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SINGAPORE

**FLOOD RISK ANALYSIS UNDER CONSIDERATION OF RIVER
SYSTEM DYNAMICS AND SPATIAL-TEMPORAL SCALES**

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2019

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SYSTEM DYNAMICS AND SPATIAL-TEMPORAL SCALES**

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A thesis submitted to the Nanyang Technological University in partial fulfilment of the
requirement for the degree of

Doctor of Philosophy

2019

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

15 April 2019

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Julien Oliver

Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

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Authorship Attribution Statement

This thesis contains material from 1 paper(s) published in the following peer-reviewed journal(s) / from papers accepted at conferences in which I am listed as an author.

Chapter 4 is published as Oliver, J., Qin, X. S., Larsen, O., Meadows, M., & Fielding, M. (2018). Probabilistic flood risk analysis considering morphological dynamics and dike failure. *Natural Hazards*, 91(1), 287-307.

The contributions of the co-authors are as follows:

- Ole Larsen secured funding and external collaborations with the World Bank and Nepalese institutes
- I prepared the manuscript drafts. The manuscript was revised by AP Qin Xiaosheng, Dr Ole Larsen, Dr Mark Fielding and Michael Meadows
- I designed the overall study, developed the pre-processed and post-processed datasets and software modules (e.g. fragility curves, structure failure, stochastic morphological variation in the 1D model) and interpreted all data results
- Michael Meadows prepared the catalogue of inundation maps with MIKE SHE
- Dr Mark Fielding prepared the continuous stochastic discharge data

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ACRONYMS

1D	One dimensional
2D	Two dimensional
3D	Three dimensional
AAL	Annual Average Loss
API	Application Programming Interface
CAPRA	Comprehensive Approach to Probabilistic Risk Assessment
CBA	Cost Benefit Analysis
CDF	Cumulative Density Function
CFQM	change factor quantile mapping method
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CN	Curve Number
CORDEX-SA	Coordinated Regional Climate Downscaling Experiment South Asia
CWC	Central Water Commission
DEM	Digital Elevation Model
DHM	Department of Hydrology and Meteorology, Nepal
DSM	Digital Surface Model
DTM	Digital Terrain model
EC	European Commission
ECMWF	European Centre for Medium Range Weather Forecasts
ERN	Evaluacion de Riesgos Naturales
ESA	European Space Agency
EVA	Extreme Value Analysis
FHS	Flood Hazard System

GCM	Global Climate Model
GEV	Generalized Extreme Value
GLO	Generalized Logistic
GLUE	Generalized Likelihood Uncertainty Estimation
GPD	Generalized Pareto Distribution
GPM	Global Precipitation Measurement
GPS	Global Positioning System
HD	Hydrodynamic
HSG	Hydrologic Soil Groups
ICIMOD	International Centre of Integrated Mountain Development
IITM	Indian Institute of Tropical Meteorology
IHAM	Inundation Hazard Assessment Model
IMD	India Meteorological Department
IPCC	Intergovernmental Panel on Climate Change
KNN	K-nearest neighbour
LEP	Loss Exceedance Probability
mASL	meter Above Sea Level
MC	Monte Carlo
MFA	Multivariate Frequency Analysis
MoAD	Ministry of Agricultural Development, Nepal
MODIS	Moderate Resolution Imaging Spectroradiometer
NAM	Nedbor Afstromnings Model
NDRI	Nepal Development Research Institute
NRC	National Research Council
NRSC	National Remote Sensing Center
PCR-GLOBWB	PCRaster Global Water Balance

PDF	Probability Density Function
PIU TA & CBDRM	Project Implementation Unit for Technical Assistance and Capacity Building for Disaster Risk Management
POT	Peak Over Threshold
RASP	Risk Assessment for Strategic Pathways
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
RFFA	Regional Flood Frequency Analysis
RP	Return Period
SHE	Système Hydrologique Européen
SOTER	Soil and Terrain Database
SRTM	Shuttle Radar Topography Mission
SMHI	Swedish Meteorological and Hydrological Institute
SWAT	Soil and Water Assessment Tool
UK	United Kingdom
UNISDR	United Nations Office for Disaster Risk Reduction
UNOSAT	UNITAR Operational Satellite Applications Programme
USACE	United States Army Corps of Engineers
USD	United States Dollar
VDC	Village Development Committee

LIST OF PUBLICATIONS

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SUMMARY

As a consequence of rapid urbanization and climate change, the frequency of flood events has increased faster than any other perils over the last decades, adversely impacting societal development and economic growth. The recent years have seen growing interests in devising risk-based solutions to support flood management. The risk-based approach focuses not only on avoiding flooding using design thresholds, but also consider flooding consequences. Quantifying flooding, including probability of occurrence together with its impacts, offer opportunities to design cost efficient strategies to address all segments of the risk management cycle: mitigation, preparedness, response and financial transfer schemes.

Flood risk quantification relies on the characterization of three main components: (i) the hazard, described in terms of intensity and frequency; (ii) the exposure, capturing assets, activities or population distribution; and (iii) the vulnerability, or damage susceptibility of exposed elements to a hazard intensity. While theoretically well established, the quantification of river flood risks still faces numerous challenges in application. Traditionally, flood risk assessment is performed based on a number of spatially uniform T-year return periods, representing a single snap-shot in time of the systems, with direct association between probabilities of flood intensity (e.g. peak discharge), inundation extents and damages. This approach is preferred because of its relative simplicity. But it fails to capture adequately flood hazard dynamics, such as non-linear processes associated with dike failure and sedimentation and changes in risk cumuli over different spatial and temporal dimensions, and to address uncertainties along the risk analysis chain.

The objective of this study is the development and application of novel and efficient flood risk assessment frameworks to investigate some of the limitations of traditional methods for flood risk estimation. Three main points are addressed: (i) the reciprocal influences of morpho-dynamics and dike failure on hazard and risks patterns, (ii) the spatial coherency of regional flood events, and (iii) future flood risk simulation and adaptation at the regional scale. The frameworks proposed rely on a modelling chain, including several or all of the following components: (i) long-term continuous and spatially coherent event set produced from historical, future or synthetic rainfall or discharge, (ii) a probabilistic river channel model able to describe different levels of uncertainties associated with the river (sedimentation, roughness, conveyance), (iii) a stochastic structure failure model, (iv) an efficient inundation model or an extensive catalogue of flood events, and (v) a probabilistic damage model that can merge uncertainties of hazard and vulnerability models.

In the first study, we investigated the influence of channel morpho-dynamics on dike failure, inundation frequencies and economic risks over 2 and 5-year periods on a 45 km reach of the Upper Koshi River, Nepal. The use of continuous simulations with a dike breach model provided an estimation of inundation probabilities and risk metrics more robust than the traditional binary treatment of flood defence (flood or no flood below design level) and/or the direct association of peak discharge and loss return periods. The results also indicated non-negligible changes in risk metrics (+4% per year for the Annual Average Loss) associated with sedimentation processes, potentially impacting the validity of risk studies relying on a single snap-shot in time of the river system.

In the second study, we investigated the limitation of using a uniform T-year return period to quantify risks at the regional scale. A risk modelling chain was developed relying on spatially coherent or simplified event sets generated from 5,000 years of synthetic data across four river basins in Uttarakhand, India. The results showed that preserving the spatial coherency of regional events lead to a spreading of the T-year local event distributions on both sides of a uniform regional T-year return period. The specificity of the exposure and the correlations between local events in Uttarakhand translated into minimal (4%) differences in losses at high return periods (>50 year) but larger difference (20%) at low return periods (5 to 10-year). The redistribution of loss frequencies led to negligible differences in the Annual Average Losses between the different event sets but more important variations in the standard deviation of losses, potentially affecting financial planning relying on such metric.

The third study investigated future flood risks and adaptation in the Upper-Ganga basin for the 2045-2065 period based on 14 climate realisations from CORDEX-SA experiments. The study identified an overall agreement between climate projections towards an increase in extreme rainfall, discharge and losses. However, the magnitude of the change remains largely uncertain partly due to the limitation of climate models to capture extreme rainfall in complex terrain, and due to uncertainties in the statistical downscaling methods. Discharge peaks and residential losses for the 100-year event could increase on average by 60% and 100%, respectively. Simulations of various structural adaptation strategies suggested that, for a medium impact climate scenario, the increase in future losses could be mitigated with targeted structural upgrades to approximately 2% to 6% of the rivers.

This research highlighted the benefits of using more advanced methods to address the complexity of flood hazard and risks dynamics over different spatial and temporal scales. It also demonstrated that integrated approaches are nowadays applicable. As researchers produce more accurate and efficient solutions to model the components of the risk chain, and as data availability and computational power increase, integrated risk modelling frameworks shall become readily applicable and support better risk management strategies for the public and private sectors.

CHAPTER 1 INTRODUCTION

1.1 Background

The devastating consequences that floods can produce are irrefutable. Over the past decades, agriculture development and urbanization have profoundly altered the response of catchments and rivers and led to the accumulation of people and assets in areas exposed to floods. As a consequence, the frequency of hydro-meteorological and specifically flood losses have increased faster than any other perils since the 1980s (Hoeppe, 2016). The costliest event ever recorded occurred in 2001 in Thailand reaching an estimated USD45 billion in economic damages. Heavy monsoons in 1998 and 2010 impacted China with approximately USD30 and USD18 billion worth of losses. India experienced in 2014 economic losses in excess of USD16 billion. Since the beginning of the twentieth century, ten of the highest damaging floods have occurred in the past 25 years (Dilinger, 2017), impacting societies and economies, and particularly the most populated Asian nations.

As floods keep on straining societies and financial resources, the recent years have seen a growing interest in risk-based solutions to support flood management. Traditional management approaches aim to control or prevent flooding by the mean of structural interventions, e.g. embankments and dams, designed to avoid inundation below a discharge peak threshold. The risk-based approach allows to additionally include knowledge of flooding impacts on the economy and population to support integrated management strategies. Quantifying such impacts presents numerous benefits for decision-making. Such benefits include the ability to identify segments of the society at risk and an objective basis for the development of cost-efficient mitigation and response plans. Finally, quantified residual risks also help the design of financial recovery plans. The approach is

today commonly applied and recommended, for instance, in the European Union, through the European Union Flood Directive (European Commission, 2007).

Quantitative flood risk is usually defined as the product of occurrence probability of an event and the associated damages. It relies on the definition of three main components: (i) the hazard, described in terms of intensity and frequency; (ii) the exposure, capturing assets, activities or population distribution; and (iii) the vulnerability, or damage susceptibility of exposed elements to a hazard intensity (UNISDR, 2009). While theoretically well established, the quantification of river flood risks still faces numerous challenges in application. Traditionally, flood risk assessment is performed based on a number of spatially uniform T-year return periods with direct association between probabilities of flood intensity (e.g. peak discharge), inundation extents and damages. This approach is usually applied because of its relative simplicity but suffers from various shortcomings.

First, all components of risk are dynamic and vary over time. It is therefore important to capture risk variations and evolution across time scales relevant to the physical and socio-economic processes affecting the risk model chain, and through the duration of risk studies (a few years) or strategic planning horizons (decades). One of the important factors that can affect flood risk analysis is river channel morpho-dynamics (Lane et al., 2007; Guan and Wright, 2015; Neuhold et al., 2009). Hydraulic models used to drive inundation maps typically capture a single snapshot in time of the river cross-sections. However, erosion and deposition processes modify river channel profile and conveyance, year after year and in some cases during a single flood event. These changes can in turn affect water levels and loadings on flood defences, possibly affecting the integrity of defence structures and altering inundation and risk patterns. Neuhold et al. (2009) and Pender et al. (2016)

proposed approaches to integrate morphological sensitivity into river channel modelling and identified possible change in water levels over different time frames and for different discharge events. However, methods and analysis to describe the potential impacts on structural defence failure, inundation patterns and damages remain to be explored.

Structural solutions such as dikes have been commonly used during the last decades to reduce flood risks in areas presenting high economic exposure. Despite its recognized efficiency to protect from low magnitude floods, dikes may fail under more extreme events leading to un-expected and potentially dramatic consequences. Traditional approaches have been looking at breach impact using pre-defined scenarios (e.g. Zhang et al., 2013; Mazzoleni et al., 2013; De Moel et al., 2014; Pinter et al., 2016) or computationally demanding detailed physical simulation (e.g. Morris et al., 2008; Viero et al., 2013). While simplified approaches have been developed for broad assessment (e.g. Dawson et al., 2005; Hall et al., 2003), only few modelling systems have been proposed to dynamically capture the reciprocal influence of flood defences and river-floodplain systems. In the recent years, two dynamic frameworks relying on unsteady flow simulations have been proposed to investigate river-structure-floodplain (defined here as the Flood Hazard System) interdependencies (van Mierlo et al. 2007; Vorogushyn et al. 2010). Their preliminary applications identified the importance of capturing the full complexity of the river system considering interactions between structural defences and river/floodplain dynamics. When considering such modelling approach, the stochastic nature of breaching can produce non-linearities between discharge, inundation and damage return periods. The traditional approach of flood risk modelling assuming the same T-year Return Period (RP) for both discharge and damages is not valid any longer. An alternative approach could consist in simulating flooding in a Flood Hazard System (FHS) model, able to capture dynamically

the interactions between the river, embankments and floodplains, forced with continuous discharge over a very long period covering all probable ways in which flood peaks and shape can occur. Damage return periods and risk metrics are then established based on local inundation probabilities originating from stochastic breaching events instead of discharge probabilities.

This continuous simulation approach was previously investigated by Falter et al. (2015) to assess river flood risks over large areas. As the area increases, applying a spatially uniform RP discharge event and associating the same RP to describe the inundation scenario and damage probability is not adequate to represent the spatial spreading and clustering of flooding (e.g. Falter et al. 2015; Thiessen et al., 2015; Schneeberger et al., 2017). Two main approaches have been proposed to represent spatial heterogeneity of events: (i) multivariate frequencies analysis (MFA) of spatially discharge peaks at multiple locations (Ghizzoni et al., 2012; Neal et al., 2013; Schneeberger et al., 2017) or losses of correlated regions (Timonina et al., 2015; Jongman et al., 2014); (ii) event-based analysis of continuous simulation (Torres et al., 2014; Falter et al., 2015). Particularly, the continuous simulation of rainfall-runoff processes can produce spatial and temporal variations in peaks, volumes and hydrograph shapes while accounting for antecedent conditions. The approach also allows to produce events independent of the presence and operation of flood control structures (dikes and dams) which can invalidate long-term flow statistics. Finally, the approach is easily extended to account for future climate perturbations. To date, few methodological approaches have been proposed to capture risk adequately at the regional scale. Besides, no studies have tried to also consider variabilities in the hazard and risk models or fully understand the limitations of traditional flood risk methods, based on uniform T-year RP to describe risks.

Finally, as strategic planning decision can span over decades, the dynamics of flood risks need to be understood over larger time frames. Risks are expected to increase in the future, as socio-economic development leads to more people and assets in flood prone zones (e.g. Visser et al., 2014), but also because of expected increases in river discharge and flooding probabilities resulting from climate change (e.g. Hirabayashi et al., 2013; Arnell and Lloyd-Hughes, 2014). Future flood risk studies have been carried out at the global (e.g. Hirabayashi et al., 2013; Ward et al., 2014; Winsemius et al., 2016; Alfieri et al., 2017) or the regional scale (e.g. Rojas et al., 2013; Alfieri et al., 2015; EA, 2009; Wing et al., 2018; Ward et al., 2015). However, these studies are of limited value for understanding local intervention needs or have focused on the most developed regions of the world. Certainly, quantitative future flood risk prediction and the evaluation of regional adaptation strategies remains scarce in many parts of the world.

1.2 Objective and research questions

The objective of this study is the development and application of three novel or enhanced frameworks for flood risk assessments to address and investigate limitations of the traditional method applied for flood risk estimation: the reciprocal influences of morpho-dynamics and dike failure on hazard and risks patterns, the spatial coherency of regional events and future flood risk simulation and adaptation at the regional scale. Particularly there is a need for risk modelling frameworks that (i) use long-term continuous simulations, (ii) capture hazard and risk dynamics, (iii) address uncertainties, and (iv) simulate ensembles of future climate impacts.

Novel approaches for present and future flood risk estimations and new knowledge regarding the limitations of current flood risk assessment practice are introduced by three research studies and questions derived from the literature review presented in Chapter 2:

- **How river morphological dynamics impact dike failure, flood hazards and risks over different time-scale?** This study will investigate variations in flood risk as a result of changes and uncertainty in river morphology, taking into consideration dike failure.
- **How risk metrics vary between spatially coherent and continuous simulations and traditional flood risk assessment methods when applied to regional scales?** This study will rely on an efficient flood risk modelling chain using continuous simulation of rainfall-runoff processes, inundation mapping and risk calculation with additional consideration of hazard and vulnerability uncertainties.
- **How future flood impacts can be predicted and cost-effectively mitigated at the regional scale?** In this study, we will develop an efficient flood risk modelling framework to establish future flood impacts and evaluate most suitable regional adaptation strategies. We will investigate changes and adaptation to future flooding risks in the Upper Ganga River basin (24,000 km²) using an ensemble of climate change scenarios. The work will focus on the development of fluvial flood hazard projections for the present climate and for a near future period 2045-2065 to assess how projected changes in hazard contribute to future changes in flood risks. Using the modelling framework, a risk-based approach will be applied to optimise structural schemes at the scale of the full basin to offset projected increases in flood risk.

1.3 Tasks, structure and author contribution

The overall structure of the Thesis is schematized in Figure 1-1. Following the introduction section in Chapter 1, a thorough literature review around the themes raised in the research questions is presented in Chapter 2. Chapter 3 gives a summary of the innovation and developments and presents the generic and common hazard and risk modelling components used to answer the three research questions.

The research questions are then addressed in three independent tasks and studies each corresponding to a chapter including detailed innovations and methodological approaches taken. Chapter 4, *Probabilistic Flood Risk Analysis Considering Morphological Dynamics and Dike Failure* addresses research question 1 and propose a modelling framework to investigate morpho-dynamic impacts on dike failure on flood risk. The modelling framework is applied to a 45 km section of the Koshi River in Nepal. In Chapter 5, *A Probabilistic Risk Modelling Chain for Analysis of Regional Flood Events*, we intend to answer research question 2 and test variation of regional risks metrics between different event set structures and uncertainties in 4 river basins in Uttarakhand, India. Research question 3 is addressed in Chapter 6, *Impacts and Risk-Based Adaptation to Future Floods in The Upper Ganga Basin*. Finally, the main results and achievements of the tasks will be summarized in the concluding Chapter 7 together with suggested orientation of future research.

The comprehensive work of setting-up the different modelling components was realized by different teams of scientists. The specific author contributions directly related to the research questions include the design and development of the full modelling framework concepts and their applications, development of new modelling components

(e.g. stochastic river geomorphology, stochastic dike failure), the tools required to perform the Monte-Carlo and ensemble simulation and the pre-processing, post-processing, analysis, reporting and mapping presented.

In addition, the hazard and risk model set-ups, calibration and simulations were done principally by the candidate with support from Michael Meadows for the MIKE SHE catalogue of simulations in Chapter 4 and from Gregers Jensen for the calibration of the rainfall-runoff model used in Chapters 5 and 6. Although the exposure and vulnerability data are not attributed to the author in this document, the author contributed to a large extent to the development of the exposure layers and vulnerability curves through data review and analysis, survey questionnaire design, technical direction for the geospatial processing and statistical analysis of survey results. The original work was prepared for related investigations in the case study areas by a larger team of GIS experts at DHI Singapore and India or relevant agencies acknowledged in the study. The original data produced were then adapted by the candidate for the research study purpose. The generation of the continuous synthetic discharge in Chapter 4 was done by Mark Fielding. Prof. Qin Xiaosheng, Dr. Ole Larsen and Prof. Henrik Madsen provided support for the conceptual design of the papers, discussion of results as well as final formulations of the manuscript. Piyoosh Rautela, Chandra Joshi and Tom Burkitt supported the study through data collection and acted as local institutional and technical advisors and final formulation for Chapter 5 and 6.

