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The spectrum of uncertainty in flood damage assessment

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ABSTRACT

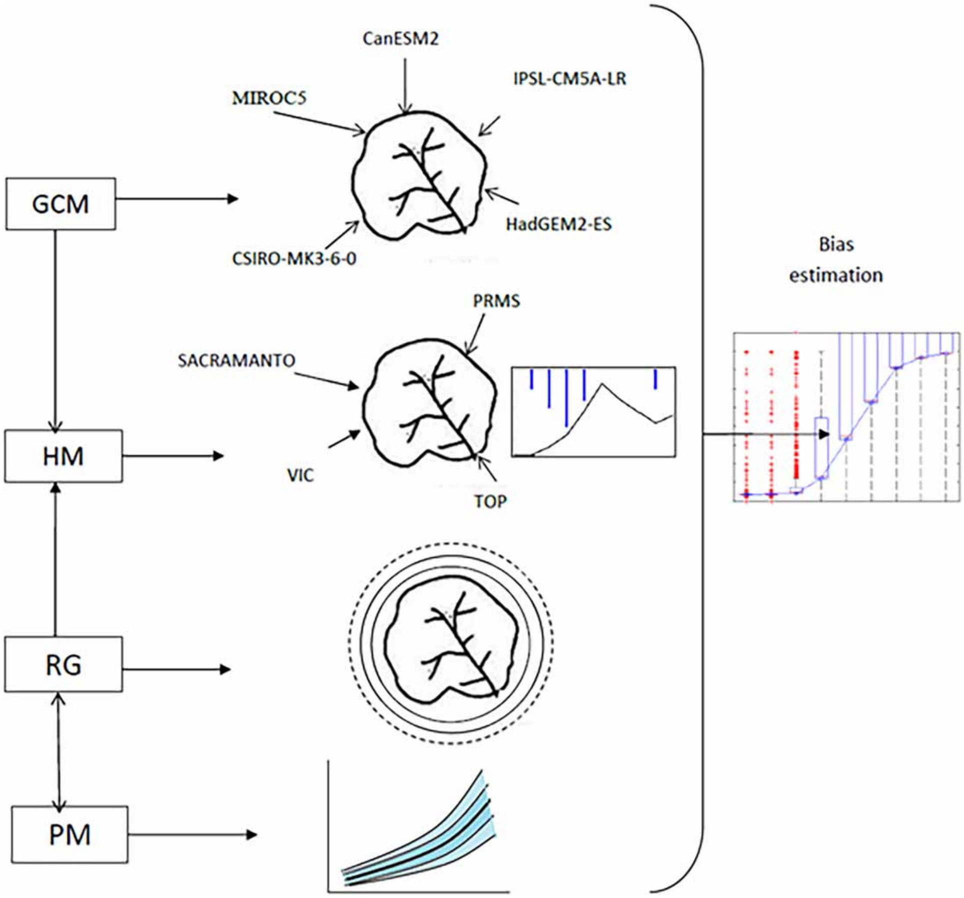
The future of the world is becoming more uncertain owing to climate change. The unfolding impacts of climate change are affecting human societies and natural ecosystems. Projections of climate change impacts are associated with a cascade of uncertainties including greenhouse gas emissions scenarios, climate models, and associated processes. Climate models are essential for predicting flow and flood peaks, necessitating proper means of quantification and re-use to help refine the predictions made. This study presents an innovative new framework to quantify flood damage assessment as the climate changes. To integrate uncertainty in modelling catchment behaviour, the Quantile Flow Deviation (QFD) metric was used to attribute different sources of uncertainty, including those from variations in climate from point measurements and from extrapolation to flood peaks from the limited observed flows that are available. The square root of error variance (SREV) calculated from global climate model (GCM) precipitation outputs was used to quantify climate change uncertainty, thereby enabling the estimation of the uncertainty in modelled streamflow to allow the extent of change in flood damage to be assessed. Using data from the Leaf River catchment in the USA, this study presents the increase in flood damage uncertainty resulting from explicit consideration of uncertainty as well as the change in the climate as a function of global temperature rise.

Key words: climate change, flood damages, global climate model, uncertainty

HIGHLIGHTS

- Uncertainty in flood magnitudes resulting from climate change for the current climate is quantified.
- A new framework for quantifying flood damage assessment considering climate change impact is developed.
- Flood damage uncertainty with temperature increases to date of 1 and of 2 °C before the end of this century is investigated.

GRAPHICAL ABSTRACT



1. INTRODUCTION

COP 26 demonstrated how the future of the world is becoming more uncertain owing to climate change. The unfolding impacts of climate change on hydrology and water resources, especially in the form of extreme hydrologic events (e.g. floods), highlight the need to determine the resilience of current approaches to hydrological modelling and associated water, and environmental and socio-economic planning and management responses (Winsemius *et al.* 2016; Ward *et al.* 2017). We have entered the era of the anthropocene, in which the cumulative impact of human activity has significantly affected the earth's ecosystems, environment, and weather patterns. It is now evident that the nature of flood extremes is changing as a result of global temperature rise (Ishak *et al.* 2013; Roxy *et al.* 2017). While moderate floods are noted to be on the decline (Wasko & Sharma 2017), rare to extreme flood events that result in significant damage and loss of life are increasing due to the intensification of storms from rising temperatures. Global mean atmospheric temperatures have risen 1 °C since pre-industrial times, and it is now generally acknowledged in the public sphere that such an increase in extreme weather is due to human-induced climate change.

The recognition of climate change and its impacts has triggered discussions over potential compensation for those people and communities who have suffered losses and damage due to associated weather extremes (Boyd *et al.* 2017). Determining a valid loss and a damage framework for climate change-induced impacts is, and will likely continue to be, a highly complex and contentious issue, particularly given the difficulties in definitively separating climate change-induced impacts from natural climatic variation. Climate change impacts include (Huq *et al.* 2013; James *et al.* 2014) slow onset events (such as salinity in coastal areas due to sea-level rise), rapid onset events (such as cyclones and floods), and associated material and economic losses, as well as non-economic losses (such as psychological impacts) (Mechler 2017). Such damage, in turn, causes forced displacement and migration, raising the increasingly urgent need to make financial provisions to support affected and displaced people around the world (Huq *et al.* 2013). The potential use of climate index-based insurance as a tool to provide compensation to those suffering losses and damage is attracting considerable international interest; however, many complex questions still need to be addressed. These include the risk that insurance could discourage government and private investment in much-needed adaptation measures to protect communities against damage and losses (Surminski *et al.* 2016) rather than to compensate them after the fact.

Against this background, more robust means of forecasting climate change impacts and ensuing damages are urgently needed. The assessment of climate change impacts on water resources is highly challenging due to the inherent uncertainties in climate projections using global climate models (GCMs) (Wu *et al.* 2015; Qi *et al.* 2016). Currently, the consensus among the scientific community is that while the overall precipitation across an entire year is not likely to change much, the pattern of rainfall will change significantly with more significant precipitation in the monsoon season and less rain in the dry season (Westra *et al.* 2014; Wasko & Sharma 2015; Pfahl *et al.* 2017; Wang *et al.* 2017). Paradoxically, despite a little change in annual rainfall totals, this will likely lead to more extreme flooding in the wet season and more droughts (and reductions in moderate floods) in the dry season (Wasko & Sharma 2017). This scenario is already apparent, as rainfall patterns become more erratic and unpredictable around the world.

