01 – STRESS TESTING DESIGN ALLOWANCES TO UNCERTAINTIES IN FUTURE CLIMATE: THE CASE OF FLOODING

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1. Introduction

Projected changes in climate are expected to increase flood risk in north western Europe (e.g., Lehner et al., 2006; Wilby et al., 2008; Murphy and Charlton, 2008). In responding to such risks, responsible authorities have set out design allowances to incorporate climate change impacts in building robust flood infrastructure. When it is cheap, particularly at design stage, Hallegatte (2009) highlights that it is prudent to add security margins to design criteria to improve the resilience of infrastructure to future (expected or unexpected) shocks. This paper sets out to subject such design allowances to a sensitivity analysis of the uncertainty inherent in estimates of future flood risk. We use Ireland as a case study where policy guidance such as the Greater Dublin Strategic Drainage Study (GDSDS) sets out that all new development must allow for a 20% increase in peak flows for all return periods up to 100 years to allow for climate change. Similarly, the Office of Public Works (OPW), the national body responsible for flood risk management in Ireland has advised an allowance of +20% of peak flows under a mid-range future scenario and +30% as a high-end scenario (OPW, 2009). Such decisions are crucial to the protection of lives, livelihoods and critical infrastructure and therefore need to be subjected to sensitivity analysis to demonstrate how robust such safety margin approaches are to uncertainty in future impacts.

In understanding local scale climate change impacts the direct application of GCMs is difficult given their coarse spatial resolution, which typically requires some form of downscaling. Regional climate models (RCMs) use a dynamic, physically based approach to downscale the larger resolution GCM variables to a higher resolution (typically 50 km) over a limited area. Such techniques are computationally expensive as they explicitly describe the physical properties affecting climate. Additionally, the output from regional climate models often require further downscaling if they are to be applied for hydrological simulation at the catchment scale. With the inclusion of more GCMs the computational cost required to better characterise the outputs from these models is immense. A computationally cheap alternative for downscaling is the statistical approach where empirical relationships are typically established between GCM-resolution climate variables and local climate. Such techniques offer the possibility of including a larger number of GCMs in the analysis. Climate change scenarios generated from statistical downscaling (e.g., using a stochastic weather generator) offer a significant computational advantage over dynamical downscaling methods in sensitivity testing and adaptation options appraisal where the focus is on populating the uncertainty space, with less emphasis placed on the precision of single scenarios.

The aim of this paper is to analyse the sensitivity of fluvial flood risk to the uncertainty in climate change by incorporating different sources of uncertainty and utilizing key features of an ensemble of climate models. In addition to uncertainties in emission scenario and climate model selection, uncertainties arising from hydrological model structure and parameters are also incorporated for four case study catchments. In doing so the safely margin allowances for food infrastructure suggested in Irish policy guidance will be stress tested.

2. Study design and data

The methodology used to assess the impact of climate change on the frequency of extreme events and their sensitivity to future change is based on the idea of a scenario neutral approach proposed by Prudhomme et al. (2010). In their method, instead of using time varying outcomes for individual scenarios, the sensitivity analysis relied upon plausible ranges of climate changes making it neutral to the scenario used. The key advantage of such an approach as outlined by the authors is that the sensitivity domain can cover the entire spectrum of the latest GCM outputs, while it can also be adjusted to include additional values at both ends of the spectrum to plan for surprise and potential new extreme projections by adjusting the sensitivity domain. Here, however, the change factor approach is used to inform the parameters of a weather generator to produce continuous time series of change and the uncertainty space includes the uncertainty from rainfall runoff models and their parameters. While hydrological model uncertainty is not as large as that from GCMs it has been shown to be a significant contribution to the total uncertainty envelope (Bastola et al., 2011a) and also interacts differently with the same scenario input. The steps adopted in this study are as follows

(1) Select a wide range of GCMs developed by various climate centres and a number of plausible emission scenarios that provide output on the future climate for the selected region. In this study we use the IPCC AR4 scenarios (17 GCMs×3 SRES emission scenarios).
(2) Derive the monthly change factors from the control and future GCM simulations.
(3) Model the monthly change factors using a simple cosine curve to reduce the dimensionality of sensitivity analysis.
(4) Select the range of parameters of the cosine curve from the ensemble of the modelled cosine curves that represent the monthly change factors.
(5) Force hydrological models with climate scenarios generated using all possible combinations of parameters of the cosine curve i.e., a full factorial experiment of parameters for sensitivity analysis.
(6) From the simulations, derived in step 5, analyse the flood frequency and estimate the flood quantiles for specified return periods.

