Hierarchical Bayesian approach for flood loss modelling – a case study of the UK floods 2015

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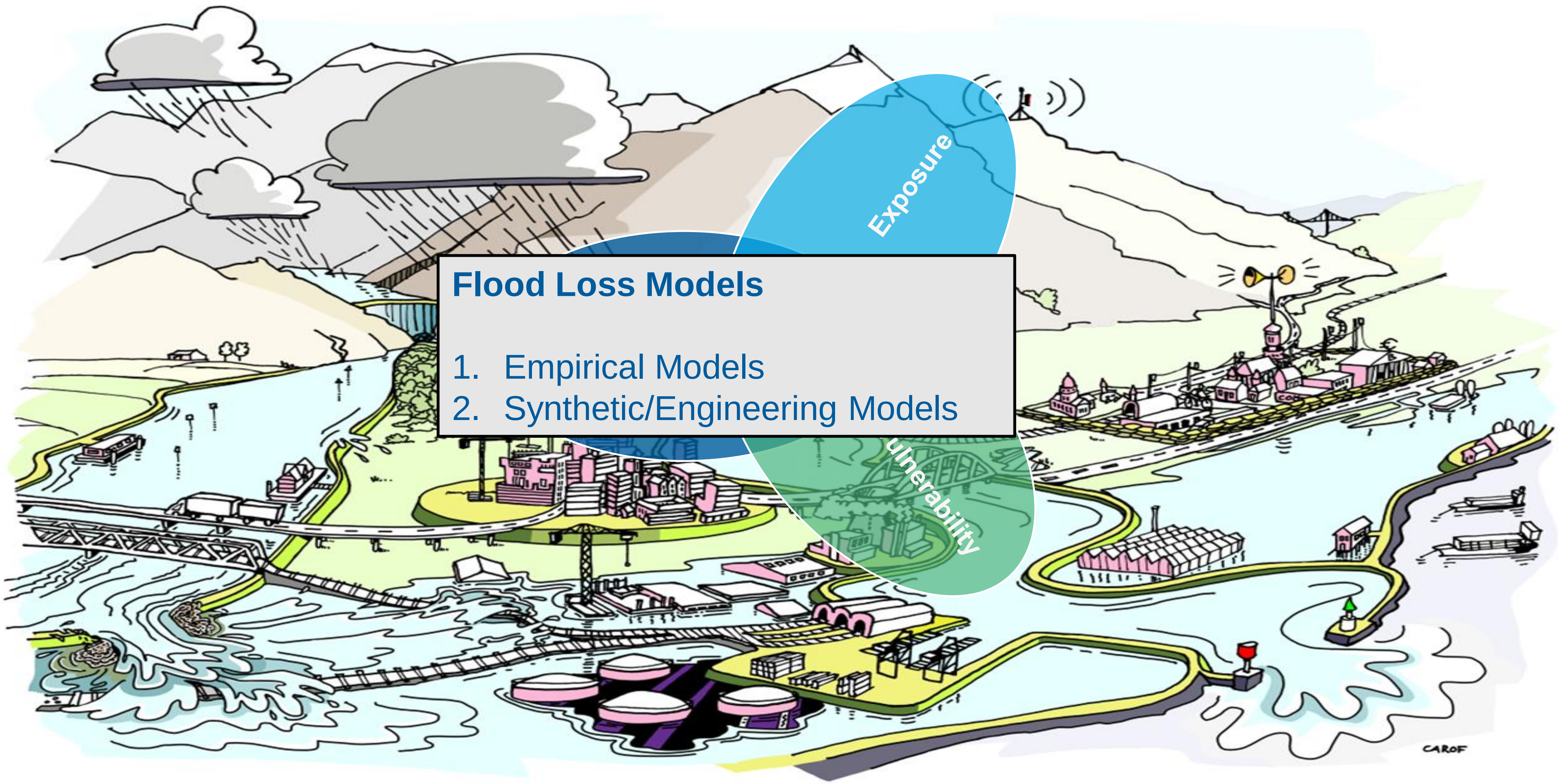
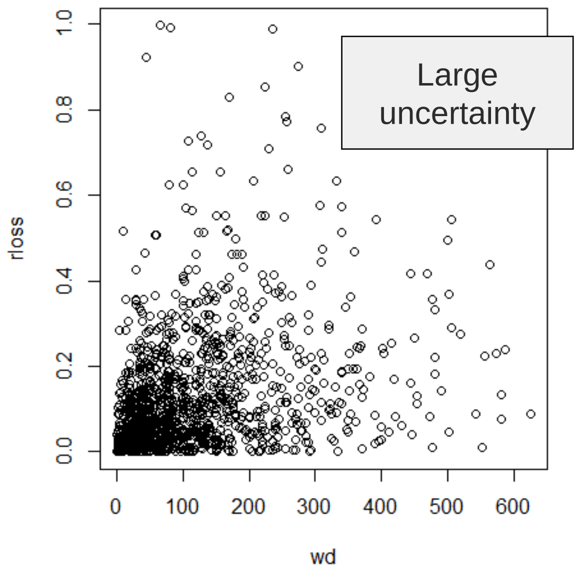


