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# Decision-making and Flood Risk Uncertainty: Statistical dataset analysis for flood risk assessment

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## Key Points:

- Changes in peak flows and the associated uncertainties are driven by diverse physical and hydro-meteorological controlling factors.
- There is a high probability that low-frequency peak flow events would become twice to four times more frequent by the 2080s across Scotland.
- Coupling bottom-up to top-down approaches in climate change impact studies would allow closing the gap between research and practice.

## Abstract

Floods are a significant issue worldwide with over 1 Bn people living in areas of potential flood risk. With climate change these risks are anticipated to increase, but there is great uncertainty associated with future projections, which poses challenges to those making decisions on flood management. Climate change projections which explicitly capture climate model parameters uncertainty are available in the United Kingdom; however their use by practitioners, rather than researchers, has so far been limited. This paper takes an inclusive approach, working with end users, to answer practitioner relevant questions regarding future climate change influence for flood hazards. The method developed demonstrates the findings across Scotland, U.K. and investigates: (i) the regional impacts to extreme flows and the associated uncertainty, (ii) the changes in extreme peak flows in terms of frequency, and (iii) the physical and hydro-climatic factors controlling these results. The method used industry standard statistical methods, driven by practitioner requirements, and explicitly includes the statistical uncertainty in the climate and extreme value distribution models in extreme flow estimates. Results are analyzed using hierarchical clustering and decision tree analysis and the subsequent trends are shown to be constrained by different hydrological, climatic, and physical catchment characteristics. Results suggest that there is a high probability that low return-period peak flow events would exceed the baseline extreme high return-period event by the 2080s, which has significant implications for future-proofing infrastructure design. This study provides a practical example and outputs resulting from collaboration between research and industry practices.

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## 1 Introduction

Flood risk is a significant issue worldwide with over 1 Bn people living in areas of potential flood risk (Jonkman and Vrijling, 2008). Flood risk is a product of both the probability of event occurrence and its consequence to society and the environment (Balica et al., 2013). Flood hazards result from excess water from one or multiple sources (e.g. coastal/estuarine, fluvial, pluvial or ground water) and the consequences can impact on: infrastructure, human health, economic activity, the environment, and cultural heritage, and arise from system exposure, susceptibility and lack of resilience to the hazard (see e.g. Beevers et al., 2016). Many factors influence flood risk, such as climatic and geomorphological factors, economic or societal drivers, and whether they may change in the future (see e.g. Osborn et al., 2000; Maraun et al., 2008; Hannaford & Marsh, 2006; Blöschl et al., 2015). Building these potential changes to flood risk into the development of new infrastructure is important when designing resilient cities. River flood maps, reflecting the best estimate of the extent of flooding associated to a given a return period event, are key components of development planning (Hall et al., 2003, Beevers et al., 2012). These can influence land use planning, land value (Lamond et al., 2007) and are industry standard for flood alleviation design (Vojinovic et al., 2017). In order to future proof development the maps should incorporate the potential impact of climate change on inundation extents.

Across Europe flood policy has adopted a risk based approach through the EU Floods Directive 2007/60/EC to deal with future changes in hazard and consequence and the associated uncertainties in these. As part of the Directive, member states have prepared flood hazard maps and risk management plans in their region. How each country should approach changes to extreme events is left up to the individual member state (Kundzewicz, et al., 2012). A precautionary approach has been taken by several countries in accounting for climate change uplift factors. The Netherlands and parts of Germany for example have taken a safety margin approach (Kundzewicz et al, 2012; Reynard et al., 2017). In the UK, until 2016, the same approach was adopted, where climate change safety factors of 10-20% (by 2025 and 2080 respectively) were adopted across the country (Reynard et al., 2017). In 2016 these factors were updated to reflect the regional influence of geographic, geological and hydrological factors on the climate change response across England and Wales (Scotland and Northern Ireland are in the process of changing their guidance). This new guidance recognises the uncertainty in climate projections and subsequent responses by providing a range of uplift factors for different time periods and catchment regions across England and Wales (Kay et al., 2014a).

It is well understood that there are many sources of uncertainty associated with predictions of flood flow, extent estimation, and climate change impacts, particularly from the impact modelling chain required in flood risk assessment, where uncertainty arises from each model input scenario, initial conditions, parameters, etc (see e.g. Kundzewicz et al., 2017). There has been much research into these uncertainties through stochastic modelling approaches (see e.g. Apel et al., 2004, 2006; di Baldassare et al., 2009, 2010). However, practitioners have tended to consider uncertainty through model sensitivity analyses that include deterministic model runs based on changing individual parameters in each scenario. For example hydraulic models may be run with higher and lower friction to understand the influence of the roughness parameters on the flood extent. The choice of scenarios for sensitivity analysis and the variation in the model parameters are selected based on professional experience, site observations and national guidelines, particularly in the case of climate change (Reynard et al., 2017). Results of such sensitivity analysis are then often used to guide freeboard allowances in flood management designs.

Recent research (e.g. Collet et al., 2017), has recognised the need to understand climate model projection uncertainty and quantify the impact this may have on flood hazards across the UK. The UKCP09 provide climatic projections for a perturbed physics ensemble for various emission scenarios, and are used to project potential changes to temperature and precipitation across the UK (Murphy et al., 2009). Additionally it provides various spatially coherent downscaled scenarios across the UK which account for the regional climate model parameter uncertainty for one emission scenario. Based on this data the Centre for Ecology and Hydrology (CEH) led a nation-wide study to assess projected river flow and groundwater levels for an 11-member ensemble (Prudhomme et al., 2013). The available river flow ensemble, the Future Flows Hydrology database, reflects the uncertainties related to the HadRM3-PPE-UK model parameters for the SRES A1B emission scenario. Collet et al. (2017) analysed this database to understand the trends and the uncertainties associated with the regional climate model parameters in extreme flow patterns across Great Britain. This research captured the regional differences and highlighted the significance of capturing uncertainties in climatic projections across the country when estimating extreme flows. However, despite the availability of such national scale results, it is clear that there is a disconnect between research and its application by practitioners. This is faced in two distinct ways:

1. Practitioners are well aware of the uncertainties in flood modelling, but research studies looking at model uncertainty have not resulted in clear guidance or methodologies that are used in practice. Results of uncertainty assessments need to be able to support clear decisions and be transparent to non-experts. Results of uncertainty analyses also need to be used to develop sustainable, but cost-effective solutions, i.e. the precautionary approach of selecting the worst case answer from an uncertainty assessment is unlikely to be practical for many applications.
2. Uncertainties in extreme flow estimation are acknowledged to be the critical uncertainty in flood model prediction, over-riding uncertainties from other sources in most applications (di Baldassarre et al., 2010). Of particular concern is the uncertainty associated with climate change and how outputs from climate models can be practically incorporated into flood management studies.

To address this disconnect, literature suggests that integrating scientific with insight from practitioners at the beginning of a study can improve the uptake and engagement of the eventual outcomes in a project. This way the results are more adequate for end-user needs (see e.g. Jahn et al., 2012; Lang et al., 2012). Therefore the aim of this study was to take an inclusive approach to the transfer of recent research (Collet et al., 2017) by working with flood risk practitioners to investigate how to use climate change projections and the associated uncertainties in a meaningful manner. It aimed to answer, in a manner that is clear to decision makers, three questions which were dictated through discussion with practitioners:

1. What are the regional impacts to extreme flows and the associated uncertainty projected by climate models?
2. What physical and hydro-climatic factors control the subsequent results?
3. How different are future extreme return period events to the present day return period events used in design?

In answering the final question, this paper explores how the uncertainties associated with predictions of future flows can be expressed in a manner that can assist flood management practitioners to make decisions in the face of uncertainty.

## 2 Materials and Methods

Collet et al. (2017) concluded it was crucial that the uncertainty arising from the climate change impact modelling chain was considered for flood risk planning. However transferring these results to industry implies a change of practice in flood risk management (e.g. moving from a deterministic to a probabilistic approach) and collaboration with practitioners is essential to ensure the practical use of research outputs. Hence this work was developed in collaboration with industry, based on UK flood management standards and policy guidance. The methodology developed and presented in this paper is demonstrated for the Scottish context and is based on Scottish Environment Protection Agency (SEPA) guidance (i.e. flood planning guidance); however the broad methods are widely transferable. This work reflects a co-operation between research and industry, resulting in mutual learning to address flood risk management in an uncertain context.