The study focuses on four catchments where the impact of climate change on flood frequency at the catchment scale is investigated using four Irish catchments, namely; the river Blackwater at Ballyduff (2302 km2), the river Suck at Bellagill (1219 km2), the Moy at Rahans (1803 km2), and the Boyne at Slane (2452 km2). Observed precipitation and temperature data were obtained from Met Éireann, the Irish National Meteorological Service. The river discharge data used to condition the hydrological models was obtained from the Office of Public Works (OPW).

A large number of climate change experiments using GCMs forced with SRES (Special Report on Emission Scenarios) emission scenarios have been completed in recent years. The results of experiments at several modelling centres are currently available from the IPCC DDC (Data Distribution Centre) at http://www.ipcc-data.org. The data period used in this study was 1971–2100 and the climatic variables analysed were monthly mean temperature and precipitation. Table 2 shows the list of the 17 GCMs. Each of these GCMs was run with the A1B, A2 and B1 SRES emission scenarios, all of which were used in this study and comprise 51 future scenarios (17 GCMs×3 SRES emission scenarios). Due to the difference in spatial resolution of the GCMs used in this study, all GCMs were suitably regridded to conform to the spatial resolution of 3.75×3.75° prior to extraction. This averaging would approximate the republic of Ireland as a single grid cell. The 20C3M experiment which represents the climate of the 20th century is used as a control run. This experiment runs with greenhouse gases increasing as observed through the 20th century.

Sn	Model (GCM)	CERA (acronym)	Modelling group	Spatial resolution mesh – (lon×lat)	No of cell
1	BCCR-BCM2.0	BCM2	Bjerknes Centre for Climate Research (Norway)	Gaussian – 128×64	2
2	CCSM3	NCCCSM	National Centre for Atmospheric Research (USA)	Gaussian – 256×128	9
3	CGCM3.1 (T47)	CGMR	Canadian Centre for Climate Modelling and Analysis (Canada)	Gaussian – 96×48	1
4	CNRM-CM3	CNCM3	Météo-France/Centre National de Recherches Météorologiques (France)	Gaussian – 128×64	2
5	CSIRO-Mk3.0	CSMK3	CSIRO Atmospheric Research (Australia)	Gaussian – 192×96	4
6	ECHAMS/MPI-OM	MPEH5	Max Planck Institute for Meteorology (Germany)	Gaussian – 192×96	4
7	ECHO-G	ECHOG	Meteorological Institute of the University of Bonn/KMA Meteorological inst., and M & D group (Germany/Korea)	Gaussian – 96×48	1
8	GFDL-CM2.0	GFCM20	Geophysical Fluid Dynamics Laboratory (USA)	Regular – 144×90	3
9	GFDL-CM2.1	GFCM21	Geophysical Fluid Dynamics Laboratory (USA)	Regular – 144×90	3
10	GISS-ER	GIER	NASA/Goddard Institute for Space Studies (USA)	Regular – 72×46	1
11	INM-CM3.0	INCM3	Institute for Numerical Mathematics (Russia)	Regular – 72×45	1
12	IPSL-CM4	IPCM4	Institute Pierre Simon Laplace (France)	Regular – 96×72	2
13	MIROC3.2 (medres)	MIMR	National Institute for Environmental Studies, and Frontier Research Centre for Global Change (Japan)	Gaussian – 128×64	2
14	MRI-CGCM2.3.2	MRCGCM	Meteorological Research Institute (Japan)	Gaussian – 128×64	2
15	PCM	NCPCM	National Centre for Atmospheric Research (USA)	Gaussian – 128×64	2
16	UKMO-HadCM3	HADCM3	UK Met. Office (UK)	Regular – 96×73	2
17	UKMO-HadGEM1	HADGEM	UK Met. Office (UK)	Regular – 192×145	6

Table 1: Details of the 17 GCMs employed. Each GCM was run with the A2, A1B and B1 SRES emission scenarios yielding 51 total simulations