The three primary sources of uncertainty in assessing climate change impacts on water resources can be seen in GCMs, i.e., uncertainties due to the selected model structure, emission scenarios, and natural variability. The Intergovernmental Panel on Climate Change (IPCC) reviews and integrates GCMs in its Climate Model Intercomparison Project (CMIP). The most recent fifth phase of the project, CMIP5 (released in 2013), incorporates a number of advances relative to its predecessor, CMIP3 (2010). These include the improved spatial resolution of models, an expanded list of variables, and a new concept of specifying future radiative forcing, among others. However, a key question is how to integrate such uncertainty in the projected climate at the global level into the flood damage assessment process at the local level where floods occur. We address this question by quantifying uncertainty in precipitation from five CMIP5 models. Uncertainty is quantified using the square root of error variance (SREV), which specifies uncertainty as a function of time and space, and decomposes the total uncertainty into its three constituents. For precipitation, the GCM uncertainty is found to be greater in particular regions of the world and those that receive heavy rainfall, as well as mountainous and coastal areas (Woldemeskel *et al.* 2016).

Uncertainty in flood damage estimates can lead to significant over- or under-investment (Wagenaar *et al.* 2016) and can result in either needlessly expensive over-preparedness or dangerously inadequate flood mitigation and protection measures. As the uncertainties and potential errors in damage estimates affect decision-making, quantifying this uncertainty can provide a useful insight into potential errors and help improve the decision-making process. USACE (1992) and Peterman & Anderson (1999) both showed that taking ranges of uncertainty into account can lead to different decisions, compared to those based on single-value estimates. Flood damage assessment is an essential aspect of flood risk management (Merz *et al.* 2010). It is used to support policy analysis and flood insurance. In developed countries such as the Netherlands, flood damage estimates are used, for example, to determine economic optimal protection standards for flood defences, to prioritize investments, or to compare the impact of different flood risk management strategies (Kind 2014).

Floods cause billions of dollars of damage every year, and flood risks are expected to increase across the globe due to increasing socio-economic development (leading to the growth of populations within flood risk zones and the impacts of construction/building on flood risks), subsidence, and the impacts of climate change (Jongman *et al.* 2014). There has been speculation that the frequency and intensity of floods will increase with warmer temperatures. However, as any future projection is uncertain does this new uncertainty alter flood damage estimates? There have been recent studies showing consideration of observational uncertainty in flood damage estimation (Merz *et al.* 2010; Jongman *et al.* 2014; Sieg *et al.* 2017). Furthermore, there is evidence that non-consideration of uncertainty in, say, rainfall, can result in a bias in the estimation of a derived variable such as streamflow (Chowdhury & Sharma 2007; Eghdamirad *et al.* 2017), where a nonlinear transformation exists. This leads us to speculate that a similar bias is present in the case of flood damage considering uncertainty in flood magnitude. Hence, the aims of the study are to (i) Step 1 – identify all sources of uncertainty that impact flood damage assessment, (ii) Step 2 – quantify uncertainty in flood magnitudes resulting from model simulations for the current climate, and (iii) repeat Step 2 for the 1 °C increase in the global mean atmospheric temperature that has already occurred and for the expected 2 °C increase before the end of the century.

This paper is organized as follows. The next section identifies the main sources of uncertainty in flood damage assessment under a changing climate. Section 3 introduces the data used for the climate change uncertainty estimation presented here along with details about the study area. Following this, the methodology used to estimate the climate change uncertainty on flood damage is explained. Section 5 presents the outcomes of the model simulation and an evaluation of the proposed scheme focusing on both model and climate change uncertainty. Section 6 discusses the results obtained with reference to the probabilistic model (PM), the hydrological model (HM), and the GCM. Finally, Section 7 summarizes the essential findings and outlines the scope of future work.

Design flood estimation is essential in evaluating the risk associated with the socio-economic impacts of flood events in any location. However, the prediction or modelling of peak flows is subject to the uncertainty related to the selection of an HM structure and related model parameters. This study uses an uncertainty metric, the QFD, to evaluate the relative uncertainty in flood simulations due to different model attributes (such as the model structure, parameters, likelihood, or driving data). Using the metric, we identified the potential uncertainty spectrum in peak flows and variability in model simulations. As flood damages are ascertained as a function of flood peaks through a nonlinear damage function, the resulting uncertainty allows for quantifying the bias in damage estimates that have not been taken into account.

This study aimed to investigate the impact of such modelling uncertainty on estimates of flood damage, with the expectation that the magnitude of the flood damage estimated exhibits bias where uncertainty is high.

A simplified illustration of the uncertainty in flood modelling as shown in Figure 1(a) is considered. The figure illustrates the uncertainty resulting from alternate assumed conceptual modelling structures, input rainfall observations, and parameter calibration techniques adopted. This uncertainty alone enables the modelled flow peak to vary by a factor of two, resulting in considerable variation across the modelled flow duration curves (or CDF). Given the nonlinear relation of the modelled flood and the corresponding demand that is estimated, this uncertainty will force a difference between the expected value of the derived damage and the damage that will result from the expected flood estimate.

2. IDENTIFYING SOURCES OF FLOOD DAMAGE ASSESSMENT UNDER CLIMATE CHANGE

Do floods feel the effect of climate change? There are signs that climate change has enhanced the impacts of extreme events on human societies and ecosystems (IPCC 2013). However, difficulties remain in quantifying these impacts at the catchment scale, given the confounding uncertainties associated with HMs and climate projections that are a necessary part of impact and mitigation assessment (Foley 2010; Refsgaard *et al.* 2013; James *et al.* 2014). In terms of climate projection uncertainties, recent studies have shown that model uncertainty dominates for lead times exceeding a couple of decades, while uncertainties in greenhouse gas emission levels will take over towards the end of the 21st century (e.g., Hawkins & Sutton 2011; Kjellström *et al.* 2011; Sieg *et al.* 2017). As these projection uncertainties must be propagated through HMs with their own sources of error (such as input data, parameter values and model structures, and process descriptions (Refsgaard *et al.* 2007; Sonnenborg *et al.* 2015)), quantifying uncertainty due to climate change impacts on water resources becomes increasingly complex (Sonnenborg *et al.* 2015). The objective of the present study is to assess the effects of climate model uncertainty and HM uncertainty for projections of future flood damages – by integrating both sources of uncertainty – with respect to stream flow. Consequently, it is useful to determine which of the different sources of uncertainty will be dominating (Peterman & Anderson 1999). Several studies have investigated the uncertainty propagation from climate projections through hydrological modelling (Bastola *et al.* 2011; Poulin *et al.* 2011; Dobler *et al.* 2012; Sonnenborg *et al.* 2015), concluding that in some cases climate model uncertainty dominates over HM uncertainty. However, accurate assessments of climate change impacts on weather and other systems remain challenging. The foremost obstacles perhaps are the unknown uncertainties in climate projections using GCMs (Sonnenborg *et al.* 2015; Woldemeskel *et al.* 2016).

In this study, to address this issue we use the SREV technique (Woldemeskel *et al.* 2016) to quantify uncertainties in CMIP5 projections and the QFD metric (Shoaib *et al.* 2016) to quantify uncertainties associated with the hydrologic component of flood estimation. Combined, these two metrics allow a comprehensive evaluation of the potential sources of uncertainty, as described in the following.