### 2.1 Regional impacts on future extreme flows

#### 2.1.1 The Future Flow Hydrology dataset

The analysis is based on the Future Flows database which was developed as part of the project “Future Flows and Groundwater Levels” (Prudhomme et al., 2013). Future Flows Hydrology (FFH) is derived from the Future Flows Climate (Prudhomme et al., 2012), a national ensemble projection derived from the Hadley Centre’s ensemble projection HadRM3-PPE to provide a consistent and spatially coherent set of climate change projections for the whole of Great Britain at both space and time resolutions appropriate for hydrological applications. FFH is to date a unique spatially coherent hydrological database that allows investigating impacts of climate change and a range of uncertainties related to climatic projections at the national scale. Future Flows Climate is an 11-member ensemble of transient climate projections for Great Britain based on HadRM3-PPE-UK, a set of transient climate projections for the UK that were developed as part of the derivation of the UKCP09 scenarios (Murphy et al., 2007). HadRM3-PPE-UK was designed to represent parameter uncertainty in climate change projections through a parameter variant experiment and was run under the SRES A1B emissions scenario (see Murphy et al., 2009 which details the climate model perturbations). SRES scenarios were used in the IPCC fourth assessment report (AR4) however a most recent approach was used in AR5 with RCPs (Representative Concentration Pathways) scenarios. In terms of CO<sub>2</sub>-equivalent concentration emissions and global temperature increase, SRES A1B is similar to RCP 6.0 and would lead to an increase in global temperature of 2-5 °C by the end of the 21<sup>st</sup> century relative to pre-industrial time (Rogelj et al., 2012). Future Flows Hydrology contains an 11-member ensemble of transient projections (1 original model and 10 variants creating an 11 member ensemble of model outputs) from January 1951 to December 2098, each associated with a single realisation from a different variant of HadRM3. Murphy et al. (2009) stipulates that daily time series from particular HadRM3-PPE member should be interpreted as plausible realisations, and as such each ensemble member was considered in this study as plausible and all equally probable.

This study analysed the change to extreme flow magnitude between two time periods in order to account for non-stationarity. The time periods chosen were the baseline (1961-1990) and the 2080s (2069-2098). Return period event magnitude and their associated 95% confidence intervals for the 1:10, 1:30, 1:50, 1:100, and 1:200-yr return periods, on the baseline and the 2080s were calculated for 95 gauging stations across Scotland, for each of the 11 climate model ensemble members.

### 2.1.2. The Flood Estimation Handbook approach for return period event estimation

In the UK the industry standard approach to flood magnitude return period event analysis is performed following the Flow Estimation Handbook (FEH) methods (Robson & Reed, 1999), which recommends fitting both the Generalised Extreme Value (GEV) and the Generalised Logistic (GL) distributions. The GEV (Coles, 2001) distribution is very widely used (Robson & Reed, 1999), however, the Generalised Logistic (GL) distribution is currently recommended in the UK for flood data analysis and practitioners tend to favour it as it provides more conservative results.

For  $x$  an independent random variable, the probabilistic function of the GL distribution is:

$$f(x) = \frac{\sigma^{-1} \exp(-(1-\xi) * Y)}{[1 + \exp(-Y)]^2}$$

where  $Y = \frac{-1}{\xi} * \log\left(1 - \frac{\xi(x - \mu)}{\sigma}\right)$

(Eq. 1)

with  $\mu$  the location parameter,  $\sigma > 0$  the scale parameter, and  $\xi (\neq 0)$  the shape parameter. For an event of return-period  $T$ , the non-exceedance probability  $F$  is such that  $T=1/(1-F)$ , and is given by (Hosking & Wallis, 1997):

$$Q(F) = \mu + \frac{\sigma}{\xi} \left[ 1 + \left( \frac{1-F}{F} \right) \right]_+^{\xi} \quad (\text{Eq. 2})$$

To fit the GL distribution, the FEH recommends using the L-Moments method (Robson & Reed, 1999) to evaluate their parameters and the return level confidence intervals (CI). See Robson & Reed (1999), Chapter 15, pp. 139–152 for a full description of the L-Moments for probabilistic distribution parameter estimation method. The GL distribution was fit to the annual maxima data with the L-Moments method across the 95 gauging stations in Scotland for the 11-member ensemble on the baseline and the 2080s.

### 2.1.3. Output analysis for decision-makers' use

National scale maps were created displaying the uncertainty related to climate model and probabilistic distributions for the 1:200-year return period runoff event, which is the industry standard design event in Scotland (Figure 1) for flood management and general planning purposes (e.g. housing developments). This return period is of particular interest in Scotland since the Scottish Environment Protection Agency produces flood risk management maps with this return period to assess the medium likelihood of flooding and dictate the use of this return period in policy and planning (see <http://map.sepa.org.uk/floodmap/map.htm>). However, in a climate change impact context, the IPCC recommends studying 30-year time periods in the past and future as they are considered as stationary. Such a short time series of flows induces significant uncertainty in assessing peak flows for such a high return period, which is captured by the 95% confidence intervals (CI). More frequent return period analysis should incur lower uncertainty (i.e. smaller 95% CI). Runoff estimates (i.e. normalized runoff depth in mm) were investigated instead of peak flows to normalize the analysis and remove the influence of catchment size from the results. The median 1:200-year return period peak

flow (medQ200, Fig 1.a), the climate model uncertainty (CMU, see Fig 1.b and Eq. 3), and the mean probabilistic distribution uncertainty associated with the GL distribution (PDU, see Fig 1.c and Eq. 4) were mapped for the baseline and the percentage change in the future.

CMU represents the range of 1:200-year return period peak flow that is computed across the 11 climate-model ensemble members. It is calculated as the relative standard deviation for each station (Eq. 3).

$$CMU = \frac{\sigma}{\mu} \quad (\text{Eq. 3})$$

with  $\sigma$  the sample standard deviation and  $\mu$  the sample mean of the distribution.

The relative standard deviation is a standardized measure of dispersion of a distribution. It is a dimensionless number, expressed in percentage, which allows the comparison between data with different means and dispersions.

PDU represents the mean range of 95% confidence intervals obtained across the 11 climate-change ensemble members (Eq. 4). This coefficient is dimensionless and allows a normative comparison of data with different peak flow estimates and confidence interval ranges.

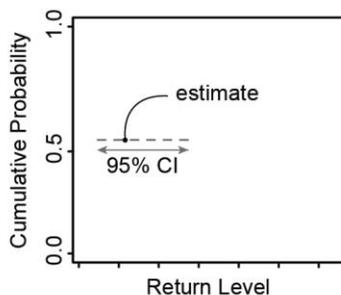
$$PDU = \frac{\sum_{i=1}^N RC_u(i)}{N} \quad (\text{Eq. 4})$$

with  $N$  ( $N=11$ ) the number of climate-change ensemble members and  $RC_u$  a relative coefficient of uncertainty computed for each climate-change ensemble member:

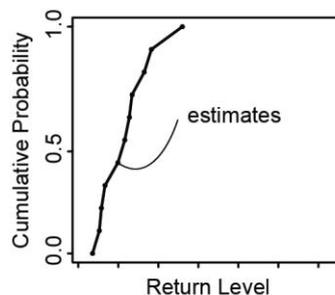
$$RC_u = \frac{CI_{up} - CI_{low}}{E} \quad (\text{Eq. 5})$$

with  $E$  the runoff estimate,  $CI_{up}$  the upper 95% confidence limit, and  $CI_{low}$  the lower 95% confidence limit.

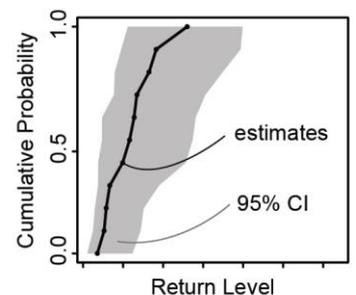
(a) For 1 ensemble member and the EV confidence interval



(b) For 11 ensemble members



(c) For 11 ensemble members and the EV confidence intervals



**Figure 1.** (a) Median 1:200-year return period runoff across the 11 climate-change ensemble members; (b) Uncertainty related to the climate model parameterisation: smoothed empirical CDF of return level estimates for the 11 ensemble members (black line); (c) Uncertainty related to the chosen EV model: return level estimates (black dot) and the 95% confidence intervals (CI, grey dashed line).