3. Methods

3.1 Change Factors

A variety of methods are available to estimate climatological variables for future times and at spatial scales that are appropriate for local scale impact assessment. Owing to the simplicity and speed at which it can be applied, the Change Factor Methodology (CFM) is still widely used in impact analysis studies. The first step of the CFM method is to establish a baseline climatology for the area of interest. Secondly, changes in the equivalent variable for the GCM grid box closest to the target site are calculated as

$$\Delta P = \left(P^{'} - P\right) / P; \quad \Delta T = \left(T^{'} - T\right)$$

where ΔP, and ΔT are the change factors for precipitation and temperature, the primed quantities correspond to the future while unprimed quantities correspond to the baseline period (control period). In the final step the changes estimated are simply added to each day in the baseline time series. The resultant scenario incorporates the station information as well as the change of the specified GCM grid box. The procedure assumes that the spatial pattern of the present climate remains unchanged in the future. The method, however, cannot be used to explore transient changes in local climate scenarios as the CF derived is specific to the selected time slice.

A number of studies have observed that the CF calculated from a specified period is sensitive to the period selected (e.g., Kendon et al., 2008; Prudhomme et al., 2010). Therefore, the effect of sampling uncertainty on the estimated CF is addressed using a block sampling method where a continuous 20-year data block is sampled from the 30 year series of data representing control and future periods. Subsequently, the ensemble of change factors is estimated from each sample of monthly precipitation and temperature for all the selected GCM projections and emission scenarios. A change factor corresponding to median value of each of the 51 climate scenarios is selected and employed hereafter. From the range of change factors, regional sequences of precipitation and temperature are derived by suitably modifying the parameters of a weather generator based on the monthly CFs for precipitation and the annual change factors for maximum and minimum temperature. For precipitation this requires sampling 12 parameters, each representing a change factor for each month. Therefore, following Prudhomme et al. (2010) a harmonic analysis was applied to model the monthly CFs and to synthesise and smooth the larger inter-annual variations, reducing the required number of parameters to three in the form of:

$$\mu_t = \bar{\mu} + A\cos\left(\frac{2\pi}{P}t - \phi\right)$$

where μt is the value of the series at time t, μ^{-} is the arithmetic mean, A and Φ are the amplitude and phases (in radian), P is the period of observation. The phase angle Φ indicates the time of year the maximum of a given harmonic occurs and was converted to months (Kirkyla and Hameed, 1989).

3.2 Weather Generator

The weather generator employed is WGEN (Richarsdon and Wright, 1984). Wilks (1992) provide a method to adapt the calibrated parameters of WGEN to changing climate. In this study, 100 sets of different precipitation and temperature scenarios were constructed. For the generation of the future climate scenarios, the parameters calibrated for Irish synoptic weather stations were adapted accordingly from Bastola et al. (2011b) and Wilks (1992). Bastola et al. (2011b) provide a full evaluation of the application of WGEN to Irish conditions. In addition to comparing observations Bastola et al. (2011b) also compared WGEN generated future climate scenarios against available regional climate scenarios developed for Ireland using alternative techniques. Here the monthly change in mean and variance of the selected variables between the simulated control and future are utilized.

The modification of the parameters related to both the occurrence and magnitude of precipitation are derived from GCMs e.g., changes in wet days probability, monthly wet days precipitation. For the two parameters that are related to the generation of temperature, both are modified based on the change in annual average temperature and the change in the coefficient of variation of temperature derived from GCM outputs. Potential evapotranspiration (PET) data was estimated using a generalized form of the Hargreaves method (Xu and Singh, 2000); a radiation based empirical model popularly used for the simulation of PET. The empirical method utilises solar radiation, minimum and maximum temperature to compute PET. The solar radiation was estimated from maximum and minimum temperature, extra-terrestrial radiation and coefficients (Hargreaves et al., 1985). The coefficients for estimating solar radiation from temperature for Ireland were taken from Supit (1994).

3.3 Hydrological Modelling

Uncertainty in the application of rainfall runoff models stems from a variety of sources including; data, parameter, model structure and state uncertainty. Despite their acknowledged limitations, conceptual rainfall runoff models continue to be widely used for assessing the impacts of climate change on water resources and for projecting potential ranges of future impacts. Their popularity is related to their availability, low data requirements and computational demands. The uncertainties associated with hydrological models have traditionally been given less attention in impact assessments in comparison to other sources. Therefore in this study the uncertainty in hydrological model structure, along with parameter uncertainty is incorporated into the uncertainty space by using a number of plausible conceptual model structures and their behavioural parameters to transform future climate scenarios into future hydrological series.

