Met Office / U. Exeter meeting

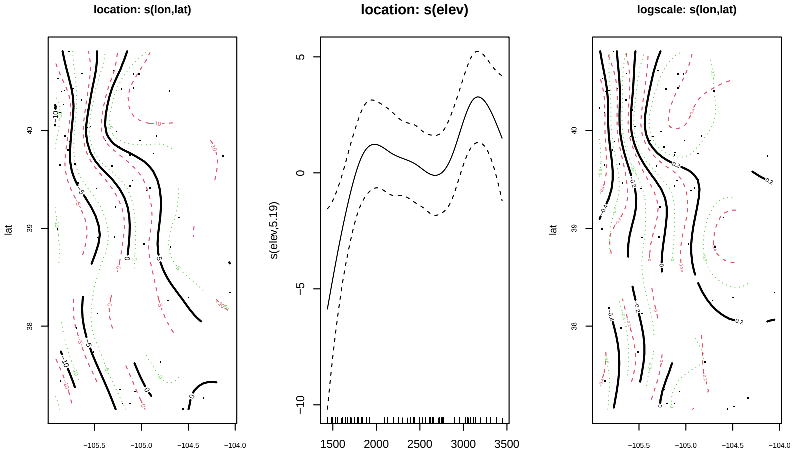
22 Sept 2025

Outline

- Historically, we might estimate a return level (defined as an extreme value distribution quantile) from a some past observations or model output
- We could build trends in to this, such as allowing for a changing climate
- But these are rather static: they're good for building defences, but not for taking evasive action
- Forecasts can help here
  - but can we couple these with extreme value statistics to better understand short-term risk (e.g. a few days)?
  - and can we better quantify our uncertainty in what might actually happen?
  - and ultimately can we quantitatively contribute to whether warnings are issued?

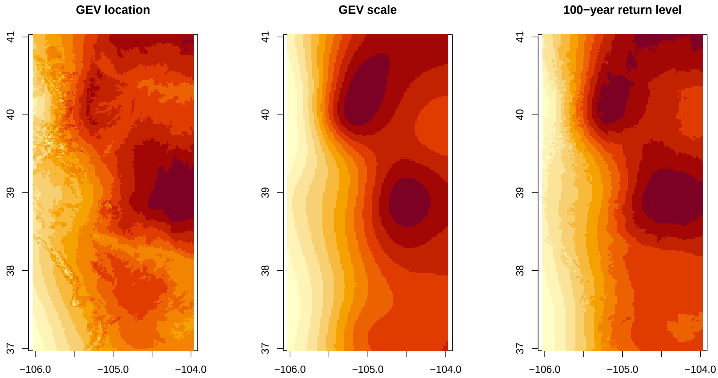
evgam: estimates of smooths

- evgam for fitting extreme value distributions in R with parameters that vary according to generalised additive models
  - we might want smooth variation over space
  - or some non-linear form with some covariate, such as extreme rainfall with elevation



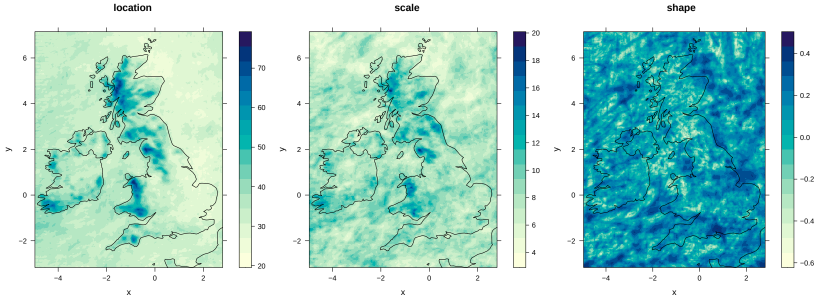
evgam: estimates of parameters

- Gives flexible estimates of extreme value distribution parameters, which can be continuous in space and time
  - e.g. infer any resolution from station data



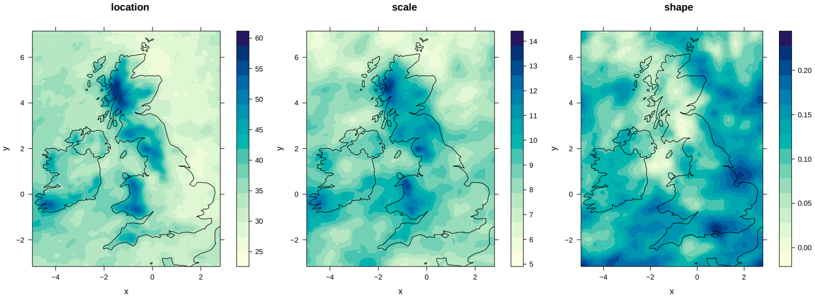
UKCP18 2.2km modelling

- With PhD student Ayu Shabrina, investigating robust data-driven models for high-resolution data
- These are parameter and return level estimates from UKCP18's daily 2.2km data



UKCP18 2.2km modelling: improved inference

- We've been working on improved inference, so that estimates better capture spatial signal and not noise
- We'll then compare estimates over different time periods, e.g. 2041-2060 vs 2001-2020



- Extending Chan et al. (2023)[1] to a more robust data-driven methodology

[1] Chan, S. C., E. J. Kendon, H. J. Fowler, B. D. Youngman, M. Dale, and C.Short. 2023. "New Extreme Rainfall Projections for Improved Climate Resilience of Urban Drainage Systems." Climate Services 30: 100375.https://doi.org/10.1016/j.cliser.2023.100375.

Recent Master's project

- Extreme value modelling of hourly rainfall
- Modelling observations at Dunkeswell aerodrome (Devon)
- Also modelling for historical forecasts at corresponding grid cell
  - Analysing properties of extremes at different lead times (up to 36 hours)
- Aiming to joint model observations and forecasts

Work package 1: marginal modelling with past obs

- Investigate whether distribution of extremes varies meaningfully with past observations
- Generalised Pareto model at time t of the form

$$Y_t - u_t \mid \{Y_t > u_t\} \sim GPD(\psi_t, \xi_t)$$

  for scale parameter ψ_t and shape parameter ξ_t and high threshold u_t
- Initial form for scale parameter

$$\psi_t = \psi(y_{t-1}, y_{t-2}, \ldots)$$

  which can be modelled via smooth functions or machine learning methods
- Do we produce better probabilistic estimates of extremes at time t if we incorporate data from $t-1, t-2, \ldots$?

Work package 1: marginal modelling with past obs and future forecasts

- Now consider known forecasts $z_t, z_{t+1}, \ldots$
- Extended scale parameter form

$$\psi_t = \psi(y_{t-1}, y_{t-2}, \ldots, z_t, z_{t+1}, \ldots)$$

- Do we better capture extremes at time t if we incorporate forecasts at $t, t+1, t+2, \ldots$, in addition to data from $t-1, t-2, \ldots$?
- Do past data offer information, given forecasts?

Work package 2: joint modelling

- Instead of return levels, a joint model might better capture the link between observations and forecasts
- With a joint model for $(Y_t, Y_{t-1}, Y_{t-2}, \ldots, Z_t, Z_{t+1}, Z_{t+2}, \ldots)$ we can simulate

$$Y_t \mid \{Y_{t-1}, Y_{t-2}, \ldots, Z_t, Z_{t+1}, Z_{t+2}, \ldots\}$$

  to give fuller understanding of tomorrow's rainfall
- Or this could go further ahead, such as

$$Y_t, Y_{t+1}, Y_{t+2}, \ldots \mid \{Y_{t-1}, Y_{t-2}, \ldots, Z_t, Z_{t+1}, Z_{t+2}, \ldots\}$$

  to give more advanced warning of the potential for extremes arriving

Work packages 3+

- Spatial or multi-site modelling
  - the observation:forecast model at multiple time points can be extended to multiple locations
    - either gridded data and forecasts
    - or multiple weather stations
    - or some combination of the two
- Multi-variable modelling
  - when modelling waves with Met Norway, we'll be looking at wave height, wave period, wind speeds, . . .
  - for flood risk, we can consider river level data alongside rainfall data
- Data fusion
  - rainfall observations and forecasts have been considered
  - incorporating radar data into the framework could bring improvement
  - or even focussing on radar data instead of station measurements