## 2.2. Analysis of the regional controlling factors

### 2.2.1. Catchment characteristic data

To analyse physical, geographical and hydrological controlling factors on extreme return period peak flows and their related uncertainties, 17 catchment characteristics were extracted from the FEH database (Bayliss, 1999) for each FFH gauging station in Scotland (see Table 1). These variables are easily accessible in the UK widely used by industry. These descriptors fall into four main categories: the land form descriptors (AREA, ALTBAR, ASPBAR, ASPVAR, DPLBAR, DPSBAR, LDP), the attenuation effect from lakes and reservoirs (FARL), the climate and soils descriptors (BFIHOST, PROPWET, RMED-1H, RMED-1D, RMED-2D, SAAR, SAAR4170, SPRHOST), and the urban and suburban land cover (URBEXT). Additionally, four variables were investigated: the centroid coordinates of the catchments (X for the eastings and Y the northings) as well as the time-to-peak ( $T_p$ , see Eq. 6) and critical storm duration ( $C_s$ , see Eq. 7) values (Houghton-Carr, 1999).

$$T_p = 4.27 * DPSBAR^{-0.35} * PROPWET^{-0.8} * DPLBAR^{0.54} * (1 + URBEXT)^{-5.77} \quad (\text{Eq. 6})$$

$$C_s = T_p * \left( 1 + \frac{SAAR}{1000} \right) \quad (\text{Eq. 7})$$

**Table 1.** Catchment characteristics investigated.

Name	Unit	Description
AREA	km <sup>2</sup>	Drainage area of the catchment
ALTBAR	M	Mean altitude
ASPBAR	-	Mean flow direction
ASPVAR	-	Invariability in flow direction
BFIHOST	-	Base flow index derived using the Hydrology Of Soil Types classification
DPLBAR	Km	Mean drainage path length
DPSBAR	m/km	Mean drainage path slope
FARL	-	Flood attenuation attributed to reservoirs and lakes
LDP	Km	Longest drainage path from a catchment node to the defined outlet
PROPWET	%	Proportion of the time that catchment soils are wet
RMED-1H	Mm	Median annual maximum rainfall for a 1-hour duration
RMED-1D	Mm	Median annual maximum rainfall for a 1-day duration
RMED-2D	Mm	Median annual maximum rainfall for a 2-day duration
SAAR	Mm	Average annual rainfall on 1961-1990
SAAR4170	Mm	Average annual rainfall on 1941-1970
SPRHOST	%	Standard percentage runoff from the Hydrology of Soil Types classification
URBEXT1990	%	Amount of the catchment covered by urban and suburban areas in 1990
X	M	Easting of the centroid coordinate (British National Grid)
Y	M	Northing of the centroid coordinate (British National Grid)
$T_p$	Hour	Time-to-peak
$C_s$	Hour	Critical Storm duration

### 2.2.2. Cluster and decision tree analysis

A regionalization analysis was undertaken to understand the trends in extreme events changes. Since the FFH database is available for only a certain amount of gauging stations across Scotland, practitioners were interested in exploring ways in which the findings could be transferred to other stations with similar physical and hydro-climatic characteristics. Following the method proposed by CEH (Chiverton et al., 2015) and SEPA (Kay et al., 2011), the regionalization analysis on the median value, CMU, and PDU for the 1:200-year RP was performed for the baseline and the percentage change to the 2080s in the three main steps described below, in order to investigate regional trends, as well as whether there was any way in which to generalize the results of the study.

First, a cluster analysis gathered the catchments into homogeneous categories for each variable. This was performed following the approach used by Chiverton et al. (2015). Different hierarchical clustering methods were tested first using a Euclidean squared distance matrix (Ward, single, complete, average, median, centroid and McQuitty) based on medQ200b. The number of catchments classified in each category was analysed and Ward's method (Murtagh & Legendre, 2014) proved to provide the most balanced number of catchments per cluster. The number of clusters (three in this study) is subjective and was chosen through a trial-and-error process across the three variables (medQ200, CMU and PDU) based on a dendrogram structure in order to obtain balanced and homogeneous groups.

Second, a selection was made amongst the 21 investigated catchment characteristics to determine the ones that explain the most differences between clusters using Chiverton et al. (2015). A boxplot analysis was performed to remove the catchment characteristics that did not show significant differences across the clusters. Then, a correlation analysis excluded highly correlated catchment characteristics, i.e. those presenting a Spearman's rank correlation coefficient higher than 0.8 or lower than -0.8 (Spearman, 1904).

Third, decision trees were built based on the clusters and the selected catchment characteristics following Kay et al. (2011). Classification trees aim to predict discrete categories in comprehensive ways for data that are constrained by variables in complex interactions (Breiman et al., 1984). Trees are built in a recursive process: first the catchment characteristic that best splits the data regarding the previously defined clusters is found and two sub-groups are generated. Then the same process is applied to each sub-group, separately, leading to four sub-groups. This binary process is repeated until reaching a minimum size of data (1 catchment) in each sub-group. Since the resulting trees were often over-fitted, they were pruned using cross-validation to remove the branches that do not add significant fit to the data (Wilkinson, 2004): the trees were pruned for the minimum value of the cross-validation estimate of misclassification error where the misclassification error (MR) was calculated as:

$$MR = Rel \times Rne \times 100$$

where :

$$Rel = 1 - R^2 \tag{Eq. 8}$$

$$Rne = \frac{Nc}{Nt}$$

with Rel the relative error, R the root mean squared error, Rne the root node error, Nc the number of catchments well classified, and Nt the total number of catchments.

The 95 gauging stations were divided into calibration (86 stations) and validation (9 stations) groups to test the robustness of the method (not shown here). Validation catchments

were used to test if they were classified in the expected clusters as defined with the calibration group. When classifying the validation catchments, all were correctly classified for values in the cluster bounds (see clusters in Figure 4).

Using results of this analysis the characteristics which control the cluster generation and thus the controls on the future changes to extreme event magnitudes were examined.

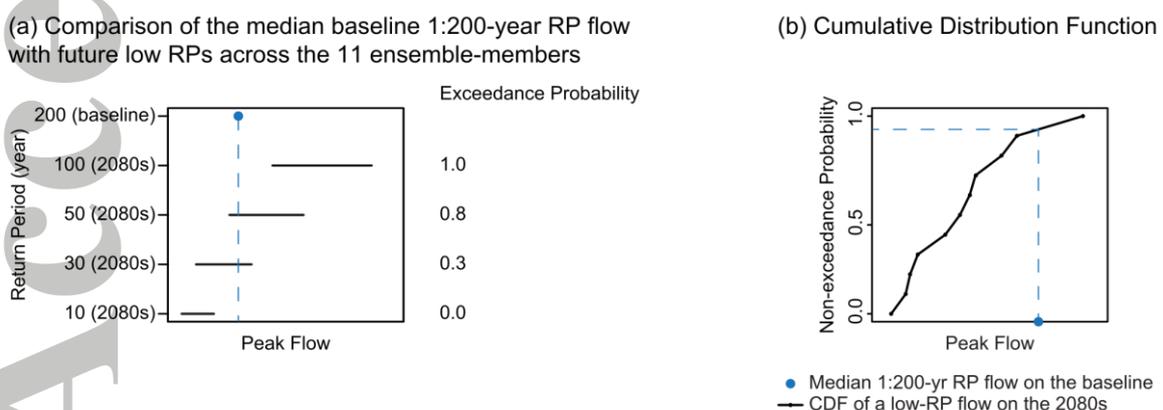
### 2.3. Probabilistic change in extreme flow frequency

To answer the practitioners' question: "What is the probability of future low return-period flows (the 1:10, 1:30, 1:50, and 1:100-year return-period flows in the 2080s) to be higher than the current high return-period flow (the current 1:200-year return period flow estimated on the baseline)?" (Fig. 2) further analysis of the changing peak flow return period estimates was required. Across the 11 ensemble-members and for each station, the median peak flow for the 1:200-year was calculated on the baseline (medQ200b), and the probability of the 2080s lower return-period flows to be higher than medQ200b was calculated (Fig. 2a). Original guidelines to account for climate change in flood management schemes included a UK-wide "20% uplift factor which would account for a potential increase in peak flows for the 21<sup>st</sup> Century (Reynard et al., 2017). This 20% sensitivity allowance was chosen based on the outcome of research applying UKCIP02 climate projections to ten catchments across the UK for a range of emissions scenarios, which showed that peak river flows generally changed by up to 20%. National guidance thus recommended a precautionary approach by using this value (+20%) to account for climate change in flood management, where plans had to show the impact of measures with and without this uplift factor applied. To compare this sensitivity allowance to the FFH outputs, the medQ200b value plus 20% (medQ200b<sub>+20</sub>) was also compared to lower RP events. Cumulative distribution functions (CDF) plot the non-exceedance probability of a variable (here the 1:10, 1:30, 1:50 or 1:100-year return-period flow). Hence the medQ200b (and medQ200b<sub>+20</sub>) was compared against each return-period flow through the CDF to assess the corresponding non-exceedance probability (Fig. 2b), and the exceedance probability was calculated as:

$$EP = 1 - NEP \quad (\text{Eq. 9})$$

with EP the exceedance probability and NEP the non-exceedance probability.