From among the large number of models used for the purpose of modelling flow in catchments, we selected four conceptual rainfall runoff models; HyMOD (see Wagener et al., 2001), NAM (see Madsen, 2000), TANK (Sugawara, 1995) and TOPMODEL (Beven et al., 1995). Each model varies in their conceptualisation of key hydrological processes and complexity, primarily related to the number of parameters requiring calibration. NAM and TANK describe the behaviour of each component of the hydrological cycle at the catchment level by using a group of conceptual elements while both TOPMODEL and HyMOD are variable contributing area models. In TOPMODEL spatial variability is accounted for through topographic indices whereas in HyMOD spatial variability is modelled using a probability distribution function. All four models employ a single linear reservoir to model groundwater. Each has been applied in numerous applications and their potential for simulating flow due to climate change has been discussed extensively in the past. The models employed are independently developed by different researchers and organisations.

In order to examine hydrological model uncertainty (parameter and structural uncertainty) a multi-model approach based on Generalised Likelihood Uncertainty Estimation (GLUE) framework is used. The GLUE method introduced by Beven and Binley (1992) has been extensively used and is based on the premise that for a physically based hydrological model, no single optimum parameter set exists; rather a range of different sets of model parameter values may represent the process equally well. Different model structures, as well as different parameter sets in a particular model structure, can be easily combined within this framework.

The application of the GLUE method requires the definition of a likelihood measure, a measure that differentiates behavioural and non behavioural simulators (behavioural threshold) and a measure that sets the relative weights of the behavioural and non behavioural simulators. The behavioural set of model parameters for each of the models and catchments used in this study were taken from Bastola et al. (2011) where we used the period of observations from 1971 to 1990 for model calibration and from 1991 to 2000 for model validation. A common assumption implicit in most climate change impact studies is that hydrological models calibrated over the historical period are valid for use in the future under a changed climatic regime.

We used the Nash Sutcliffe Efficiency (NSE) criteria as an informal goodness-of-fit measure which is based on the sum of squared errors. An NSE threshold value of 0.6 was selected and fine tuned for each catchment so that the prediction interval encapsulates as much observation as possible, and maintains a good population of behavioural solutions. Bastola et al. (2011), which used same set of models and catchment, show that prediction interval and their reliability estimated from each of the four models are different among each catchment indicating the important role multimodel simulations can play. Each of the calibrated hydrological models was forced with the generated scenarios.

3.4 Frequency Analysis

The impact of climate change on flood frequency is defined here as the percentage change in the flood peak of a given return period. This definition results in different figures for different return periods and different time slices. A number of researchers have conducted flood frequency analysis using the output from a continuous simulation of river flow (e.g., Kay et al., 2006; Cameron, 2006). In such approaches, the analysis of flood frequency involves the selection of a flood frequency model, a statistical distribution and a method for estimating the parameters of the selected distribution. Both the annual maximum series (AMS) and peak over threshold (POT) methods are widely used for frequency analysis. In relation to the statistical distribution for the flood data Ahilan et al. (2011) recommend the Generalised Extreme Value (GEV) distribution for Irish flood data constructed from annual maximum series. Therefore we fit the AMS series using the Generalised Extreme Value distribution (GEV) using the method of probability weighted moments (Hosking et al., 1985), a method equivalent to L-moments.

4. Results

4.1 Establishing the sensitivity domain

Box and whisker plots in Fig. 1 show the mean and uncertainty in monthly change factors for temperature and rainfall for the A2, A1B, and B1 SRES emission scenarios for the 2020s, 2050s and 2080s. They are all treated with equal weight. The seasonal signal for precipitation is more pronounced than temperature, with the seasonality in precipitation becoming more pronounced with time. Given that the monthly climatological values of precipitation and temperature influence the calculation of change factors and subsequently the generation of climate scenarios, the influence of sampling uncertainty is evaluated by sampling continuous blocks of 20-year time series from within the control period 1961–2000 and from the three future time slices output from the GCMs. The distribution of seasonal mean precipitation derived from 20 year continuous blocks for each of the three scenarios and future time periods revealed (not shown) that the effect of sampling uncertainty on monthly climatological values is minimal. Therefore, a median value for seasonal mean precipitation and an estimation of the range of values derived from the selected GCMs are used for estimating the change factor in seasonal mean precipitation.