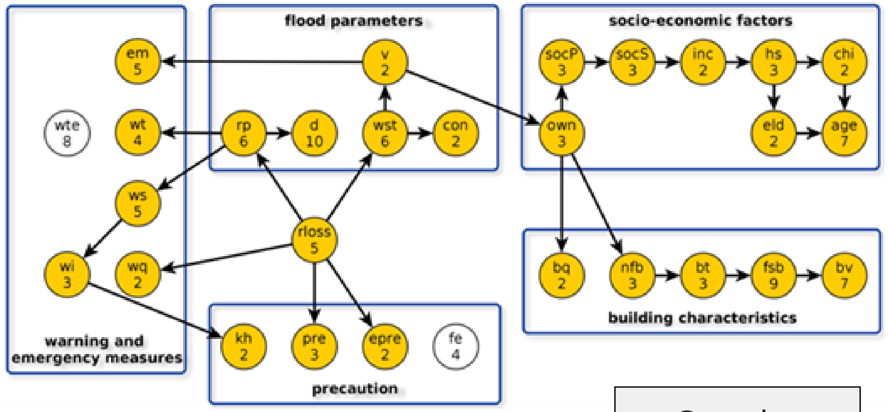
Flood Loss Models

1. Empirical Models
2. Synthetic/Engineering Models

Empirical Flood Loss Models

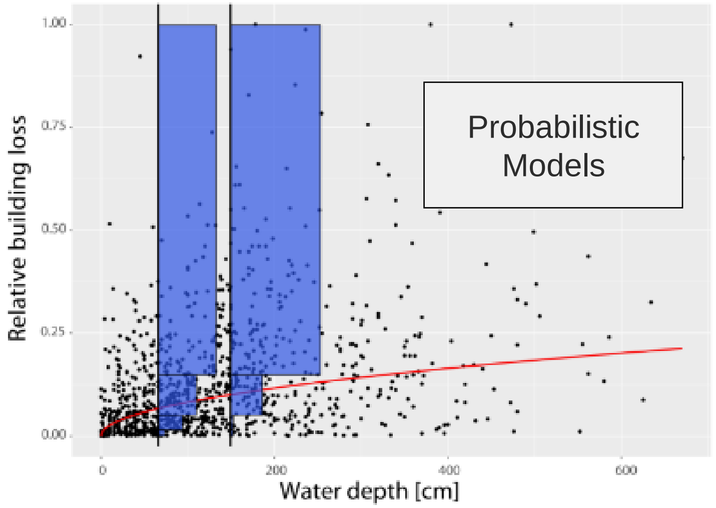
1. Learns patterns and dependencies from **empirical data** to predict building damage
2. Complex models require **large sample** of observed loss cases along with **detailed hazard, exposure and vulnerability** of the building.
3. **Probabilistic models** account for uncertainty in data, model structure and parameterizations