This analysis allows the assessment of possible shifts in peak flow statistical distributions as a result of climate change. It accounts for the climate model uncertainty when evaluating the change in statistical distribution of peak flows as a result of climate change.



**Figure 2.** RP: return period, CDF: Cumulative Distributive Function. For a hypothetical case study: (a) On the left: Comparison of peak flows for the median 1:200-year RP value on the

baseline (blue dot) against value ranges across the 11 ensemble-members of lower RP on the 2080s (black lines); on the right: corresponding exceedance probability. **(b)** CDF of a 2080s low RP peak flow across the 11 ensemble-members, and comparison against the baseline 1:200-year RP peak flow to assess the non-exceedance probability.

### 3 Results

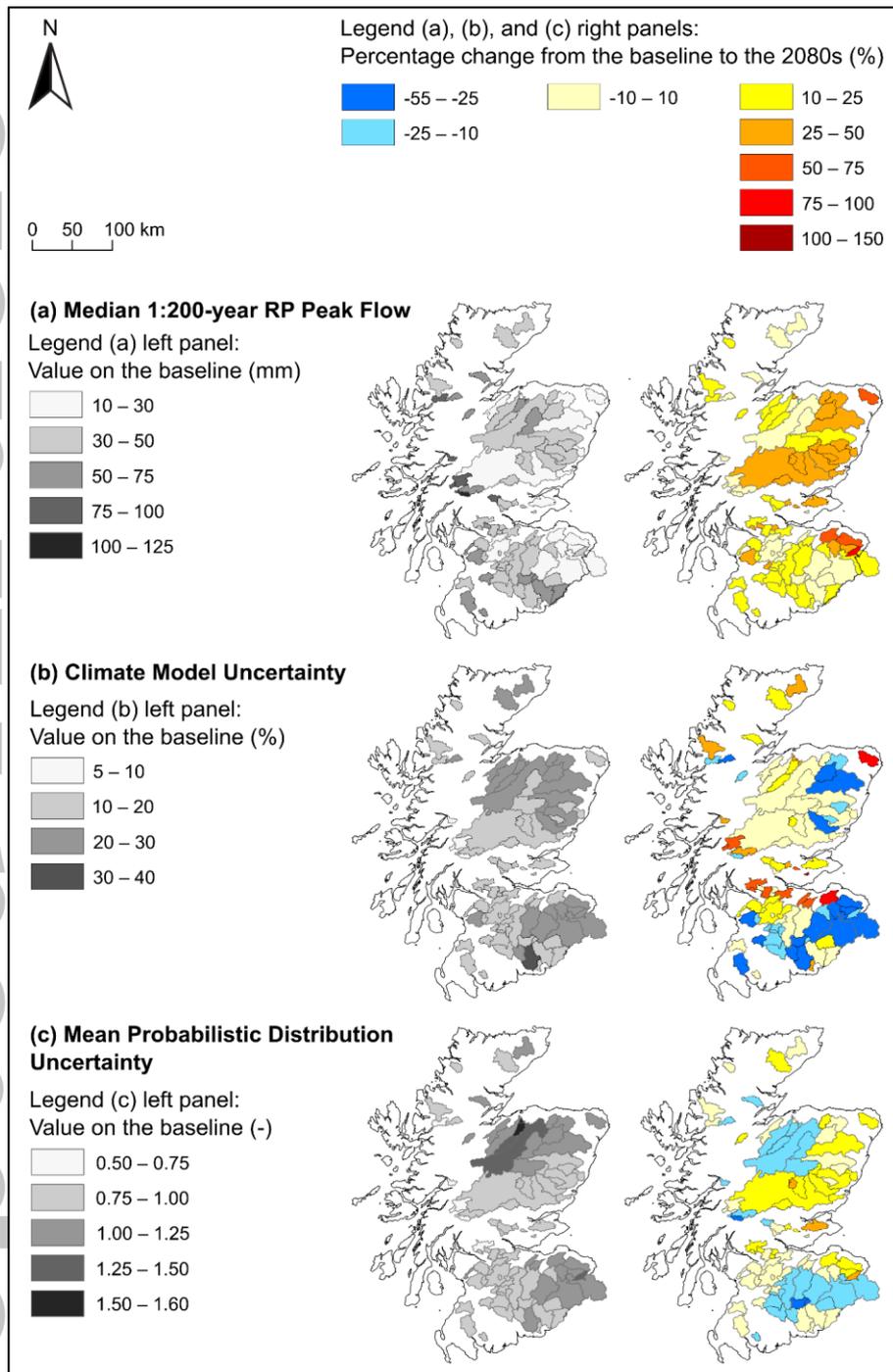
#### 3.1. Probabilistic 200-year return-period flow mapping

Figure 3a shows the medQ200 calculated across Scotland with the GL distribution on the baseline (left panel) and the percentage change to the 2080s (right panel). Figure 3a left panel shows an east-west gradient in medQ200 across Scotland with the highest values on the west coast (up to 114 mm/day for the Falloch River at Glen Falloch) and lower values on the east (down to 17 mm/day for the Eden River at Kemback). Figure 3a right panel shows the highest increase in medQ200 for catchments on the east part of Scotland (red shades, up to +76% for the Leet Water at Coldstream), and no significant change for 30% of the catchments across Scotland (white).

Figure 3b shows the CMU calculated across Scotland with the GL distribution on the baseline (left panel) and the percentage change to the 2080s (right panel). Fig. 3b left panel shows catchments with higher CMU on the baseline in the northeast and southeast of Scotland (up to 31% for the Annan at Brydekirk), while the lowest CMU are found on the west coast (down to 7% for the Falloch at Glen Falloch). Fig. 3b right panel shows a significant decrease in CMU to the 2080s (blue shades) for 34% of the catchments in the east and south of Scotland (down to -52% for the Tweed at Sprouston) and a significant increase (red shades) for 37% of the catchments in the north of Scotland and across the Central Belt (up to +146% for the Lochty Burn at Whinnyhall). 29% of the catchments show no significant change in CMU.

Figure 3c shows the mean PDU calculated across Scotland with the GL distribution on the baseline (left panel) and the percentage change to the 2080s (right panel). Fig. 3c left panel shows catchments with higher mean PDU on the baseline on the north and southeast of Scotland (up to 1.54 for the Divie at Dunphail). Lower mean PDU are found for catchments on the west coast (down to 0.50 for the Falloch at Glen Falloch). Fig. 3c right panel shows a significant decrease in mean PDU to the 2080s for 32% of the catchments (blue shades, down to -35% for the Etrick Water at Brockhoperig) and a significant increase for 27% of the catchments, particularly on the east coast (orange shades, up to 28% for the Eden at Kemback). 41% of the catchments show no significant change in mean PDU from the baseline to the 2080s.

The raw values are plotted in figure S2 and S3 in Supporting Information, showing ranges of uncertainty (between the minimum and maximum values) for the baseline and the future respectively. The maps represent both the CMU and PDU uncertainty ranges. On the baseline the range of uncertainty around the mean estimate for CMU is in the range of 5mm to 25-30mm. For the future a similar range is observed across similar stations (as discussed in the analysis section). For PDU this range is larger, varying from 16-20mm to 80-100mm on the baseline. Again a similar range is observed in the future. Unlike the CMU range which is largely consistent between return period estimates (i.e. 1:10-, 30-, 50-, 100-, and 200-years), the PDU range is less for lower return period events (not shown here).



**Figure 3.** Results across Scotland on the baseline (left panels) and percentage change to the 2080s (right panels) for the **(a)** median 1:200-year return period peak flow, **(b)** Climate Model Uncertainty, and **(c)** mean Probabilistic Distribution Uncertainty.