The change factors for precipitation were then modelled using a simple three parameter cosine curve to synthesise and smoothen the inter-annual variation. The distribution of the phase parameter for each future time period showed that for most of the data and for each time period, the phase parameter is located between the months of June and August. To reduce the dimensionality of the sensitivity testing and thus the computational burden the phase parameter is fixed at July. The Nash Sutcliffe Efficiency (NSE) criteria and root mean square error is used to evaluate the goodness of fit between change factors derived from the GCMs and those derived using the harmonic function. The goodness of fit plotted in Fig. 2 shows that agreement is better for later time periods as changes become more pronounced. While a large number of efficiency criteria exist (e.g. NSE, coefficient of determination, index of agreement etc.) that can be used to judge the goodness of fit, the selection of particular criteria is predominantly a subjective decision.

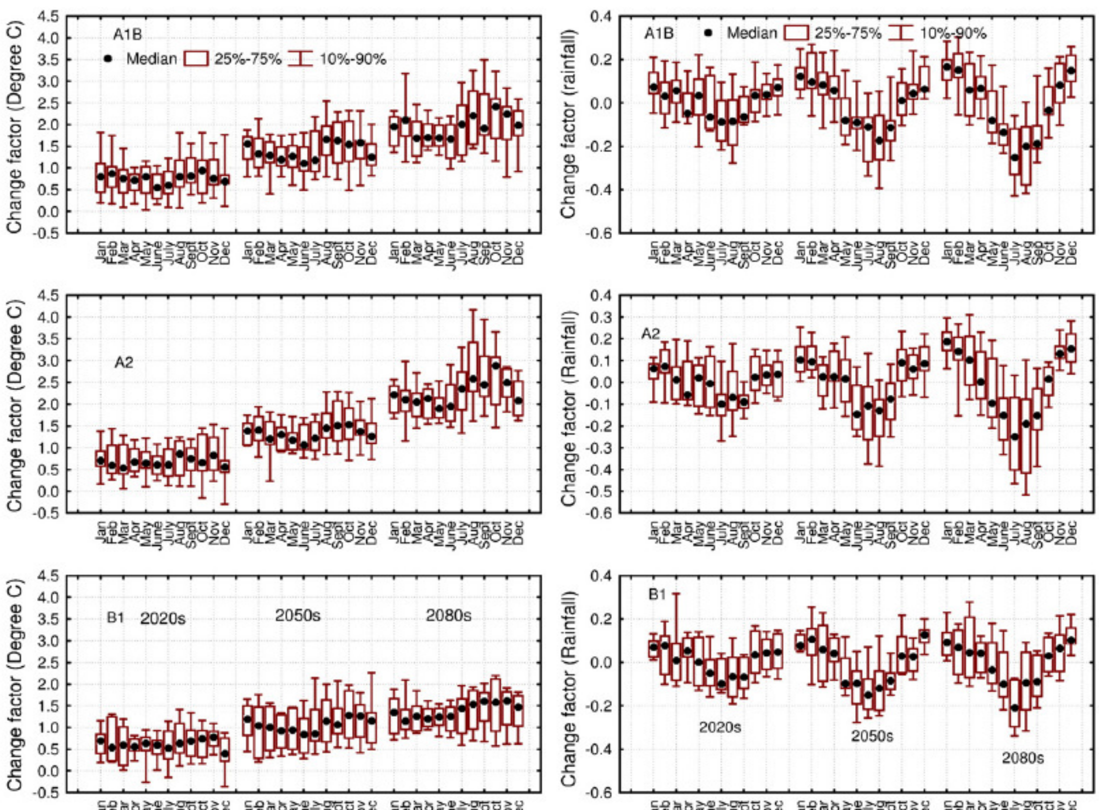

Fig 1: Change factors for the output from 17 GCMs and the A1B, A2 and B1 SRES emission scenarios for a cell representing Ireland based on 30-year average for the 2020s (2011–2040), 2050s (2041–2070) and 2080s (2071–2100) compared to 20C3M control (1961–1990).

