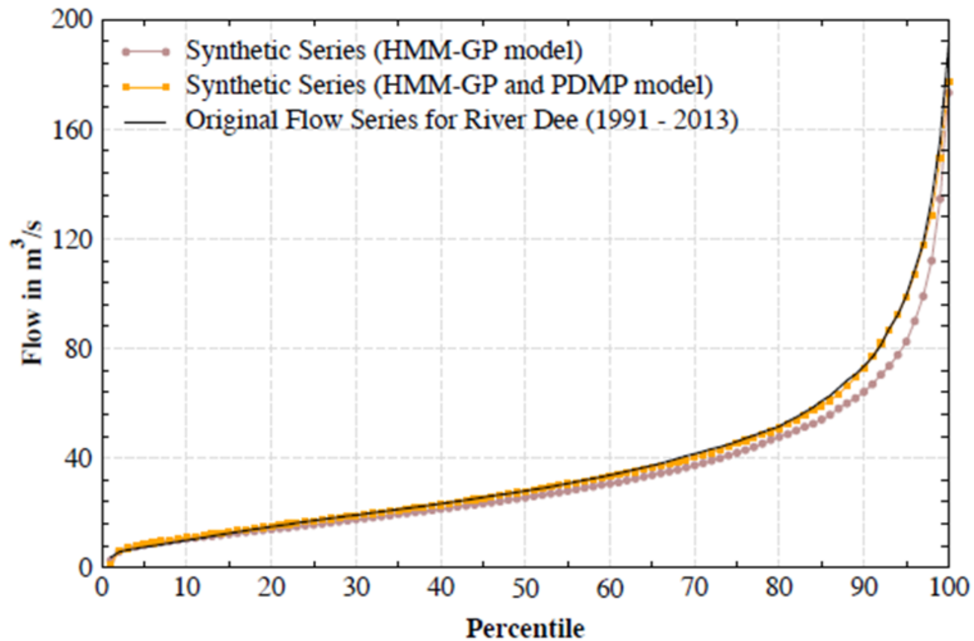
Upper panel - HMM-GP Model has been trained using 1960-1990 daily river flow and precipitation data.

Clearly HMM-GP model follows closely with original flow data

Lower Panel – Model trained on 1960 -1990 data has been used to synthesis synthetic flow series for 1990 – 2013.

Demonstrate capabilities of PDM-HMM-GP modelling approach in effectively incorporating influence of precipitation with flow series.