### 3.2. Analysis of the regional controlling factors

Figure 4 shows results of the analysis of the regional controlling factors which influence the percentage change from the baseline to the 2080s in the median 1:200-year RP flow Climate Model Uncertainty and the mean Probabilistic Distribution Uncertainty across Scotland. Results on the baseline are not shown. Maps on the left panels show the Cluster analysis and diagrams on the right panels illustrate the Decision Tree analysis. To read the latter, each line corresponds to a question (e.g. in Fig 4.a first line: “is BFIHOST greater or

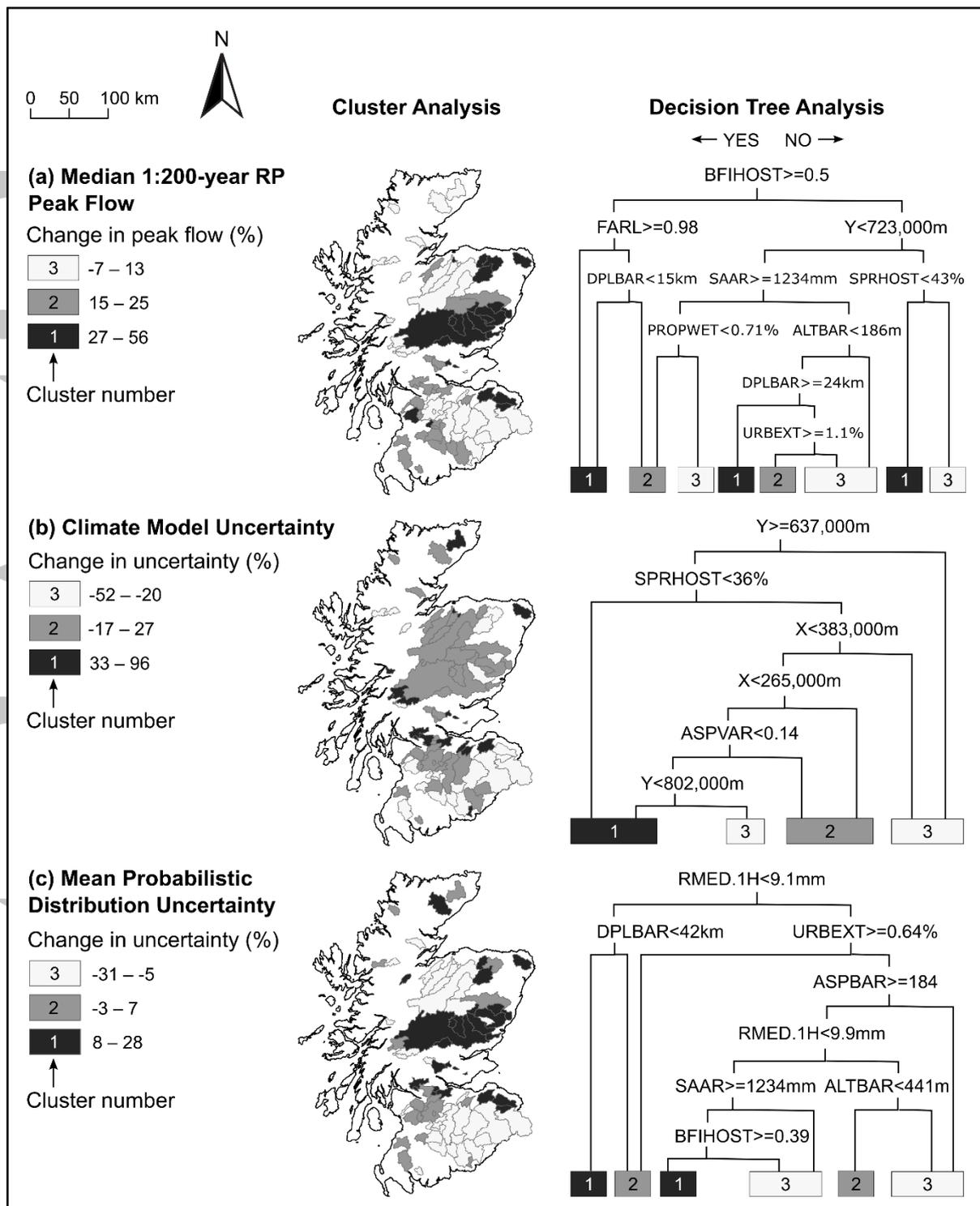
equal to 0.5?") that is answered by "YES" when going to the sub-categories on the left and by "NO" when going to the right. The bottom line (terminal nodes) corresponds to the cluster number identified in the Cluster analysis (Fig. 4 left panels) where the catchments are classified. In other words, Decision Trees in the right panels show how the clusters defined in the left panels can be discriminated based on the catchment characteristics (see Table 1). E.g. in Fig. 4a: if a catchment has a  $BFIHOST \geq 0.5$  and a  $FARL \geq 0.98$ , then it belongs to Cluster 1 (i.e. it shows an increase in Median 1:200-year RP peak flow of 27-56%).

Fig. 4a shows the analysis for the percentage change in 1:200-year RP peak flow. On the left panel, the Cluster analysis reflects three categories previously shown in Fig 3.a (right panel): no significant trend (Cluster 3), a small increase (Cluster 2), and a larger increase (Cluster 1) in peak flow. Nine catchment characteristics are required to discriminate these three clusters ( $BFIHOST$ ,  $FARL$ ,  $Y$ ,  $DPLBAR$ ,  $SAAR$ ,  $SPRHOST$ ,  $PROPWET$ ,  $ALTBAR$ , and  $URBEXT$ ). The misclassification rate for this pruned tree is 6%.

Fig. 4b shows the results of the Cluster and Decision Tree analysis for the change in Climate Model Uncertainty. Three main clusters were defined (left panel): a significant decrease (Cluster 3), no significant trend (Cluster 2), and a significant increase (Cluster 1) in uncertainty. Only four catchment characteristics were needed to discriminate the clusters ( $Y$ ,  $SPRHOST$ ,  $X$ , and  $ASPVAR$ ) (right panel), but the misclassification rate is higher (22%) for this pruned tree.

Fig. 4c shows results for the regionalization analysis of the Probabilistic Distribution Uncertainty. Again the three clusters illustrate different trends in change in uncertainty: a slight decrease (Cluster 3), no significant trend (Cluster 2), and a slight increase (Cluster 1). Seven catchment characteristics are used to explain the differences between clusters (right panel):  $RMED.1H$ ,  $DPLBAR$ ,  $URBEXT$ ,  $ASPBAR$ ,  $SAAR$ ,  $ALTBAR$ , and  $BFIHOST$ . The misclassification rate for this pruned tree is 13%.

Accepted



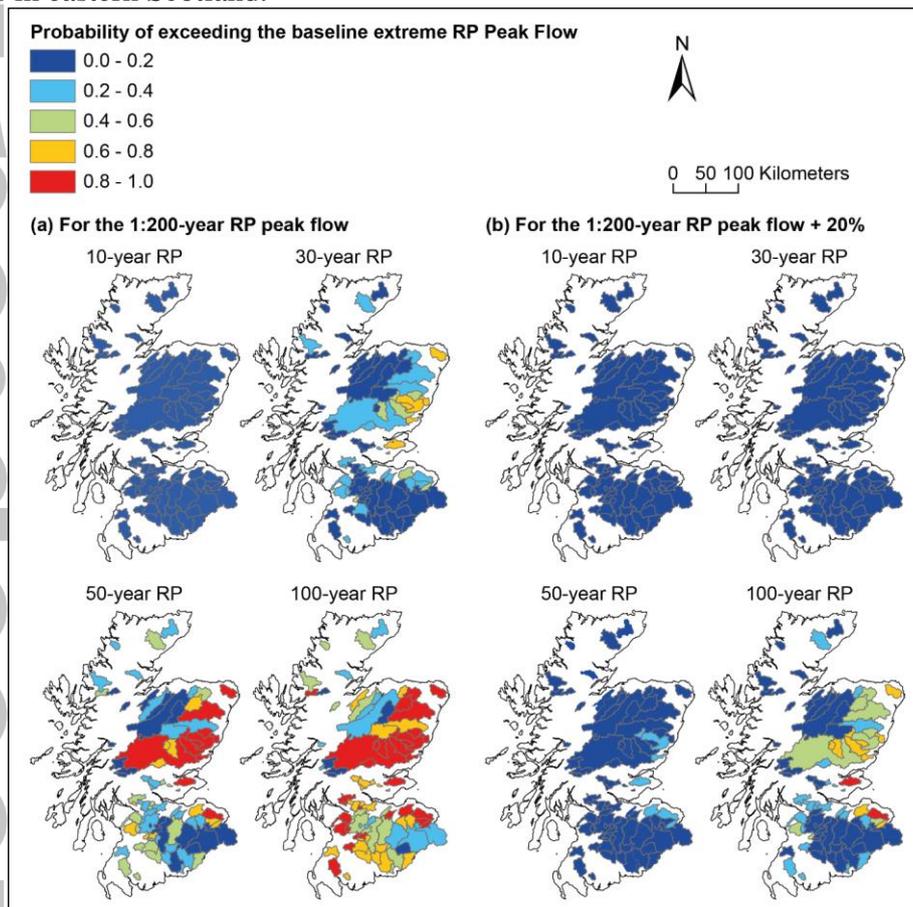
**Figure 4.** Cluster analysis (left panels) and Decision Tree analysis (right panels) across Scotland on the percentage change from the baseline to the 2080s in (a) the median 1:200-year return period peak flow, (b) the climate model uncertainty, and (c) the mean probabilistic distribution uncertainty.