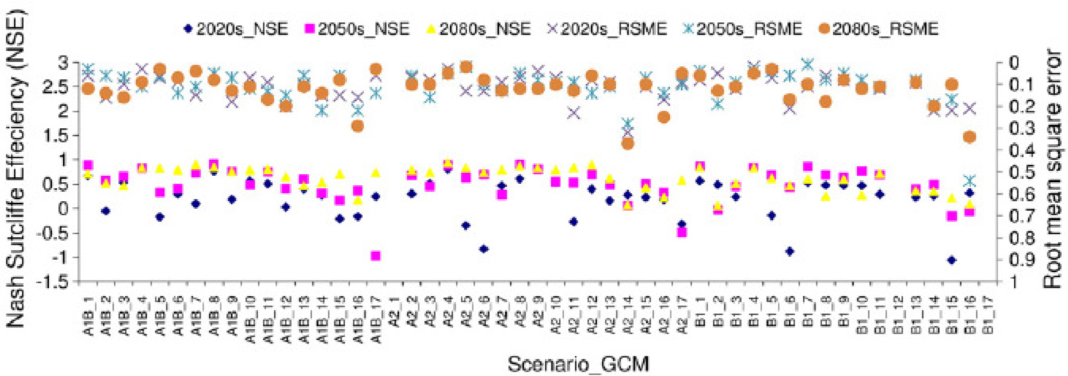

Fig 2: Nash Sutcliffe Efficiency and root mean square measures of goodness of fit between modelled and GCM estimated monthly change factors for precipitation.

Climate change scenarios are generated by adjusting the parameters of the WGEN weather generator based on the monthly change factors estimated from the harmonic function i.e., with mean and amplitude parameters of the cosine curve. Table 2 shows the range of the mean and amplitude parameters characterising the monthly change factor for precipitation. As highlighted above the phase parameter is fixed assuming a maximum in July. The parameter ranges used for the sensitivity analysis are 1.5 times greater than the range derived for the modelled change factor. A widened sensitivity domain is employed to include extra values at both ends of the GCM estimated range to allow for potential new extreme projections.

Sn	Scheme	Parameter of cosine curve characterising the monthly change factor for precipitation				Annual average changes in temperature			
		Mean		Amplitude		Mean		Coeff of variation	
		Min	Max	Min	Max	Percentile (5)	Percentile (95)	Percentile (5)	Percentile (95)
1	2020s	−0.0483	0.063	0.1	0.14	0.1648	1.4661	−0.192	0.173
2	2050s	−0.05	0.0765	0.1	0.256	0.5357	1.8650	−0.221	0.152
3	2080s	−0.08	0.0765	0.1	0.347	0.9502	2.7383	−0.274	0.088
4	Sensitivity analysis	−0.125	0.125	0.001	0.5	0.1648	2.7383	−0.2737	0.1729

Table 2: Summary of the parameters of the cosine curve characterising the monthly change factor for precipitation. Also shown are the parameters characterising the change factor in temperature.

By approximating change factors using a harmonic function, it is quite possible that the resulting sensitivity domain for the seasonal signal may be different from that built upon the signatures derived from modelled change factors. On the other hand, building a sensitivity domain on the signature of individual GCMs would increase significantly the number of parameters and thus the complexity of the analysis. Therefore it is important that the limits of the sensitivity derived from modelled change factors encapsulate the change factors estimated from different GCMs. Analysis (not shown) highlights that for the majority of months the modelled domain encapsulates the change factor derived from the selected GCMs indicating that the range used for sensitivity testing is justifiable.

4.2 Sensitivity analysis of flood peaks

The purpose of the sensitivity analysis is to assess the effectiveness and residual risks associated with climate change allowances for peak flows in Irish river catchments, the results of which are visualized using a response surface for each catchment. The hydrological simulation involved approximately 20,000 model runs with 4 structurally different hydrological models, each with 50 behavioural parameters and 100 different daily precipitation and temperature scenarios. The temperature scenarios were subsequently used to generate an equal number of scenarios for potential evapotranspiration. Both precipitation and temperature scenarios were generated by modifying the parameters of WGEN as discussed earlier. The range of the amplitude and mean parameters of the cosine curve for precipitation and the mean and coefficient of variation parameter for temperature (shown in Table 2) were used to analyse the sensitivity of flood frequency. The analysis is based on a fully factorial experiment where the two parameters of the cosine curve are sampled at 10 discrete, equally spaced increments. The simulated time series of flow were then used to estimate 20,000 sets of annual maximum flood events, each of thirty years duration. Probability weighted moments is then used to fit the GEV distribution to each annual maximum series. Following Prudhomme et al. (2003) stationarity is assumed for each thirty year period.