Vogel et al. 2013
Schröter et al. 2014

Complex Models

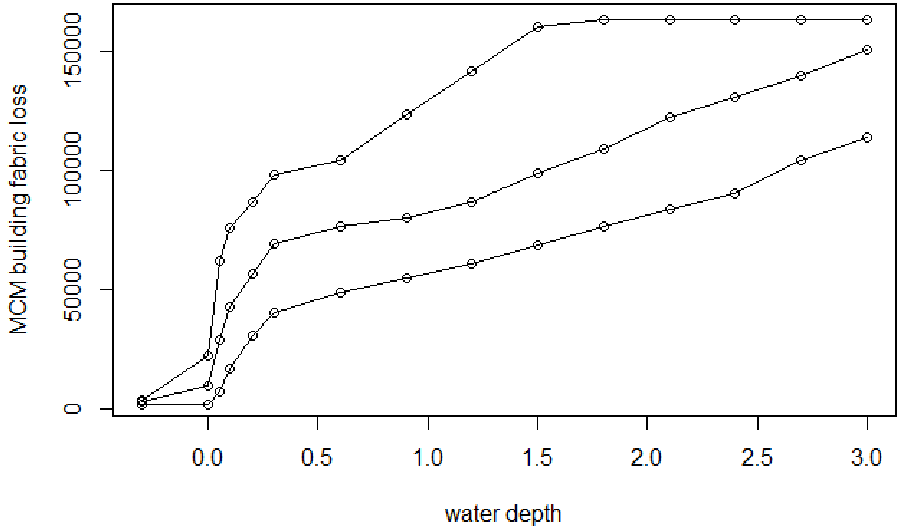


Examples taken from case studies in Germany for illustration

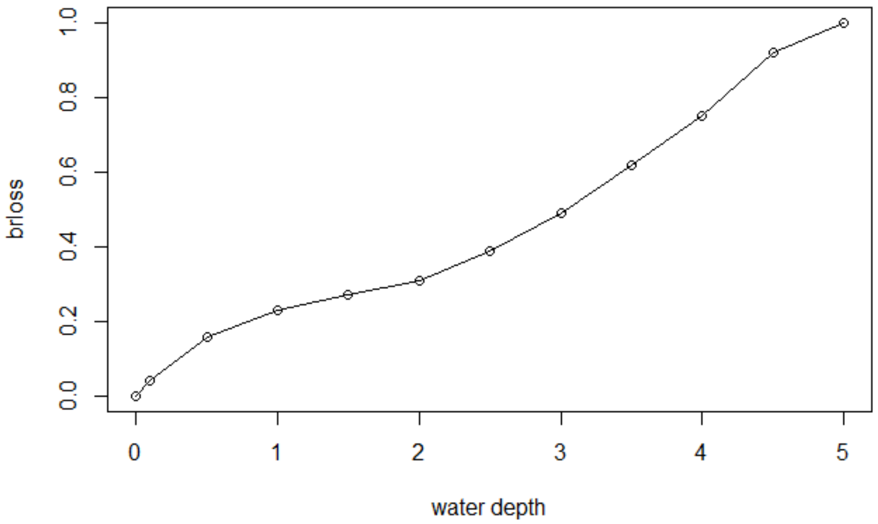
Synthetic Flood Loss Models

1. Synthesized using various data sources, expert opinions and Engineering perspectives.
2. **Data requirements** for development of synthetic models are very less.
3. In practice, synthetic flood loss models are **often deterministic** and **rarely validated** against empirical data.
4. Synthetic models **generalize** better than empirical models and perform well during spatio-temporal transfer (application of INSYDE in several Italian flood cases; Amadio et al. 2019).