### 3.3. Probabilistic change in peak flow frequency

Figure 5a shows the probability of the baseline median 1: 200 year return period (medQ200b) flow of being exceeded by four future return-period floods (2080s) across 95

catchments in Scotland (1: 10 year, 1:30 year, 1: 50 year and 1:100 year return period flows). Five probability categories are displayed: the very low (dark blue), low (light blue), medium (green), high (orange) and very high (red) probability. The 1:10-year return period flood for the 2080s shows a very low probability of exceeding the baseline medQ200b. The 1:30-year flood shows a majority of catchments with very low to low probability to exceed medQ200b, with some catchments on the east coast showing a medium to high probability (6% of the catchments). For the 1:50-year flood, a high to very high probability of exceeding medQ200b is found in east and central Scotland (24% of the catchments), and this trend spreads to the 1:100-year flood for catchments in the west and south of Scotland (61% of the catchments), leaving a minority of catchments with low to very low probability. In other words, it is likely that the 1:200-year flood calculated on the baseline becomes twice to four times more frequent in the 2080s for a significant number of catchments in Scotland.

Figure 5b compares the lower return period floods in the future to the median 1:200-year flood calculated on the baseline plus 20% (medQ200b<sub>+20</sub>). It shows that the 1:10-, 1:30-, and 1:50-year floods, are very unlikely to become higher than medQ200b<sub>+20</sub> in the 2080s. 12% of the catchments, mainly on the east coast, show a high to very high probability for the 1:100-year flood to become higher than medQ200b<sub>+20</sub> in the 2080s. In other words, it is likely that the estimated 1:200-year flood used for climate change impact assessment in traditional approaches would be twice more frequent in the 2080s and that it is under-estimated for some catchments in eastern Scotland.



**Figure 5.** Probabilistic maps of low-return period floods (1:10-, 1:30-, 1:50-, and 1:100-years) to become higher in the 2080s than (a) the medium baseline 1:200-year flood, and (b) the medium baseline 1:200-year flood + 20% of its value.

## 4 Discussion

### 4.1. Main results

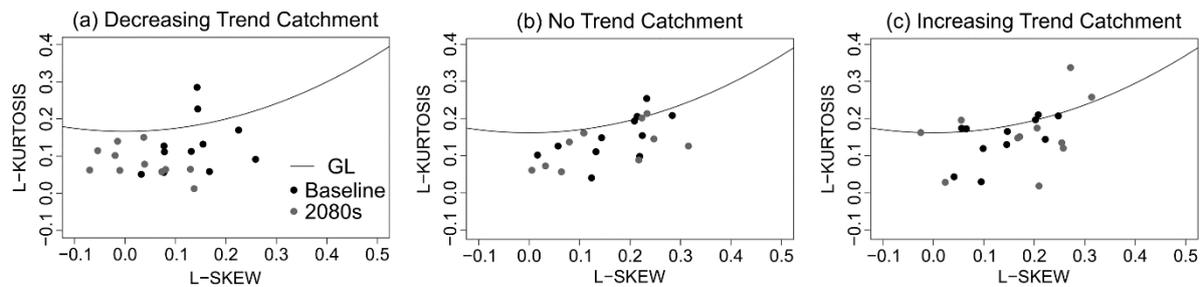
#### 4.1.1. Changes in extreme peak flows

The regional trends displayed in the analysis largely follow the east west split that is observed in measured records across Scotland. This east-west gradient, which is evident in the medQ200 values on the baseline, is correlated to the known precipitation gradient across Great Britain (Hannaford & Hall, 2012). What is interesting however is that this study suggests a greater increase in future extreme flows for easterly flowing catchments, with the most significant changes for the Leet Water at Coldstream by 76%. This is considered to be due to the catchment characteristics in these catchments, and is explored in more depth through the analysis of controlling factors.

The changes highlighted in Figure 3a are consistent with that reported by Collet et al. (2017), which used both the Generalised Pareto (GP) method (fitting to Peak over Threshold data) and the GEV method (fitting to Annual Maxima series) to analyse changes in extreme flows. Large increases in multi-day and extreme precipitations are expected as a result of climate change in the north and west of the UK (Wilby et al., 2008), which translates into rising peak flows in Scotland as shown in Figure 3a. These results mirror that presented by Kay et al. (2014b) where increases in the 1:20-year return period flows were suggested across Scotland. These authors used the UKCP09 weather generator (Murphy et al., 2009) with a range of emission scenarios, generalised the findings to a regional level, and presented uncertainty ranges as uplift factors rather than probabilistic distributions. Contrary to this study, they report greater changes for the 1:20-year return period event to the estimates in the west, but with greater uncertainty. This reflects the greater range of climate emission scenarios captured by the Kay et al. (2014b) study. Differences are particularly marked as the range of the climatic database used for the FFH data does not capture the full range of the climate variable space since it is based on the projections from HadRM3-PPE-UK with the SRES A1B emission scenario, a downscaled subset of the UKCP09 database (Prudhomme & Williamson, 2013). Across Figure 3b there are significant catchments where the uncertainty arising from climate model parameters decreases in the 2080s, most notably in the south east around the Tweed catchment. This suggests that there is greater agreement between the Regional Climate Model ensemble members in the future. In these catchments climate model parameters have less influence on the range of river flow projections and the more significant controlling factors of the climate-flow transformation are the hydrographic and geographic catchment characteristics. There are several catchments where this trend is reversed, particularly across the Central Belt and in the north of Scotland. These catchments are thus more sensitive to the Regional Climate Model signal.

Figure 3c highlights three broad catchment categories; those which show a decreasing uncertainty arising from the distribution function parameters in the future, those that are largely unchanged and those where the uncertainty increases. Figure 6 shows the L-Moments ratio diagram for the GL distribution (solid line), and the L-Skewness and L-Kurtosis values computed across the 11 ensemble members on the baseline (black dots) and the 2080s (grey dots) with a fitted GL distribution (the figure is zoomed around the computed values). L-Moments ratio diagrams were originally developed to assess goodness-of-fit measures for a wide range of distribution functions (see Hosking, 1990; Vogel & Fennessey, 1993). Three contrasted catchments were chosen in this Figure: the Ardlie at Kindrogan shows the highest increase in median Probabilistic Distribution Uncertainty (+28%), the Clyde at Daldowie shows no significant change (-0.8%), and the Annan at Woodfoot shows the highest decrease

(-31%). Figure 6a shows that a decreasing uncertainty in distribution parameters results when the GL distribution fits the annual maxima series better in the 2080s than on the baseline. This suggests that across the 11 ensemble members, the L-Skew and L-Kurtosis relationship follows the theoretical relationship of the GL distribution better in the 2080s than on the baseline, as illustrated by a wider spread of the baseline values on the graph. Figure 6b highlights that for the no change catchments there is no discernible trend in the relationship between the baseline and the 2080s, whilst Figure 6c suggests a diverging trend for catchments with an increasing uncertainty in the 2080s.