Uncertainty comes in many stages evaluating flood damages (Figure 1(b)). Each of these is discussed below.

(1) *Probabilistic model (PM)*: PMs incorporate random variables and probability distributions into the model of an event. Flood frequency analysis is usually performed with different PMs like the log-Pearson type 3 (LP3), Gumbel distribution, and generalized extreme value distribution. LP3 has been one of the most frequently used distributions for hydrologic frequency analyses since the U.S. Water Resources Council of the United States recommended its use as the base method. Generally, the functional representation of a PM would probably have too many parameters to be of much practical use (Martins & Stedinger 2000). Hence, the practical challenge is how to select a reasonable and simple probability distribution to describe

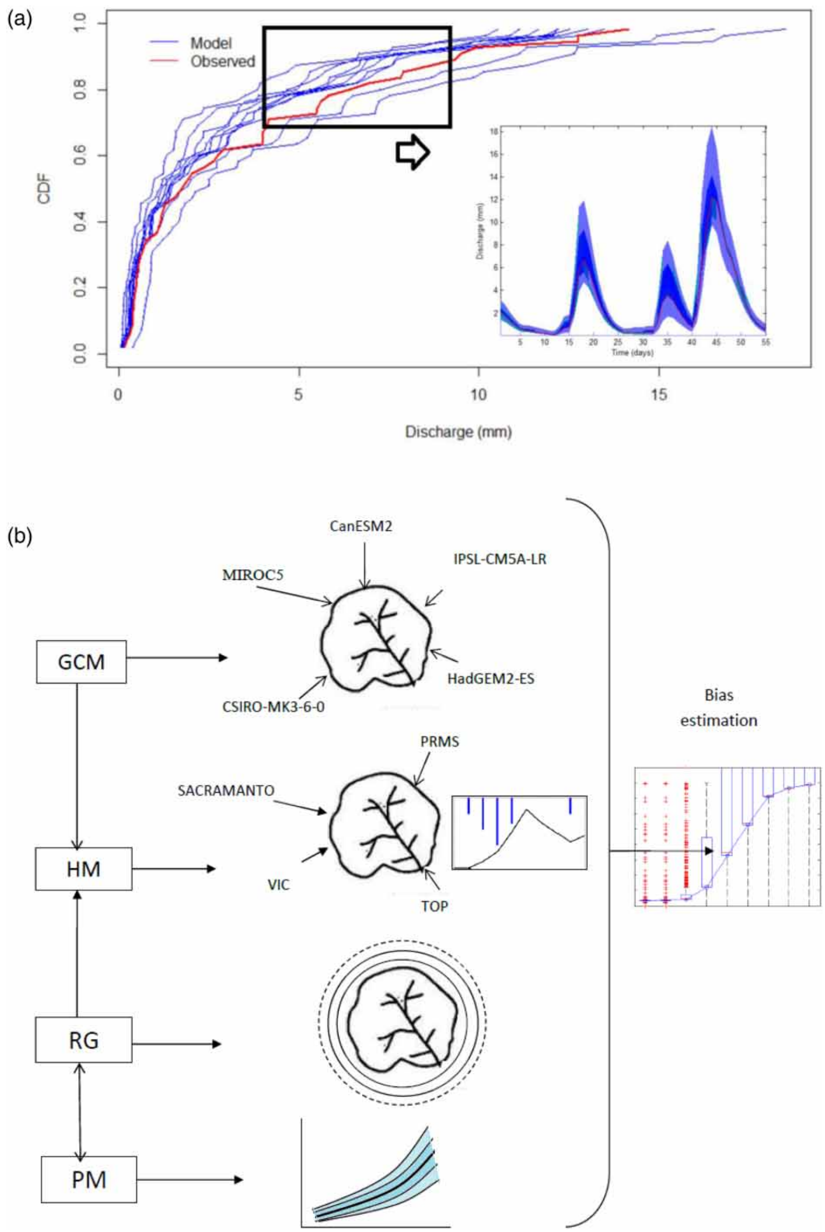


Figure 1 | (a) Hydrological extremes and model simulations show variability in higher quantiles to quantify uncertainty. (b) Conceptual illustration of climate change uncertainty in flood damage assessment.

the phenomenon of interest, so that the practitioner can make reliable quantile estimates (Martins & Stedinger 2000; Daneshkhah *et al.* 2016). LP3 was used in this study, as it is a widely used distribution in flood frequency analysis.

(2) *Rainfall generator (RG)*: Many problems in hydrology and water resources management require extensive records of rainfall for specific locations. Temporal and/or spatial coverage of rainfall data is often limited; therefore, stochastic models are required to generate long-term synthetic rainfall records. In this study, we used a programming tool developed by Mehrotra *et al.* (2015) to generate rainfall to represent the implications of using limited rain gauges for our study catchment.
(3) *Hydrological model (HM):* An HM helps in understanding, predicting, and managing water resources by attributing a real-world system. Both the streamflow and quality of water are usually studied using HMs. Four different HM structures were used (TOPMODEL, ARNOXVIC, PRMS, and SACRAMENTO) to represent model structural uncertainty.

(4) *Global climate model (GCMs) or general circulation models:* These are the most advanced tools currently available for simulating the response of the global climate system to increase greenhouse gas concentrations. GCMs represent physical processes in the atmosphere, ocean, cryosphere, and land surface. Five GCMs (CanESM2, CSIRO-Mk3.6.0, HadGEM2-ES, IPSL-CM5A-LR, and MIROC5) are used in this study. Details of the selected GCMs are given in Table 1.

3. STUDY AREA AND DATA

Forty-five projections of precipitation from CMIP5 datasets were used in this study from five GCMs (CanESM2, CSIRO-Mk3.6.0, HadGEM2-ES, IPSL-CM5A-LR, and MIROC5), three Representative Concentration Pathways (RCPs; van Vuuren *et al.* 2011) (RCP2.6, RCP4.5, and RCP8.5), and three ensembles (r1i1p1, r2i1p1, and r3i1p1). Precipitation as precipitation flux at the surface includes both liquid and solid phases from all types of clouds (both large-scale and convective). The unit of CMIP5 dataset is $kg{\cdot}m^{-2}{\cdot}s^{-1}$, which, in this study, is changed to $mm{\cdot}day^{-1}$. All data were re-gridded into the same grid size of NCEP-NCAR as 2.5°×2.5°. One grid point was chosen at 32.5 N, 90 W to cover the Leaf River basin (LRB) in the Mississippi, USA (Figure 2). This grid point covers an area between latitude 31.25 N to 33.75 N and longitude 88.75 W to 91.25 W.

Yearly projections of CanESM2, CSIRO-Mk3.6.0, IPSL-CM5A-LR, and MIROC5 are based on 365 days a year. However, the yearly projection of HadGEM2-ES is based on 360 days a year (each month 30 days). The time period used is from 2006 to 2100.