UK: Sample MCM DD curves for different duration and warning scenarios



Netherlands: Damage Scanner DD curves for residential sector

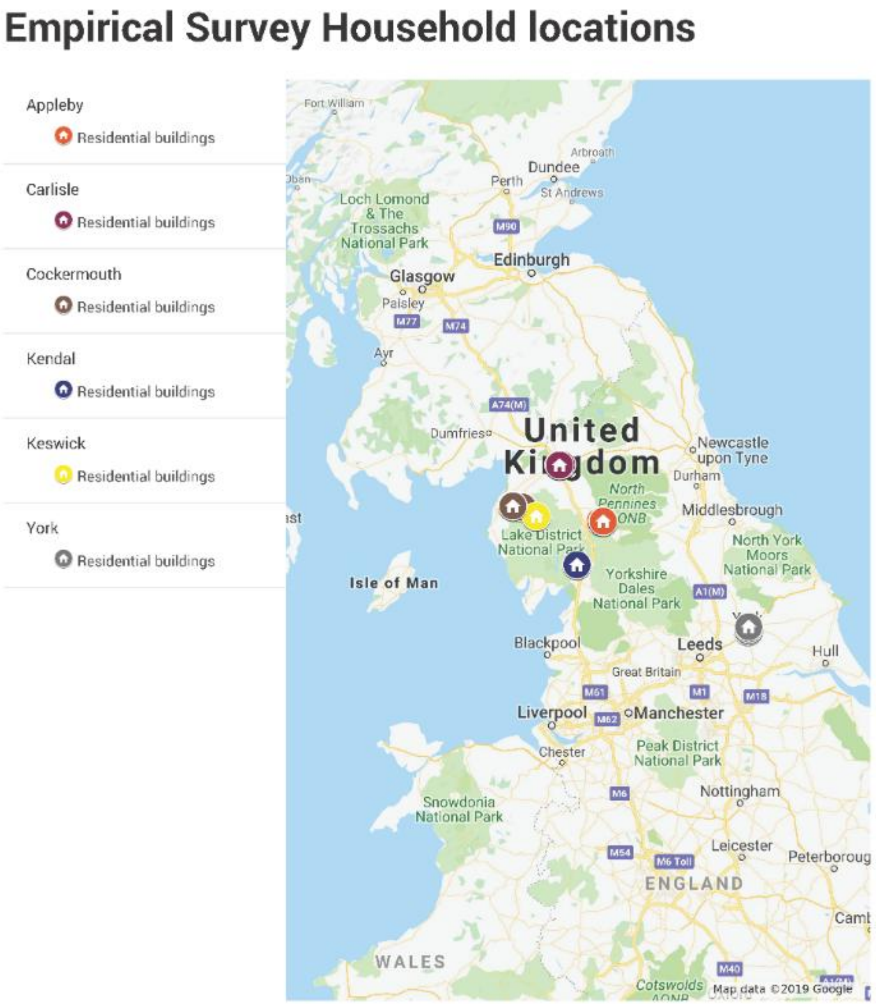


Synthetic Model: Full-scale Appraisal Using MCM

- Household level information as predictors:
  - water depth
  - duration
  - warning lead time
  - building type
  - construction year
  - social class
- Prediction:
  - Building fabric loss in GBP (corrected for 2015 inflation)
- Case Study:

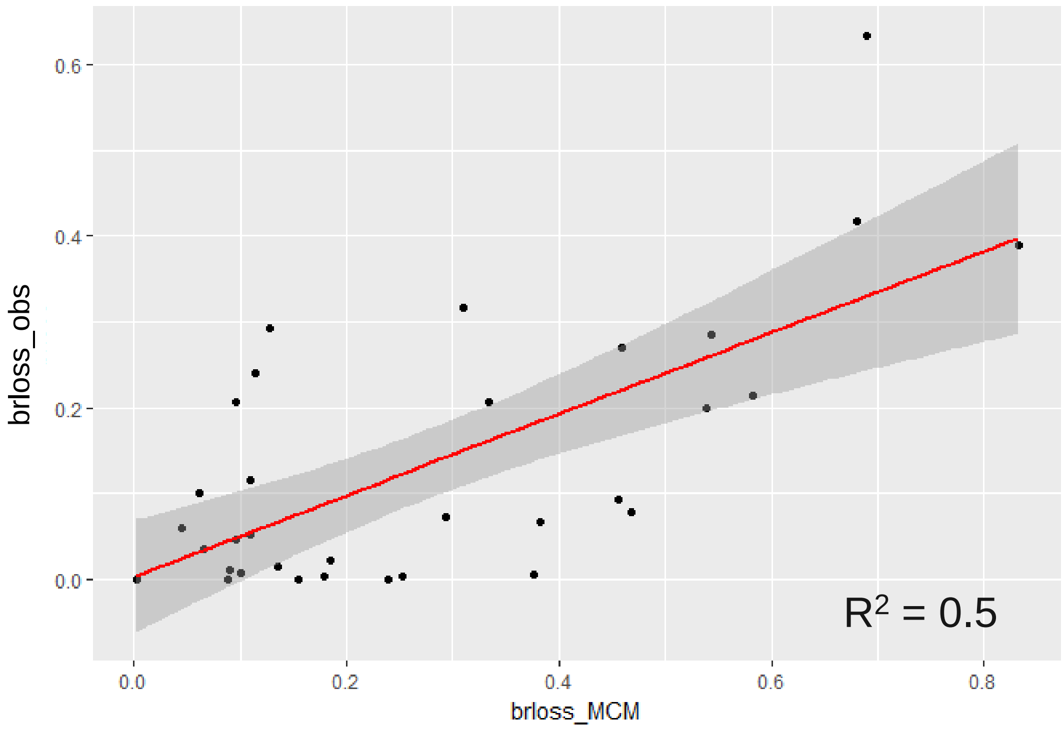
Household level survey data from different regions in UK

- **Appleby, Keswick, Kendal, Carlisle, York and Cockermouth**
- n = 35 residential buildings