**Figure 6.** L-Moments Ratio Diagrams for the Generalized Logistic (GL) distribution function (solid line) and computed values across the 11 ensemble-members on the baseline (black dots) and in the 2080s (grey dots) for contrasted catchments showing: (a) a decrease in Probabilistic Distribution Uncertainty, (b) no significant trend, and (c) an increase in Probabilistic Distribution Uncertainty.

#### 4.1.2. Analysis of the regional controlling factors

Analysing the outcomes from the regionalization study shows that there are strong, complicated physical and hydrological controls which influence the hydrological response to climate change in a catchment (see Figure 4a). Catchments with a high percentage change to the medQ200 in the 2080s (cluster 1) tend to have a larger attenuation resulting from lakes and reservoirs within the basin, be larger (have a longer drainage path), or have a lower standard percentage runoff. These trends are much more complex than those seen in Figure 4b, where it is very clear that the response in climate model uncertainty in the 2080s has a strong geographical influence. Fundamentally the analysis is picking up the east-west precipitation gradient and indicating the influence this has on extreme flows both now and in the 2080s. Finally, Figure 4c unpicks the relationships which influence the uncertainty arising from the distribution fitting. Catchments with reducing uncertainty in the 2080s tend to have higher 1-hour rainfall depths, low urban extents, and either be at high altitudes or have little influence from groundwater. These features suggest that the GL distribution works best in catchments which are not complicated by complex attenuation processes or urban drainage influences.

There are limitations to the method presented here as there is considerable uncertainty in the application of decision trees and thus the application of these to ungauged catchments is not considered to be appropriate. This has previously been highlighted by Kay et al. (2014a, 2014b) and reiterated by Reynard et al. (2017). However this paper has used the results of such analysis to explore changes in future hydrological series and catchment influence on this.

#### 4.1.3. Probabilistic change to return period estimates in the future

Figure 5 investigates the probabilistic change to the baseline 1:200 year return period event in the future for lower return period events. Figure 5a shows clearly that for the lower return period events (1:10 and 1:30 year return period) there is a very low probability that the current 1:200 year RP event would exceed this. However by the 1:50 year and 1: 100 year return period events there is a high likelihood that for some catchments (e.g. the Dee River at Polhollick) the current 1:200 year event will become four times more frequent in the future (i.e. 1:200 year RP event becomes a 1:50 year RP event). These trends mirror the recent research findings for climate related risks across Europe, where Aberdeen was identified at particular risk (Guerreiro et al., 2018). Figure 5b puts these results into the context of the current 20% uplift factors that practitioners use to account for climate change. It shows that the policy errs on the side of caution for many catchments. However it is projected that some catchments may be twice as likely to see the extreme 1:200 year RP event in the future.

The presentation of probabilistic model results in Figure 5 allows the discussion of flood risk to move towards a probabilistic framework using language that encourages discussion between a wide range of stakeholders; a key aim of this study. The concept of a return period and the risk associated with a flood of any given return period is well understood, not only by practitioners but also non-experts and members of the public (Strathie et al., 2017). Planning policy in Scotland is explicit in its use of the 1:200-year flood and in defining the 1:200-year floodplain as the one beyond which most types of development are permitted. Reporting of recent flood events in the media has regularly discussed the probability of occurrence of the flood and residents who have been flooded are able to assess risk in terms of flooding history. Figure 5 effectively asks a practitioner or regulator the question: 'What level of flood risk (in terms of return period) would you be willing to accept by the 2080s based on a decision made today?'. For example, if development is permitted on the basis that it would not flood in a 1:200 year event at the present day, by the 2080s would a 50% risk that this development would only be protected with a level of risk consistent to a 1:50 year event be acceptable? The results presented in this paper do not provide guidance, but rather it frames the results of complex uncertainty analysis in a form that allows engagement with a range of stakeholders or practitioners and would allow decisions to be clearly defined in terms of uncertainty and risk. For example, a local authority may decide that a development should be designed so that there was a 90% chance that a present day development would still be protected up to a 1:200 year level by the 2080s. Results communicated in the manner demonstrated here explicitly provides the likelihood of extreme peak flows to become more frequent and would allow to make decisions as to which future flow should be taken as the design condition.

#### 4.2. Main limits

Some limits of this study are related to the use of the Future Flow database. As reported by Collet et al. (2017), some catchments were calibrated with an emphasis on the representation of the water balance, and low flows and the extreme high flows might thus be under-estimated. A validation exercise was undertaken where the Future Flows Hydrology dataset was used to determine the 1:200 year return period event for each station for the hydrological period 1981-2010. As described in section 2.1.3. (Figure 1), the uncertainty bounds were determined for each station. These were compared to the estimates calculated from the gauged data provided by the Scottish Environmental Protection Agency (SEPA) for the same hydrological period (1981-2010). Analysing the estimates shows that for the majority of gauges (83%) the FFH represents a reasonable statistical estimate of the 1:200 year return period level (i.e. the estimate from gauged data falls within the range estimated by

the FFH dataset estimate). For 17% of gauges there is a statistical underestimate of the return level using the FFH. This occurs most noticeably in the South West Region where a number of stations (8) are underestimated. These are located on the River Clyde (4 stations), the upstream section of the River Nith (2 stations) and the Rivers Esk and Orchy. In the other regions isolated gauges on some rivers (Tay, Spey, Dee, Findhorn and Tweed) are underestimated however in each case other gauges on these rivers have estimates which lie within the uncertainty range. Supporting figures and data can be found in the Supporting Information document (see Fig S1). Given the low frequency return period estimates used in this paper (as dictated by practitioner requirement to assess medium likelihood of flooding), and based on the standard approach to non-stationary climate for impact studies (use of 30-year time periods); significant uncertainty in the 1:200 year return period estimate is found. However this is the reality faced by practitioners who are required to integrate complex new model projections with high levels of uncertainty into established, policy-required methods and techniques. The issues which arise around this are discussed further below.

This study investigates the uncertainty related to one climate model only (HadRM3), under one emission scenario (SRES A1B), and thus does not capture the full uncertainty related to climatic modelling (see e.g. Kundzewicz et al., 2017). Using outputs from diverse General Circulation Models (GCMs) would allow estimating a wider set of possible futures in impact studies and quantifying the uncertainties related to the climate models structure and input data (Wilby, 2010). GCM and emission scenarios are two major sources of uncertainty in impact studies (Kundzewicz et al., 2018). When comparing UKCP09 to the Coupled Model Inter-Comparison Project Phase 5 (CMIP5) projections, which were used in AR5 and reflect on the uncertainties related to the GCM structure, the current recommendation is that UKCP09 provides consistent results for future changes to summer and winter temperature and winter rainfall (Met Office Hadley Centre, 2016). The main differences were found for future summer rainfall changes: while both experiments agree on a likely future reduction on the long-term, CMIP5 suggests a smaller likelihood of substantial future reductions, especially for England and Wales (ibid). The FFH database is based on a downscaled subset of the UKCP09 database, the HadRM3-PPE-UK, which does not capture the full range of the climate variable space projected by UKCP09 (Prudhomme & Williamson, 2013). For example, when using outputs from the UKCP09 weather generator (Murphy et al., 2009) with a range of different emission scenarios, changes in peak flows show a different spatial distribution (higher increase of 1:20-year return period events in the west), with a wider uncertainty (Kay et al., 2014a; 2014b). Investigating hydrological data derived from climatic projections forced by a wider range of emission scenario would thus probably lead to a larger range of possible changes in extreme peak flows (Wilby & Dessai, 2010). Consequently this study presents a suggested methodological approach, jointly developed between researchers and practitioners, capable of incorporating and communicating changing flood hazard estimates.

#### 4.3. The uncertainty gap: which way forward from research to practice?

The difficulty for practitioners to account for climate change impacts in flood risk assessments resides mainly in the uncertainty ranges that characterize changes in extreme peak flows. Two main sources of uncertainty were investigated in this study: (i) the climate model parameters (CMU), that is cascaded into hydrological modelling, transferred into river flow estimation, and quantified as a range of peak flow estimation; and (ii) the extreme value model parameters (PDU), which is quantified using confidence intervals estimation. Figures such as those shown in Figure 1 condense these results into a single plot. However, when presenting these to practitioners it was clear that they were not easily interpreted. Thus maps of the form presented in Figure 3 were developed, that clearly show geographical variability

in uncertainty and allow comparison of uncertainty sources. These are easy to interpret, but do not lead to any clear conclusions as to which level of uncertainty or what precise percentage change in flow should be used by practitioners in flood risk assessments. This gives rise to two questions:

1. How can practitioners make decisions on the most appropriate increase in future extreme flows to be considered for any flood management project?
2. How can the uncertainty in the return period estimates, based on the climate model projections, be incorporated into flood management decisions and how can this uncertainty be reduced?