Fig. 3 shows the impact of hydrological model structure and parameter uncertainty on flood quantiles for the Boyne. Each model displays the varying effect of parameter uncertainty on different flood quantiles using a climate scenario generated from a single value of the mean and amplitude parameters. The highest uncertainty is associated with low frequency flood quantiles simulated with TANK and TOPMODEL and can be attributed to the nonlinear structure of both models. Stores are common components of all lumped rainfall–runoff models used in this study. HYMOD, NAM and TANK use the linear store i.e., the output from each is proportional to the amount of stored water. Unlike HYMOD and NAM, TANK uses two outlets to simulate surface runoff. This nonlinear structure in the surface reservoir allows TANK to represent diverse hydrograph types (see Sugawara, 1995). TOPMODEL uses an exponential store where output is exponentially related to storage. The exponential store is generally considered to be a tool for recession and base flow simulation but, as part of a rainfall runoff model, it can also play an important role in the simulation of high flow events. The differences and extent of uncertainty highlighted in Fig. 3 emphasise the importance of incorporating model structure and parameter uncertainty in estimating climate change impacts on flood quantiles, particularly for larger extremes with lower frequencies of occurrence.

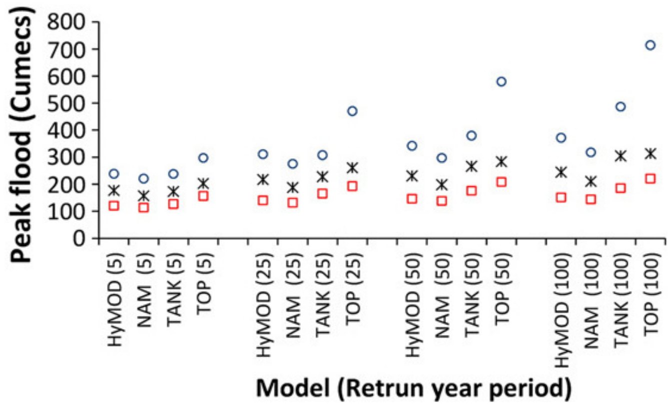

Fig 3: The 95th, 5th percentile and median value for modelled flood quantile (5, 25, 50 and 100 year return year period), that represent the uncertainty in model parameters for the Boyne

The results of the sensitivity analysis of precipitation scenarios are summarised using the 3D contour plots in Fig. 4 which show the percentage changes in the 95th percentile flow of the specified return period, estimated with respect to the 95th percentile flow of the same return period from present climatic conditions. The colours represent intervals, whereas the legend corresponds to the threshold values. The plots help in assessing the design allowances or safety margins identified for dealing with climate change. As expected, an increase in the frequency of all return periods (5, 25, 50 and 100 years) analysed is found for an increase in the mean and variability of rainfall. However, the magnitude of changes in flood frequency varied considerably for different catchments. Results show that floods with a high recurrence period (e.g., 5 year return period event). The impact of climate change is not as great for flood peaks with smaller return periods. Consequently, for low frequency events, the risk of exceedence of design allowances of +20% of flood peak is greater, with considerable implications for critical infrastructure, e.g. culverts, bridges and flood defenses whose design is normally associated with higher return period events.