Figure 1-1 Overview of the Thesis structure

CHAPTER 2 LITERATURE REVIEW

Traditionally, flood risk assessment is performed based on predefined return periods, using a single snapshot in time to describe the different components and factors influencing flood hazards and risks. The approach is commonly applied, for instance, in the European Union, where the Floods Directive (2007) asks Member States to base flood management plans on hazard maps produced for three return periods and to be updated every six years. To date, the greatest part of the flood risk research has been dedicated at identifying the impacts of different sources of uncertainty originating from (i) the statistical analysis of extremes (Apel et al., 2004; Merz and Thielen, 2005), (ii) the parametrization of hydraulic models (Aronica et al., 2002; Bates et al., 2004; Pappenberger et al., 2005), (iii) the model boundaries (Apel et al., 2004; Pappenberger et al. 2006; Domeneghetti et al., 2013;), (iv) the dike failure processes (Apel et al., 2004; Van Mierlo et al., 2007; Vorogushyn et al., 2010, 2011), and (v) the damage estimations (Merz et al., 2004; Merz and Thielen, 2009; de Moel et al., 2011; Vorogushyn et al., 2012). However, despite the acknowledgement that flood hazards and risks are driven by dynamic processes (Mazzorana et al., 2012; Merz et al., 2015), the literature remains scarce on evaluating the variability and dynamics of flood risks in time and space.

2.1 Dynamics of river-structure-floodplain systems

River morpho-dynamics

One factor that can have considerable influence on flood hazard patterns is the morpho-dynamics of the river (Lane et al., 2007; Neuhold et al., 2009, Pender et al, 2016; Guan et al., 2015). Inundation simulations typically use a fixed description of the channel geometry, assuming that the river bed, usually surveyed months or years before the

completion of the flood risk study, would not change. However, in many river systems, deposition and erosion processes can influence channel conveyance and friction, increasing loadings on flood defences and potentially altering inundation patterns. Previously, a few studies are reported on the influence of morphological changes on flooding or inundation, considering sediment transport and hydrological variability.

Wong et al. (2015) used a simplified sediment transport model to produce probable channel erosion produced by a 2,000-year recurrence interval flood wave in Cockermouth, UK. The channel changes are produced in a Monte Carlo simulation to modify a coupled 1D-2D hydrodynamic model, accounting for sediment grain size and roughness uncertainties. The results showed that for a single flood wave of an event with such magnitude, the effects on the inundation patterns are negligible. However, the study did not address the changes in inundation produced from the accumulation of successive flood waves.

In a study of the River Wharfe, UK, Lane et al. (2007) used field data and numerical simulations to identify morphological changes accumulated over a 16-month period. The assessment of channel change was performed using historical and repeated survey data of cross-sections and monitoring of sediment delivery and sedimentation processes at the scale of the reach over a 2-year period. Their results indicated for a short term (7 years), for 0.5 and 2-year return period events, using the historical discharge scenarios of 2002 and 2004, an increase in bed level of up to 0.12 m, translating to a 6% decrease of bank full conveyance and a 7% increase in inundation extents.

Using two-dimensional hydro-morphodynamic model, Guan et al. (2015) illustrated the cumulative impact of a sequence of four hypothesized scenarios of glacial outburst flood waves in southern Iceland. The effects on erosion and deposition patterns produced

by the events lead to increases in water surface elevation of up to 0.7 m in some locations demonstrating the need to account for sequences of events rather than single event scenarios.

Neuhold et al. (2009) established variations in water surface elevation within the Ill River, Austria, taking into consideration the uncertainties in temporal and spatial distributions of design rainfall, initial catchment conditions and river bed elevation. The simulation included 126 different combinations of hydrologic loading scenarios coupled with 12 random sediment scenarios to describe river bed changes using 1D hydraulic and sediment transport models. The method allowed to identify an increase of 12.3% in dike overtopping for a 100-year peak design event.

More recently, Pender et al. (2016) proposed a method to incorporate morphological sensitivity into flood inundation modelling. Their approach relied on the stochastic generation of flood sequences associated with a 1D hydraulic and sediment transport model to assess morphological changes over long-term periods. Predictions in bed level changes could then be used to update a coupled 1D/2D model to derive inundation extent and damages. The model was successfully applied in the River Caldey, England, to identify possible channel geometry changes over a 50-year period. The 8 design flow events and 100 flow sequences simulated showed that the water levels up to 1.6 m would potentially increase the frequencies of overtopping and flood defence structure failure.

River-structure-floodplain systems

Rivers, channels, floodplains and structures form a complex system with strong dynamic interactions during flooding. Van Mierlo et al. (2007) introduced the concept of “river system behaviour”, advocating for the need to account for the complex interactions

between different river systems, flood defence layers and floodplains. Merz et al. (2015) stressed that current flood risk management practice requires a thinking shift by fully considering “surprises” inherent to the complex of the flood hazard and risk systems, dominated by nonlinear, inter-dependents and the non-stationary processes.

Flood control structures such as dikes are some of the most pre-dominant elements in the river-floodplain systems. Dikes and structural engineering solutions have been commonly used over the last decades to control floods. Despite its recognized efficiency to protect from low magnitude floods, dikes may fail under more extreme events leading to un-expected and potentially dramatic consequences. Broad scale flood hazard and risk analyses are commonly performed using binary patterns (flood/no flood) using the designed protection level of the flood defences as a threshold for flooding and losses computation. However, such approach fails to reproduce dynamic variations and potential capping of the flood wave leading then to an error in hazard frequency estimations at the reach scale (Apel et al., 2009, Vorogushyn et al., 2010). Ward et al. (2011) also showed that a simplified treatment of dike systems introduce considerable uncertainty in the risk calculations Detailed flood impact studies considering dike breaches have been frequently carried out using predefined breaching locations and parameters from historical records (Hesselink et al., 2003; Alkema and Middelkoop, 2005; Castellarin et al., 2011; Van Emelen et al., 2012) or hypothetical scenarios (Aureli and Mignosa, 2004; Viero et al., 2013; Zhang et al., 2013; Mazzoleni et al., 2013; De Moel et al., 2014; Pinter et al., 2016). Many of those studies proved to be useful to understand the effects of dike failure terms of inundation extents, damages and uncertainties associated with breach developments. However, the analyses were usually performed only on short reaches (20-100 km) and for a limited number of breaching scenarios.

Physically based models have also been proposed and used to identify objectively breach locations, dimensions and dynamics (see for instance Morris et al., 2008). However, the application of such models can be computationally challenging for probabilistic simulations where large number of simulations are required (Viero et al., 2013). To overcome such limitations, recent approaches proposed to describe failure as a stochastic process based on the application of the fragility curve concept introduced by the U.S. Army Corps of Engineers (USACE, 1996). Conceptually, fragility curves quantify the probability of failure of a structure as a function of possible loading parameters (e.g. water level, impoundment duration, flow velocity). The benefit of fragility curves is that they allow to consider failure consistently over large areas (e.g. Risk Assessment for Strategic Pathways RASP produced a nationally consistent set of fragility curve for the UK) without a complete ground dataset at the expense of additional uncertainty introduced in the analysis.

Fragility curves were first used in flood hazard analysis by Hall et al. (2003) then Dawson et al. (2005) as part of the RASP project (Wallingford, 2004) in the UK. A similar fragility curve-based approach also formed the basis of the PC-RING software (Steenbergen et al. 2004) in the Netherlands. Hall et al (2003) first proposed a flood risk estimation method with consideration of overtopping failure mechanisms with national scale application in the UK. Subsequently, Dawson et al. (2005) enhanced the approach by considering wall instability and piping processes in the failure mechanisms affecting river defences. However, the modelling approach assumed a uniform water loading at all time along the flood defences, independently of breaches already occurring upstream the defence system. The method thus failed to capture potential capping of the flood wave and was judged more adapted to coastal situation (Vorogushyn, 2010).

The recent work of Apel et al. (2004, 2006) then Vorogushyn et al. (2009) in Germany extended the worked previously done under RASP and PC-RING and further enhanced the consideration of defence failure to incorporate in the fragility curves varying spatial and temporal loading of the defences for overtopping, piping and micro-instability failure mechanisms. To make full use of these advances, Vorogushyn et al. (2010) developed the Inundation Hazard Assessment Model IHAM, a novel stochastic-deterministic inundation model coupling dynamically 1D and 2D hydrodynamic models with a stochastic dike breach model.

Only few other modelling framework, fully dynamic and integrated, have been proposed to capture the reciprocal influence of flood defence systems and hydrodynamic models. The modelling framework proposed by Van Mierlo et al. (2007) relied on a simplified coupled hydrodynamic/breach model used to identifying breach scenarios at predefined locations followed by full scale two dimensional hydrodynamic simulations for the subset of identified scenarios. The application of the model along dike ring 41 along the river Rhine and Meuse, in the Netherlands, illustrated the cascading effects of defence failures in a complex system layering (Courage et al., 2013) but also raised concerns on the computational efforts required for applications in more complex or larger scale river systems (Van Mierlo, 2007). Following the work initiated by Apel et al. (2004, 2006, 2009), Vorogushyn et al. (2010) introduced the IHAM, a dynamically coupled hydrodynamic/breaching model using one dimensional channel flow models and a 2D Cartesian storage cell inundation modelling approach to compute the water loadings and pre-processed 3-dimensional fragility curves to quantify failure probabilities for the simulated loadings. The overall modelling framework allowed for the first time to describe flood hazard and risk under consideration of sequential and stochastic dike failures and

driven by unsteady flow simulations. The deterministic hydrodynamic model forms the core of a Monte Carlo simulations used to assess probabilistic dike and inundation hazards and uncertainties. One of the advantages of the IHAM model compared to other approaches is that the restriction of identical loading is removed and sequential defence failure can be considered along the river reach. The modelling framework proposed allowed to dynamically account for breaching processes and floodplain storage effects on a 90 km section of the Elbe River, Germany. These studies emphasized the improvement ported to the representation of the flood wave (particularly in terms of frequency of extreme events) as it travels along the longer river reaches. The IHAM model proved to be a valuable tool to assess effectively mitigation strategies using polder systems (Vorogushyn et al., 2012) and to assess the uncertainty associated with dike failure processes in flood risk analysis (Vorogushyn et al., 2011; Domeneghetti et al., 2013).

The early study of Neuhold et al. (2009) and the recent work from Pender et al. (2016) provided a detailed framework to include cumulative morphological changes in flood risk assessment. However, their studies only quantified changes in terms of water level confined to the river channel. Here, the framework of Vorogushyn et al. (2010) could be extended further to describe the potential impacts of morphological changes on flood defence integrity, inundation patterns and economic losses. There is particularly a need for an efficient and comprehensive modelling system able to describe the variability and dynamics between the different components of the river-embankment-floodplain system, accounting for both river morpho-dynamics and dike failure.

2.2 Spatial heterogeneity of regional flood events

The assumption of a spatially uniform RP and the association of the same RP to describe the event, inundation scenario and damage frequency holds for small scale studies but not necessarily when larger scales are considered. Falter et al. (2015) demonstrated that spatial variations could exist in terms of hazard and losses for realistic event scenarios at the reach scale. Thiessen et al. (2015) and Schneeberger et al. (2017) concluded that the use of uniform RPs over large-scale systems could lead to an overestimation of the flood risks. Different approaches should then be proposed to define regional scale risk management plans and policies, and account for the spatial spreading and temporal clustering of flooding across different administrative units, regions or countries to better describe risk cumuli (e.g. Kundzewicz et al., 2013; Jongman et al., 2014).

Recent research works have investigated new methodologies to capture the spatial heterogeneity of risks over large areas. The flood risk modelling chain can rely on the definition of an event set based either on multi-site weather generator or Multivariate Frequency Analysis (MFA) of discharge (Figure 2-1). Most methods make use of MFA to model spatial dependencies of discharges (or hazard) at multiple locations (Ghizzoni et al., 2012; Neal et al., 2013; Schneeberger et al., 2017) and between losses of correlated regions (Timonina et al., 2015; Jongman et al., 2014).

Ghizzoni et al. (2012) tested multivariate skew-t distribution and the Student Copula with arbitrary margins to describe flood event intensity, spatial spread and frequency across 18 gauging locations in the Upper Mississippi River. Both approaches were able to provide a good representation of frequencies and preserve the spatial correlation structure of peak discharge events in such context of high dimensionality. Neal et al. (2013) produced 20,000 flood events with realistic spatial dependences between three rivers gathering at the city of Carlisle. A multivariate peak over threshold approach similar to

Hefferman & Tawn (2004) based on copula statistics is used. The approach differentiates flow distribution at each site, with local marginal distribution fitted above a threshold, and the spatial dependence structure between sites, from a composite model fitted to the data available whenever one of the sites shows discharge values above the local threshold. However, these approaches failed at capturing the dependencies of temporal processes that drive flooding.

To overcome these limitations, Schneeberger et al. (2017) produced long-term time-series of spatially coherent discharge values and damages across the Federal Province of Vorarlberg, in the Eastern Alps. Temporal extrapolation of flood events is produced from the discharge river gauges measurements based on the approach of Hefferman & Tawn (2004). Between gauges, a top-kriging spatial interpolation procedure is used to produce discharge peaks. Damages are calculated locally using relations between discharge and losses from previous studies considering 5 return periods (30, 50, 100, 200, 300-year) and aggregated at the Province level. Serinaldi and Kilsby (2017) also applied MFA with a continuous simulation approach to produce spatially and temporally correlated weekly discharge maxima. However, these approaches are still limited to the reproduction of instantaneous discharge peaks and do not include other flood hydrograph characteristics (e.g. volume) important for hazard and risk accumulation estimation.

While more complex and adding uncertainties in the modelling chain, using continuous rainfall and runoff simulation, instead of direct discharge observation and MFA methods, can present several benefits: (1) the event set quality can be enhanced as the simulation accounts for antecedent conditions (see Grimaldi et al., 2013; Haberlandt & Radtke, 2014); (2) the spatial and temporal variation in peaks, volumes and hydrograph shapes are represented using the full description of the routing and accumulation processes;

(3) the historical precipitation records are independent of anthropogenic influences that can alter the flow over time (e.g. dikes, dams or land-use); (4) the event set can be perturbed for climate change studies.

Figure 2-1 Flood risk modelling chain based on either synthetic weather events or multivariate frequency analysis of discharge

The application of a continuous hydrological simulation will generate a realistic set of hazard scenarios spatially and temporally coherent at the regional scale. With this approach, no pre-defined assumption is made between the RP of the discharge peak locally and a possible RP of the event hazard at the regional scale. The continuous simulation concept can then be extended and applied to the last link of the risk modelling chain: by simulating regional losses for each regional hazard scenario, regional risk metrics can be established without any assumption made between the RPs of the loss and the hazard. Falter et al. (2015) introduced this approach and proposed a coupled model chain relying on a multi-site weather generator, a rainfall-runoff model, a river channel and floodplain model, and a loss model. The coupled model chain was applied to the meso-scale Mulde catchment in Germany and forced with 10,000 years of synthetic rainfall. Using this approach, they demonstrated that variability exists between peak discharge and loss RPs at the catchment and sub-catchment scales.

To date, few studies have tried to describe adequately risk at the regional scale or understand the limitations of using a uniform T-year RP as currently practiced. Existing

methods allow to capture the spatial heterogeneity of flood events but rarely reproduce the temporal dependencies of flooding processes. Besides, no approaches have been proposed that can account for other possible variabilities in the hazard or loss models.

2.3 Future flood and climate adaptation

Changes in climate are expected to alter rainfall patterns and in turn modify river discharge extremes, flood frequencies and impacts on the population and economies. In this context, more and more studies have been dedicated to establishing possible changes in future flood damage. A typical modelling chain for the estimation of future flood risks is presented in Figure 2-2 and relies on (e.g. Rojas et al., 2013; Alfieri et al., 2015; Alfieri et al., 2017; Wing et al., 2018): (i) future weather conditions downscaled for given climate scenarios and periods, (ii) continuous hydrological and routing simulation of discharge, (iii) estimation of discharge RP events based on extreme value analysis, (iv) mapping of inundation extents for the RP discharge events, (v) computation of losses from current or projected (Wing et al., 2018; Muis et al., 2015; Budiyo et al., 2016) exposure and vulnerability models.

Figure 2-2 Modelling chain typically applied to estimate future flood risks

Global flood risk predictions have been investigated (e.g. Hirabashi et al., 2013; Ward et al., 2014; Winsemius et al., 2016; Alfieri et al., 2017) providing critical information for understanding intervention needs and value at the continent or country scale. Several regional studies have been carried out particularly in the most developed regions at the national or continental scale (Rojas et al., 2013; Alfieri et al., 2015; EA, 2009; Wing et al., 2018; Ward et al., 2015). However, the literature remains scarce on future flood impacts in the developing world and particularly India and the Himalayan region.

In India, most preceding studies have investigated the impact of climate change on rainfall (e.g. Choudhary & Dimri, 2018; Singh et al., 2016; Kumar et al., 2006) and in some cases hydrology and discharge extremes. Gossain et al. (2011) used distributed hydrological models to predict variation in blue and green water availability at the scale of India. The study was performed using the Soil and Water Assessment Tool SWAT (Arnold et al., 1998; Neitsch et al. 2000), a physical based model particularly efficient to simulate continuous hydrological processes and the RCM-PRECIS from the Indian Institute of

Tropical Meteorology (IITM) for the A1B IPCC concentration pathway scenario in the near term (2021-2050) and long term (2071-2098). The results, integrating long-term simulation of rainfall, temperature and evapotranspiration, illustrated the expected changes in water balance, water and sediment yield as well as high flow and low flow frequencies across and within 19 river basins in India.

Numerous studies focused on the Brahmaputra River and predicting future extreme flows using different ensembles of climate models and streamflow modelling approaches (Gain et al., 2011; Ghosh & Dutta, 2012; Apurv et al., 2015; Mohammed et al., 2017; Wijngaard et al., 2017). For example, Gain et al. (2011) investigated the impact of climate change on low and high flows in the lower Brahmaputra. They applied a discharge-weighted ensemble modelling technique using a global hydrological model PCR-GLOBWB (van Beek and Bierkens, 2009) forced by 12 GCMs and 2 emission scenarios A1B and A2 for 3 future periods, as a weighted ensemble following the approach of Weiland et al. (2010; 2012). The GCMs weights are derived from the capacity of the GCMs driven hydrological simulations to reproduce historical streamflow. In all scenarios, both low flow periods and peak discharge were found to increase considerably (e.g. a 20-year peak discharge is expected to increase at least by 75%). More recently, Mohammed et al. (2017) applied bias corrected weather data originating from 11 climate projections of the CORDEX regional experiment to a SWAT model of the Upper Brahmaputra Basin to predict future flows. The results showed an expected increase of the 100-year peak discharge between 12 and 24% by the end of the century for RCP4.5 and RCP8.5 respectively. Wijngaard et al. (2017) used a distributed cryospheric-hydrological model and 8 downscaled GCMs over the Hindu Kush-Himalayan region (Upper Indus, Ganges

and Brahmaputra) predicting an increase in high flows (e.g. up to +108% for the 50-year discharge in the Upper Ganga) principally due to increasing precipitation extremes.

While much has been done to predict future hydrological hazard in India, literature on quantitative future flood risk and possible adaptation remain scarce. Hallegate et al. (2010) and Ranger et al. (2011) investigated future floods in Mumbai. They predicted direct and indirect impacts of future floods for residential, industrial and commercial assets and infrastructure. Based on these first analyses, they explored the benefits of adaptation options including structural measures to control flood hazard and increased construction flexibility and insurance penetration to reduce indirect flood losses. However, their study remained limited to the city scale of Mumbai and addressed a single climate change scenario.

2.4 Summary

The literature review identified different knowledge gaps within the current flood risk modelling practice as listed below and articulated around the three research questions:

- **How river morphological dynamics impact dike failure, flood hazards and risks over different time-scale?** Few frameworks have been proposed to date to capture the effect of morpho-dynamics on flood levels. The potential impacts on flood defence integrity, inundation patterns and economic losses are still unexplored. There is particularly a lack of efficient and comprehensive modelling system able to describe the variability and dynamics between the different components of the river-embankment-floodplain system.
- **How risk metrics vary between spatially coherent and continuous simulations and traditional flood risk assessment methods when applied to regional scales?**

To date, few studies have tried to describe adequately risk at the regional scale or understand the limitations of using a uniform T-year RP as currently practiced. We propose here to investigate the differences between simplified event set structures (e.g. uniform T-year RP) and spatially coherent and continuous simulations on flood hazard and risks.