Combining Empirical data with MCM predictions

$$Build \quad Fabri \quad Relati \quad loss \ (brlo^{S}) = Build \quad fabri \quad loss \ / reconstru \quad cost$$

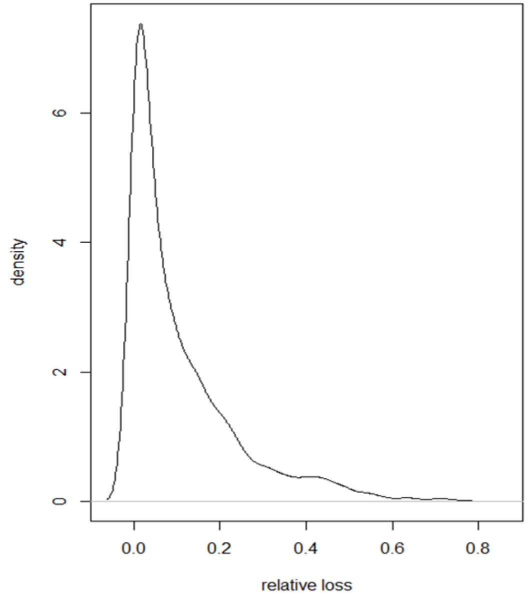


$$brlo_{s}\_ob^{S} | brlo_{s}\_MC^{M} \sim Beta(\alpha, \beta)$$

$$\alpha = \mu \times \varphi$$

$$\beta = (1 - \mu) \times \varphi$$

$$\mu = \theta \times brlo_{s}\_MC^{M} + \varepsilon$$



What do we know about the 2015 Floods in UK?

- **Rainfall, temperature and soil moisture** were exceptionally high during the 2015 flood event.

- **Multi-layer safety measures** were implemented in not all regions (e.g. Keswick, Carlisle)

- Inefficient **communication of residual risk.**

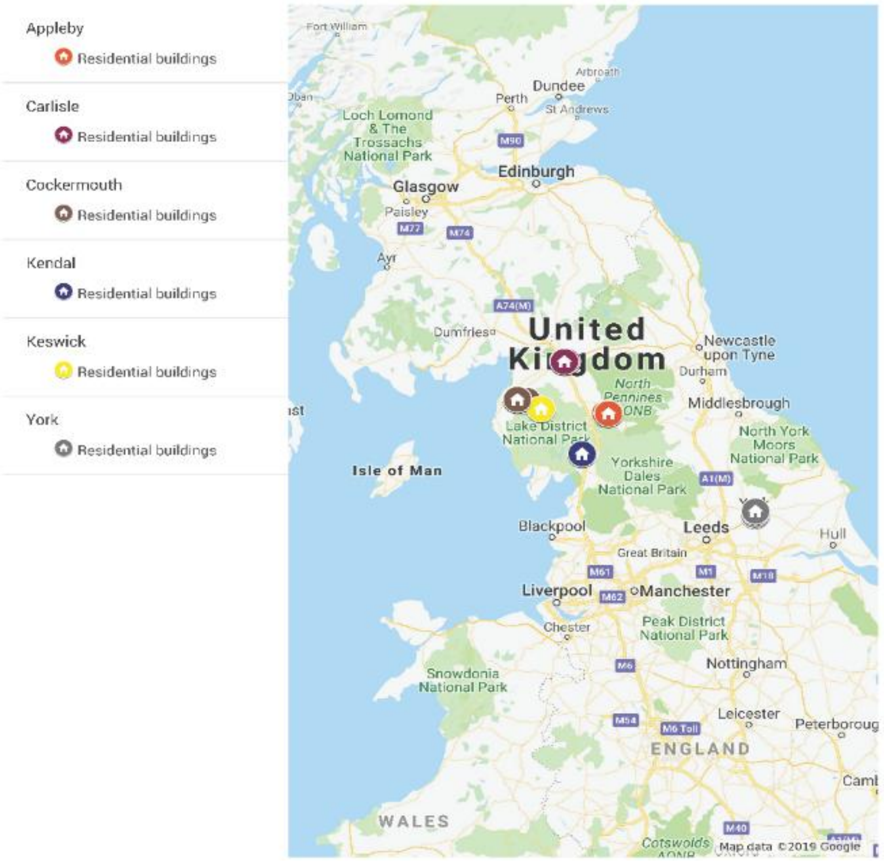
- **Awareness of flood risk** seems to be higher in smaller towns without much structural protection as compared to the bigger cities where **big flood protection schemes** are implemented (e.g. Carlisle).