Table 1 | List of models in CMIP5 as well as their atmospheric horizontal resolutions

Model	Institution	Atmospheric horizontal resolution (°)
CanESM2	Canadian Centre for Climate Modelling and Analysis, Canada	2.8×2.8
IPSL-CM5A-LR	Institute Pierre-Simon Laplace, France	3.75×1.8
CSIRO-MK3-6-0	Commonwealth Scientific and Industrial Research Organization in collaboration with the Queensland Climate Change Centre of Excellence, Australia	1.8×1.8
HadGEM2-ES	National Institute of Meteorological Research/Korea Meteorological Administration	1.8×1.25
MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	1.4×1.4

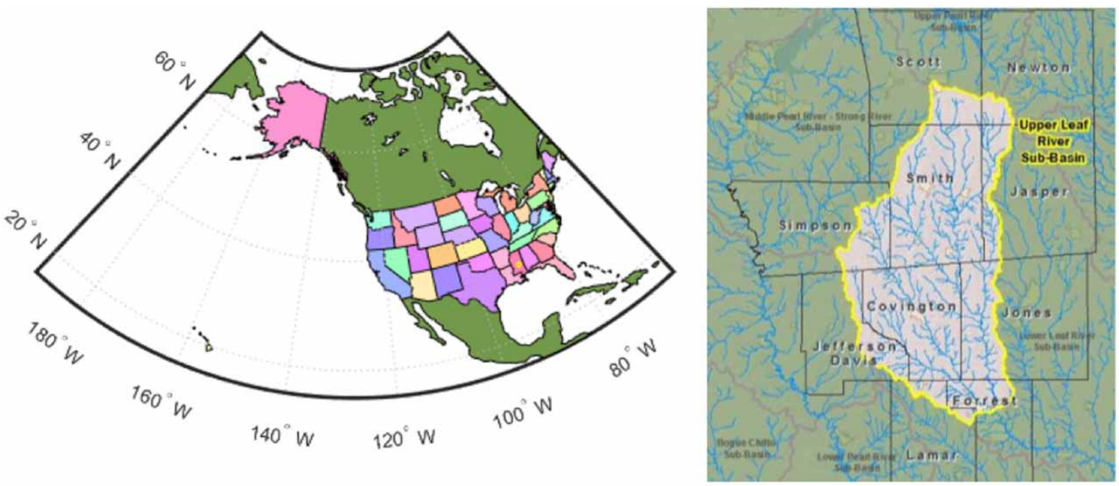


Figure 2 | Leaf River catchment, Mississippi, USA (*source*: Mississippi Department of Environmental Quality).

We used data from five models from CMIP5 projections. The models were selected based on the availability of data of at least three realizations for all the RCPs (in case of CMIP5) and recommendations from past studies (Johnson *et al.* 2011). The names of these five models and relevant details are presented in Table 1. The smallest spatial resolution of the models is 1.4°× 1.4° latitude/longitude for CMIP5. In addition, RCPs are implemented in CMIP5, a different concept to the scenarios used in CMIP3. For an objective comparison of the uncertainties in CMIP5, we used three future RCPs (RCP2.6, RCP4.5, and RCP8.5) that represent low, medium, and high radiative forcing, respectively.

In this study, we have used historical damage data for the Leaf River catchment, Mississippi, USA (http://www.flooddamagedata.org/). The LRB is located in the southeastern Mississippi of the East Gulf Coastal Plain. The contributing area is ~4,600 km^2 and flows through the city of Hattiesburg, Mississippi (the contributing area is 4,527 km^2 at the city). The headwaters of the LRB are initiated in Scott County, and the stream generally flows through southward before entering the Hattiesburg city limits. The Bouie River is a key tributary to the Leaf River and connects the main stem as it flows via Hattiesburg. The terrain is generally flat, and most of the watershed is rural except the city of Hattiesburg. The LRB is subject to flooding due to heavy rainfall events/days during the spring and summer season, while the hurricane season in fall also brings substantial volumes of rain from the Gulf of Mexico. Such catastrophic rainfall events in the LRB result in massive flooding and flood-related damage in the city of Hattiesburg. The LRB is of specific hydroclimatic interest as this region has been experiencing more catastrophic and extreme climatic events over last 2 years. The future climate change scenario by various models expects more and more catastrophic and extreme climatic events in the 21st century in this region; the development of our methodology in the LRB is a timely contribution. In addition, the LRB is widely used in hydrological analysis (Ajami *et al.* 2007; Gong *et al.* 2013) and selected here to demonstrate the methodology given the availability of flood damage data to derive a flood damage curve.

4. METHODOLOGY AND EXPERIMENTAL DESIGN

Climate change affects all the mechanisms that drive uncertainty in decision-making, especially in the face of extreme weather events (Winsemius *et al.* 2016; Wang *et al.* 2017). A flood event with climate change uncertainty is the result of different dynamic mechanisms, each with an associated degree of occurrence (Sikorska *et al.* 2015). Modelling flood and related damage – while taking into account climate change – is a highly complex problem (Rosner *et al.* 2014; Schröter *et al.* 2014). Flood damage estimates currently rely on a modelled value of streamflow (Q) as the basis of quantification. This modelled value of streamflow exhibits uncertainty (Figure 1). However, in subsequent damage calculations, climate change impacts are currently ignored (Sarhadi *et al.* 2016). The objective of this study is then to incorporate all possible sources of uncertainty into the estimation of flood damage. This section outlines our proposed methodological design in attributing climate change uncertainty in this study.

4.1. Assessing climate change uncertainty

(i) *Square root of error variance*

First, the uncertainty of climate projections of daily precipitation was derived using the SREV method introduced by Woldemeskel *et al.* (2012). Uncertainty is defined as the disagreement of climate projections of a climate variable. The SREV, developed by Woldemeskel *et al.* (2012), quantifies uncertainty in GCM outputs for the three main sources of uncertainty, i.e., model structure, emission scenario, and natural variability, as well as their total uncertainty. We use the terms model, scenario, and realization to refer to these three sources of uncertainty in the remainder of the paper. We provide a brief description of the SREV method in Appendix A, and the readers are referred to Woldemeskel *et al.* (2012) for a more detailed account.

(ii) *Rainfall generator*

In this study, we then used an RG to simulate daily precipitation. As temporal and/or spatial coverage of rainfall data is often limited, stochastic models may be required to generate long-term synthetic rainfall records. We have used a multi-site rainfall simulator (MRS) to stochastically generate daily rainfall for our selected catchment. Observational records are often short and only represent a single realization of the possible future patterns of rainfall, so stochastic models are often used to augment the observational records. The synthetic rainfall sequences should accurately reflect the statistical characteristics of the historical rainfall records. An MRS is a multi-site Markov model designed to account for low-order dependence, by making use of (a) aggregated time-scale predictor variables to preserve the longer time-scale dependence (i.e., low-frequency variability) and (b) spatially correlated random numbers to maintain the desired spatial correlations in the generated rainfall sequences (Mehrotra *et al.* 2015). In this study for the Leaf River catchment, Mississippi, USA, 100 simulation replicas of rainfall were generated using the observed rainfall data and the time period.

4.2. Assessing flood uncertainty

(iii) *QFD estimation*

The prediction or modelling of peak flows for use in flood estimation is subject to uncertainty associated with the selection of an HM structure and related model parameters. In this study, we used a new uncertainty metric, the QFD (Li *et al.* 2016b), to evaluate the relative uncertainty in flood simulations due to different model attributes (such as the model structure, parameter sets, and likelihoods). Through the metric, we identified the potential spectrum of uncertainty in peak flow and variability in our model simulations that can then be propagated to the uncertainty in flood values. By using a quantile-based metric, the change in uncertainty across individual percentiles could be assessed, thereby the complete uncertainty quantified as a function of flood recurrence interval. Mathematical expressions for the estimation of QFD are shown in Appendix B, and readers are referred to Shoaib *et al.* (2016) for a more detailed discussion.