The discussion in Section 4.1.3 suggests a means of addressing the first question and part of the second question. The traditional way that an increase in flows for climate change is considered in flood management is where a national regulatory body identifies a percentage increase in flow to be applied to a region for a given design horizon. There is then little project by project discussion by engineers and hydrologists working on flood management projects to change this guidance for any specific project. Presenting the uncertainty in terms of the likelihood of exceedance of future return periods allows an investigation of the percentage increase in flows in terms of questions that can be understood by a multi-disciplinary project team and associated stakeholders.

A further limitation of the current top-down approach is that there is in-built inertia, in that guidance is not updated to match improvements in the knowledge of climate change; it is a significant effort and cost for regulators to update guidance. In Scotland the current standard 20% increase in 200-year flow conditions has been in place for two decades, although it is well understood that there is more up-to-date science that would tend to argue for different values across the country. Therefore, methods where uncertainty is better understood, communicated, and discussed on a project by project basis may also have the benefit of encouraging updates to national guidance or a more bottom-up approach, where practitioners make use of more up-to-date research. In tandem with this researchers also need to understand that available data sets (although not perfect) can still be used to improve decision making. In a rapidly changing field such as climate research there is always going to be a 'better' data set available or just over the horizon and one of the reasons that research does not make its way through to application is that research can be trapped in a circle where methods can always be improved and tested on the latest datasets. Hopefully this study shows that although datasets such as the FFH may not be able to be used as is to assess future peak flows, they provide a solid basis to investigate climate change projection uncertainties.

To further address the uncertainties in climate model predictions one way is to improve understanding of probabilistic shifts in the statistical distribution as a result of climate change. This is also an opportunity to push the industry towards probabilistic approaches, instead of deterministic modelling, and develop new collaborations with research to assess probabilistic flood maps (see e.g. di Baldassarre et al., 2009). A drawback of probabilistic modeling such as Monte Carlo analysis is often seen as the computing power needed to run a high number of times a model, with linked 1D/2D flood models of large rivers requiring several hours to perform a single run. Reduced Monte Carlo techniques for hydraulic modelling have been being developed (see e.g. Aitken et al., 2018), which could be transferred to the industry and allow them to analyze probabilities of change in floodplain as a result of climate change. However, the key limitation to the application of these methods will remain the difficulty in interpreting the resulting flood maps produced by probabilistic simulations. As discussed in Section 4.1.3 the issue that limits practical application of research ideas is often one of the presentation of final model outputs in ways that promote

discussion and understanding, rather than the lack of desire of industry to take up new approaches. For example, running dozens of flood model simulations is very achievable for most engineering consultancies, but it is only a practical option if the model outputs assist rather than confuse decision making. For most flood management projects the end result is still an agreed flow or flood level that flood infrastructure or development needs to be designed against and researchers looking into uncertainty need to keep that final output in mind when presenting the results of their investigations.

In terms of reducing uncertainties, this study assessed the 1:200-year return period flow event which is the industry standard in Scotland for flood risk management. Return periods of 1:100-year up to 1:1,000-year are in common practice in engineering design. However, as recommended by the IPCC for climate change impact assessment in a non-stationary context, 30-year time periods were used to compute these, which generates large uncertainty bars (see SI). In practice such issues are addressed using a pooling group method in order to increase the length of the flow series for analysis (standard guidance is a time series of 5 times the return period interval which is rarely possible); thus reducing the confidence intervals. Use of lower return period events would also reduce the uncertainty associated with the estimate. For example, other practitioners, such as the insurance industry, use a 75-year return-period event for flood risk assessment. However this may still be too low frequency to be compatible with climate change impact assessment. So how can practitioners resolve this tension between uncertainty and standard, established methods? Will future climate model projections be able to constrain the future uncertainty to levels which make decisions more tenable? While we are not able to answer the latter question, interestingly, recent studies showed that when we translate these uncertainties in peak flow through to hydraulic modelling to predict flood extents, the uncertainty range can be reduced by the physical boundaries and topographical thresholds of the river bank (see e.g. Aitken et al., 2018).

## **5 Conclusions and Perspectives**

This work is a collaboration between researchers and practitioners that aims to quantify changes in extreme peak flows and the associated uncertainties as a result of climate change in Scotland and to understand the controlling factors driving these results. It developed a means of presenting the results that will promote understanding and discussion of probabilistic flood predictions among practitioners, a key limitation to the adoption of research developments in flood risk in industry.

Results showed that in Scotland the increase in 1:200-year return period peak flow would be higher for eastern catchments, which present a larger attenuation resulting from lakes and reservoirs, are larger, or have a lower standard percentage runoff. The uncertainty related to the regional climate model parameters shows significant increases by the 2080s in the Central Belt and north of Scotland while south-eastern catchments show significant decreases. These trends are mainly driven by geographical characteristics of the catchments, and show a wide range of sensitivity to the climatic signal across the country. The uncertainty to the distribution parameters is constrained by diverse hydro-meteorological and urban extent features which includes the annual maximum rainfall, the drainage path length and the urban extent. Finally, the probabilistic frequency analysis showed that there is a high probability that low-frequency peak flow events (for the 1:200-year return period) would become twice to four times more frequent by the 2080s (i.e. become a 1:100- or a 1:50-year return period event). This shows that climate change would induce a significant shift in the

peak flow statistical distribution by the 2080s and that this needs to be accounted for in development planning and flood protection schemes.

This work is not an attempt to present the most state-of-the-art climate change projection chain, but rather a methodological approach to transfer research outputs on climate change impact and uncertainty quantification for flood risk assessment, driven by practitioners' questions and practices. As highlighted by Kundzewicz et al. (2018), the academic community needs to improve their communication on climate change impact and understand how decision-makers respond to uncertainty in order to frame risk assessment and adaptation plans better. This paper provides a step towards addressing these issues, in that it takes climatic projections and the large associated uncertainty bounds and analyses results in a way that is comprehensively accessible and meaningful to users. A key component of the assessment is the presentation of future flood flows as a probability of exceedance of a present-day return period flow.

The FFH database is a unique spatially coherent UK-wide statistical river flow database which provides an opportunity to develop methods which quantify the uncertainty associated with climate change on extreme peak flows. Other large-scale statistical hydrological products are emerging today, such as the End-to-end Demonstrator for improved decision-making in the water sector in Europe experiment (EDgE, <http://edge.climate.copernicus.eu/>), showing a growing interest to large-scale impacts of climate change on the hydrological cycle by stakeholders. Similarly, the upcoming UKCP18 (<http://ukclimateprojections.metoffice.gov.uk/24125>) based on AR5 RCPs should also provide appropriate downscaled climatic projections for the UK, the development of these new climate scenarios being driven by both the climatic and the end-user communities. With more products becoming available there is a clear need for practical end-user available data, and tools for analysis which improve the accessibility and utility of such products.

This study provides a practical example and outputs from a collaboration between research methodologies and industry practices. It provides a Scottish-wide analysis of changes in extreme design floods in terms of magnitude, frequency, but also in different uncertainty sources, as a result of climate change. It highlights the tension between standard flood risk practice and the need to assess climate change impacts in a non-stationary context. This opens the dialogue with practitioners on methods to account for climate change impacts and advocates moving from deterministic to probabilistic approaches. To be implemented into flood prevention schemes, these results would need to be cascaded into probabilistic flood mapping (see e.g. di Baldassarre et al., 2009) to reframe uncertainty in terms of risks and develop appropriate adaptation measures (Kundzewicz et al., 2018). This would require case studies to be implemented in probabilistic hydraulic modelling and would allow site-specific analysis of the different sources of uncertainty cascading through the modelling framework.

### **Acknowledgments and Data**

The Future Flow Hydrology dataset is available from the Centre for Ecology and Hydrology website at <https://www.ceh.ac.uk/services/future-flows-maps-and-datasets>. This work was carried out as part of the EPSRC EP/L026538/1 project 'Accounting for Climate Change Uncertainty in Flood Hazard Prediction'. The authors would also like to thank the anonymous reviewers, the Editor-in-Chief, and the Associated Editor for their constructive comments that helped strengthening this work.

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