- Some communities implemented **ineffective precautionary measures** due to lack of guidance (e.g. Appleby).

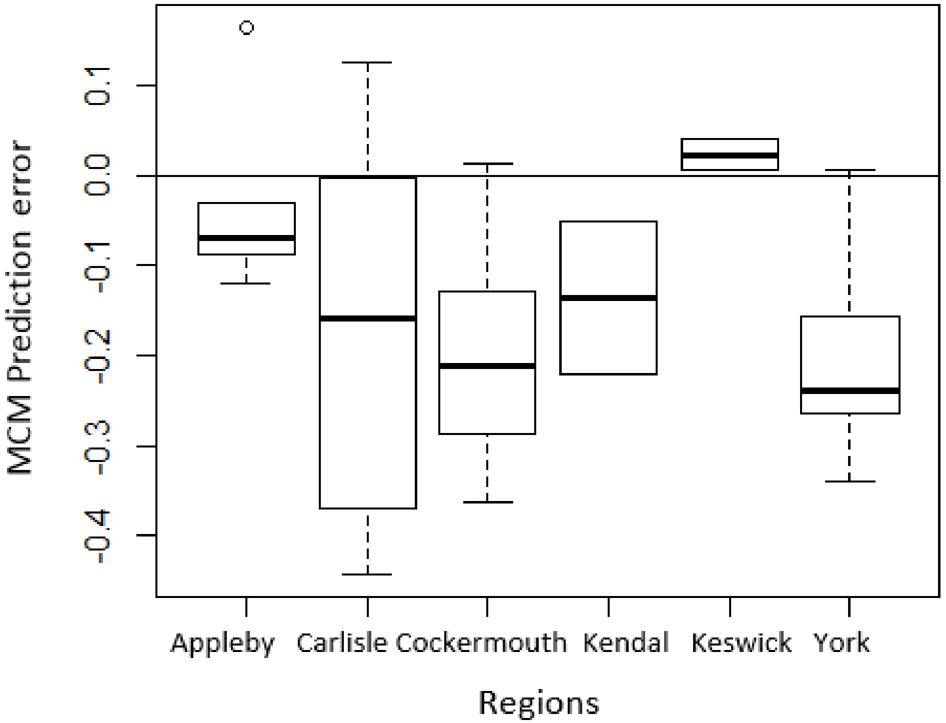
SystemRisk: Flood Task Force, 2019

Combining Empirical data with MCM predictions by Region

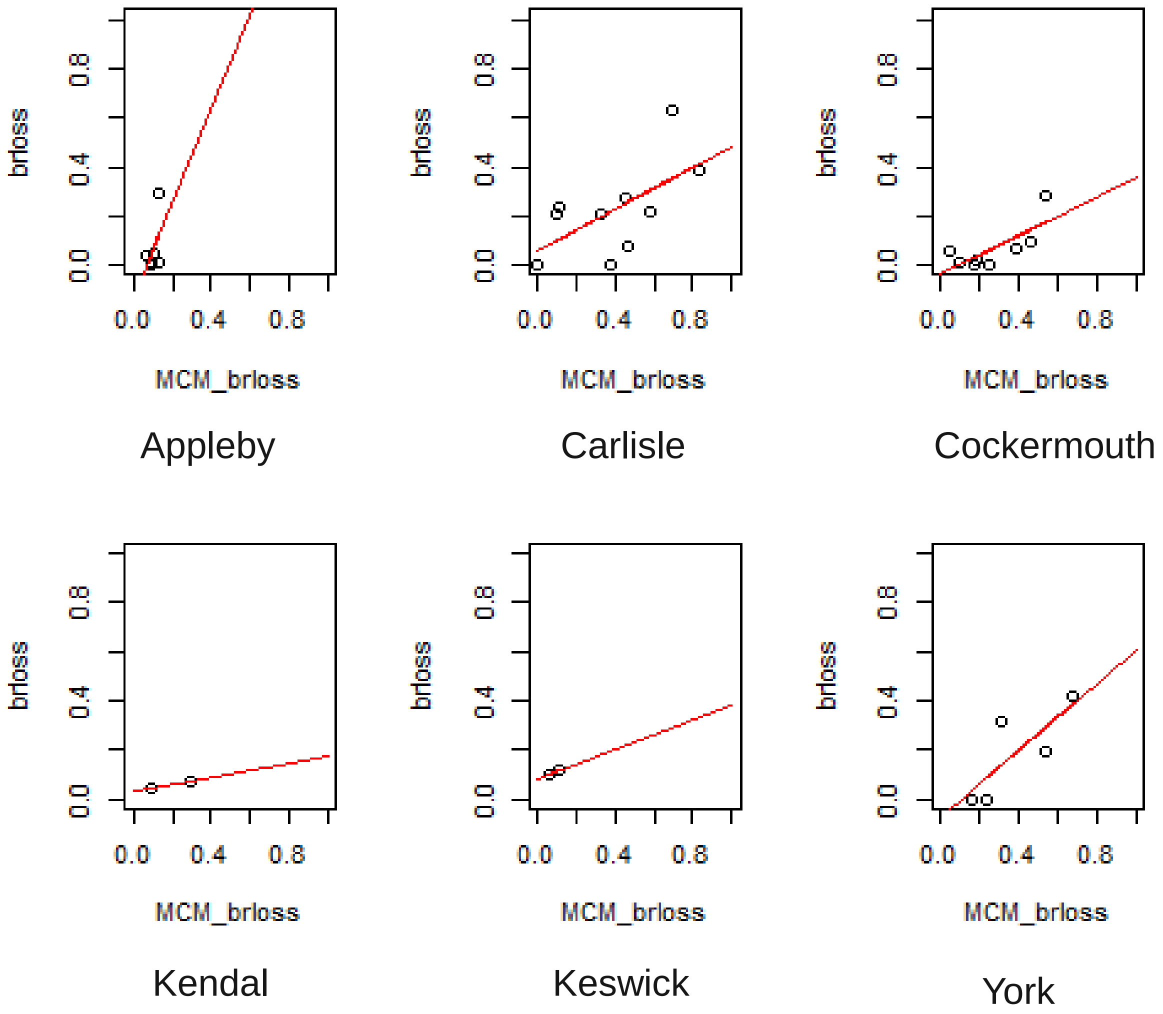
Empirical Survey Household locations



$$MCM\ predict\ error = brlos\_obs - brlos\_MCM$$

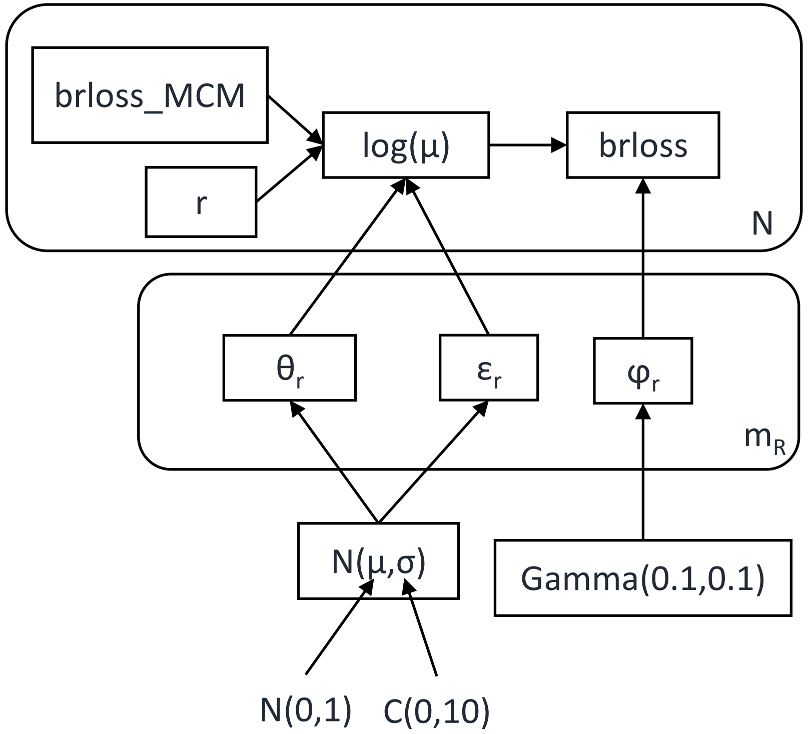