(iv) *PM – flood frequency*

Flood frequency analysis is a direct means of estimating a probable flood based on the available flood-flow data for the catchment (Rahman *et al.* 2002; Sarhadi *et al.* 2016). The results of frequency analyses and their confidence limits depend on the length of time for which data are available. These flood-flow data series are characterized using a range of extreme value probability distributions (Merz & Thieken 2005; Chen *et al.* 2015). In this study, we adopted the LP3 distribution to illustrate the proposed method.

The LP3 distribution is a member of the family of Pearson Type 3 distributions, which is also referred to as the Gamma distribution. The LP3 distribution uses three parameters, location (μ), scale (σ), and shape (γ) (Griffis & Stedinger 2007). A problem can arise with the LP3 as it tends to generate low upper bounds of the precipitation magnitudes, which is undesirable (Lima *et al.* 2016). Along with an expected flood quantile for a given ARI, the uncertainty associated with the derived flood quantile can also be ascertained (McInerney *et al.* 2017).

(v) *Integrating QFD into flood quantile estimation*

To estimate the possible extent of flood damage, the uncertainty due to model structure, likelihood, and structural identifiability is included via the QFD metric. As flood damage estimates are ascertained for extreme flood peaks, the derived QFD needs to be expressed as a function of the flood quantiles of interest. To achieve this, we extrapolate the QFD, with respect to the ARI associated with the flood quantile of interest. This extrapolated QFD is then incorporated into the uncertainty spectrum to characterize the full uncertainty associated with each flood quantile.

4.3. Flood damage assessment

(vi) *Flood damage function selection*

Flood damage is specified as a function of the estimated flood quantile. Commonly used flood damage functions applied in flood damage estimation are S-shaped curves, such as the Gompertz function, logistic function, and hyperbolic tangent function (Li *et al.* 2016a). This study uses the Gompertz function (1), as illustrated below.

$$D = Ae^{-e^{-k(Y-Y_c)}} \tag{1}$$

In Equation (1), D is the derived flood damage, A is an upper limit of the damage possible, Y is the return period of the flood, Y_c is a critical return period, and K is an integrated loss coefficient. The function assumes a minimum value of zero, a maximum value of A, with an abscissa for the critical point as Y_c, and a maximum slope of Ak/e (Li *et al.* 2016a, 2016b). Li *et al.* found that the general type of damage loss mimics an S-shaped curve. Yu *et al.* (2013) developed direct economic loss curves for the minimum, maximum, and most likely floods based on a Monte Carlo method. These loss curves are all S-shaped, depicting the accepted form of the assumed relationship between flood damage and the severity of events (Chen *et al.* 2015).

The maximum value of flood damage A, critical return period Y_c, and integrated loss coefficient K are the three main parameters of the relationship, which can be determined through experience, experimental simulations, or curve fitting.

Historical or simulated data can be used to estimate the parameters. Mathematical and statistical analysis tools can be used to determine the parameters' values and draw diagrams of the R–D function curves. In this study, we used historical damage data from the USA (http://www.flooddamagedata.org/) and the MATLAB Curve Fitting Toolbox (Alcalá-Quintana & García-Pérez 2013; Arciniega-Esparza *et al.* 2017) to estimate the maximum value of flood damage A, critical return period Y_c, and integrated loss coefficient K.

(vii) *Uncertainty in flood damage estimation for the case study catchment*

To estimate flood damage, in this step, we needed three important relationships: (a) the flood quantile with respect to the return period/ARI, (b) the QFD added flood quantile with respect to the return period/ARI, and (c) damage with respect to the return period. To establish the relationship between flood damage and the return period/ARI, flood damage data were taken from the National Weather Service (NWS), which has maintained a reasonably consistent long-term record of flood damage throughout the USA (http://www.flooddamagedata.org/). Flood damage data for Leaf River, Collins, Mississippi, USA, are available from 1933 to 1975. These data are fitted with the selected damage function with a defined damage of a particular return period. The resulting values of the damage function coefficients from this assessment are A=86,531.27, k=−0.0221, and Y_c=56.15, with the resulting damage D being expressed in US dollars indexed for inflation to the year 2005.

The above damage relationship can be expressed as a function of an associated flood quantile by expressing the quantile as a function of its ARI. This way, a damage-flood relationship is specified.

(viii) *Flood damage uncertainty estimation*

Expected damage can be estimated for each annual recurrence interval (ARI) or return period using the damage function. From the estimated uncertainty, one can ascertain the bias in the damage through a Monte Carlo simulation as detailed below:

a. Quantify the uncertainty of derived flood quantiles as per Steps 1–6:

$$Q_y = Q_{yf} + Q_{yqfd}$$

where $Q_{yf} = LN(\log(Q_i), S/\sqrt{N})$, $S^2 = \mathrm{var}(\log(Q_i))$, Q_i represents the annual maximum flow for year i, and $Q_{yqfd} = N(0, QFD_y)$, where QFD_y is the derived QFD for an ARI of y.

b. Perform a Monte Carlo simulation to sample flood damage D for sampled flood quantiles Q_y for ARI of y.

c. Calculate the mean damage for each annual recurrence interval and compare this with the expected damage estimated from the damage function used.

4.4. Climate change assessments using 1 or 2 °C rise in temperature

The globally averaged 20th and early 21st century rate of increase in annual maximum daily rainfall intensity was recently estimated to be between 5.9 and 7.7% per 1 °C increase in globally averaged near-surface atmospheric temperature (Westra *et al.* 2013, 2014; Wasko & Sharma 2015; Wang *et al.* 2017). We assumed an increase in the daily rainfall intensity of 7.5% per 1 °C rise, considered the catchment location, and analysed the resulting precipitation variability to estimate possible streamflow. Increased precipitation increases the climate change uncertainties that are estimated through SREV (Woldemeskel *et al.* 2016). This approach was preferred over the option of using rainfall simulations from GCMs, given the relative stability temperature simulations exhibit when compared to rainfall (Johnson & Sharma 2009).

5. RESULTS AND ANALYSIS

5.1. Climate change uncertainty

Forty-five projections of precipitation from CMIP5 datasets were used in this study from five GCMs (CanESM2, CSIRO-Mk3.6.0, HadGEM2-ES, IPSL-CM5A-LR, and MIROC5). Each model was attributed with three RCPs (van Vuuren *et al.* 2011) (RCP2.6, RCP4.5, RCP8.5), and three ensembles (r1i1p1, r2i1p1, and r3i1p1). Nine different scenarios of precipitation for each GCM are shown for the LRB in Mississippi, USA (Figure 3).