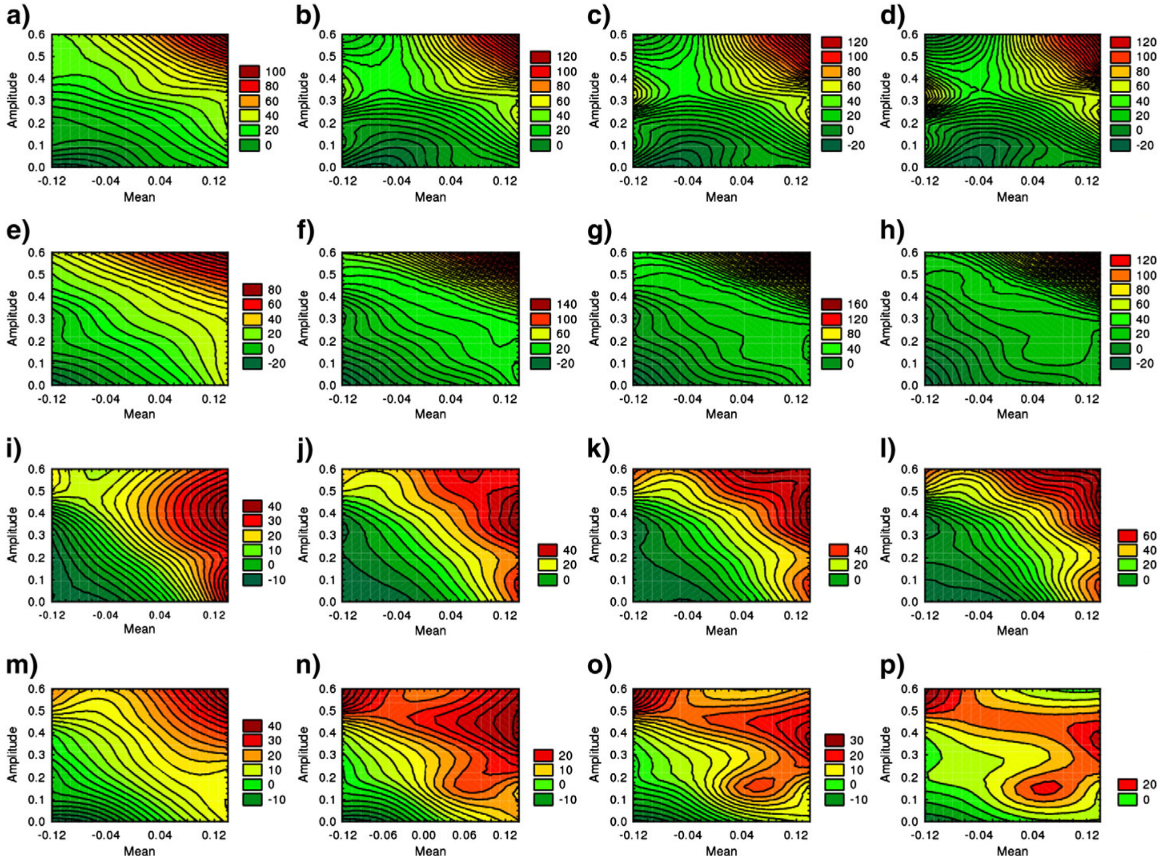

Fig. 4: 3D contour plot showing percentage changes in the 5, 25, 50 and 100-year return period peak flows for each catchment; Blackwater (a–d for 5, 25 50 and 100 year return period events respectively), Boyne (e–h), Moy (i–l), Suck (m–p) under the range of scenarios constructed from the change factors synthesised by amplitude (0–0.5) and mean (−0.125–0.125) of the cosine curve.

5. Conclusions

Future projections of climatic change are subjected to large uncertainties. Consequently, impact assessments lead to a wide range of possible outcomes that are practically very difficult to handle. In moving from top down predict and provide approaches to climate change adaptation this study aims to build on previous work internationally to establish best practice for stress testing important adaptation decisions. For each of the selected catchments the sensitivity analysis is used to stress test design and safety margin allowances made for climate change in critical infrastructure to uncertainties in hydrological response. Results show that there is a considerable residual risk associated with allowances of +20% when uncertainties are accounted for and that the risk of exceedence of design allowances is greatest for more extreme, low frequency events with considerable implication for critical infrastructure, e.g., culverts, bridges, flood defences whose designs are normally associated with such return period events. In terms of hydrological models, the differences and extent of uncertainty emphasise the importance of incorporating model structure and parameter uncertainty in estimating climate change impacts on flood quantiles, particularly for larger extremes with lower frequencies of occurrence. Each of the models used here displays the varying effect of parameter uncertainty on different flood quantiles. The highest uncertainty is associated with low frequency flood quantiles and with models that use nonlinear surface storage structures. Though the flood frequency analysis analysed in this study recognised the fact that frequency distributions are not stationary, the uncertainty associated with the fitting of the annual maximum series to the generalised extreme value distribution is not explored. Furthermore, it should also be noted that for the frequency analysis, a 30 year period is used to generate 100 year return period event. Therefore, results based on such extrapolation should be taken with caution.

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