Combining Empirical data with MCM predictions by Region

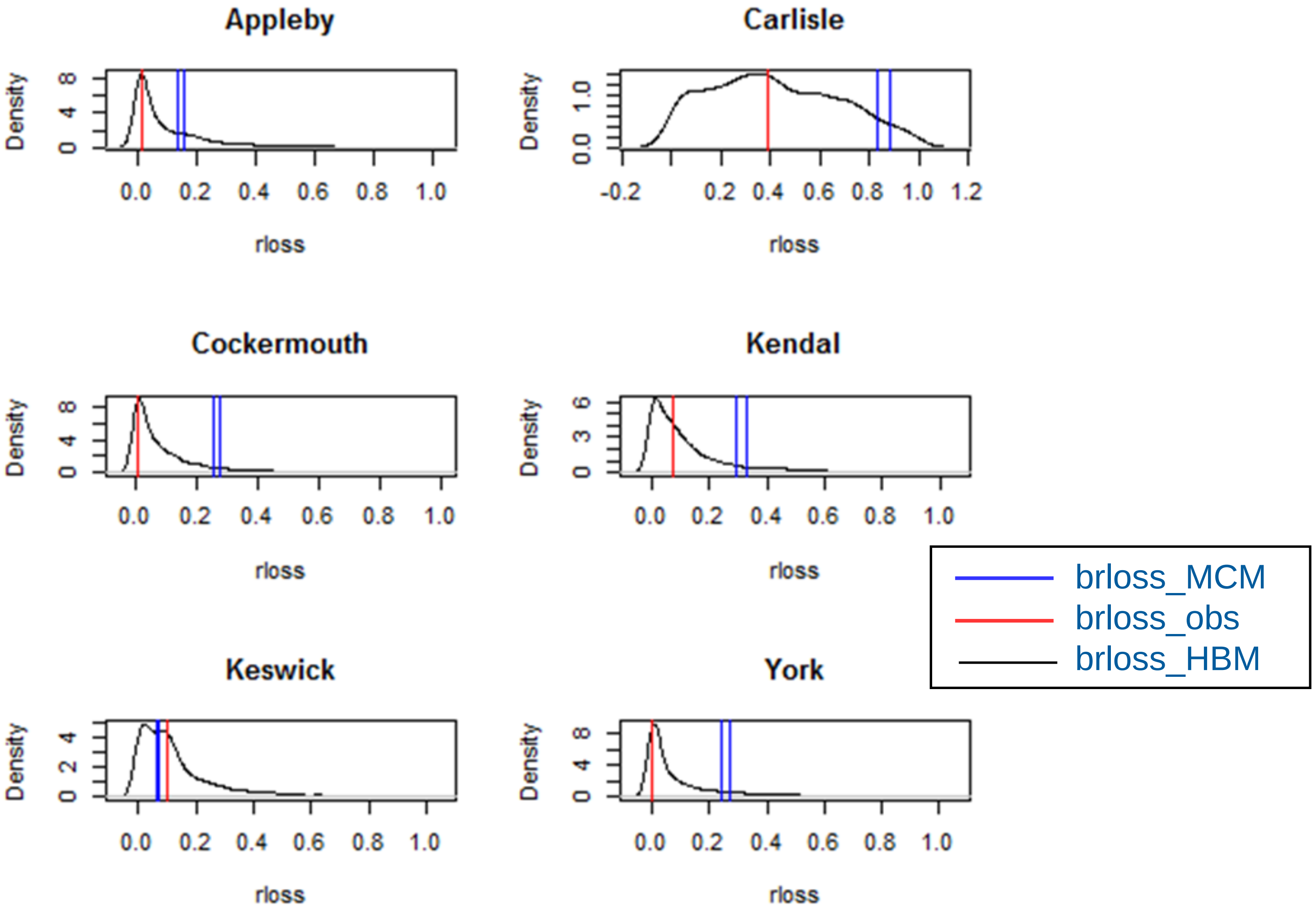


Hierarchical Bayesian Model (HBM)

$$E(brloss) = \theta_r \times brloss\_MCM + \varepsilon_r$$



Predictions from HBM
- Leave-one-building-out cross-validation



brloss_MCM – uncertainty range due to missing predictors

Inferences

1. Using HBM, empirical evidence from new flood events can be integrated with the established synthetic models.
2. HBM inherently provides **reliability of the loss prediction** for each building and group of buildings in each region.

Limitations and Future Work

1. The approach is validated using empirical loss data from UK 2015. This case study has only a few useful data points (35 buildings) for empirical validation.
2. The methodology will be tested for other regions, e.g. Germany and Netherlands based on the synthetic models Rhine Atlas and Damage Scanner.