- **How future flood impacts can be predicted and cost-effectively mitigated at the regional scale?** Knowledge of climate change impacts on flood risks is still largely lacking in regional and local scale applications, especially in India and the Himalayas. Particularly there is a need for an efficient risk modelling framework to assess how projected changes in hazard contribute to future changes in flood risks and to optimise structural schemes at the scale of the full basin.

CHAPTER 3 METHODS AND MODELLING COMPONENTS

This Chapter introduces some of the modelling components that have been most commonly used to develop the different modelling frameworks applied in the studies of Chapters 4 to 6. The Chapter also provides an overview of the specific developments realized by the author as required to address the research questions. Full details of the methodological approaches are available for each independent study.

3.1 River channel model

The flood wave propagation in the river channel uses the MIKE1D unsteady one-dimensional hydrodynamic model based on the full St Venant equations (DHI, 2017a). The equations are transformed in a set of differential equations over a computational grid consisting of a network of branches schematized using alternate Q- (discharge) and h- (water level) points and solved using the MIKE1D engine. The MIKE1D engine is a re-engineering and merger of the calculation capabilities of MIKE's collection system and river simulation packages (MIKE URBAN / MOUSE and MIKE11) into one engine. The engine brings the range of functionalities available from both engines into one with optimised performance. The new engine is parallelised and allows the use of multiple cores when available during simulations. For open channels, the MIKE1D hydrodynamic module uses an implicit, finite difference scheme (Abbott and Ionescu, 1967) for the computation of unsteady flows using a double sweep algorithm (Abbott and Basco, 1989). The module relies on a numerical scheme able to adapt to the local flow conditions (in time and space) to represent sub-critical or super critical flow. It also provides opportunities to compute flows over hydraulic structures or describe operational system behaviour.

Water level computation (and h-point locations) are done where cross-sections (section of river perpendicular to the flow) are defined by the user and identified along the river branch at defined chainages. The cross-section information is inserted in the form of (x,z) coordinates capturing the 2-dimension cross-section geometry. This information is processed by the model to describe the cross-sectional area and conveyance over series or regular or user-defined z-level intervals directly used by the engine to perform the calculations.

The hydrodynamic (HD) river model can be accessed through the MIKE1D Application Programming Interface API (see Unphon 2009), used under C# programming environment, to extend the functionalities of the classic 1D components. In these studies, the MIKE 1D API has been used to develop the structure failure model, generate Monte Carlo simulation, pre and post process results and input data and extend the MIKE1D model capabilities to account for uncertainty and variability in cross-section conveyance, reach profile or bed roughness.

Where overland flow patterns are parallel to the main river, the treatment of flow routing in channels can be extended to simulate floodplain flows, producing good approximations of the main flood characteristics (Horritt and Bates, 2002). The 1D river channel model could also be coupled dynamically to 2D hydrodynamic models to represent more complex floodplain flow patterns. The model is used in all studies (Chapter 4, 5 and 6).

3.2 Rainfall-runoff model

Hydrological modelling relies on the NAM rainfall-runoff model developed by Nielsen and Hansen (1973) at the Institute of Hydrodynamics and Hydraulic Engineering,

Technical University of Denmark. The model has been widely applied in hydrological studies (see for example: Rulin et al., 2008; Wang et al., 2016). The NAM model is a lumped, conceptual model simulating continuously rainfall-runoff processes as a function of weather variables (including precipitation, evaporation, temperature) and accounting for water availability in four interconnected storage compartments including groundwater, root zone, surface and snow (Figure 3-1). The model uses continuous rainfall, temperature and potential evaporation fields to produce continuous discharge that can be distributed uniformly or as point source along the river channel model at specific chainages. The model is used in Chapter 5 and Chapter 6 studies.

Figure 3-1 NAM model structure (source: Madsen, 2000)

3.3 Hydrological and overland flow model

For hydrological and overland flow simulation, the deterministic, fully distributed and physically based model MIKE SHE (DHI, 2017b), built upon the SHE (Système Hydrologique Européen; Abbott et al., 1986a and Abbott et al., 1986b) is used in Chapter 4.

MIKE SHE is a comprehensive and integrated framework for modelling the complete land phase of the hydrological cycle, including sub-surface and surface processes. The modelling framework, illustrated in Figure 3-2, is modular and gives access to process models for evaporation, channel flow, overland flow, unsaturated flow, groundwater flow and their interactions. It comprises pre- and post-processing tools and several solution techniques, from simple to complex, to describe these processes. In the unsaturated zone, flow can be simulated with the Richard's equation (Richards, 1931) or alternative versions neglecting the capillary forces. Actual evapotranspiration is calculated from potential evaporation using the empirical formula of Kristensen & Jensen (1975). Overland flow routing follows a two-dimensional diffusive wave approximation of the St Venant's equation and is initiated at top-soil saturation. Groundwater flow is solved using the three-dimensional governing equations of Refsgaard & Storm (1995). The MIKE SHE model can be also be coupled with the 1-D HD model MIKE1D to simulate river flow. MIKE SHE allows to describe the modelled processes at varying levels of complexity and spatial distribution depending on the data available, study objectives and modeller choices. For example, MIKE SHE can be used to investigate local crop requirements from a single soil profile or applied to large regions and multiple river basins (see for example Andersen et al., 2001). It has been extensively applied in research and consultancy projects and over varying climatological and hydrological conditions.

Figure 3-2 Hydrologic processes which can be simulated using MIKE SHE (source: DHI, 2017b)

3.4 Loss model

Risk analysis is performed in Chapter 4 and Chapter 5 using the CAPRA (Comprehensive Approach to Probabilistic Risk Assessment) platform (ERN-AL 2009a). The platform was designed as an open source modular system for disaster hazard and risk modelling and is frequently applied in risk analysis studies (Salgado-Gálvez et al., 2014; Velasquez et al., 2014; Marulanda et al. 2013; Cardona, 2012; Torres et al., 2013). CAPRA-GIS (ERN-AL, 2011) is used to derive the Loss Exceedance Probability curve (LEP) and the Average Annual Loss (AAL). The LEP curve calculates the frequencies of occurrence of different levels of loss generated from the exposed elements and associated

with the occurrence of flood events. Annual loss frequency or exceedance rate is calculated using the following equation (ERN-AL, 2009b):

$$E(l) = \sum_{i=1}^N P(L > l | Event_i) F(Event_i) \quad (3.1)$$

where l [\$] is a loss level; $E(l)$ [-] is the rate of exceedance of loss l ; $F(Event_i)$ [-] is the annual frequency of occurrence of the flood $Event_i$ ($i = 1, 2, \dots, N$); N is the total number of events; $P(L > l | Event_i)$ is the probability of a loss L greater than l , conditional on the occurrence of the i th event.

The return period of the loss is then computed using the inverse of $E(l)$. The probability of exceedance of l , for an event i can be given by (ERN-AL, 2009b):

$$P(L > l | Event_i) = \int_D P(L > l | D) f(D | Event_i) dD \quad (3.2)$$

where $P(L > l | D)$ [-] is the probability that the loss exceeds l given the local water depth D [m], accounting for the uncertainty which varies in relation to vulnerability. $f(D | Event_i)$ [-] is the PDF of the water depth, conditional on the occurrence of the event i .

The Average Annual Loss (AAL) [\$] is the mean value of the LEP distribution. It provides an estimate of the expected yearly loss averaged over many years. The AAL is obtained by (ERN-AL, 2009b):

$$AAL = \sum_{i=1}^N L(Event_i) F(Event_i) \quad (3.3)$$

where $L(Event_i)$ is the mean loss value associated with $Event_i$.

3.5 Specific developments and innovation

The research relies partially on the use of available modelling packages as presented before. However, such modelling packages need to be further adapted and integrated and

new modelling components are required to be able to address the research questions. This section presents the main software components developed around the existing modelling packages. The methodological innovations and how these relate to previously applied approaches are described in detail in each study (Chapters 4 to 6).

The overall hazard and risk modelling chain design and linkages between components needed to be re-engineered. DHI hazard tools, particularly for inland applications, are traditionally designed for deterministic scenario simulation and analysis and traditionally applied for local scale studies. The probabilistic approach taken and the larger scale at which the hazard model was applied asked for the development of specific methods (Chapter 4) or specific Monte-Carlo simulation handlers developed in C# (Chapter 4 and 5) and automated mapping routines in ARCGIS. The simulation handlers made use specific model components developed for the study including a stochastic structure failure model (Chapter 4 and 5) and stochastic river geomorphology model (Chapter 4) that allows to modify stochastically and during run-time the hazard models. To generate the fragility curves used by the structure failure model, it is necessary to pre-process the reliability functions of dike collapse mechanisms using Monte-Carlo simulations (Chapter 5).

It was also necessary to link the hazard and risk modelling components which comes also from conceptually different system. DHI's MIKE software traditionally produces deterministic results while CAPRA is designed for probabilistic hazard and risk simulation. Here is it was required to establish the adequate data structure and linkage through hazard data postprocessing and mapping to ensure compatibility between the two modelling systems.

Finally, in Chapter 6, the simulations of hazard ensembles and the exposure risk database and loss computation models for Climate Change analysis were fully developed for the study purpose.

CHAPTER 4 Probabilistic Flood Risk Analysis Considering Morphological Dynamics and Dike Failure¹

4.1 Introduction

Today, many cities are built on floodplains or in coastal areas that are easily exposed to floods. The physical alterations to the environment associated with rapid urbanization and agriculture development have affected the response of catchments to extreme rainfall and attempts have been made to manage flows and avoid inundations (Jongman et al., 2015). As techniques and building capability grew, the engineered response to control flood increased accordingly. Levees, dykes, diversion channels and dams helped to respond to the periodic extreme flow and encouraged urban development and the accumulation of assets in naturally flood sensitive zones. To better prepare societies, a purposeful assessment of the hazards and risks is nowadays recognized as the first step required for the development of cost-effective disaster prevention and mitigation strategies.

Traditionally, flood risk assessment is performed based on predefined return periods, using a single snapshot in time to describe the different components and factors influencing flood hazards and risks. The approach is commonly applied, for instance, in the European Union, where the Floods Directive (2007) asks Member States to base flood management plans on hazard maps produced for three return periods and to be updated every six years. Despite the acknowledgement that flood hazards and risks are driven by dynamic processes

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(Mazzorana et al., 2012; Merz et al., 2015), the literature remains scarce on evaluating the variability of flood risks in time.

One factor that can have considerable influence on flood hazard patterns is the morpho-dynamics of the river (Lane et al. 2007; Neuhold et al. 2009, Pender et al, 2016; Guan et al., 2015). Inundation simulations typically use a fixed description of the channel geometry, assuming that the river bed, usually surveyed months or years before the completion of the flood risk study, would not change. However, in many river systems, deposition and erosion processes can influence channel conveyance and friction, increasing loadings on flood defenses and potentially altering inundation patterns. In the River Ill in the Western Austrian Alps, Neuhold et al (2009) identified an increase of 12.3% in dike overtopping for a 100-year event.

More recently, Pender et al. (2016) proposed a method to incorporate morphological sensitivity into flood inundation modelling. The method was successfully applied in the River Caldeu, England, to identify possible channel geometry changes over a 50-year period. The results showed an increase in water levels up to 1.6 m that would potentially increase the frequencies of overtopping and flood defense structure failure. While the early study of Neuhold et al. (2009) and the recent work from Pender et al. (2016) provided a detailed framework to include morphological changes in flood risk assessment, their studies only quantified changes in terms of water level confined to the river channel. The potential impacts on flood defense integrity, inundation patterns and economic losses remain to be explored. There is particularly a lack of efficient and comprehensive modelling system able to describe the variability and dynamics between the different components of the river-embankment-floodplain system.

Thus, this study aims to investigate variations in flood risk as a result of changes and uncertainty in river morphology, taking into consideration dike failure. A dedicated and efficient modelling framework is proposed which combines the use of a continuous synthetic discharge forcing, a stochastic dike breach model, an unsteady one-dimensional hydraulic model (MIKE1D) for river channel, a catalogue of pre-run probabilistic inundation maps (MIKE SHE) capturing possible dike breaching events, and a damage and loss model (CAPRA). The Upper Koshi River, Nepal, which experiences constant bed aggradation and the consequent potential for failure of river embankments, will be used as a case study. The study will be the first of its kind in investigating the simultaneous effects of river morphology variability and dike failure and their consequences on flood risk patterns. The efficient modelling system will also provide the unique advantage of allowing continuous and long-term simulation to avoid any assumption between discharge, inundation and loss frequencies.

4.2 Study area and data

The study domain considers the stretch of the Koshi River along the Terai plains, located between the Chatra Gorge, Nepal and the Koshi barrage near the Nepal-India border (as shown in Figure 4-1). At Chatra, flows vary significantly from around 3,700 m³/s during the south-west monsoon down to approximately 600 m³/s during the dry season (Hooning 2011). During the two largest flood events recorded, flows have risen between 24,000 – 26,000 m³/s in 1954 and 1968 (Kale 2008). Due to heavy sediment loads carried down from the Himalaya mountains and deposited when the river debouches onto the Terai plains, the Koshi River has historically been highly dynamic morphologically (Dixit 2009; Chakraborty et al. 2010). In an attempt to control the shifting of the river, embankments

and river training works were constructed during the implementation of the Koshi Barrage Project (1958-1962). This enabled significant irrigation projects within both Nepal and India and prevented floods. However, embankment failures, as occurred in August 2008 under average discharge conditions ($5,000 \text{ m}^3/\text{s}$), pose significant flood risks to both human lives and physical assets; risks that are likely to increase over time, as the embankments degrade, and the river bed gradually silts up. To better describe flood risks, it is thus imperative to capture the uncertainties and variabilities associated with changes in river bed morphology and the likelihood of embankment failures.

The probabilistic flood risk modelling is carried out using existing software packages (MIKE SHE, MIKE1D, CAPRA) enhanced with newly developed components and functionalities (structure failure, morphological changes). The event sets and embankment fragility curves are pre-processed using the statistical software R. Data used for the flood hazard model were collected from the Department of Hydrology and Meteorology (DHM), Nepal, the Water Resources Department (Government of Bihar, India), publicly available datasets (e.g. SOTER, SRTM), and field surveys. The exposure and vulnerability models were developed based on data from the Nepal Development Research Institute (NDRI), published socio-economic statistics and studies, publicly available dataset (e.g. OpenStreetMap, Wikimapia) and site surveys.

Figure 4-1 1D and 2D model domains and embankment locations along the Koshi River between the Chatra Gorge (Gauge Station 695) and the Koshi Barrage in Nepal

4.3 Flood hazard and risk modelling framework

We analyse the impact of river morphological changes on dike breach and inundation hazard and risks using the modelling framework described in Figure 4-2. The framework relies on a straightforward Monte Carlo (MC) simulation of a Flood Hazard System (FHS) model with pre-processed inputs coupled to a probabilistic loss model (CAPRA).

The FHS model is defined in this study as a model able to capture dynamically the interactions between the river, embankments and floodplains, similarly to the approach proposed by Van Mierlo et al. (2007) and the Inundation Hazard Assessment Model (IHAM) of Vorogushyn et al. (2010). The FHS proposed here simulates stochastic failure events similarly to the IHAM but also include morphological variability. In addition, this study uses the FHS within a wider probabilistic risk modelling chain relying on continuous simulation.

In details, the FHS comprises an unsteady 1D hydrodynamic model for river channel routing and a probabilistic structure breach model (Structure links) coupled at run times.

The components software architecture is based on the MIKE1D Application Programming Interface API (see Unphon, 2009) and the C# programming language is used for their development. To maximize computational efficiency, the FHS is, in this application decoupled from the inundation model and does not explicitly simulate sedimentation processes. Instead, the FHS provides the possibility to parametrize stochastic bed level variations following dedicated morphological investigations. The MC results are post-processed and analysed to sample pre-run inundation maps and produce a flood hazard event set. The event set is then used to produce probabilistic flood hazard maps and combined with exposure layers and damage functions for risk analysis using CAPRA.

Figure 4-2 Schematization of the main modelling components adopted for probabilistic simulation of the breach and flood hazards and risks

4.3.1 River model and morphological variations

The MIKE1D model was used to simulate unsteady 1D hydrodynamic flows based on the St Venant equations (DHI, 2017a). The 1D hydrodynamic model describes the 44.5

km river stretch between Chatra-Kothu (Station No. 695) and the Koshi Barrage. Operating rules for the 56 gates of the barrage and 45 cross-sections describing the river bed have been acquired from Water Resources Department (Government of Bihar, India). In the absence of adequate water level data required for calibration of the riverbed and floodplain roughness, a pragmatic approach was adopted. Expert judgement, supplemented by land-use analysis and the roughness guidelines of Chow (1959), was applied to define Manning's n as an uncertain variable following a truncated log-normal distribution (Ghosn et al., 2003) with parameters ($\mu = 0.06$; $\sigma = 0.025$ μ ; $\min = 0.04$, $\max = 0.08$).

In the FHS model, sedimentation is not explicitly simulated. Instead, bed levels and cross-sectional areas are stochastically updated following expected morphological variations established along the river from observations or dedicated morphology studies. For this application, we compiled yearly averaged morphological changes simulated over the 1998-2008 and 2003-2007 periods from the early work of Hoening (2011). With available morpho-dynamic information being temporally averaged over several years, it was not possible to establish spatial dependencies or exert mass balance control. A pragmatic approach was taken, and synthetic case scenarios were derived to estimate sedimentation trends over the next few years using yearly bed level increase and cross-sectional area loss independently resampled from truncated normal distributions with statistical moments illustrated in Figure 4-3. At each cross section, statistical moments are linearly interpolated between the nearest available values.

Figure 4-3 Statistical moments (mean, standard deviation) applied along the 1D river for (a) yearly bed level increase; (b) yearly cross-sectional area loss below bank full level model; and (c) baseline bed level and statistical moments (mean, standard deviation)

4.3.2 Structure links and fragility curves

Structure links are MIKE1D components connecting the river and the floodplain through a structure describing the embankment sections. A broad crested weir formulation is used to compute free overflow. The river model and structure links are coupled at set-up and a unique matrix is used by the MIKE1D implicit solver at run time. To maximize computational efficiency, the inundation model is not coupled at run time with the river

and embankment models. Breach outflow is removed from the 1D model and peak breach discharge and timing are logged for post-processing and selection of pre-run inundation maps. The left and right embankments have been discretized in sections of an approximate length of 1 km. Dike crest elevation probability density functions (PDFs) are derived independently for each modelled dike segment, assuming a normal distribution of elevation points acquired with differential Global Positioning System (GPS). Dike toe elevation PDFs are produced from DEM difference between the floodplain and the river bed (see example for the left embankment in Figure 3).

Each structure link is associated with fragility curves (see Buijs et al., 2007) describing failure probability for overtopping, piping and micro-instability mechanisms. A given failure mechanisms can usually be described as a sequence of dependent events affecting the integrity of a dike structure. Each individual event can be represented by a reliability function with a conceptual form (e.g. Vorogushyn, 2009):

$$Z = R - L \quad (4.1)$$

where R is the resistance, L the load and Z the event state considering R and L values. Failure occurs when Z becomes negative. R and L are defined by a series of parameters linked to the physical and geomorphological properties of a structure. Such parameters can be resampled in a Monte-Carlo simulation to generate the probability that failure ($Z < 0$) occurs. For more complex failure mechanisms, failure probability is computed according to the probability multiplication rules for the series of dependent events, each characterized by a reliability function, leading to dike collapse.

In this study, failure due to overtopping is incorporated based on the work of Apel et al. (2004, 2006). To describe piping and micro-instability, the technique of Vorogushyn

et al. (2009) is used with a simplification of the seepage reliability formulation. As an example, the probability of failure due to micro-instability can be described as the probability two dependent processes (Vorogushyn, 2009):

$$P(\text{microFailure}) = P(\text{Seepage}) \cdot P(\text{micro}|\text{seepage}) \quad (4.2)$$

Where $P(\text{Seepage})$ is the probability of seepage through the dike core and $P(\text{micro}|\text{seepage})$ is the probability of slope failure conditional to the occurrence of seepage.

Seepage probability can be given by the reliability function (Vorogushyn, 2009):

$$Z_s = W_b - x(t) \quad (4.3)$$

where W_b is the width of the embankment base [m] and $x(t)$ is the time varying seepage length [m] calculated according to (Vorogushyn et al., 2009):

$$x(t) = \sqrt{2 \frac{K_f}{n_a} \int_0^D h(t) dt} \quad (4.4)$$

where K_f is the saturated hydraulic conductivity [m s^{-1}], n_a is the air-filled porosity [-], $h(t)$ is the time varying impounding water level [m] and D is the total impounding duration [s].

Vorogushyn et al. (2009) proposed an approximation of the hydraulic potential $\int_0^D h(t) dt$ resulting from a gradual impoundment by discretizing the dike height h_0 in three equidistant intervals $[(0 \sim 1/3 h_0), (1/3 h_0 \sim 2/3 h_0), (2/3 h_0 \sim h_0)]$ with water levels in those intervals averaged by the stages $(1/6 h_0, 1/2 h_0, 5/6 h_0)$. With the embankment height up to 10 m, this approach would average out any water level variations less than 3 m. Instead, a single interval $(0 \sim h_0)$ is used and the water level averaged within this interval using a proportion (α) of the impounding water level. The remaining fragility functions for each

breach mechanism and each embankment section were built using the geophysical and geotechnical properties collected during field surveys, the SOTER database (Dijkshoorn and Huting, 2009) or derived from the literature (see Vorogushyn et al., 2010). Using historical discharge and the FHS model, annual failure probabilities of the overall embankment system were computed to identify suitable α values. Three breaches have been recorded in the study area since 1963 (Dixit et al., 2009), giving an historical annual breach probability of 5% achieved with $\alpha = 4/5$. With incomplete information regarding historical breach dimensions, the breach total width is assumed to follow a truncated normal distribution with parameters ($\mu = 750$ m; $\sigma = 250$; min = 250, max = min (1250, max section length)). The breach dimension increases linearly over a fixed 1-day duration and a single breach is allowed during each simulation. Breach location, dimension and peak breach outflow and timing are logged during the simulation.

4.3.3 Inundation model and flood hazard catalogue

Inundation modelling is performed using the deterministic, fully distributed and physically based model MIKE SHE (Abbott et al., 1986a and Abbott et al., 1986b). The overall model is presented in Chapter 3. Two main hydrological processes are used to describe flood propagation: (1) 2D overland flow based on the two-dimensional Saint Venant equations, (2) unsaturated sub-surface flows capturing infiltration of ponded flood waters and evapotranspiration in the root zone based on the 2-Layer Water Balance Method of Yan and Smith (1994). The 2D overland flow model relies on the 30m resolution SRTM digital elevation model (DEM) enhanced using a biorthogonal wavelet filter as proposed by Falorni et al (2005) and ground spot measurements. MIKE SHE multi-cell overland flow solver is used explicitly with computation of flow velocities on a 300m grid and water

level on a 30m grid. A uniform surface roughness value (Manning's $n = 0.056$) was calibrated using the 2008 flood extents.

The inundation model is used to generate 2,295 deterministic flood maps. Each map $dF(L_i, Q_j)$ corresponds to a breach occurring at location L_i with peak outflow Q_j . The maps are produced using a synthetic breach hydrograph defined by the time to peak t_a , the time at peak t_b (Q_j is considered constant between t_a and t_b) and time to recede t_c (Figure 4-4). Sensitivity of flood depths and extents to these time constants was investigated. A suitable hydrograph with parameters ($t_a = 1$ day; $t_b = 2$ day; $t_c = 14$ day) was identified and then validated using flood extents produced by a reconstitution of the 2008 event (Figure 4-5).

Figure 4-4 Conceptual illustration of the synthetic breach hydrograph structure ($t_a = 1$ day; $t_b = 2$ day; $t_c = 14$ day). The end of the synthetic hydrograph occurs at $t_a + t_b + t_c = 17$ days.

Figure 4-5 Comparison of the 2008 flood extents (a) acquired by UNOSAT (2008) on 27 July (before the breach) and 31 August (13 days after the breach) with (b) a synthetic breach hydrograph ($t_a = 1$ day; $t_b = 2$ day; $t_c = 14$ day). The peak discharge is estimated at $4,445 \text{ m}^3/\text{s}$ the equivalent of 85% of the main Koshi river discharge observation (Sinha, 2009).

For each of the 45 locations L_i , a synthetic breach hydrograph is applied to 3 grid cells of the 2D model ($3 \times 300\text{m}$) with peak outflows Q_j , varying from $700 \text{ m}^3/\text{s}$ to $37,450 \text{ m}^3/\text{s}$ with progressive increments from 200 to $1,000 \text{ m}^3 \cdot \text{s}^{-1}$ between peak values. To account for flood depth uncertainty, the final flood maps catalogue consists of probabilistic maps $pF(L_i, pQ_h)$ identified by the mean pQ_h [m^3/s] of two consecutive peak breach outflow scenarios Q_j and Q_{j+1} . Each probabilistic flood map contains, for each grid point in the 2D model domain, the mean μ and standard deviation σ of the local water depth

assumed to be normally distributed and established using the deterministic flood maps $dF(L_i, Q_j)$ and $dF(L_i, Q_{j+1})$ given by:

$$pQ_h = \frac{Q_j + Q_{j+1}}{2} \quad (4.5)$$

$$\mu[pF(L_i, pQ_h)] = \frac{dF(L_i, Q_j) + dF(L_i, Q_{j+1})}{2} \quad (4.6)$$

$$\sigma^2[pF(L_i, pQ_h)] = \sum_{l=j}^{l=j+1} (dF(L_i, Q_l) - \mu[pF(L_i, pQ_h)])^2 \quad (4.7)$$

where $i \in [1: 45]$ and $j, h \in [1: 50]$. In practical terms, each breaching event occurring at a given location L_i with a peak Q_i can be associated with the nearest pQ_h value as referenced in the flood maps catalogue. For the given event, the two statistical moments of the flood depth are subsequently used with the damage function to establish the event loss distribution.

4.3.4 Hydrological forcing

Probabilistic flood risk analyses are commonly produced for a number of return periods under the assumption that the loss return period is equal to the discharge return period. This approach relies on the simplification of the flood hydrograph structure and the application of well-established extreme value statistics, with the advantage of reducing the computational burden required for simulation. However, using fully continuous simulations, Falter et al. (2015) identified a considerable variability between the peak discharge and the damage probability at the sub-basin scale.

A similar continuous approach is applied here, and probabilistic hazard and risk results are established from all possible loadings occurring over a 1,000-year period. Thirty-three years (1977-2010) of historical daily discharge and yearly maximum discharge (1947-2013), capturing the most extreme events of 1954 and 1968, are used to

generate 1,000 years of synthetic daily data. The generation is carried out using the following approach:

- The peak discharges are treated using a Peak Over Threshold (POT) analysis and ranked by decreasing discharge intensities. The POT analysis assumes independent identically distributed observations. This is confirmed over a threshold of 7,000 m³/s by examination of an autocorrelation function (no significant autocorrelation at lag 1 or more). Peak values in synthetic discharge are regenerated according to a fitted Log-Pearson III distribution (shape = 4.48; scale = 6.36; threshold = 8.34) and redistributed over the original peak values according to their original ranks for remaining representative of historic patterns.
- A regression is applied to explain each day's discharge as a function of the discharge up to 3 days prior and 3 days after. The purpose of the regression is to leave only unexplained residual variation without any underlying patterns. Such residuals freely allow random resampling. Residuals associated with peak discharge are treated separately and taken instead over the threshold established from the POT.

The historical and synthetic annual maximum discharge densities and extreme levels (5 to 500 years) are illustrated in Figure 4-6. Water loading variations in the river model are generated using the synthetic daily discharge continuously over a 4-month monsoon period (June-October).

Figure 4-6 (a) Historical and synthetic annual maximum discharge density plots; and, (b) comparison of extreme levels for historical data, theoretical Log-Pearson III fitted to historical data and synthetic data

4.3.5 Exposure and vulnerability

In the terminology of flood risk assessment, exposure describes the assets susceptible to be damaged/affected if a hazard event occurs. Damage functions describe the susceptibility (e.g. economic loss) of the exposed assets to the hazard intensity (e.g. water level). In this study, rice crops and households are considered following the work done under the DHI-NTU Research Centre (2015). Land-use data (ICIMOD, 2010) and manually digitized settlements have been used to distribute spatially the elements at risk. A quantification of the exposure value for each element is proposed using the dasymetric mapping (Wunsch et al., 2009). Damage functions are developed using the ERN-Vulnerability package (ERN-AL 2009a).

Rice exposure is defined using the rice yield and market value available at the Village Development Committee (VDC) level and published by MoAD (2013) and adjusted to 2015 prices. The damage curves for rice for durations equal to or greater than 7 days are available from Shrestha et al. (2014), covering all growth stages. With these results, 6,000 ha of affected crops in Sunsari district (physical value of 9.43 NPR/m²) would lead to a 3.6 million US dollar (USD) loss (assuming 70% damage) which is in line with the 3.7 million USD crop damage recorded during the 2008 event (Devkota and Gyawali, 2015).

For residential assets, two types ('Cement' and 'Other') were considered. Vulnerability curves for cement and non-cement houses were developed from the field surveys conducted previously around the West Rapti River Basin by the Nepal Development Research Institute (NDRI) and adjusted to 2015 prices. The final distribution of exposed assets and damage functions is shown in Figure 4-7.

Figure 4-7 (a) Physical value (Nepalese Rupiah NPR/m²) of rice and residential assets in the flood prone area; (b) Damage curves for rice (DHI-NTU Research Centre, 2015:

adapted from Shrestha et al., 2014) and residential assets (DHI-NTU Research Centre, 2015; adapted from Perera et al., 2015).

4.3.6 Loss model

Risk analysis is performed using the CAPRA (Comprehensive Approach to Probabilistic Risk Assessment) platform (ERN-AL 2009a) as described in Chapter 3.

4.4 Result Analysis

Three morphological scenarios have been considered: Scenario 0Y (S0Y) using the surveyed river bed and Scenario 2Y (S2Y) and Scenario 5Y (S5Y) accumulating probable yearly morphological changes over 2-year and 5-year periods. For each scenario and each year of the 1,000-year of synthetic discharge 100 hydrodynamic simulations are performed leading to a total of 100,000 simulations per scenario. If failure occurs during a simulation i , breach location $L_{b,i}$ and peak outflow $Q_{b,i}$ are logged and the nearest $(L_{b,i}, Q_b)$ couple available in the inundation map catalogue is identified. In this study only breach flow is logged, under the assumption that overtopping always leads to failure and that overtopping flow volumes are negligible compared to those generated after breaching. The relevant inundation maps are finally assigned a frequency of occurrence for probabilistic hazard and risk analysis.

4.4.1 Impact on dike breach probability

For each scenario, the convergence of the Monte-Carlo simulation is tested. Breach frequencies after i simulations ($i \in [60,000; 70,000; 90,000; 100,000]$) are extracted and the percentage of frequency variations between batches $B_1(i \in [60,000; 70,000])$ and

B_2 ($i \in [90,000; 100,000]$) are compared at each location L_b . The locations with the most frequent breaching (Return Period $< 1,000$ year) show a reduction in percentage change of mean μ , standard deviation σ and maximum m from B_1 ($\mu = 0.7\%$; $\sigma = 2.1$; $m = 4.1\%$) to B_2 ($\mu = -0.06\%$; $\sigma = 1.4$; $m = 3.1\%$). The locations with less frequent breaching (Return Period $> 1,000$ year) still show considerable variations after 100,000 simulations (B_2 [$\mu = -7.7\%$; $\sigma = 24.8$; $m = 80\%$]). These results indicate that the simulations describe well breach hazards with return intervals less than 1,000 years but more simulation runs are required to adequately establish the rarest breach events.

With the terrain naturally higher along the right embankment, breaches are found to occur only along the left embankment. Changes in breach occurrences are analysed by failure mechanisms and probability of failure of the dike section associated with water loading when failure occurs (Table 4-1). Overall breach occurrences increase in a linear fashion from 4.8% (S0Y) to 5.65% (S5Y) with an approximate increase rate of 0.17%/year. The proportion of failure aggregated by failure mechanisms present less than 1.5% variation between S0Y, S2Y and S5Y. Piping failures represent around 75% of the total breaches while overtopping and micro-instability failure mechanisms share a similar proportion around 12%. Those results translate into an overall breach frequency starting at 22-year for S0Y and reduced to 18-year for S5Y. In comparison, overtopping frequencies, traditionally used as static criteria for structure design and flood risk evaluations, are lesser with overtopping occurring with a 184-year return period in S0Y further reduced to 153-year in S5Y. The number of breaches increase relatively uniformly (6.3%-9%) across the different mechanisms during S2Y with a slightly sharper increase (+20%) noticed for the piping mechanism in S5Y.

Table 4-1 **Statistics for breach occurrences for the full ensemble of simulations, proportion of the breach mechanisms triggering failure for Scenarios S0Y, S2Y and S5Y and breach variations**

Breach mechanism	Proportion (% of total breaches)			Number breaches	Breach variation (% of S0Y breaches)	
	S0Y	S2Y	S5Y		S2Y	S5Y
Overtopping	12.05	12.22	11.52	576	+ 9.0	+ 12.5
Piping	75.04	75.01	76.48	3,586	+ 7.5	+ 20.0
Micro-instability	12.91	12.77	12	617	+ 6.3	+ 9.4
Breach occurrence (% of total simulations)	4.80	5.16	5.65			

Breach variations are further analysed by locations along the left embankment. For S0Y, breaching occurred at 14 locations in total, of which 6 showed a breach frequency below 1,000 years (Figure 6a). The highest frequencies were recorded at L27 and L34 with respective return periods of 61 years and 71 years. A cluster of 3 consecutive sections L19, L20 and L21 in the upstream reach (Km 25) produced breaches in the same order of frequencies (160, 177 and 454 years). The analysis of variations in breach frequencies for S2Y and for breach return periods less than 1,000 years (Figure 6a) exacerbate failure of the most fragile embankment sections (L21, L27 and L34) with a marked increase in frequencies (between 8% and +12%) at those locations. In this scenario, a decrease (-7%) of L20 failure frequencies is notable and attributed to the local dike crest and toe elevation distribution rather than the minimal difference in bed level change and cross-sectional area

loss. In S5Y, all sections showed an increase (+20% on average) in failure frequencies with a more marked increase (+23%) in the upstream sections (L19, L20, L21) compared to the remaining downstream sections (+16% for L27, L31 and L34).

This spatial redistribution of failure frequencies is attributed to the difference in bed level increase distributions at Km 22 ($\mu= 47\text{mm/year}$; $\sigma=7$) and Km 37 ($\mu= 33\text{mm/year}$; $\sigma=19$) (Figure 4-8a and b). In S2Y, the higher standard deviation at Km 37 can frequently produce bed level increases higher than those at Km 22 sections. However, in S5Y, the higher mean and lower standard deviation values of morphological change distributions at Km 22 lead (after 5 sampling) to a consistently higher bed levels and failure frequencies. With the adjacent floodplain sloping south, it can be expected that some areas can be inundated independently of the breach location. Breach frequencies are then accumulated long the embankment for the 3 scenarios (Figure 4-8c). Three distinctive drops are identified at L21, L27 and L34. For S0Y, drops occur at the 70, 32 and 21-year return periods. An increase in accumulated frequencies is clearly visible for S5Y at L19, L20 and L21 sections, producing a reduced return period of 57 year at L21 and 27 and 17-year at L27 and L34.

Figure 4-8 Analysis summary of breaches along the left embankment between 20 km and 45 km with (a) Breach frequencies for each section for Scenario S0Y; (b) percentage change in frequencies for Scenarios S2Y and S5Y and for section with breach return period less than 1,000Y; (c) accumulated breach frequencies downstream the embankment for Scenarios S0Y, S2Y and S5Y

4.4.2 Impact on flood hazard

Probabilistic flood hazard maps capturing the overall probability of flooding at a given point have been produced for the 25, 50, 100 and 500-year return period. The convergence of flood hazards is tested for the three scenarios by quantifying changes in flood depths between batches B_1 and B_2 and for inundation return periods 25 and 500 year.

The analysis showed that, across all scenarios, flood depth differences greater than 10 cm are reduced for the 25-year from 0.5% to 0.01% of total flood extents for B_1 and B_2 respectively and from 0.7% to 0.3% for the 500-year. It is assumed that the convergence for those return intervals ensure convergence of the return periods below 1,000-year.

Table 4-2 Statistics for flood extent increase for S2Y and S5Y, total and for 3 different flood depth intervals

Return Period [year]	S0Y - Flood extent [km ²]	Flood extent increase [% extent of S0Y]		Flood extent increase for different water depth [m] intervals [% extent of S0Y]					
				S2Y			S5Y		
		S2Y	S5Y	0.1-0.3	0.3-0.5	>0.5	0.1-0.3	0.3-0.5	>0.5
25	118	22.6	56.6	61.6	6.2	0.9	71.5	36.5	18.9
50	296	2.3	6.6	11.1	0.0	0.0	34.8	5.9	0.2
100	438	3.1	8.9	8.3	0.2	0.0	35.8	3.6	1.3
500	604	0.1	0.5	1.5	0.1	0.0	4.0	0.3	0.0

The 25, 50, 100 and 500-year inundation maps (Figure 4-9 a) illustrate the sudden changes in flood extents from the South-West of the model domain towards the North following the embankment and in line with the accumulated failure frequencies at L34, L27 and L19 described in Table 4-2. Differences in inundation depth for S2Y and S5Y (Figure 4-9 b and c) clearly suggest that higher frequency inundation extents are the most impacted by morphological and failure frequency changes. The South-Eastern floodplain being inundated by nearly all flooding events show the largest aggravation in terms of flood extents and depths, corresponding to an increase in failure frequencies along the full embankment and larger variations in breach outflow regimes. For the 25-year, flood extents increase by 22.6% under S2Y and 61.6% of the S0Y inundation area increases by 10cm to 30cm (Table 4-2). In the case of S5Y, flood extents increase by 56.6% and the equivalent of 19% of the original S0Y flood extent increase by more than 50 cm. The increase in flood extents is lower for the 50 and 100-year (around 3% for S2Y and 8% for

S5Y) with an impact on the flood depth limited to around 10% and 30% of the original S0Y area and confined below 30cm. With L19 having a failure return period of 454 year and nearly no failure occurring in the embankment section upstream L19, variation in inundation extents for the 500-year inundation map are only marginal (0.5% for S5Y). Main changes in flood depth (4% of the area less than 30cm) are localized near the embankment breach location and more susceptible to the randomized breach dimensions.

Figure 4-9 (a) 25, 50, 100 and 500-year flood depth maps for Scenario S0Y; (b) flood depth differences for 25, 50, 100 and 500-year between Scenarios S2Y and S0Y; (c) flood depth differences for 25, 50, 100 and 500 year between Scenarios S5Y and S0Y

4.4.3 Impact on flood risk

Annual Average Loss (AAL) and Loss Exceedance Probability (LEP) metrics are used to analyse flood risks. As for breach and inundation hazard, convergence is tested by computing changes in AAL between B_1 and B_2 . Across the three scenarios the mean and maximum AAL variation are reduced from 1.43% to 0.73% and 1.69% to 1.01% respectively. An overall increment in loss frequency is captured by the AAL (Figure 4-10a). The AAL increases quasi linearly with the expected yearly averaged morphological changes leading to a 7% and 20% AAL increase for S2Y and S5Y compared to S0Y. The AAL increase due to morphological variations is expected to reach 3-4% per year.

The LEP curves have been established for the three scenarios (Figure 4-10b). Losses are found to start occurring at 21, 19 and 18-year return periods for S0Y, S2Y and S5Y scenarios respectively and below the design level of the embankment (estimated to be above 150 year). Losses are reproduced up to approximately 1,000-year where the full convergence of the MC simulation was achieved for embankment failure. Losses are described continuously without sudden jumps around the embankment design frequency

as commonly experienced when using a binary approach (loss/no loss) when estimating losses behind structures. The LEP curves show an overall reduction of S0Y return periods for S2Y and S5Y at similar loss levels.

Details of the variations across the LEP curve indicate an overall sustained impact of the morphological change across the higher frequency losses (20-400 year) (Figure 4-10c). Three phases are noticeable: 1) a relatively constant increased frequency between 21 (highest loss frequency) and 40 year for both scenarios (S2Y:6% and S5Y:16%); 2) the rate of increased frequencies rises from 5% to 10% between 40 and 330 year for S2Y and more sharply from 16% to 22% between 40 and 115 year for S5Y; 3) the rates of frequency increase fall significantly after the 115 year peak for S5Y and the 330 year peak for S2Y with almost no change in loss frequency above the 1,000 year for S2Y. Phase 1 is attributed to the relatively constant increase in breach frequency over S2Y and S5Y of the 2 most sensitive embankment sections L27 and L34. Phase 2 sees an increase in breach frequencies of the remaining sensitive embankment sections L21. The sharper increase of S5Y is attributed to the higher increase in frequency of L21 between S2Y and S5Y (12% vs 15%) but is also associated with the consequent increase in breach frequencies of the sections L19 and L20 directly surrounding L21 in S5Y (Figure 4-8). In phase 3, lower variation in inundation extent and depth (Table 4-2 and Figure 4-9) translate into a reduction in risk level variations.

Figure 4-10 (a) Evolution of Annual Average Loss as a function of accumulated yearly averaged bed level changes (S2Y = 2 year, S5Y = 5 year); (b) Loss Exceedance Probability curve for Scenario S0Y (baseline), S2Y and S5Y; (c) reduction of S0Y return period associated with Scenario S2Y and S5Y for a series of loss thresholds

4.5 Discussion

The development of the innovative Flood Hazard System FHS modelling framework described here allowed for the first time the quantification of flood risk variation accounting for embankment breaching and river morpho-dynamics.

4.5.1 Lessons for flood risk analysis

The application of the FHS on the Upper Koshi River, Nepal, showed a clear impact of morpho-dynamics on hazard and risk patterns. Over 2 and 5-year time windows, corresponding to typical durations for risk assessment studies, the AAL was found to increase by 7% and 20%. The results also indicated changes in loss distribution across the 20-1,000-year interval with higher variability (up to +20%) in loss frequency for the low return period events (20 to 300-year in this specific case) and lower for the infrequent losses. These results presented here are very dependent on the river reach under consideration. In the case of the Koshi River, the high sediment influx and fast aggradation rate of the river bed can largely affect the time scale and impacts on the risks results. Other river systems might react differently, possibly requiring longer time scale to experience significant changes or even showing a decrease in risks where erosion is a dominant process. With this in mind, the overall results are well aligned with the previous studies of Pender et al. (2016), Lane et al (2007) and Neuhold (2009) which identified the larger variation in flood hazards within the lower return periods used for analysis (0.5 year to 100-year events). With risk understanding and planning decisions relying largely on the assessment of the most frequent losses, this study illustrated the potentially significant role of morpho-dynamics in the overall risk picture.

The study also illustrated the importance of considering dike breach and continuous simulations in flood risk studies. Losses have been established continuously from a 20-year return period in areas protected by embankments with design criteria above 150 years. The consideration of stochastic structure breaching processes clearly provides an improved picture of flood hazards and risks compared to a binary approach in which the potential of flooding or not would be associated with the protection level of the designed structures. Using a simplified analysis of the LEP curve, Ward et al. (2011) previously identified that a binary consideration of dike system to calculate flood losses might lead to a 50% error in annual losses. Using a similar approach and assuming no losses below the 150-year level, the AAL for S0Y would be reduced by approximately 80%.

The full range of potential hydrological loadings were considered without constraining the analysis to pre-defined flow return periods, as commonly done in flood risk analysis. By allowing the computation of the overall probability of inundation in a single point it is possible to get inundation and losses without forcing the frequency for which we expect the flood or losses to occur. In this study, losses were incurred for single discharge events of 5-year return period or less against a minimum of 20 year with the continuous approach. These results illustrate the benefit of continuous simulations for improved risk metrics and support the findings of Falter et al. (2015) which identified large variability between peak discharge and damage frequencies at the sub-basin scale.

Ultimately the study illustrated that, by considering continuous simulations and probabilistic defense failure, it is possible to produce cost optimized flood management strategies. In this application, sediment management and maintenance and rehabilitation of the existing defense system at critical locations should be prioritized to control flood hazard increase over time. The approach would also help develop and optimize variable

performance criteria to design flood defense structures at the reach scale taking into consideration the specificities of the flow dynamics and exposure accumulation in the river and floodplain system.

4.5.2 Limitations and recommendations

In contrast to the methods of Neuher et al (2009) and Pender et al. (2016), the model proposed does not explicitly simulate sedimentation processes. This choice allows increases in modelling efficiency and the consideration of a wider range of scenarios but requires in return an adequate assessment of bed level variation distributions. In the present application, yearly average estimates of past morphological variations extracted from Hooning (2011) and the specific morphological impacts in absolute terms, suffer for assuming stationarity of the past sedimentation trends over the next 5 years. The parametrization of the morphological variations in this study or future applications should be best applied in conjunction with detailed sediment transport studies using, for example, the framework proposed by Pender et al. (2016). With more detailed morphological information, the modelling system would also benefit from additional control of the sediment mass balance along the reach.

Using the most advanced formulations proposed by Apel et al (2006) and Vorogushyn et al. (2009), the study considered three failure mechanisms: overtopping, piping and micro-instability. Those processes are known for being pre-dominant in river system such as the Elbe, Germany (Vorogushyn et al., 2010) or the Po River

(Domeneghetti et al., 2012) but might be an over-simplification of the breaching processes along the Upper Koshi River dike. The high sediment load deposited, and high flow velocities can lead to frequent lateral migration of the main river course within the embankment itself, potentially weakening sections of it. Since 1963, three breaches have been recorded (Dixit, 2009) but little evidence exists regarding failure mechanisms, frequencies and characteristics. Hoening (2011) suggested the 2008 breach was a consequence of channel deepening at the inner side of the embankment followed by dike toe erosion and then collapse. In the Koshi River, more complex sedimentation modelling should ideally be included for an improved understanding of breach hazards. However, considering such processes within a probabilistic framework as applied here is limited by 1) the computational burden associated with simulating complex 2 or 3-dimensional flow and deposition patterns and 2) the availability of fragility curves able to describe toe erosion and dike collapse as a function of varying spatial and temporal loadings (including both water level and flow velocities). The stochastic failure model and simplified processes are considered suitable in this study to understand the variability of breach frequencies under changing morphological scenarios. Fragility curves provide the opportunity to describe failure in a stochastic manner for areas where ground data is limited. However, the breach frequencies and risk metrics might suffer, in absolute terms, from the simplification of the processes and from the limited data sources used for the fragility curves development. Additional surveys would help reduce the uncertainty associated with the fragility curves used.

While morphological and breaching processes are particularly complex in the Koshi River, the River-Floodplain system is more simple than other systems. A single layer of flood defenses exist and two-way flow exchanges between the river and floodplain or

multiple breaches are most unlikely due to the high gradient between the river bed and floodplain. The simplified FHS modelling framework, with a decoupled 1D network and a catalogue of pre-run 2D model, is particularly suited for the simple river-floodplain systems as it allows for a large number of simulations capturing uncertainty and variability within the river and embankment system. Similar approaches have been developed by van Mierlo (2007), Vorogushyn et al. (2010) or Courage et al. (2013). The decoupled inundation model informed by a predetermined inundation catalogue is an innovative and distinct methodology, as it provides a very efficient approach to test the influence of morpho-dynamics or provide the opportunities to easily update the hazard and risk metrics with new information, potentially even in real-time. However, despite the advantages it provides, the use of a synthetic breach hydrograph and the predetermined inundation catalogue introduce additional uncertainty into the risk modelling chain. Further analysis should aim at quantifying such uncertainties by simulating the exact breach hydrograph and subsequent inundations with a dynamically coupled FHS model such as the IHAM (Vorogushyn et al, 2010). Finally, while the simplified FHS model is judged adequate for the present case study, it might not be suitable for application in more complex floodplain systems.

4.6 Summary

This study presented an efficient probabilistic hazard and risk modelling approach using continuous simulations, which were able to capture uncertainty and variability associated with river conveyance and dike failure potential. The application of the model in the Koshi River, Nepal, allowed the identification, over a 5-year period of river bed aggradation, potential changes in expected dike failure locations and frequencies,

probabilistic inundation extents, and the distribution of flood depths and losses. Due to limitations in available data and model structure, the absolute failure and loss frequencies for the Koshi River should be regarded as indicative. The results were also deeply dependent on the case investigated. However, the relative variations produced by the different scenarios support the general conclusions that river bed aggradation impacts the distribution of higher frequency losses which might be critical for proper cost-benefit analysis and decision-making. In the case of river reaches protected by embankments, the loss frequencies to be affected can be expected to occur below the design criteria of the protection scheme in place. The use of continuous simulations and a probabilistic dike breach model also pointed out the potential considerable differences in risk metrics when compared with traditional approach for flood risk analysis based on binary treatment (flood/no flood) of flood protection structures or direct association of between discharge and loss frequencies.

In summary, the consideration of the variability of the full flood hazard system under continuous simulation provides an improved understanding of flood risks required to derive cost optimized management strategies. The modelling framework and the approach proposed have the potential to be transferred to many river systems where dike failure potential or changes in channel conveyance, originating from sedimentation or debris blockage of bridges and structures, must be accounted for.

CHAPTER 5 A Probabilistic Risk Modelling Chain for Analysis of Regional Flood Events

5.1 Introduction

Flood management practice is increasingly addressed from a risk perspective. The related approaches aim at quantifying the hazard, e.g. inundation depths and extents, with its consequences represented by the elements at risk and their susceptibility to flood (e.g. Kron, 2005; Merz et al., 2010). Such a practice forms today the basis required by planners and decision makers to establish portfolios of cost-effective measures to minimize the impact of floods on their economy and population. Flood risk analysis is traditionally carried out in a series of steps involving: (i) the definition of several (or one) T-year return period (RP) discharges or rainfall events developed from extreme value analysis of historical records within a catchment; (ii) the mapping of the T-year inundation scenarios using a T-year event applied uniformly at the reach or catchment scale; (iii) the computation of the T-year damage associated with each T-year flood map using geospatial layers of exposed elements and associated damage functions. As an example, the European Flood Directive on the Assessment and Management of Flood Risks recommends its member states to perform this exercise for 3 (low, medium and high) RPs (European Commission, 2007).

The assumption of a spatially uniform RP and the association of the same RP to describe the event, inundation scenario and damage frequency holds for small scale studies but not necessarily when larger scales are considered. Falter et al. (2015) demonstrated that spatial variations could exist in terms of hazard and losses for realistic event scenarios at the reach scale. Thiessen et al. (2015) and Schneeberger et al. (2017) concluded that the use of uniform RPs over large-scale systems could lead to an overestimation of the flood

risks. Different approaches should then be proposed to define regional scale risk management plans and policies, and account for the spatial spreading and temporal clustering of flooding across different administrative units, regions or countries to better describe risk cumuli (e.g. Kundzewicz et al., 2013; Jongman et al., 2014).

Recent research works have investigated new methodologies to capture the spatial heterogeneity of risks over large areas. Most methods make use of multivariate frequency analysis (MFA) to model spatial dependencies of discharges (or hazard) at multiple locations (Ghizzoni et al., 2012; Neal et al., 2013; Schneeberger et al., 2017) and between losses of correlated regions (Timonina et al., 2015; Jongman et al., 2014). However, these approaches failed at capturing the dependencies of temporal processes that drive flooding. To overcome these limitations, Serinaldi and Kilsby (2017) applied MFA with a continuous simulation approach to produce spatially and temporally correlated weekly discharge maxima. However, these approaches are still limited to the reproduction of instantaneous discharge peaks and do not include other flood hydrograph characteristics (e.g. volume) important for hazard and risk accumulation estimation.

While more complex and adding uncertainties in the modelling chain, using continuous rainfall and runoff simulation, instead of direct discharge observation and MFA methods, can present several benefits: (1) the event set quality can be enhanced as the simulation accounts for antecedent conditions (see Grimaldi et al., 2013; Haberlandt & Radtke, 2014); (2) the spatial and temporal variation in peaks, volumes and hydrograph shapes are represented using the full description of the routing and accumulation processes; (3) the historical precipitation records are independent of anthropogenic influences that can alter the flow over time (e.g. dikes, dams or land-use); (4) the event set can be perturbed for climate change studies.

The application of a continuous hydrological simulation will generate a realistic set of hazard scenarios spatially and temporally coherent at the regional scale. With this approach, no pre-defined assumption is made between the RP of the discharge peak locally and a possible RP of the event hazard at the regional scale. The continuous simulation concept can then be extended and applied to the last link of the risk modelling chain: by simulating regional losses for each regional hazard scenario, regional risk metrics can be established without any assumption made between the RPs of the loss and the hazard. Falter et al. (2015) introduced this approach and proposed a coupled model chain relying on a multi-site weather generator, a rainfall-runoff model, a river channel and floodplain model, and a loss model. The coupled model chain was applied to the meso-scale Mulde catchment in Germany and forced with 10,000 years of synthetic rainfall. Using this approach, they demonstrated that variability exists between peak discharge and loss RPs at the catchment and sub-catchment scales.

To date, few studies (Falter et al., 2015; Schneeberger et al., 2017) have tried to describe adequately risk at the regional scale or understand the limitations of using a uniform T-year RP as currently practiced. Many proposed methods allow to capture the spatial heterogeneity of flood events but rarely reproduce the temporal dependencies of flooding processes. Besides, no approaches have been proposed that can account for other possible variabilities in the hazard or loss models. In this study, we aim to investigate in details the differences between simplified event set structures (e.g. uniform T-year RP) and spatially coherent and continuous simulations on flood hazard and risks. To the author knowledge, comprehensive analyses of this type have not been intended to date. For this purpose, we developed a continuous risk modelling chain. The system relies on synthetic weather data produced with a multi-site multivariate weather generator. The generated

weather fields are used to run continuously a rainfall-runoff model that provides inflow to a river routing and floodplain model. The spatially coherent inundation maps are then used to generate different event sets (with or without spatial variations). The different event catalogues are used to produce losses using a probabilistic loss model. The model chain is applied to four of the main tributaries of the river Ganges draining the State of Uttarakhand, India.

5.2 Flood risk modelling chain

Figure 5-1 shows the modelling chain for flood hazard and risk calculations. The modelling chain is similar to Falter et al. (2015) but enhanced with a probabilistic representation of the hazard and losses and a specific segregation of the events structure components (particularly the spatial temporal heterogeneity of the sets). The chain relies on the generation of long-term continuous weather variables synthetically derived from a multi-site weather generator. The long-term time series are used to produce continuous discharge and inundation maps. Different event sets are produced from the continuous and spatially coherent data and different degrees of simplification of its underlying structure (e.g. spatial and discharge variability) are passed to investigate the significance of its different components. Catalogues of inundation maps corresponding to each event set are combined and used for damage modelling.

The probabilistic flood risk modelling is carried out using existing software packages (i.e. ARC GIS, MIKE, and CAPRA). The overall hydrodynamic and Monte-Carlo simulations rely on the MIKE1D Application Programming Interface (API) (see Unphon 2009), implemented in C#. Three open-source multi-site weather generators have been tested including MulGETS (Chen et al., 2014) and TripleM (Breinl et al., 2013; Breinl et

al., 2015) implemented in MATLAB and a modified version of KNN-CAD v4 (King et al., 2015) in Python (Mandal et al., 2017). Pre- and post-processing of data and results and extreme value analysis are performed with the statistical software R and ‘extRemes’ package.

Figure 5-1 Schematization of the main modelling components and event set preparation adopted for flood hazard and risk calculations

5.2.1 Synthetic weather generation

In recent years numerous statistically based multi-site weather generators have been developed (e.g. Hundecha et al., 2013; Breinl et al., 2013; Evin et al., 2018; Chen et al., 2015). They have in most cases been tested in temperate climate and in terms of their capacity to reproduce historical rainfall correlations and statistics. Besides, few direct comparisons of multi-site weather generator performance have been done. In their study, Vallam & Qin (2016) demonstrated that performances may vary with the specific characteristics of rainfall to be preserved (i.e. extreme values and spatial correlation). The

application of multi-site weather generators over large scale and their capacity to reproduce hydrological extremes remains largely unexplored. Falter et al. (2015) demonstrated the ability of the multi-site rainfall generator of Hundedcha et al. (2012) to reproduce discharge extremes in the Mulde catchment (7,400 km²), Germany. Chen et al. (2015) demonstrated the ability of MulGETS to reproduce, although with some overestimation, the extreme flows characteristics of Lac-Saint-Jean watershed (73,800 km²) in Quebec. Three multisite weather generators are applied to produce daily weather variables. The weather generators have been selected according to the following criteria: (i) they are open-source and their algorithm are readily available, (ii) they include several type of generation algorithms including parametric and non-parametric models, (ii) their underlying algorithms have been validated in numerous case studies. The representativeness of the three weather generators to reproduce discharge extreme observations are tested and the best performing weather generator, according to this criteria, is used for the rest of the study.

k-nearest neighbour – KNN-CAD v4

The KNN-CAD v4 is a block-bootstrap non-parametric generator with perturbation based on the K-nearest neighbour (KNN) algorithm (King et al. 2015). KNN types of weather generators have been well documented and applied in many research studies, proving to produce adequately rainfall and temperature (Sharma & Lall, 1999; Buishand and Brandsma, 2001; Bannayan & Hoogenboom, 2008; Ly & Qin, 2014; Vallam & Qin, 2016) and extreme flows (Leander & Buishand, 2007; Wit & Buishand, 2007).

In this version, King et al. (2015) introduced two features to the KNN resampling procedure. First, a block resampling procedure is used to improve temporal correlations of particularly for temperature, which can affect hydrological simulation where snow accumulation and melting are crucial for flooding events (King, 2012). Instead of

resampling one day at a time, the block resampling approach consists in resampling B days to preserve the intrinsic historical variable correlation. Secondly, a perturbation of the observed data, resampled by block, is introduced to produce values outside the observed range. Perturbated variable p expressed in weather variable units (e.g. [mm] for precipitation) or of the resampled variable v (with same unit as p) is given for a location j and a day t as (King et al., 2015):

$$p_t^j = v_t^j + (1 - \lambda)Z_t \quad (5.1)$$

Where λ is a chosen perturbation factor between $[0;1]$ kept as high as possible to preserve spatial correlation and Z_t is sampled from a probability distribution defined differently for precipitation and temperature.

For precipitation, the perturbation factor Z_t comes from a two-parameter log distribution. The parameters are estimated using the method of moments (Singh, 1998) with the mean equal to v_t^j and the standard deviation established from the window of non-zero rainfall at j centred in t and with length B . For temperature Z_t comes from a normal distribution with mean v_t^j and standard deviation established from the k-nearest neighbour vector, with the perturbed value controlled within the minimum and maximum observation range.

Multisite Markov Model – TripleM

The Multisite Markov Model (TripleM) is a reduced complexity multi-site generator developed by Breinl et al. (2013). The model, semi-parametric in nature, relies on a Markov process to simulate rainfall occurrence and a parametric sampling and reshuffling of the precipitation amounts (see Clark et al., 2004). The overall process is explained in details by Breinl et al. (2013, 2015, 2017) and summarized as follows: (1) daily snapshot of precipitation occurrences are clustered according to their similarities (using binary or k-

means methods); (2) a Markov process simulates synthetic time-series of clustered vectors as function of a number of previous days; (3) each clustered vector is replaced by a daily precipitation snapshot sampled from the same cluster; (4) synthetic rainfall values are generated at each location using a fitted distribution (e.g. Weibull) and optionally using a correlated Cholesky decomposition (Watkins, 2010); (5) sampled rainfall amounts are reshuffled based on their original ranks in the vectors produced in step (3) to preserve correlation between stations. The TripleM generates precipitation field which can be complemented by temperature and evaporation fields simulated using KNN.

MulGETS

The MulGETS weather generator (Brisette et al., 2007; Chen et al., 2014) follows the approach of Wilks (1998) to simulate daily precipitation and minimum/maximum temperature using temporally independent but spatially correlated random numbers. The MulGETS generates precipitation and temperature fields which can be complemented by evaporation fields simulated using KNN. In MulGETS, correlation matrices for precipitation occurrence and amounts are first created. Serial rainfall is described, over the length of the simulated period, using serial precipitation occurrence and amounts with preserved rank correlation based on the distribution-free method of Iman and Conover (1982).

Each location is then treated as a single site weather generator to produce the spatially correlated rainfall occurrences or amounts. Occurrences are generated from a first-order two-state Markov chain considering wet and dry status of the 2 previous days. Amounts are produced from a multi-gamma (or multi-exponential) distribution as proposed by Brisette et al. (2007) that link mean precipitation amounts to occurrence at the watershed scale. The multi-gamma distribution is based on indexing of rainfall occurrence

at the scale of the basin for each non-zero rainfall day at each location. The indices produced are grouped by classes (and seasons) to produce at least 50 events in each class (e.g. 9 classes are produced in a first step, merging of classes occurs if neighbour classes contain less than 50 events). For each class, a gamma distribution is defined using the mean and standard deviation of precipitation produced by the events. This approach ensures that rainfall amounts (mean and standard deviation) are linked to the rainfall occurrence at the catchment scale, i.e. larger precipitation amounts are generated when the number of wet locations increases.

5.2.2 Flood hazard modelling

Hydrological modelling is carried out using the NAM rainfall-runoff model developed at the Institute of Hydrodynamics and Hydraulic Engineering at the Technical University of Denmark (Nielsen and Hansen, 1973) and widely used in hydrological studies (see for example: Rulin et al., 2008; Wang et al., 2016). The NAM model is presented in Chapter 3. The continuous rainfall, temperature and potential evaporation fields are generated using the multisite weather generator and the hydrological model run continuously. The events above the 5-year RP are identified and used for hydrodynamic simulation.

The hydrodynamic modelling is performed with the one-dimensional engine MIKE1D (DHI, 2017a), which is based on the full St Venant equations (see Chapter 3). Where overland flow patterns are parallel to the main river, such treatment of flow routing in channels can be extended to simulate floodplain flows, producing good approximations of the main flood characteristics (Horritt and Bates, 2002). The 1D river channel model

could also be coupled dynamically to 2D hydrodynamic models to represent more complex floodplain flow patterns.

5.2.3 Event sets preparation

Three main types of event sets are generated at the regional level to identify the contribution of different elements of the event set structure: (i) Event Set A capturing all possible events occurring during the simulation period while preserving the spatially coherency at the regional scale, (ii) Event Set B capturing all possible events at the regional scale but assuming full correlation between the RP of the local events (uniform T-year RP regionally), and (iii) Event Set C, similar to Event Set B with uniform T-year RP at the regional scale, but for only a few events of selected RP.

Event Set A represents a realistic and exhaustive set of scenarios capturing both discharge and spatial-temporal variability. Continuous simulations are performed and yearly discharge peaks identified and ordered by rank at each location l where risk analysis is performed. To reduce the number of hydrodynamic simulations, only local events with a peak exceeding the 5-year RP are conserved (e.g. for 5,000 year of data, the 1,000 largest peaks are conserved at each location) under the assumption that no losses will occur below this RP. An event is defined using a 5-day window around the date of a peak at each location. Each event is associated with the same frequency of occurrence equal to the inverse of the number of years simulated. In this scenario, we can expect to have one regional event composed by local events of different RPs.

$$Event\ set\ A \left\{ \begin{array}{l} Event_i = \cup_l Event_l(p) \\ F(Event_i) = 1/X \end{array} \right. \quad (5.2)$$

where Event Set A is composed by N Events ($i = 1, 2, \dots, N$); N [-] is the total number of peak combinations considering the periods when local events occur at each location l ; $l = \{Loc1, Loc2, \dots, LocL\}$ the L locations considered for risk analysis; $Event_l(p)$ is the event occurring at location l during period p ; $F(Event_i)$ [-] is the annual probability of occurrence of $Event_i$; X [-] is the number of years of synthetic weather data simulated.

Event Set B assumes full correlation regionally between RPs of local events. The regional event set is built from Event Set A but the spatial-temporal structure of the regional events is destroyed. Here, instead of grouping the events by date of occurrence, the events are grouped by their rank in terms of discharge at each location:

$$Event\ set\ B \left\{ \begin{array}{l} Event_j = \cup_l Event_l(j) \\ F(Event_j) = 1/X \end{array} \right. \quad (5.3)$$

where Event Set B is composed by Y events ($j = 1, 2, \dots, Y$); *Limited discrete events*; $Event_l(j)$ is the event occurring at location l with rank j ; $F(Event_j)$ [-] is the annual probability of occurrence of $Event_j$.

Event set C is analogous to the event set structure typically used for risk analysis. Here, a few T-year RPs are used to map hazards and estimate risks. The event set is built by extracting single events by using their ranks from Event Set B, where the rank indexes should correspond to the T-year RPs used. With this formulation, Event Set C is constituted by a limited number of events representing an exceedance level in risk estimation:

$$Event\ set\ C\ \left\{ \begin{array}{l} Event_k = \cup_l Event_l(k) \\ F(Event_k) = k/X \end{array} \right. \quad (5.4)$$

where Event Set C is composed by k events ($k = 1, 2, \dots, K$); K is the fixed number of ranked events (or RPs) investigated; $Event_l(k)$ is the event occurring at location l with rank k ; $F(Event_k)$ [-] is the annual probability of occurrence of $Event_k$.

5.2.4 Risk modelling

The open-source “Comprehensive Approach to Probabilistic Risk Assessment” platform (CAPRA) (ERN-AL 2009a) is used for risk computation. The platform design allows to perform probabilistic hazards (e.g. earthquakes, flooding, and hurricanes) and risk analysis (see Chapter 3). The platform has been frequently used in risk studies (Marulanda et al. 2013; Salgado-Gálvez et al., 2014; Velasquez et al., 2014; Oliver et al., 2018). CAPRA-GIS (ERN-AL, 2011) computes risk metrics such as Average Annual Loss (AAL) and Loss Exceedance Probability (LEP) from catalogues of hazard footprints and assets (exposure) associated with their damage functions. The LEP curve establishes the frequencies of occurrence of losses originating from flooding events and exposed assets across an event set of all plausible scenarios and accounting for the uncertainties in water depth and the damage potential. The Average Annual Loss (AAL) [\$] is calculated as the integral value of the LEP curve. Formulation details are provided in ERN-AL (2009b) and Oliver et al. (2018).

It is common practice, in flood risk analysis, to produce an event set limited to only a few selected and unique exceedance probabilities (e.g. Event Set C). In this case the AAL can be approximated using the trapezoidal rule (Meyer et al., 2009):

$$AAL = \sum_{i=1}^{N-1} \frac{L(Event_i) + L(Event_{i+1})}{2} [F(Event_{i+1}) - F(Event_i)] \quad (5.5)$$

where N corresponds to a number of single and unique probabilities of losses in the event set, $L(Event_i)$ [\$] is the loss associated with $Event_i$ and $F(Event_i)$ [-] is the annual probability of $Event_i$.

5.3 Application to the Uttarakhand Province

5.3.1 Study area

The study domain covers four catchments in Uttarakhand Province, India: the Yamuna (YAM), Sarda (SAR), Kosi (KOS) and Upper Ganges (GAN) (Figure 5-2). Physio-graphically, the Uttarakhand Province can be divided into three zones: Himalayas, the Shivaliks and the Tarai regions. Elevation ranges from 200 m to 7,818 m (Mount Nanda Devi) with approximately 50% of the area characterized by steep slopes and above 2,000 m altitude. Uttarakhand presents two main climatic regions. The climate in the northern and largest part of Uttarakhand is typically Himalayan with cold winters and snowfall, intense rainfall during the monsoon, and mild summers. The area is bestowed with a relatively high average annual rainfall (around 1,200 mm) reaching up to 2,400 mm in some areas with 82% received during the monsoon season (Kumar, 2017). The mountain range itself exerts an appreciable extent of influence on monsoon and rainfall patterns depending on altitude and orientation. The southern slope receives high rainfall with longer sunshine duration and thus the area normally remains dry due to high rate of evapotranspiration. On the contrary, the northern slope receives lesser rainfall, though remains moist due to short sunshine duration.

Uttarakhand hosts 10.1 million inhabitants and is prone to natural hazards mainly caused by water (e.g. floods, flash floods, heavy precipitation, avalanches, landslides, Glacier Lake Outburst Flow) as well as cold waves and earthquakes. The recent calamity due to heavy downpour and subsequent devastating floods in various rivers on 16-17 June 2013 led to heavy losses of life and property (see Das, 2013; Rana et al., 2013). While flash floods are predominant hazards in the mountain zones, the low-lying areas in the Terai and Dun valleys, which are more densely populated and economically active, could be affected more severely by fluvial flooding. To better understand the susceptibility of the State to natural disasters, this study investigates the spatial dynamics of flood hazards and risks at the outlet of the four main rivers draining the State.

Figure 5-2 Study domain including the four major river catchments in Uttarakhand with hydrological and hydrodynamic model components (sub-catchments and river network) and flood mapping locations

Data used for the flood hazard model were collected with the support of the Project Implementation Unit (PIU) and originated from the Central Water Commission (CWC), the India Meteorological Department (IMD), the Uttarakhand Irrigation Department, the National Remote Sensing Center (NRSC), publicly available datasets (e.g. GPM, SRTM), and field surveys. The exposure and vulnerability models were based on DHI et al. (2017) and published socio-economic statistics and studies, publicly available dataset (e.g. OpenStreetMap, Wikimapia) and site surveys.

5.3.2 Historical weather and discharge data

Due to the complex and heterogeneous terrain, weather systems are expected to present large variations in the study domain. In view of the limited number of ground monitoring stations, particularly in the high mountains, a variety of weather data products have been used:

- The long-term (from 1901 to 2015) gridded (0.25°) daily rainfall field produced by the Indian Meteorological Department (IMD) (Pai et al., 2014). The product is based on archived records of 7,000 rain-gauge stations and interpolated in space and time using an Inverse Weighted Distance (IWD) method (Shepard, 1968). The IMD rainfall dataset has been applied in numerous hydrological studies (Prakash et al., 2016; Parida et al., 2017).
- The hourly gridded (0.1°) but short-term (2014–2015) GPM calibrated V03D data (Hou et al., 2014). The data is considered capable of describing rainfall in the high mountains poorly covered by the synoptic network. The dataset is used to identify correction ratios of low and medium rainfall to be applied to the IMD dataset using the mean yearly rainfall accumulation between GPM and IMD products for catchments with mean elevation above 3,500 m. The correction factors suggest a spatial redistribution of rainfall with an accumulated depth reduction in the high mountains and an increase in Himalayan foreland, which is consistent with the rainfall behaviour regime expected in the Himalayas (Dhar et al., 2004; Bookhagen et al., 2006).
- The daily gridded (0.25°) Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) rainfall product (Funk et al., 2015). It is applied for areas covering Nepal.

- The gridded (0.25°) daily data from the European Centre for Medium Range Weather Forecasts ECMWF ERA-Interim daily data (Dee et al., 2011). They are used for estimating evaporation and temperature.

Discharge data is provided by the Central Water Commission (CWC) as 10 days averaged values covering the monsoon period (June-October) for the period 2010-2014 and daily averaged Annual Maximum Series (1980-2015) for selected locations along the rivers Bagirathi, Alaknanda and Mandakini (directly downstream the highest mountain zones where rainfall data quality is uncertain). The Annual Maximum Series (1980-2015) of the Ganges discharge at the Bimghoda Dam near Haridwar was also made available by the Indian Irrigation Department.

5.3.3 Synthetic weather data

Three multisite weather generators are used to produce daily weather variables. For this study, different configurations of the three weather generators are tested based on their capabilities to reproduce hydrological extremes and preserve rainfall spatial correlation. In the case study area, hydrological extremes are principally controlled by extreme precipitation (Wijngaard et al., 2017). The testing and the validation of the weather generator configuration found most suitable, and subsequently used for the rest of the study, are presented in the results section. For testing, a 500-year period is chosen to produce extreme discharge values representative up to the 30-year RP and corresponding to the duration of annual maxima observations used for comparison. The different weather generator configurations applied for testing are described below. After performance evaluation, 5,000 years of synthetic data are produced with the selected weather generator.

The 5,000-year duration is chosen to adequately represent event variability in the 5 to 500-year RP, critical for loss estimation.

The parameters of KNN-CADv4 are typically selected on a trial and error basis (Vallam & Qin., 2016). The KNN-CADv4 requires a set of three main parameters. The temporal window w , which controls the neighbours sample size k , is usually optimized on a trial and error basis with objective to minimize seasonality disruption (e.g. Vallam & Qin, 2016). Literature suggests w values of 14 days in Europe (Sharif and Burn, 2006) or 20 days in tropical climate (Vallam & Qin, 2016). Preliminary testing of different window sizes, ranging from 10 to 20, suggests little influence of w to reproduce extreme discharge. A longer window of 20 days, maximizing the sample size 'k' value to 24 values according to the formulation of Yates et al. (2003), is selected for subsequent configurations. The two remaining parameters required in KNN-CADv4 include the size of the resampling block B , and the amount perturbation factor λ . The block B size helps preserve climate temporal correlation which is useful to control temperature and snow melt release for basin subject to such type of flooding. In the Upper Ganga basin, fluvial flooding events are controlled mostly by extreme precipitation events (Wijngaard et al., 2017) occurring over a few days period (e.g. Rana et al., 2013). For testing purpose, two configurations of size B are used: 1 day (no temporal correlation preservation) and 10 days. The perturbation factor λ , which controls the generation of extreme rainfall beyond observed values, is tested for two perturbation levels of 0.8 and 0.9 (corresponding to 20% and 10% perturbation of the resampled amounts respectively). A fixed perturbation factor of 0.9 is applied to the temperature and evaporation data. As recommended by Mandal et al. (2017), a log-normal perturbation is applied to the rainfall and evaporation fields while normal perturbation is applied to temperature.

The TripleM weather generator has been tested using Weibull and a mixture of Weibull-GPD distributions. The Weibull-GPD distributions are combined using a Peak-Over-Threshold (POT) approach with the threshold established using the ‘parameter stability plot’ method (see Coles, 2001). Finally, the MulGETS weather generator has been tested using both multi-exponential and multi-gamma distributions, with a first order Markov chain and monthly clustering.

5.3.4 Runoff simulation

The NAM model domain is divided in 89 sub-catchments (see Figure 5-2 and Table 5-1) of spatial resolution similar to the weather data (600 km²) and each associated with time series of climate variables. Within each sub-catchment, orographic effects on rainfall are accounted for using correction factors and regional regression established between GPM and elevation. Lumped conceptual rainfall-runoff models such as NAM typically require continuous discharge observations and rainfall data over several years to derive accurately the catchment model parameters (Madsen, 2000). Regionalization techniques can also be applied to derive model parameters in un-gauged locations (Hundecha et al., 2002; Bárdossy et al., 2006).

Table 5-1 Summary of model domains and hydrological distributions

River	Abbreviation	Catchment size [km ²]	Sub-catchments	Total rivers length [km]
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Ganges	GAN	21,100	38	1,206
Sarda	SAR	14,980	26	766
Yamuna	YAM	11,600	20	368
Kosi	KOS	1,860	5	159

Considering the limitation of the hydrometric datasets, a manual calibration of the NAM model parameters is done based on expert judgement and supported by the analysis of the geomorphic characteristics of the catchments. In the NAM model, the parameters with largest influence on discharge peaks are the overland flow runoff coefficient (CQOF) and routing time constant (CK1,2) (see Madsen, 2000) which are analogous to the runoff curve number, developed in 1954 by the SCS, and the lag time of the Unit Hydrograph Method (UHM), respectively. Those parameters are derived here to guide the manual calibration process of the NAM model. The Curve Number is derived using an approach similar to Hong and Adler (2008) based on reclassified land cover from the European Space Agency (ESA) - Climate Change Initiative Land Cover project (CCI LC 2012) and soil types from the Harmonized World Soil Database (USDA-NRCS) reclassified in 4 Hydrologic Soil Groups HSG following Rawls & Brakensiek (1989). The lag time is computed according to the Soil Conservation Service (SCS) formula (ASCE, 1996):

$$T_{lag} = \frac{(3,28.10^3 . L)^{0.8} (\frac{1000}{CN} - 9)^{0.7}}{1900 . Y^{0.5}} \quad (5.5)$$

where L is the hydraulic length [km], Y the average slope [%], and CN the areal weighted Curve Number [-].

The CQOF and CK1,2 parameters are first assumed identical to the CN and lag-time values and then adjusted uniformly across all sub-catchments to achieve the best fit of simulated annual peak flows with the observed. The remaining parameters controlling

interflow, baseflow and snow storage and melt are established manually to fit the rising and receding limbs of the 10 days average monsoon flow data and annual water balances.

5.3.5 Hydrodynamic model and inundation mapping

The approach, which assumes that the overland flow patterns are parallel to the main river, is judged acceptable for the study area presenting relatively steep river gradients and well-defined U-Shaped floodplains. The approach is also computationally efficient to allow for the required large number of simulations.

The river network is extracted from the 10 m (LSE20: 8 m) Cartosat Digital Surface Model (DSM) produced by the National Remote Sensing Centre (NRSC). The DSM is hydrologically corrected using the carving technique proposed by Soille et al. (2003) and buildings removed using a block minimum smoothening filtering procedure relying on manually digitized building polygons. Following river delineation, cross-sections are extracted from the Digital Terrain Model (DTM) every 3 km and the NAM simulated runoff is distributed along the river network. The main dams and reservoirs are simulated using a simple broad-crest weir formulation and considered at full reservoir level.

At the four locations where flood mapping is intended, cross-sections, are extracted every 500 m to 2 km from the DTM and represent river bed and floodplain elevation. At these locations where the river is meandering across a large and flat terrain, low flow conveyance, not captured in the original DSM, is considered minimal compared to high flow conveyance and no correction is applied. The water retention structures are assumed fully open during the flood event and able to accommodate the peak flow. The Upper Ganges (GAN) river section features a 100-year flood protection embankment. Planar

surface interpolation of water level between computation nodes and overlaid with the DTM is then used to produce inundation maps.

5.3.6 Exposure and vulnerability

Exposure and vulnerability functions were developed by DHI et al. (2017) from reports, field surveys or extracted from the literature (Figure 6-5). The exposure considers two categories of assets most susceptible to flooding: agriculture and residential. Damage curves associated with fluvial flooding are defined as a function of the household contents/assets (e.g. furnishings, electric equipment) susceptible to be damaged for single, double and multiple stories houses. The curves do not account for structural damages. They were derived from detailed surveys of more than 1,250 households across the Uttarakhand State and validated against other household contents damage curves published in the relevant literature (e.g. Reese & Ramsay, 2010). A single composite damage curve capturing the main crops present in the area (paddy, sugarcane, dry crops, beans and potato) and based on Huizinga et al (2017) is used for agriculture. Assets valuation has been established from surveys and published production data.

Figure 5-3 Examples of vulnerability curves (a) composite agriculture (b) residential multi-story
(Data source: DHI et al., 2017)

5.3.7 Event sets and subsets

From the 3 main event sets proposed, sub-scenarios including variabilities in different parameters are investigated (Table 5-2). The results of the fully continuous simulation performed are used in both Events sets A and B with A preserving the spatial structure of the events. A and B implicitly capture the variability of discharge by accounting for all potential events that occur within the 5,000 years and without making assumption between loss and hazard RPs. We tested how the probabilistic risk estimates compare against those based on combinations of different flood hazard maps. By considering a few numbers of uniform RPs, Event sets C do not account for discharge variability around the RPs selected and assume identical RPs between hazard and losses. C1 considers 8 RPs as recommended by the PIU for analysis in Uttarakhand. C2 considers the same RPs below the 100-year threshold. C3 and C4 follow the European Flood Directive (2007/60/EC) (European Commission, 2007) and uses three hazard maps of low, medium and high probabilities. The 100 and 1,000 years are typical design criteria for hydraulic infrastructure in

Uttarakhand and are used for medium and low probabilities. The low RP is 5 years for C3 and 10 years for C4 to investigate the impact of choice on the lowest RP. Vulnerability uncertainty is accounted for in A and B1. Only the mean of the damage functions is used in B2 and C.

Table 5-2 Summary of event sets and scenarios considered with variabilities included in different parameters

Event set	Loss estimation approach / fixed probability levels considered [year]	Variabilities considered			
		Hazard			Vulnerability
		Spatial	Discharge	Roughness	
A	Fully continuous	x	x	x	x
B1	Fully continuous		x	x	x
B2	Fully continuous		x	x	
C1	5,10,25,50,100,250,500,1000			x	
C2	5,10,25,50,100			x	
C3	5,100,1000			x	
C4	10,100,1000			x	

5.4 Results

5.4.1 Flood hazard and risk model performance and limitations

A manual calibration of the hydrological NAM model has been performed by comparing simulated and observed annual peaks for the 1980-2015 period in the GAN basin. After quality control, 3 years, presenting excessive (>60%) deviations between rainfall and discharge observations, were removed from the historical dataset. Of the remaining years, an average positive bias of 22% between observed and simulated peaks (RMSE=360 m³/s), ranging between 15 to 30% at individual location, is considered acceptable to account for the differences between the daily averaged observations and the instantaneous simulations (Figure 5-4a). The regional calibration approach is validated at

the catchment outlet in Haridwar, where flood mapping is produced, with a mean peak error of 1.9% (Figure 5-4b). The calibration of the GAN basin and the overall regionalization approach is judged satisfactory considering the data limitation. For the 3 remaining basins (KOS, SAR, and YAM), without discharge observations, the same regionalization approach, relying on specific basin land-use and catchment characteristics, is used to estimate the NAM parameters.

Figure 5-4 Simulated versus historical annual peak discharges for (a) calibration at 4 locations upstream Haridwar in the Ganges catchment (see Figure 5-2), and (b) validation of the regional calibration approach in Haridwar. The discharge for the year 2013 is back estimated at 21,519 m^3/s (Agrawal, 2017) without the Tehri Dam (not modelled)

Inundation depths and extents are principally driven by discharge peaks, topography and roughness. With no adequate calibration data for flood levels and extents, roughness (Manning's n) is treated pragmatically as an uncertain and spatially uniform variable. It is resampled at each location from a truncated lognormal distribution (see Ghosn et al., 2003) with parameters ($\mu = 0.045$; $\sigma = 0.025$ μ ; $\min = 0.035$, $\max = 0.07$) derived from land-use and literature guidelines (Chow, 1959).

5.4.2 Synthetic discharge performance evaluation

The performance of the weather generators was evaluated by comparing the flood frequency curves derived from the hydrodynamic model simulations using generated and observed weather data. 500 years of synthetic climate data are first produced using the different WG. The flood frequency curves for the different configurations were estimated by resampling. 300 random samples of length 32 were taken with replacement from each of the 500 years of annual maxima. Each sample was fitted to the Generalised Extreme Value (GEV) with an estimation of the parameters based on the method of L-moments (Hosking and Wallis, 1997). The median was derived from the 300 flood frequency curves in each configuration and compared to the Weibull plotting positions of the annual maxima based on the simulation with observed weather data.

Figure 5-5a shows the range of variations in flood quantiles generated by the different WG configurations. MULGETS severely underestimates the discharge extremes with both distributions (Gamma or exponential). TripleM performs similarly to the MULGETS with a single rainfall distribution (Weibull) but shows improvement when using a mixture of distributions (Weibull and GPD) to describe low-moderate and high extreme rainfalls. The KNN with a perturbation factor of 0.9 leads to a better preservation of the extremes when using a block resampling of 10 days, which allows to capture better the longer time scale of routing and accumulation processes taking place over the full catchment. The increased perturbation factor of 0.8 (20% of the rainfall amount perturbed) leads to the best representation of the extreme value distribution. Figure 5-5b depicts the distribution of changes in cross-correlation between each of the 56 stations and between

the historical data and synthetic data achieved for the different weather generator configurations. Mean correlation changes vary between -2 to +5% with the KNN with block size of 10 and perturbation factor of 0.8 showing the largest increase in correlation. The spatial correlation of the different weather generators is judged well-preserved and suitable for subsequent analysis.

Figure 5-5 (a) Comparison of annual peak discharge frequencies based on generated and observed weather data for Haridwar. Dots are the simulated historical annual maxima; the different lines correspond to the median of derived frequency curves for different weather generator configurations. (b) distribution of cross-correlations changes of all 56 rainfall time-series between historical and 500 years of synthetic rainfall for different weather generator configurations

The KNN-CAD weather generator with block size 10 and perturbation factor 0.8 was selected to produce 5,000 years of synthetic climate data. To validate the model chain, flood frequency curves were derived at the 4 locations where flood mapping is performed, using the same resampling approach but with 1,000 random samples. The median and the 50% and 95% confidence intervals are estimated from the 1,000 fitted frequency curves. The resulting frequency curves (Figure 5-6) show a very good agreement between the

derived flood quantiles and the historical peaks and confirm the suitability of the event model chain configuration selected.

Figure 5-6 Comparison of annual peak discharge frequency curves based on generated and observed weather data: (a) GAN; (b) SAR; (c) YAM; and (d) KOS. Dots are the simulated historical annual maxima; the different lines correspond to the median, 50% and 90% confidence intervals of the derived frequency curves

5.4.3 Impacts on frequencies of discharge events

From the 5,000 synthetic years, the largest 1,000 peaks - capturing events above the 5-year RP - from each individual location were used for inundation mapping. Event Set A was constructed using the peak occurrence periods and this led to 1,866 unique and spatially coherent regional events from which 54% occurred simultaneously at all 4

locations. At each location, discharge RPs were established by rank (from the 1,000 largest local peaks) or set to 1 if no event occurred (events with RP below 5 year). For each regional event in Event Set A, local event RPs are plotted between locations (Figure 5-7). Event Sets B and C implicitly assume full correlation (uniform T-year) of event RPs locally. The results illustrate the diversity of local event magnitudes that can be expected at the regional scale from the spatially coherent Event Set A.

Figure 5-7 Example of correlation plots of peak discharge RP between the different catchments for the spatially coherent Event Set A. Event sets B and C implicitly assume full correlation between RPs (1:1 line)

Table 5-3 summarizes the regional frequency of occurrences, as they occur in Event Set A, of local event RPs conditional to the occurrence of the local event RP in at least one or all the locations simultaneously. Again, the uniform threshold RP can be considered representative of the Event Sets B or C. The combinations of locations vary from 2 to 4 for threshold RPs ranging from 5 to 500 years. The results show a consistent increase (all locations above the threshold RP) and decrease (at least one location above the threshold RP) when the number of locations considered increase. For example, a 100-year event triggered in any of the locations occurs with a 62-year RP frequency across the regional

event set while the same 100-year triggering threshold occurs with a 278-year RP. A second observation can also be made: the decorrelated local events lead to increase in frequencies of local T-year events at the regional scale (e.g. the 50-year local event would occur every 33 years at the regional scale) which can have implication in the loss estimation.

Table 5-3 Regional events probabilities in the spatial coherent Event Set A for different RP and across different spatial scale. Event Sets B and C can be represented by the spatially uniform RP (column 2)

Local event simultaneously above RP in	RP [year]	Mean regional probability [year] of local events above RP considering		
		4 locations	3 locations	2 locations
1 or more catchments	5	3	3	4
all catchments		14	11	9
1 or more catchments	10	6	7	8
all catchments		21	18	15
1 or more catchments	25	15	16	19
all catchments		48	44	37
1 or more catchments	50	33	35	39
all catchments		102	88	71
1 or more catchments	100	62	67	76
all catchments		278	214	159
1 or more catchments	500	179	222	306
all catchments		-	5,000	3,333

5.4.4 Impacts on risk metrics

Figure 5-8 shows the exposure distribution, LEP curves and variation of loss frequencies for the different event sets. The exposure exceedance curves (Figure 5-8a) illustrate an uneven distribution of exposed assets between locations. Residential exposure is dominated (85%) by the GAN location above the 100-year RP, which corresponds to the protection level at this location. The residential exposure in SAR and YAM increases quickly but stabilizes after the 50-year RP. Consequently, little variation is seen between

exposure exceedance level of Event Sets A and B. Despite the spatial variation in local RPs, events of 100-year RP and above in the GAN location are most frequently associated with events above the 25-year RP in the remaining locations, leading to a very similar range of exposure despite the variations in discharge. The agriculture exposure distribution is dominated by the KOS location (>60%) but more variations exist between locations. The main variations between locations are within the 5 to 30-year RP range leading also to more variation between Event Sets A and B within this range. After the 30-year threshold, the variability of exposure at the regional level is considerably reduced as most locations start to approach their maximum possible loss.

The LEP curves (Figure 5-8b) show a behaviour similar as the exposure exceedance curves. Interestingly, losses start to occur, in Event Set A and for both classes of assets, with a higher level of probability than in other events sets. Event Set A also clearly displays, for agriculture assets, a decrease of the low RPs losses (approximately -50% and -10% for the 5 and the 10-year RP respectively). After the 20-year RP the losses fluctuates between +/- 4% depending on the scenarios. The minimal variations in losses experienced between the 20-year and 300-year RP, particularly visible for agriculture, follow the same patterns as the exposure distribution curve (Figure 5-8a). The differences between Event Sets A and B are minimal for residential assets dominated by losses at a single location (GAN). There, the influence of vulnerability uncertainty (A or B1 against B2) is more important for the higher RPs (>300-year).

Variations in probabilities for identical loss levels between Event Sets (Figure 5-8c) also allow to clearly identify the main zones where differences occur, and the significance of the variabilities considered. The 3 to 5-year RP corresponds in all cases to a decrease in loss probability as Event Set A can generate losses below 5-year RP (Table 3) and no losses

are expected to occur below a uniform 5-year RP (Event Set B and C). Loss probabilities decrease between the 5 to 25-year RPs. The 25 to 500-year RP zone shows more stable results between event sets with higher perturbations (negative and positive) around the 100-year mark for residential assets being protected at this RP in the highest exposure location (GAN). After the 500-year RP, losses are overestimated when considering a spatially uniform RP (Event Set B1) and underestimated when not considering vulnerability uncertainty (Event Set B2 and C1).

Figure 5-8 (a) Exposure exceedance curves, (b) Loss exceedance curves and (c) variation in frequencies at the same loss level for agriculture and residential assets and Event Sets A, B.1, B.2 and C.1

Table 5-4 shows the variation in AAL between event sets for the different asset classes. The difference in AAL only due to the spatial variations are negligible (Scenario A vs. B1 and B2). In this application, the increase and decrease in loss frequencies

experienced in the LEP curves cancel each other. Still larger differences are experienced in the standard deviation of the individual event losses. The standard deviation of agriculture losses is more than twice the standard deviation produced by the other events sets. This result is a direct consequence of the spatial redistribution of local event intensities in Event Set A. More surprisingly the standard deviation of Event Set A is slightly below (-25%) for residential assets. This result is attributed to the extreme losses occurring in GAN for a limited number of events and in all event sets (50 events above the 100-year design protection occurring over the 5,000 year) and the much large number of low losses with limited variations produced by Event Set A (1,840 events) compared to Event Set B (1,000 events). The 8 RPs used for AAL estimation (Scenario C1) (less than 1%) present a very good approximation of the risks. For residential assets, the 22% of error for Event Set C1 can be reduced to less than 5% if an additional RP just below the 100-year design protection level is used in the integration procedure to account for the sudden loss increase.

Table 5-4 Average Annual Losses, standard deviation of losses and percentage variations for agriculture and residential sectors considering the different event sets and sub-sets

Scenario	Agriculture				Residential		
	AAL	σ	AAL variation [%]		AAL	σ	AAL variation [%]
	[INR x10 ⁶]		from A	from C.1	[INR x10 ⁶]		from A from C.1

A	3.06	6.22	-	-	84.98	848	-	-
B.1	3.06	2.62	0.0	-	84.91	1149	0.0	-
B.2	3.06	2.62	0.0	-	84.59	1148	0.0	-
C.1	3.02	4.94	-1.0	-	103.82	2805	22.3	-
C.2	2.91	3.32	-5.0	-4.0	74.82	1778	-12.5	-28.4
C.3	3.34	5.74	9.1	10.1	496.64	2598	484.9	378.4
C.4	1.83	4.38	-40.0	-39.4	266.37	2591	213.7	156.6

5.5 Discussion

This study presented an efficient probabilistic flood hazard and risk modelling chain relying on 5,000 years of continuous climate simulations to produce exhaustive and spatially coherent discharge events at the regional scale. The model was applied to four river basins in Uttarakhand, India to investigate agriculture and residential economic risks.

The different elements of the model chain have been developed using expert judgement and the best available datasets, complemented by site surveys. However, in Uttarakhand, as in many regions of the world, there is a lack of consistent and comprehensive data for flood hazard and risk model validation. The river systems in Uttarakhand can be complex with man-made structures (levees) and reservoirs (e.g. Tehri dam) able to assert control on part of the high flow. For clarity, these structures have been simplified in the present analysis. With this in mind, the risk results in absolute terms should be used with care but the relative variations between event sets are considered valid and relevant for the study purpose. Also, the flood hazard mapping relies on the assumption of unidirectional flow, which is considered valid in the study context. The modelling approach should be revised in more complex floodplain systems with an efficient 2-dimensional floodplain model.

Overall, the parametric multi-site weather generators tested performed similarly or better than the KNN weather generator in preserving spatial correlation with the added advantage of preserving local extreme distribution. However, in the study context, the KNN type of weather generator using block resampling and perturbations, worked best to reproduce the extreme historical discharge patterns at the catchment scale. The MulGETS and TripleM underestimated, in some case considerably, the discharge extremes. The difference of performance of the MulGETS when compared to the results of Chen et al. (2015), can be attributed to the larger number and more dense rainfall data applied here (28 locations for a catchment area of 21,100 km² against 15 locations over an area of 73,800 km²) and the large difference in rainfall pattern between the Himalayan monsoon and Quebec. It also illustrates the limitation of the Markov chain process to deal with spatial variability (e.g. Wilks, 1998; Brissette et al., 2007; Khalili et al., 2009). Parametric models might need further attention to be able to reproduce the geo-spatial and temporal pattern of heavy and extreme rainfalls and the extreme discharge accumulation if those models are to be used in flood risk studies.

The continuous climatic and hydrologic simulations were used to investigate risk metrics derived from the continuous and spatially coherent event set and from the application of T-year return periods events uniformly at the regional scale. From a discharge event perspective, preserving the spatial coherency at the regional scale led to a spreading of local T-year event distributions (and their possible losses) on both sides of a regionally uniform T-year RP (i.e. a 100-year event will be exceeded regionally with a 278-year RP but local 100-year events can occur with a 62-year RP regionally).

The specificity of the exposure distributions and the correlations between local events magnitude translated into smaller differences (2-4%) in losses at high RPs (above

50-year) but larger differences (20%) at low RPs (5-10-year). These results are consistent to the results of Theiken et al. (2015) and Schneeberger et al. (2017) although the differences of the spatially varied event set are much less marked for the high RPs due to the high discharge correlation, exposure concentration and limited number of locations. Most importantly, this study illustrated another phenomenon that differentiates spatially coherent and uniform RP event sets: the redistribution of losses in the spatially coherent event set led to a shift in the minimum RP generating losses from 5-year (assuming a uniform T-year event set) to 3-year corresponding to the de-correlated events occurring at individual locations. These variations (both positive and negative) led to negligible differences between the average annual losses derived from the spatially coherent and continuous event set or appropriate uniform T-year events.

Here the number and choice of the T-year RPs should be made with care. The use of too few or not adequate RPs could lead to large errors (-40 to +200%) in the regional averaged risk metrics. These results, aligned with the work of Ward et al. (2011), illustrate the importance of selecting the right RPs to describe more accurately the LEP curve: the RPs should be (i) as low as possible to effectively capture where losses start (e.g. in this study a 1 or 2-year RP threshold could have provided more accurate results), and (ii) adequately resolve sudden changes in losses caused by protection design criteria used for critical assets groups (e.g. 100-year flood protection of residential assets in the Upper Ganges basin).

Finally, the spatially coherent event set produced higher standard deviation (above 200% increase) compared with uniform T-year RP event sets. These differences could adversely affect financial plans such as contingency funds or risk transfer schemes designed using such risk metric.

5.6 Summary

In summary, the spatial variability of flood events, exposure and the critical frequencies at which changes occur in the risk metrics and across different spatial scales need to be better understood and captured. The present study investigated the impact of spatial variability in the risk modelling chain and risk cumuli. It identified a possible modelling approach and the different tools available with their limitations. Some challenges remain, for example, proper representation of extreme hydrological events at the regional scale - using weather generators or joint probability approaches, and efficient simulations of a large number of inundation events. Many studies address these challenges individually, but more studies are required to develop, investigate and promote the integration of these different parts in the risk modelling chain.

CHAPTER 6 Impact Assessments and Risk-Based Adaptation to Future Floods in the Upper Ganga Basin

6.1 Introduction

Recent years have seen the emergence of the concept of risk management of flooding. While traditional management approaches aim to prevent flooding for a specific return period, active risk management integrates knowledge of flooding impacts on the economy and population to ensure sustainable economic growth and support societal development. Quantifying such impacts presents numerous benefits for decision-making, including ability to identify segments of the society at risk and development of cost-efficient mitigation and response strategies.

Flood risk can be described as the combination of three main components: (i) the hazard described in term of magnitude and frequency; (ii) the exposure, capturing assets, activities or population distribution; and (iii) the vulnerability of these exposed elements to possible damage under varying hazard intensities (UNISDR, 2009). All these components vary over time, and risks are expected to increase over the coming decades. Such a rise in risk is due, primarily, to an increase of exposure in flood prone zones associated with socio-economic development (e.g. Visser et al., 2014), and because of expected increases in river discharge and flooding probabilities resulting from climate change (e.g. Hirabayashi et al., 2013; Arnell and Lloyd-Hughes, 2014). In this context, more and more studies have been dedicated to establishing possible changes in future flood damage. Global flood risk predictions have been investigated, providing critical information for understanding intervention needs and value at the continent or country

scale (e.g. Hirabashi et al., 2013; Ward et al., 2014; Winsemius et al., 2016; Alfieri et al., 2017).

Several regional studies have been intended particularly in the most developed regions at the national or continental scale (Rojas et al., 2013; Alfieri et al., 2015; EA, 2009; Wing et al., 2018; Ward et al., 2015). However, the literature remains scarce on future flood impacts in the developing world and particularly India and the Himalayan region.

In India, most preceding studies have investigated the impact of climate change on rainfall (e.g. Choudhary & Dimri, 2018; Singh et al., 2016; Kumar et al., 2006) and in some cases hydrology and discharge extremes (Gossain et al., 2011; Gain et al., 2011; Ghosh & Dutta, 2012; Apurv et al., 2015; Mohammed et al., 2017; Wijngaard et al., 2017). The impacts of future floods in India have to date received little attention. Hallegate et al. (2010) and Ranger et al. (2011) predicted direct and indirect consequences on the population and economy with possible adaptation options. Nevertheless, this work was limited in scale to the city of Mumbai and using a single high emission climate scenario. Despite these advances in understanding future flood impacts, the literature on quantitative future flood risk prediction and possible adaptation remains scarce in India or the Himalaya region.

Therefore, we aim to investigate the future flood impacts in the Upper Ganges Basin in the State of Uttarakhand, India, using an ensemble of climate change projections. Firstly, we develop a modelling framework based on best available data to evaluate flood risks under present and future scenarios at the scale of the Upper Ganga Basin (24,000 km²). Secondly, the fluvial flood hazard projections for the present climate and for a near future period 2045-2065 will be carried out. Thirdly, the current day exposure and vulnerability

information with hazard projections will be combined to evaluate how such changes in hazard would potentially affect future changes of flood risk. Lastly, we will assess to what extent enhanced structural flood protections strategies could offset the projected increases in flood risk at the scale of the full basin.

6.2 Methods

Figure 6-1 shows the modelling framework for flood hazard modelling and the risk calculations in consideration of various climate change scenarios. The framework relies on continuous rainfall-runoff and hydrodynamic models forced with observed and statistically downscaled weather variables. A catalogue of inundation maps is first produced from discharge design events across the basin for the current climate. The maps are used to build an Exposure-Hazard database containing, at each exposed element, water depths simulated for each event, associated with the discharge magnitude of the nearest simulation point in the hydrodynamic model. Each exposed element references the closest embankment section associated with a flood protection level. The loss model makes direct use of peak discharges produced from extreme value analysis of continuous discharge simulated by the hydrodynamic model under the climate change projections. Here, we use the relationship between discharge at the river simulation nodes and water depth at each exposed element, as previously derived for the current climate, to predict water depths for the future climate. The design events for the current climate are produced for probabilities lower than the probabilities investigated for future projections (e.g. 10,000-year for current climate to produce future losses up to 1,000-year). The projected water depth and damage functions are then used to establish losses locally and produce risk metrics at the local or catchment scale.

The statistical downscaling and flood risk modelling are carried out by using existing software packages (i.e. ARC GIS, MIKE, and R). The downscaling is performed using methods implemented in MIKE OPERATIONS. The overall hydrodynamic simulations rely on the MIKE1D Application Programming Interface (API) (Unphon, 2009), implemented in C#, and the mapping is done in ARCGIS. The loss model is implemented in C#. Pre- and post-processing of climate change model outputs, data results and extreme value analysis are performed either in C# or with the statistical software R and the relevant libraries (i.e. “eXtremes” and “lmomRFA”).

Figure 6-1 Flood risk modelling framework for climate change impacts analysis (white boxes use present day information)

6.2.1 Statistical downscaling

The downscaling method needs to ensure a proper representation of extreme precipitation, as this is expected to be driving flooding events at the scale of the Upper Ganga Basin (see Wijngaard et al., 2017). This study uses the change factor quantile mapping method (CFQM) to downscale daily precipitation (e.g. Boé et al., 2007; Olsson

et al., 2009; Sunyer et al, 2015). The method establishes correction factors for different probability intervals in the empirical Cumulative Density Function (CDF) of wet days estimated from observed data at monthly scale, and the control and future periods of the climate model data. Similarly, CFQM is applied to downscale temperature.

The perturbation of the observed precipitation is carried out as follows: (1) in the observation data, the probability of the precipitation intensity of each wet day is established from the CDF of the observed data for the corresponding month, (2) the relative change α is calculated from the CDFs of the control and scenario precipitation for this month and probability based on regional climate model data, (3) the observed values are multiplied by the change factor corresponding to the precipitation probability and month estimated to produce the future time-series (see Sunyer et al, 2015).

$$\alpha(P, i) = \frac{R_{scenario}(P, i)}{R_{control}(P, i)} \quad (6.1)$$

$$R_{future}(t) = R_{obs}(t, P) \cdot \alpha(P, i) \quad (6.2)$$

where $\alpha(P, i)$ [-] is the delta change factor established for a probability P for the month i , $R(P, i)$ [-] is the inverse of the rainfall CDF for P and i for the control or scenario of the climate projection, $R_{future}(t)$ [mm] is the future rainfall at time t , and $R_{obs}(t, P)$ [mm] is the observed rainfall at t during month i with probability P .

In this application, days are defined as wet for precipitation above 1 mm and dry for the rest. Monthly change factors are established for each probability of the empirical CDF following the Cunnane plotting position (Cunnane, 1978). Same rainfall values can occur several times over the same month creating step-wise jumps in CDF probabilities. The plotting position approach used in conjunction with different non-zero rainfall sample sizes between the control and scenario can lead to rainfall values not directly present for a given probability level in the control or scenario CDF. In this case, in order to obtain the

precipitation intensity for these probabilities, linear interpolation is applied between the rainfall intensities with nearest probabilities. The tail of the control and observations are fitted with a gamma distribution for extrapolation of the monthly change factors.

Temperature data are downscaled using the same procedure, except that absolute changes in temperature between control and future climate model simulations are used for the quantile mapping.

Changes in potential evapotranspiration are estimated using the downscaled temperature data with the formulation of Kay & Davies (2008):

$$\Delta PE_T = \frac{R_e}{\lambda \rho_w 100} \Delta T \quad (6.3)$$

where ΔT is the change in temperature, λ is the latent heat flux [J/kg], ρ_w is the density of water [kg/m³] and R_e [J/m²/s] is the extra-terrestrial radiation (Allen et al., 1998).

6.2.2 Flood hazard and design events

Runoff simulation is conducted using the lumped, conceptual NAM rainfall-runoff, developed by the Institute of Hydrodynamics and Hydraulic Engineering at the Technical University of Denmark (Nielsen and Hansen, 1973). The model simulates runoff continuously as a function of rainfall, potential evapotranspiration and temperature and has been widely used in hydrological studies (e.g. Rulin et al., 2008; Wang et al., 2016). The one-dimensional engine MIKE1D is used for hydrodynamic simulation (see Chapter 3). The model uses a high order fully dynamic wave approximation to solve the shallow water equations using a 6-point Abbot-Ionescu numerical scheme (DHI, 2017). The one-dimensional model can be used alone or coupled with a 2-dimensional hydrodynamic model to produce inundation hazard maps.

Continuous simulations are performed with the rainfall-runoff and hydrodynamic models using the observed and future periods data. Annual Maximum Series of discharge are extracted from the hydrodynamic simulations at various discharge nodes located at regular intervals (5-10 km) along the river network or directly after confluences. Extreme value analysis is then performed to derive a set of peak discharge probabilities and intensities for each discharge node. A catalogue of basin-wide flood maps is derived using, at each node, a set of peak discharge probabilities covering the range of discharge values expected to be produced across all future scenarios. The flood maps are then used to establish water depths reached at each exposed element as a function of the discharge intensity of the nearest discharge location node. The approach allows to quickly produce flood hazard and risk metrics considering changes in discharge peaks and embankment protection levels without the computational burden associated with the generation of inundation maps.

6.2.3 Risk modelling

The risk model allows to produce economic losses from flood hazard scenarios, the exposure data and vulnerability functions. It relies here on: (1) an accurate spatial database of elements exposed to flooding including their type and value, (2) a catalogue of damage functions capturing the susceptibility of the exposed elements to the flood magnitude (e.g. water level), (3) an estimation procedure of the flood magnitude reached at each exposed element for different flooding probabilities, and (4) a calculation procedure for local and basin-wide risk metrics based on the damages occurring of the exposed elements for different discharge magnitudes and probabilities.

The exposure data is combined with the catalogue of flood maps to produce an Exposure-Hazard database linking each exposed element to a set of water depths reached for specific discharge intensities at a discharge node. Based on the established relations, discharge levels simulated based on future climate projections are translated into local water depths through linear interpolation between the discharge and water depth values previously established. Each exposed element can also be associated with a virtual embankment section with a defined protection level corresponding to a discharge magnitude under current climate.

Flood risk is measured using Loss Exceedance Probability (LEP) curves and Average Annual Loss (AAL) (see Meyer et al., 2009). The LEP curve establishes losses for different probabilities. In this simplified form, losses for a probability P_i are assumed equal to the sum of losses occurring at each exposed element. For each exposed element, the discharge peak used to generate the loss corresponds to a probability P_i , with P_i being uniform across all exposed element at the scale of the basin. The Loss Exceedance Probability L [-] occurring with a probability P_i is calculated as:

$$L(P_i) = \sum_{j=1}^m D(T_j | W_{j,P_i}) \cdot V_j \cdot P_j(Q_{P_i}) \quad (6.4)$$

where W_{j,P_i} is the water depth [m] at element j established for a discharge Q_{P_i} [m³/s] with the probability P_i ; $D(T_j | W_{j,P_i})$ [-] is the ratio of damage experienced by the element j of typology T at the water depth reached; V_j is the total value [\$] of the element j ; m is the total number of exposed elements and $P(Q_{P_i})$ [-] is given by:

$$P_j(Q_{P_i}) = \begin{cases} 1 & \text{if } Q_{P_i} > Q_{Dj} \\ 0 & \text{if } Q_{P_i} \leq Q_{Dj} \end{cases} \quad (6.5)$$

where Q_{P_i} [m³/s] is the discharge intensity for P_i and Q_{D_j} [m³/s] is the discharge design protection level of the element j.

The Average Annual Loss (AAL) [\$] is calculated as the integral of the LEP curve which can be approximated with the trapezoidal rule (Meyer et al., 2009):

$$AAL = \sum_{i=1}^{n-1} \frac{L(P_i) + L(P_{i+1})}{2} [P_{i+1} - P_i] \quad (6.6)$$

where $L(P_i)$ [\$] is the loss associated with the probability P_i and n corresponds to the number of probabilities used for describing the losses.

6.3 Application to the Upper Ganga Basin

6.3.1 Study area and data

The study domain covers the Upper Ganga Basin (24,000 km²) in Uttarakhand Province, India (Figure 6-2). Elevation ranges from 200 m in the Terai region to 7,818 m (Mount Nanda Devi) with approximately 50% of the domain above 2,000 m in altitude. The area receives an average of 1,200 mm annual rainfall (up to 2,400 mm in some locations) with 82% received during the monsoon season (Kumar, 2017). The climate, mostly Himalayan, depends of summer monsoon currents and westerly disturbances. Large scale weather systems orographically locked by the higher Himalayan ranges can lead to very intense rainfall in the southern rims of the Himalayan valleys (1000-3000m elevation), producing highly destructive floods particularly in the hills (see Wasson et al. 2013) but also threatening the Terai floodplains and most populated river reaches.

People, assets and production exposed to flooding are unevenly distributed across the basin. The northern regions are less populated although thousands of tourists usually

congregate towards remote pilgrimage sites during summer months. A few urban centres are located along the main rivers in the hills (e.g. Uttarkashi, Srinagar, Karanprayag). However, the greatest proportion of the population exposed to flooding is distributed downstream within the Terai and Shivaliks regions of Dehradun and Haridwar districts.

Data used for the flood hazard modelling originates from public sources (e.g. GPM, SRTM) and government bodies (the Central Water Commission CWC, the India Meteorological Department IMD, the Uttarakhand Irrigation Department, the National Remote Sensing Centre NRSC), and has been acquired with the support of the Project Implementation Unit for Technical Assistance and Capacity Building for Disaster Risk Management (PIU TA & CBDRM) of the Uttarakhand Recovery Project. The exposure and vulnerability models were developed based on DHI et al. (2017).

Figure 6-2 Upper Ganga basin in Uttarakhand, India with main rivers, sub-catchments, gauge locations and elevation (source: data SRTM)

6.3.2 Historical weather and discharge data

Monitoring weather in such rugged terrain is a challenging task and reliable ground observations in the area are limited. In this study, a variety of weather observation products relying on ground and satellite observations and climate models have been used to produce an enhanced set of daily historical weather variables (1980-2015). Rainfall time-series are produced from gridded (0.25°) daily rainfall data produced by the Indian Meteorological Department (IMD) through spatial and temporal interpolation of ground observations (Pai et al, 2014). These data are redistributed spatially, for the northern and higher elevation areas (above 3,000 m) where ground observation coverage is very low, using yearly

average factors established using the GPM calibrated V03D data (Hou et al., 2014). A regional precipitation correction factor is also applied over these higher catchments to ensure a proper water balance with monsoon runoff at the gauging stations during the calibration process. Evaporation and temperature are estimated from the gridded (0.25°) European Centre for Medium Range Weather Forecasts ECMWF ERA-Interim data (Dee et al., 2011). Ten days averaged monsoon discharge data (2010-2014) and daily averaged Annual Maximum Series (1980-2015) are used for water balance and peak discharge calibration at 4 locations.

6.3.3 Regional Climate models

The climate model data used in this study is an ensemble of 14 Regional Climate Models (RCM) from the Coordinated Regional Climate Downscaling Experiment-South Asia (CORDEX-SA) project (Giorgi et al., 2009). Table 6-1 gives the detailed climate model combinations and their sources. The 14 simulations are based on 3 RCMs driven by 6 different General Circulation Models (GCMs) of the Coupled Model Inter-comparison Project Phase 5 CMIP5 with 3 RCP scenarios. The spatial resolution of the RCMs is 0.44° or approximately 50 km. For all the RCMs, the periods of 1986-2005 and 2046-2065 are considered for the study as control and future periods, respectively. Daily precipitation and temperature have been extracted from the RCMs using nearest neighbour interpolation of the RCM grids to the centroid of the catchment polygons as described in the rainfall-runoff model.

Table 6-1 Climate scenario combinations from CORDEX-SA experiments and sources.

RCM\GCM	CCCma CanES M2	CNRM -CM5	CSIRO -Mk-3- 6-0	IPSL- CM5A -LR	EC- EARTH	MPI- ESM- LR	RCP	Institute
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RegCM4-4	X	X	X	X		2.6	Indian Institute of Tropical Meteorology (IITM)
						4.5	
	X	X	X	X		8.5	
RCA4					X	2.6	Swedish Meteorological and Hydrological Institute (SMHI)
					X	4.5	
					X	8.5	
REMO2009						X	2.6
						X	4.5
						X	8.5

6.3.4 Runoff simulation

The Upper Ganga basin is divided into 52 NAM catchments of spatial resolution similar to the weather data (see Figure 2). The Himalaya range is subject to highly complex and hard to capture altitudinal variation of precipitation (see Immerzeel et al., 2014; Dahri et al., 2016). Preliminary testing of the rainfall-runoff models compared with baseflow runoff observation suggested an overestimation of rainfall and associated snow accumulation in the higher elevation zones. To correct this, linear regressions were established between the 2 years of GMP data rainfall time-series and SRTM grid elevations in the upper ranges of the Himalayas and considering four different geographical zones. In view of the limited ground observation data (none in the higher altitude), the approach can be considered too crude to accurately capture the precise complexity within each NAM basins. However, the approach can be validated at the regional scale by comparing simulated baseflow, dependent of snow accumulation and release, with observed baseflow at the few gauging stations available.

A regionalization approach is applied to derive the NAM parameters for the 52 catchments. With only limited data (e.g. monsoon 10-days averaged and daily annual

maxima of discharge data), the NAM parameters are established manually based on expert judgement and through analysis of the geomorphic characteristics of the catchments.

In the NAM model (see Madsen, 2000), the overland flow (CQOF) and routing time constant (CK1,2) parameters control peak discharge timing and magnitude. These two parameters are assumed to present variations across catchments similar to the variation produced by the Curve Number (CN) and lag-time parameters (SCS, 1954). The CN values are established similarly to Hong and Adler (2008) using 4 Hydrologic Soil Groups HSG (Rawls & Brakensiek, 1989) reclassified from soil types from the Harmonized World Soil Database (USDA-NRCS) and reclassified land cover from the European Space Agency (ESA) - Climate Change Initiative Land Cover project (CCI LC 2012). The lag time is established based on the Soil Conservation Service (SCS) formula (ASCE, 1996):

$$T_{lag} = \frac{(3.28 \cdot 10^3 \cdot L)^{0.8} (\frac{1000}{CN} - 9)^{0.7}}{1900 \cdot Y^{0.5}} \quad (6.7)$$

where L is the hydraulic length [km], Y the average slope [%], and CN the areal weighted Curve Number [-].

The NAM parameters controlling interflow, baseflow and snow storage and melt are considered identical for all catchments. They are established manually by fitting the rising and receding limbs of the 10 days average monsoon flow data and annual water balances at the gauge locations. At first, the CQOF and CK1,2 parameters are set equal to the derived CN and lag-time values, respectively. They are then adjusted uniformly across the basin to find the best fit between the observed and simulated annual peak flows.

6.3.5 Hydrodynamic model

The study area is characterized by distinct V-Shaped floodplains and channels with, generally, a steep gradient. River and overland flow patterns are assumed to be uniform and parallel to the main channel and adequately represented by a 1D schematisation. The river network has a length of 985 km and is derived from the 10 m Cartosat (LSE20: 8 m) Digital Surface Model (DSM) available from the National Remote Sensing Centre (NRSC). A preliminary analysis of the DSM indicates substantial errors in mountainous areas and particularly the narrowest valleys, where the DSM can produce downstream river section elevation up to 30m higher than the direct upstream ones. To establish river flow path and low flow elevation, the DSM is hydrologically enforced using the carving technique proposed by Soille et al. (2003), demonstrated to be superior to other hydrological enforcement techniques particularly in mountainous regions (Samanovic et al., 2017). In flatter terrain, manually digitized building polygons developed for exposure mapping are used to remove buildings using a block minimum smoothening filtering procedure to produce a Digital Terrain Model (DTM).

Following river delineation, cross-sections are extracted from the DTM at intervals varying between 200 m and 2 km according to changes in river slope or alignment and densities of built-up areas. A total of 1477 cross-sections are used to cover the domain and for flood mapping. The terrain model acquired does not capture low flow conveyance. Although this is less critical for larger floods (like 100 years and above), an estimation of the low flow conveyance is derived assuming a bounded exponential relationship between drainage and cross-sectional areas established from available surveyed cross-sections (Modrick et al., 2014; Gardner and Waite, 2013). Roughness is considered transversally uniform with Manning's roughness coefficient (n) ranging from 0.06 to 0.07 in the

mountains (depending on elevation and slope) and from 0.04 to 0.05 in the floodplains depending on the braiding and floodplain extents.

The NAM simulated runoff is distributed uniformly or as point source (for contributing drainage area exceeding 70 km²) along the river network. A few dams and reservoirs are simulated using a simple broad-crest weir formulation with consideration of full reservoir levels. Water retention structures scattered along the river network are assumed fully open during the flood event and designed to accommodate the peak flow. The datasets available do not allow to represent with precision the locations and geometries of existing and planned embankment and training walls. Instead, the level of protection granted by such structures are accounted for in the risk model.

6.3.6 Design events and inundation mapping

The NAM and MIKE1D hydrodynamic models are run continuously for the historical observations and downscaled climate-change projections. The series of annual maximum discharge is extracted from the hydrodynamic simulation at 120 nodes (every 5-10 km) based on distribution of exposed elements and river confluences. The Regional Flood Frequency Analysis (RFFA) of annual maxima is performed using the index flood method based on L-moments (Hosking and Wallis, 2005). The method consists of 4 key steps: (1) identify homogeneous regions, (2) select regional flood frequency distribution, (3) develop regional growth curves, and (4) estimate at-site quantiles. At each site, 80 quantiles are estimated to capture the discharge peaks with probabilities ranging from 5 to 10,000-year RPs. The distribution of quantiles aims to maximize quantile density for the high probability events (i.e. every 1-year RP between 5 and 20-year RP; 5-year between

20 to 100-year RP; 10-year interval between 100 to 250-year RP) to reduce uncertainties in the AAL computation.

The flood hazard model is used to map 9,600 inundation scenarios, covering the full basin, produced from the 80 discharge peaks from extreme value analysis at each of the 120 nodes. The discharge peaks are used to generate synthetic trapezoidal hydrographs of 12-hour durations with uniform peak intensity sustained for 3 hours. The synthetic hydrographs are inserted into the hydrodynamic model to establish water levels in the river section between discharge nodes. At confluences, both tributaries are used with a discharge peak of identical probability to account for backwater effects. The stage curves produced by the hydrodynamic models show large variations within the model domain according to the terrain morphology and the drainage area. Figure 6-3 illustrates such variation between the floodplains in Haridwar and the mountainous zones in Joshimat. Here it can be seen that the larger floodplains present in the downstream and most populated regions are less sensitive to water depth changes that can be experienced between discharge scenarios.

(a)

(b)

Figure 6-3 Examples of stage-discharge relation in (a) Haridwar, downstream in the latter floodplain and (b) Joshimat, in the upstream mountain gorges.

The topography and narrow and steep valleys suggest that floodplain flows can be assumed unidirectional and parallel to river channel flows and a 1D representation is suitable to approximate inundation characteristics (Horritt and Bates, 2002). For mapping, planar surface interpolation of water levels between the 1,470 derived cross-sections are overlaid with the terrain model to produce water depth and inundation maps at a 10-m resolution. The maps generated are subsequently used to establish inundation depth-discharge relationships which are used for estimating inundation depth from RFFA of discharge simulations for future scenarios.

6.3.7 Exposure and damage functions

Figure 6-5 shows the residential exposure distribution across the basin and its accumulated value as distributed along the main rivers. Residential exposure and damage functions are developed by DHI et al. (2017) from satellite imagery, socio-economic statistics, and the survey of approximately 1,250 households across the Uttarakhand State. