Supplementary Material for ‘Assessing Financial Risk to Property Portfolios from Physical Rainfall Extremes’

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S1 Rainfall Extreme Value Spatial Model

This section provides a detailed description of the statistical extreme value model used to model the return-level curves for rainfall, introduced in Section 2.2.3 of the main manuscript.

S1.1 EV-GAM model

The point-over-threshold Extreme Value Generalised Additive Model (EV-GAM) used to model extreme rainfall for a given time period (historical or future), climate model ensemble member and season, is specified mathematically as:

$$(Y(s) - u(s)|Y(s) > u(s)) \sim GPD(\sigma(s), \xi) \tag{1}$$

$$\sigma(s) = f(slon(s), slat(s), mppt(s)) \tag{2}$$

$$u(s) = P_{98}(Y(s)|Y(s) > 0.1) \tag{3}$$

Where

- s is a location / grid cell in space,
- $Y(s)$ is daily total rainfall at location s,
- $u(s)$ is a threshold in the rainfall data at location s, above which the data is modelled (here the 98$^{\text{th}}$ percentile of non-zero rainfall),
- GPD is the Generalised Pareto Distribution which has two parameters, the scale (σ) and the shape (ξ). Here the scale parameter varies in space so is a function of s,
- f is a smooth function capturing how the GPD scale parameter varies in space ($\sigma(s)$), here modelled in a Generalised Additive Model (GAM) framework as a smooth spline of three spatial inputs $slon(s)$, $slat(s)$ and $mppt(s)$,

- $slon(s)$ is a spatial unit in the horizontal direction which is a rotated and scaled version of longitude
- $slat(s)$ is a spatial unit in the vertical direction which is a rotated and scaled version of latitude
- $mppt(s)$ is the mean daily total rainfall at location s over the modelled time period, scaled by taking away its median and dividing by its range,
- P_{98} is the 98^{th} percentile

Holding the shape parameter constant in space is common practice in spatial modelling, because it has high sensitivity to small fluctuations in the data. Granting it too much flexibility can result in unstable and unreliable estimates, ultimately compromising the robustness of the model. This assumption is typically most suitable in applications where the spatial domain is moderate in size and where systematic, large-scale variation in higher-order distributional properties (such as skewness or tail behaviour) is not expected. While there may be genuine spatial variation in the rainfall tail behaviour within our study region (e.g., due to orography), evidence from spatial extremes modelling shows that adding unnecessary spatial flexibility to higher-order parameters risks overfitting and poor tail dependence characterisation; robust practice prioritises parsimonious marginal models over highly parameterised, spatially varying shapes (**?**).

S1.2 Additional EV-GAM Validation Plots

EV-GAM validation Quantile-Quantile plots equivalent to Figure 3 in the main manuscript but for all combinations of time period (historical/future) and UKCP RCM ensemble member can be viewed via this link: https://www.dropbox.com/scl/fo/g0xgdz08nelqrjif3429c/AAtZLXdFtkw_MaDamDnySh4?rlkey=5761rjqmi8l4gg3qqnxcrvegv&st=05y6ktr8&dl=0.

Further EV-GAM validation is carried out by plotting maps of the difference between the median of the rainfall data used in the model fitting (the upper 2% of wet days) and the equivalent statistic estimated from the EV-GAM. This difference is scaled by dividing by the observed metric to give a relative bias. These plots are produced for each combination of time period (historical/future), UKCP RCM ensemble member and seasonal model. The subsequent plots can be viewed via this link: https://www.dropbox.com/scl/fo/ecs8nj1ab90837sfp9spe/AM_zIqqRkTA1LBcSFNRFVxg?rlkey=uxpjlc51tshqazw49tge9jvw4&st=hb9qdrqz&dl=0. These are a further indication of good model fit, as for each EV-GAM fitted, these indicate that there are only small and non-systematic model biases in the model estimates across the study region.

S1.3 Representing return-periods

Let Q represent quantile and T represent return-period. Then, if using simulations of annual maximum:

$$Q_{annual} = 1 - 1/T \tag{4}$$

e.g. the quantile of the annual maximum rainfall distribution representative of the 1 in 10 year event is 1-1/10 = 0.9 (or the 90th percentile).

In our case we have modelled daily rainfall from climate projection data which contains 360 days per year. We must therefore adjust the quantile to represent the 1 in X *years* event rather than the 1 in X *events* event, i.e.

$$Q_{daily} = 1 - 1/(T \times 360) \tag{5}$$

so the quantile of the daily rainfall distribution representative of the 1 in 10 *year* event is 1-1/3600 = 0.9997222.

Our EVGAM is fitted to daily rainfall data in excess of the local 98$^{\text{th}}$ percentile of non-zero rainfall (i.e. using a peak-over-threshold (POT) approach). We therefore require an adjustment to the quantiles that takes into account (1) we are only simulating wet days and a proportion of the distribution of rainfall will be zeros, and (2) we are only modelling and simulating from the top 2% of wet-day rainfall. The proportion of wet and dry days varies by location, hence we first calculate from the climate projection data the average annual proportion of dry days at each location ($P_0(s)$). Then, for a given location, s, the EVGAM is fit above the $Q_{POT}(s) = 0.98 \times (1 - P_0(s)) + P_0(s)$ quantile of all rainfall (rather than wet-day rainfall only). We therefore adjust the return-period quantiles to capture how we are only simulating rainfall from the model that is above this quantile of the full (wet and dry) rainfall distribution as:

$$Q_{daily\&POT}(s) = \frac{(1 - 1/(T \times 360)) - Q_{POT}(s)}{(1 - Q_{POT}(s))} \tag{6}$$

Return-period (years)	10	20	30	40	50	75	100	200	500
Q_{annual}	0.900000	0.950000	0.966667	0.975000	0.980000	0.986667	0.990000	0.995000	0.998000
Q_{daily}	0.999722	0.999861	0.999907	0.999931	0.999944	0.999963	0.999972	0.999986	0.999994
$Q_{daily\&POT}$(Gothenburg) P_0(Gothenburg) $= 0.343313$	0.978850	0.989425	0.992950	0.994713	0.995770	0.997180	0.997885	0.998943	0.999577
$Q_{daily\&POT}$(Edinburgh) P_0(Edinburgh) $= 0.286831$	0.980525	0.990263	0.993508	0.995131	0.996105	0.997403	0.998053	0.999026	0.999611
$Q_{daily\&POT}$(Hamburg) P_0(Hamburg) $= 0.287037$	0.980519	0.990260	0.993506	0.995130	0.996104	0.997403	0.998052	0.999026	0.999610
$Q_{daily\&POT}$(London) P_0(London) $= 0.330144$	0.979266	0.989633	0.993089	0.994816	0.995853	0.997235	0.997927	0.998963	0.999585

Table S1. return-periods and corresponding EV-GAM quantiles used to represent the associated return-levels for a selection of locations (i.e. as shown for Gothenburg and Edinburgh in Figure 7 a and c in the main manuscript). Here these are based on the EV-GAM fitted to UKCP18 RCM ensemble member 01 for consistency with Figure 2 in the main manuscript.

S2 City Maps

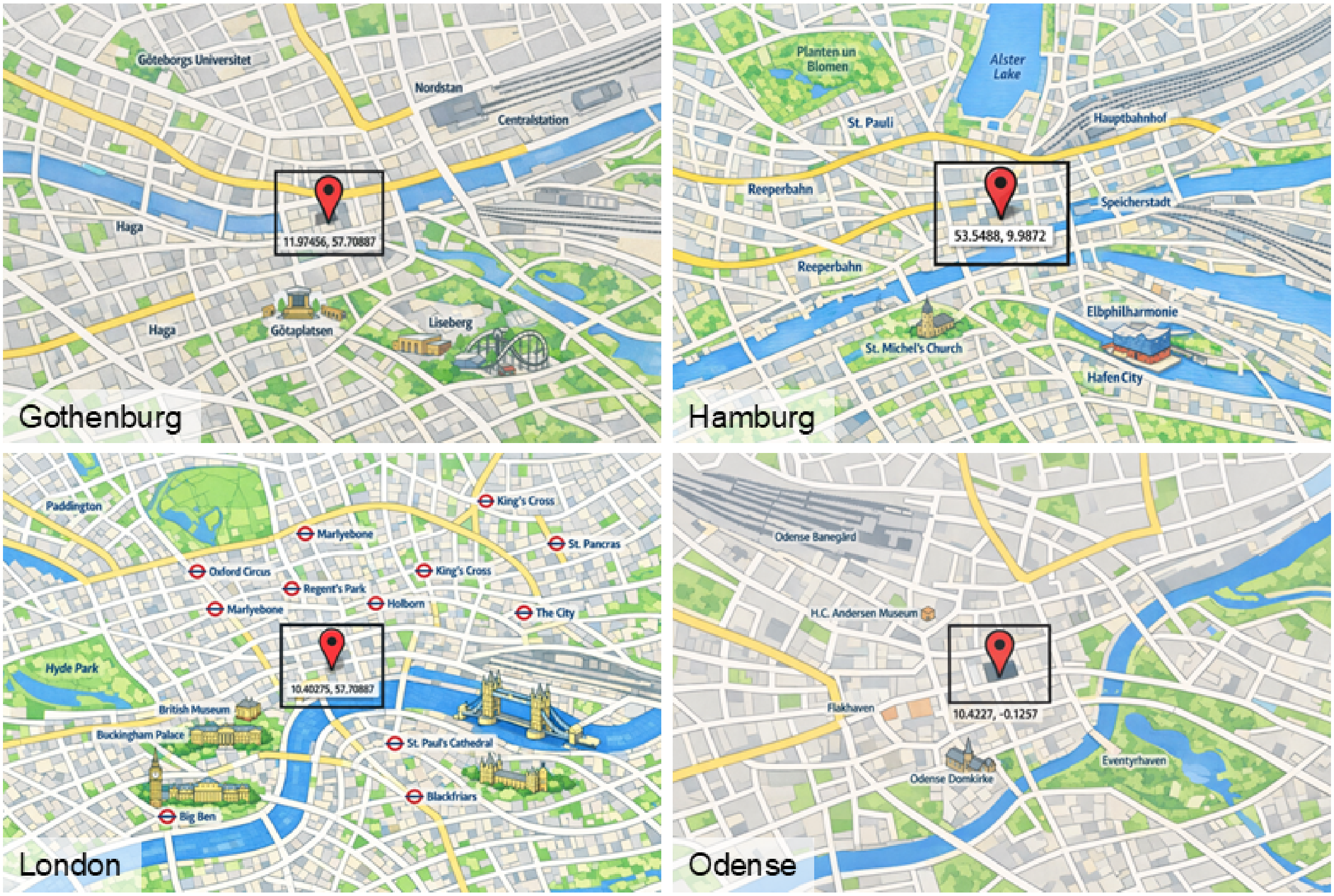

Figure S1. Maps showing the location and size (black box) of the 100 m x 100 m grid boxes used to represent four of the city centre locations described in Table 1 of the main manuscript. These maps were generated using Microsoft Copilot.

S3 Additional Flood Depth Return Level Curves

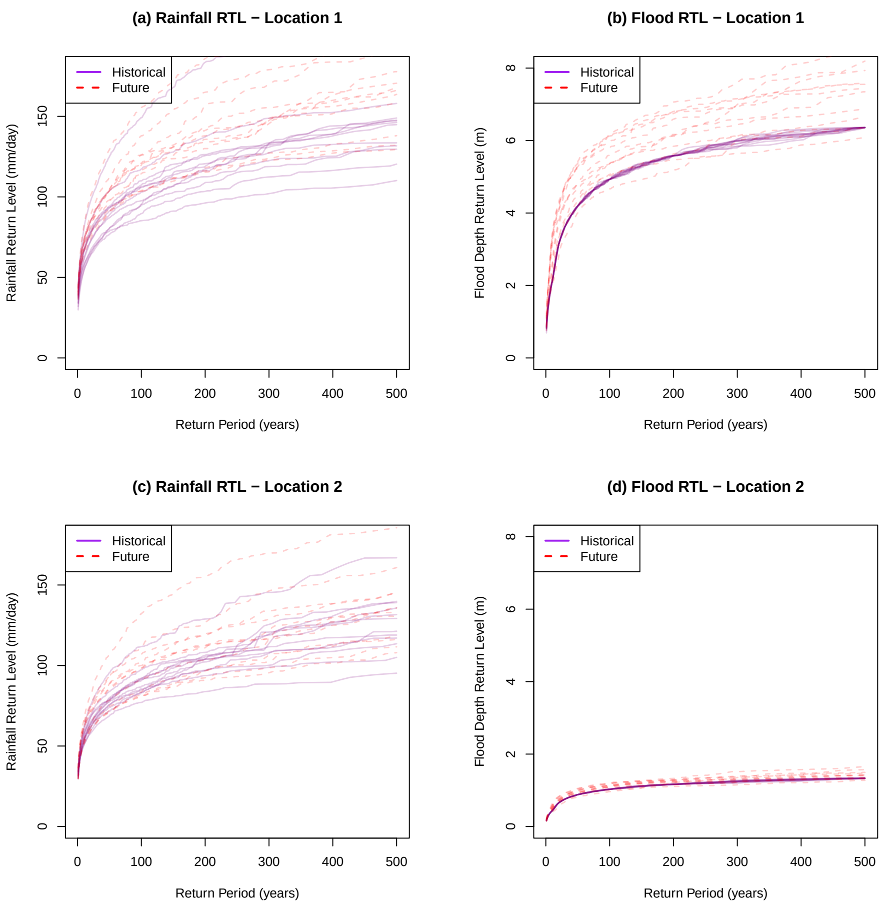

Figure S2. Equivalent to Figure 7 in the main manuscript but for all UKCP18 RCM ensemble members: Illustration of the rainfall-to-flood distribution mapping process for two 100 m × 100 m grid cells representative of the city centres of Gothenburg and Edinburgh. Panels (a) and (c) show historical and future rainfall return-level curves derived from statistical extreme value models. These curves are combined with location-specific spline functions (estimated based on each UKCP18 ensemble member) to estimate flood depth return-level curves. Panels (b) and (d) display the resulting historical and future flood depth curves.