The highest variability was observed in HadGEM2-ES with nearly 100 mm. CanESM2 and MIROC5 follow a similar pattern for the LRB, with nearly 80 mm in peak rainfall. CSIRO-Mk3.6.0 and IPSL-CM5A-LR showed nearly identical patterns

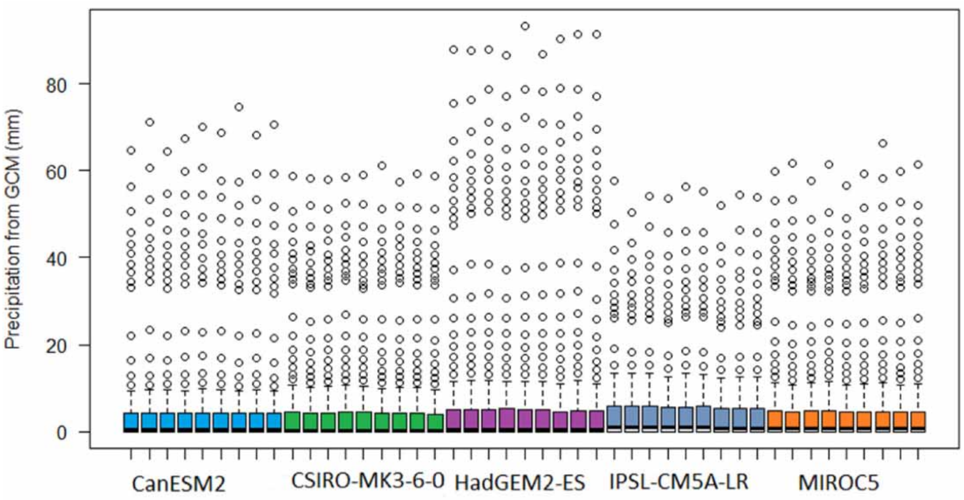


Figure 3 | Variabilities in GCM precipitation projections (2018–2100) in quantiles of different GCMs.

of variability, with peaks in a range of 60–64 mm (Figure 3). Variability in the five GCMs reflects the uncertainty in precipitation projections.

Following the steps for calculating the SREV in Section 3.1., climate change uncertainty was estimated by incorporating three different sources of uncertainty: model structure, scenario, and ensembles (Figure 4).

Model structure uncertainty was very high in all percentiles compared to different scenarios and ensembles (Figure 4). Variability in scenarios and ensembles was identical with increasing percentiles. Analysis revealed that more attention must be paid to the selection of model structure to constrain uncertainty in future projections. Uncertainty due to the model structure varied from 2 mm (91th percentile) to 14 mm (99.9th percentile). On the other hand, uncertainty due to different scenarios attributed to different climate models varied from 0.32 mm (91th percentile) to 2.3 mm (99.9th percentile). Ensembles of different model structure uncertainty varied from 0.22 mm (91th percentile) to 2.0 mm (99.9th percentile) (Figure 4).

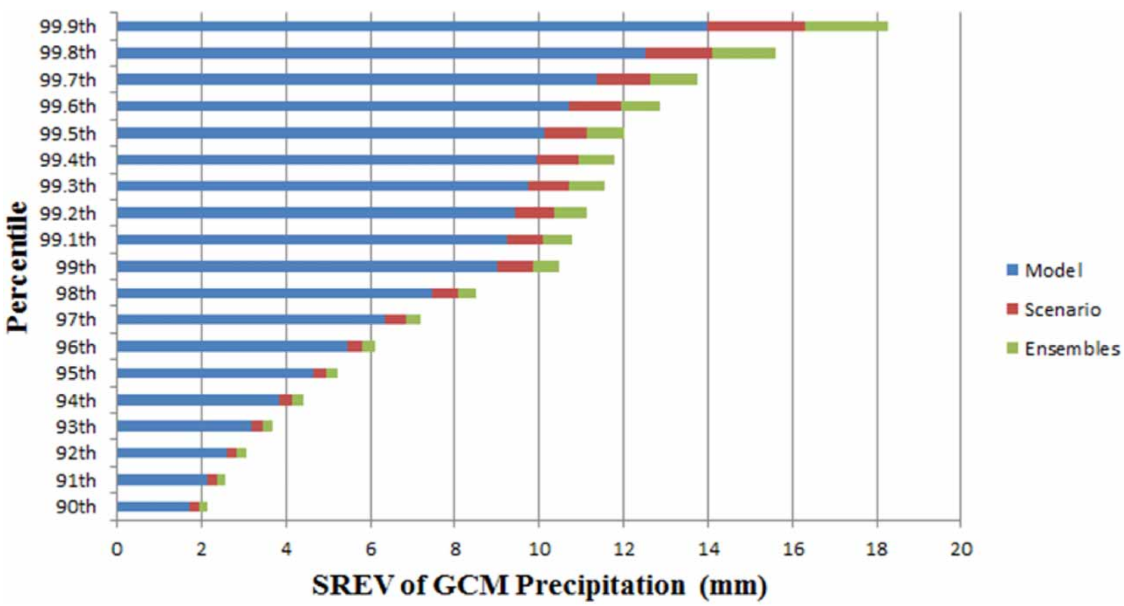


Figure 4 | Different components of the SREV from five GCMs with three scenarios and three ensembles.

5.2. Flood uncertainty estimation

As discussed earlier, to quantify flood uncertainty, a four step procedure is presented. First, uncertainty due to the model structure, objective function, and structural identifiability was estimated as a measure of the uncertainty metric, or QFD (Shoaib *et al.* 2016). To derive the QFD for the LRB, we use the same experimental design as in Shoaib *et al.* (2016), consisting of four HM structures, three objective functions, and five structural identifiabilities. As such, the QFD represents the total hydrologic simulation uncertainty associated with the streamflow data. Second, a programming tool, RG (Mehrotra *et al.* 2015), was used to generate 100 simulation replicas of rainfall using the observed rainfall data and the time period of the Leaf River catchment, Mississippi, USA. To attribute the uncertainty of the simulated rainfall, the SREV of the 100 simulations of rainfall time series was calculated. Third, using the results of Steps 1 and 2, a relationship between precipitation variability and the QFD metric was developed (Figure 5). This relationship was then used to relate GCM precipitation uncertainty to streamflow uncertainty (Figure 5). Using this relationship, for each quantile of GCM precipitation uncertainty, streamflow uncertainty could be estimated. For instance, for 22 mm of GCM precipitation uncertainty, the corresponding streamflow uncertainty is nearly 34 mm (Figure 5). Similarly, for other GCM precipitation uncertainty quantiles, streamflow uncertainty can be attributed.

Fourth, after evaluating streamflow uncertainty due to climate model uncertainty (Figure 5), this value was added with the flood quantile, considering HM and PM uncertainties (Figure 6). The values of the annual maximum flood data from the Leaf River catchment for 55 successive years (1948–2002) constitute the hydrologic data series used for flood frequency analysis. Using the LP3 model, flood quantiles and associated uncertainty values were extrapolated to an ARI of 1,000 years. The resulting expected flood quantile was nearly double (113.2 mm) the observed maximum flood flow, extending to nearly three times this magnitude (191.7 mm) at the 95% predicted uncertainty limit (Figure 6). To estimate the total potential uncertainty, the HM uncertainty or the QFD_t was added to this, which made the predicted magnitude of a 1 in 1,000 years flood in the 95th percentile uncertainty limit nearly four times (237.1 mm) the observed maximum flood flow. After adding the climate model uncertainty that predicted the 1 in 1,000 years flood magnitude, the 95th percentile uncertainty limit is nearly five times (272.88 mm) the observed maximum flood flow.

5.3. Damaging uncertainty assessment

Considering all potential sources of uncertainty, estimating flood damage is a huge challenge. Integrating hydrological data and climate model data to estimate damages involves considerable uncertainty. In this study, damage data for the Leaf River catchment were analyzed and the catchment damage function was fitted with a defined annual recurrence interval. Following this, the probable damage was estimated using. Four different conditions were designed to observe the variability in flood

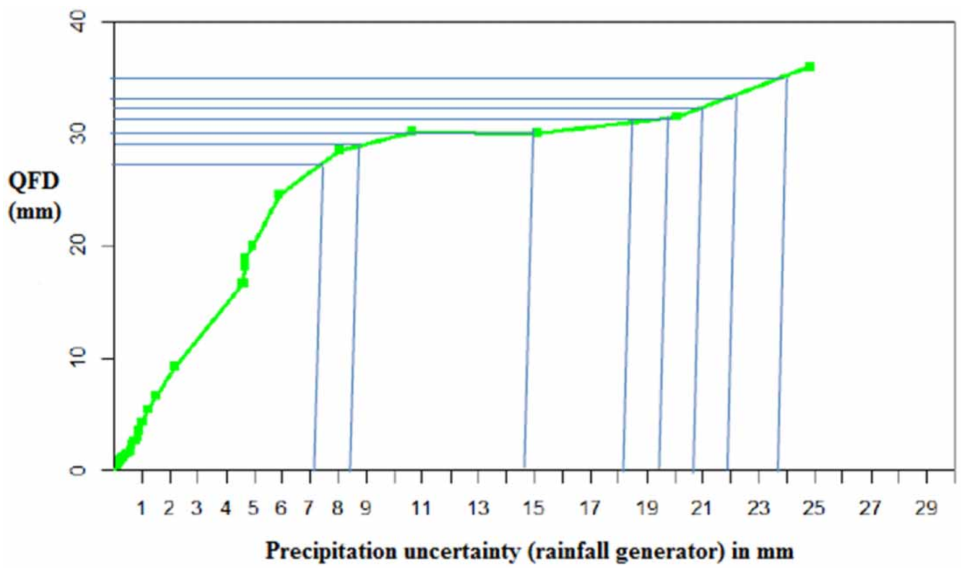


Figure 5 | Exploring streamflow uncertainty from the SREV of the GCM.

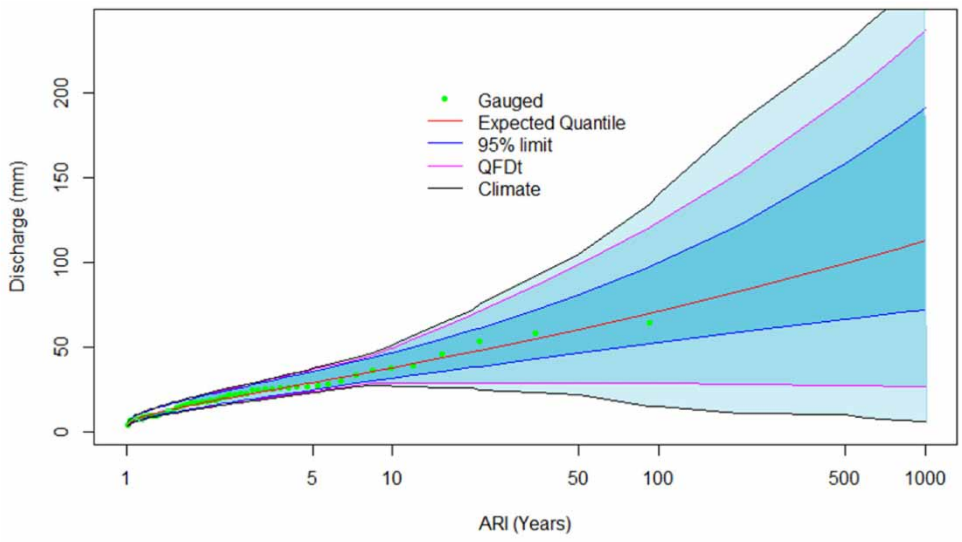


Figure 6 | Probable variability of streamflow discharge including climate change impact. Here, the 95% limit refers to the uncertainty associated with the fitted flood frequency model, the QFD_t refers to the total QFD associated with different flood quantiles (reflecting hydrologic simulation uncertainty), and climate refers to the uncertainty associated with precipitation of future climate scenarios.

damage estimation (Figure 7). First, how flood damage uncertainty varies when the HM uncertainty is taken into account was determined through the QFD. Second, flood damages were estimated incorporating the climate change uncertainty focusing on GCM uncertainty and the quantification of SREV. Third, we quantify the impact of a 1 °C rise in global temperatures and, fourth, we quantify the impact of a 2 °C rise in global temperatures.

Considering the different annual recurrence intervals, the probable bias compared to uncertainty in the expected flood damage was significant in the higher flood quantiles, especially in the range of the 1 in 100 to 1 in 500 years floods. On the contrary, lower bias was found in the lower flood quantiles, especially in 1 in 2 to 1 in 50 years floods (Figure 7). This is due to the magnitude of the flood values and the lower impact of the nonlinearity associated with the damage function

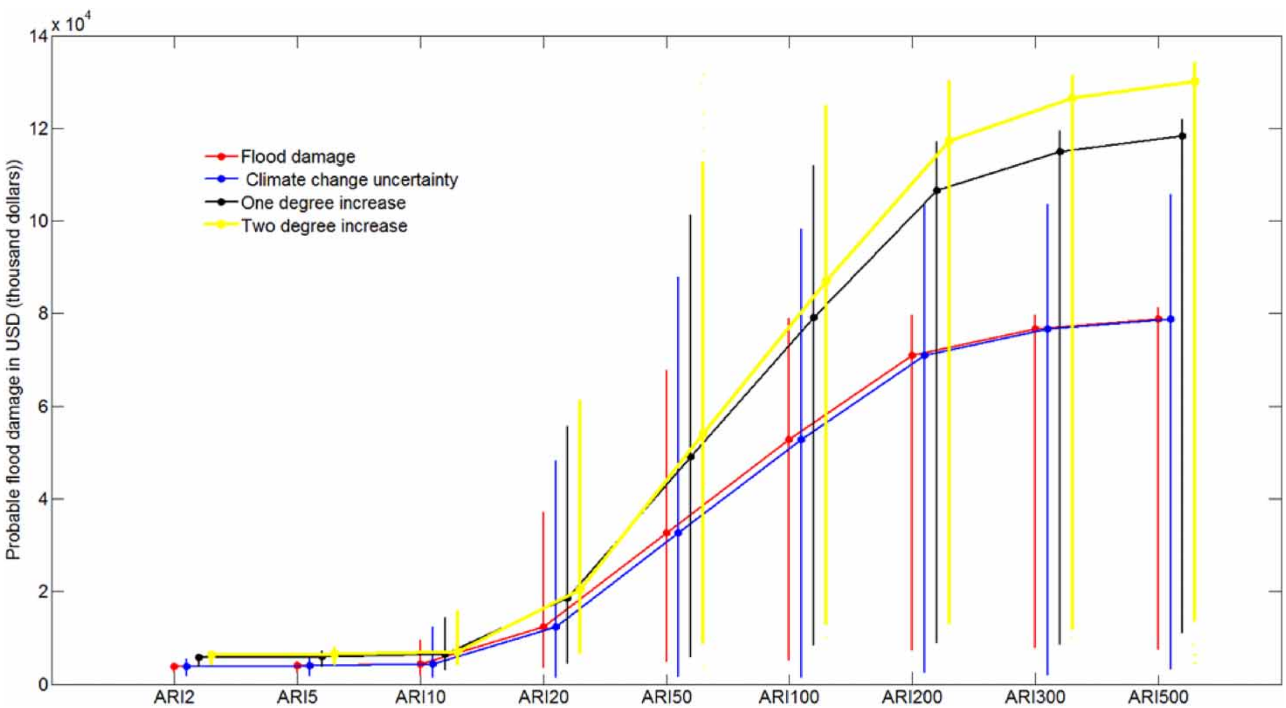


Figure 7 | Probable flood damage uncertainty with changing climate.