Integrating precipitation with HMM-GP model for synthesising flows sequences

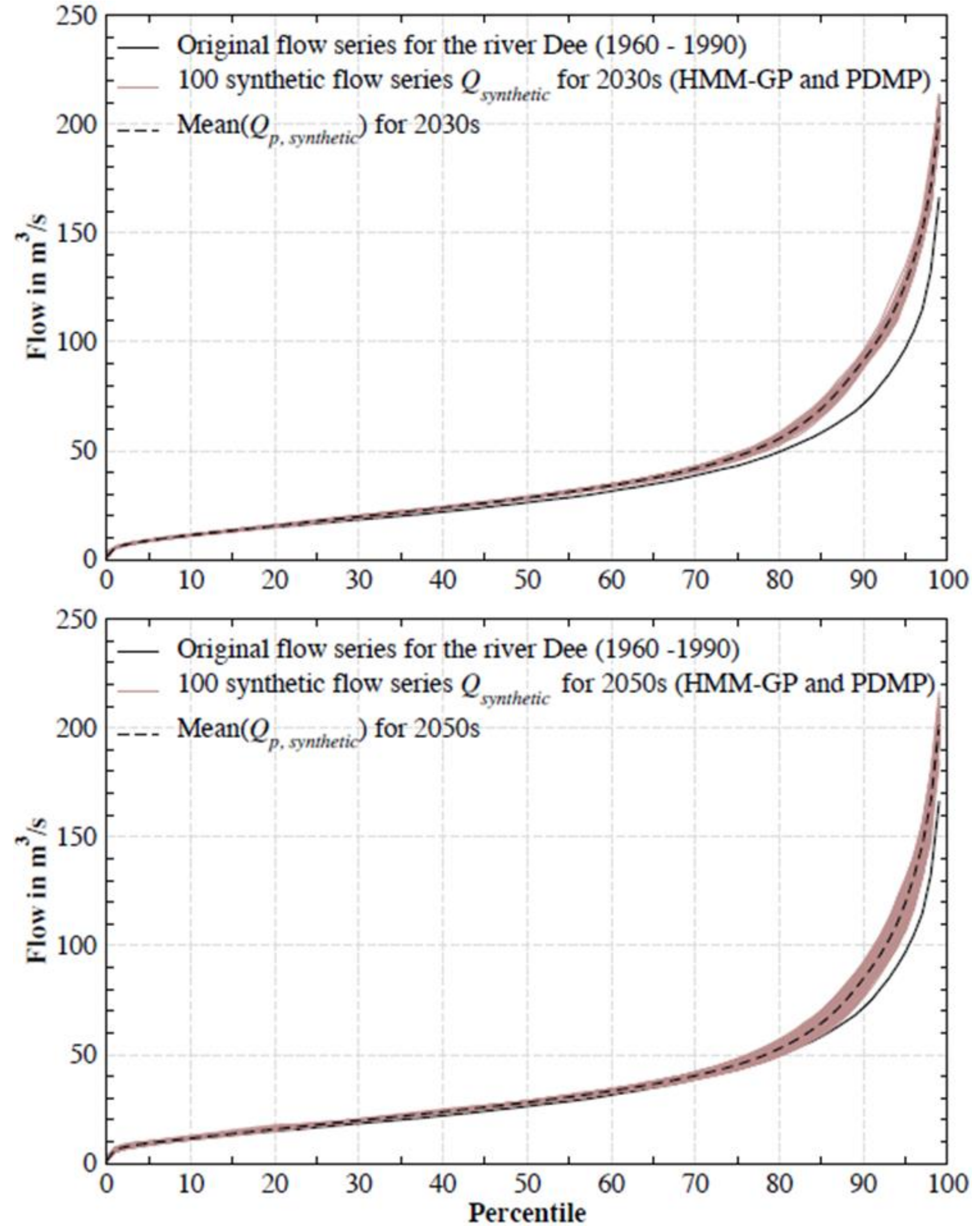
Application of PDM-HMM-GP Model to generate future flow series using daily probabilistic precipitation projections (available from UKCP09) for two future time periods:

Upper Panel
2030s – 2020 to 2049

Lower Panel
2050s – 2040 to 2069

Some notes

Method need to be rigorously refined and possibilities for including other influencing variables need to be assessed.



Work in progress (IAA – 6 months)

Aim to improve & constrain methods towards practitioner needs …

Objective 1: Climate change within the HMM-GP

- ✓ use of 15 minute gauge data
- ✓ which UKCIP scenarios?
- ✓ use of multiple gauges (pan-Scotland & downstream translation of sensitivity)

Objective 2: Constrain sequence → clusters of influence

- ✓ use of 15 minute gauge data to run sequences
- ✓ describe clusters better (POT thresholds, event duration, cluster kurtosis)
- ✓ compare cluster-in-sequence (CIS) to equivalent cluster-from-benchmark (CFB)
- ✓ minimum timeframe to capture change (≥CFB?)
- ✓ compare hazard analysis by conveyance, capacity, WSE, extent

Objective 3: Consider downstream translation of sensitivity

Many thanks for attention ☺

Journal papers

Pender, D., Patidar, S., Pender, G. & Haynes, H. (2016) *Stochastic simulation of daily streamflow sequences using a hidden Markov model.* Hydrology Research, Vol. 47, no. 1, pp. 75-88.

Pender, D., Patidar, S., Hassan, K. & Haynes, H. (2016). *Method for Incorporating Morphological Sensitivity into Flood Inundation Modeling*. Journal of Hydraulic Engineering, Vol. 142, Issue 6.

Conference papers

S. Patidar, K. Hassan, H. Haynes and G. Pender, *Statistical modelling approach for integrating probabilistic climate projections with the river flow data*, River Flow, St. Louis, Mo., July 12 – 15, 2016.

S. Patidar, K. Hassan, H. Haynes, G. Pender and D. Pender*, A model for stochastic simulation of daily streamflow,* River Flow, St. Louis, Mo., July 12 – 15, 2016.

Pender, D., Patidar, S. & Haynes, H. (2015) *Incorporating River Bed Level Changes into Flood Risk Modelling,* 36th IAHR World Congress, At The Hague, the Netherlands, Volume: E-proceedings of the 36th IAHR World Congress.

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