used at the lower flood quantiles. Our analysis shows (Figure 7) that the extent of probable bias is low in derived flood damage for the flood with recurrence intervals of 2, 5, and 10 years, with an average annual damage projected at nearly 3,500 USD, and that the fluctuation between the upper and lower limit is also insignificant. The extent of probable bias increases significantly at an annual recurrence interval of 1 in 20 years, with an average annual damage of nearly 10^4 USD and the fluctuation between the upper and lower limits in a range of 4×10^4 USD. Significant probable bias exists with increasing ARIs. For instance, at an ARI of 1 in 50 years, the estimated annual flood damage is about 3×10^4 USD, with a potential range of bias in the order of 7×10^4 USD. Similar patterns are visible ARIs of 1 in 100 years, 1 in 200 years, and so on. On the contrary, the impact of 1 and 2 °C rise in global temperature is very significant. Peak damages increase up to 13.5×10^4 USD. The outcome reflects the huge increase in uncertainty with the increase of global temperature. Modelling simulations are usually unable to predict extreme flood events precisely; however, the variability of the model structure, likelihood, and parameter uncertainty estimation through the QFD would be an effective way to evaluate the probable bias.

6. DISCUSSION

The impact of climate change is already apparent around the world. Recent extreme weather events in different regions reflect the global scientific community's conclusions about the impacts of human-induced climate change. Uncertainty in flood damage estimation remains a significant challenge and is becoming particularly complex, given the additional uncertainty over rising levels of global greenhouse gas emissions and the resulting increases in global temperatures and extreme weather events.

6.1. The flood vs. damage relationship

The relationship between floods and damage is changing as evidenced by recent floods. Damage is a function of the volume of water as well as its peak. A simplistic representation of damage was adopted for this study. Future work needs to consider a more comprehensive framework that takes into account the complexities in these relationships. It should be noted that damages for future climate change-driven events need re-indexing for likely future inflation.

6.2. Representing real rainfall patterns with GCM projections

GCM rainfall is a poor representation of real rainfall (Rocheta *et al.* 2014). General circulation models (GCMs) have limits in simulating variables important for water resource management at regional to catchment scales. GCM simulations suffer from a range of uncertainties leading to transient (changing over time) and systemic (consistent over time) biases in the output when compared to observed records. An important GCM bias in managing water resource infrastructure is the underrepresentation of low-frequency variability, a characteristic central to the simulation of floods and droughts. Unfortunately, GCM precipitation simulations are less robust than other GCM fields, such as temperature. For example, precipitation simulations fail to replicate some characteristics of observed twentieth-century precipitation (Perkins *et al.* 2007), differ substantially across GCMs for future simulations (Johnson & Sharma 2011), and fail to adequately capture important precipitation characteristics (Rocheta *et al.* 2014). This study assumes that GCM extremes are unbiased. A more detailed estimation could consider downscaling and bias correction to understand the potential impact of GCM bias on extreme precipitation values.

6.3. Future global mean temperature increase

The assumed 2 °C rise in global mean temperatures is conservative, and many research projects indicate a likely greater rise. For a comprehensive assessment of the likely future damage, a range of emission trajectories and temperature rise scenarios could be investigated. Future damages/changes must also consider changes in lifestyle (leading to urbanization) and population (exposing us to greater damage). These considerations have not been made in our assessment due to the complexity in integrating such changes into a damage function. Future work is needed to consider these important trends and variables.

7. CONCLUSION

Our research promises to better support policy-makers in assessing the climate change threat and designing the optimum adaptation and resilience measures and responses. This study makes use of two novel metrics of uncertainty quantification of climate change projections (SREV) and streamflow data (QFD) to estimate total uncertainty in flood frequencies for improved evaluation of future extreme events. By integrating the forecasts of climate change and the expected impacts with flood damage-related metrics, we can better predict, quantify, and understand the potential extent and impact of flood damage as global temperatures rise. In particular, we can derive the extent of uncertainty in flood damage estimates to improve the ability of national, international, and private organizations to implement engineered protections and other polices and plans to help mitigate flood risks and associated damage. The framework presented in this study can be used to identify regions where investments in river-flood protection measures should be prioritized, or where other risk-reducing strategies should be emphasized.

In summary of the research, considering the different ARIs, the probable bias compared to uncertainty in the expected flood damage was significant in the higher flood quantiles, especially in the range of the 1 in 100 to 1 in 500 years floods. On the contrary, lower bias was found in the lower flood quantiles, especially in 1 in 2 to 1 in 50 years floods (Figure 7). This is due to the magnitude of the flood values and the lower impact of the nonlinearity associated with the damage function used at the lower flood quantiles. Our analysis shows (Figure 7) that the extent of probable bias is low in derived flood damage for the flood with recurrence intervals of 2, 5, and 10 years, with average annual damage projected at nearly 3,500 USD, and that the fluctuation between the upper and lower limits is also insignificant. The extent of probable bias increases significantly at an annual recurrence interval of 1 in 20 years, with an average annual damage of nearly 10^4 USD and the fluctuation between the upper and lower limits in a range of 4×10^4 USD. Significant probable bias exists with increasing ARIs. For instance, at an ARI of 1 in 50 years, the estimated annual flood damage is about 3×10^4 USD with a potential range of bias in the order of 7×10^4 USD. Similar patterns are visible ARIs of 1 in 100 years, 1 in 200 years, and so on.

Many countries are in the process of diversifying their strategies for flood risks in the face of climate change (Wiering *et al.* 2017). Floods have gained increasing global attention recently given their devastating nature and the potential for substantial economic and human losses (Saharia *et al.* 2017). One of the biggest challenges for successful flood risk management is quantifying the uncertainty associated with climate change and its influence on flood events. Accounting for the uncertainties in climate model prediction necessitates a probabilistic approach incorporating ensemble model inputs which recognize the uncertainties in the prediction process. It is essential that flood risk projections adopt such an approach to deal with the propagation of these uncertainties through the modelling process.

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DATA AVAILABILITY STATEMENT

All relevant data are available from an online repository or repositories. Detailed access to the data: In this study we have used historical damage data for the Leaf River catchment, Mississippi, USA (http://www.flooddamagedata.org/); the C/M ratio data from the GFDS (http://www.gdacs.org/flooddetection/ (accessed on 15 February 2022)); and the DEM data from Shuttle Radar Topographic Mission (SRTM; http://www.cgiar-csi.org/ (accessed on 22 February 2022)). https://climateknowledgeportal.worldbank.org/download-data (accessed on 22 February 2022).

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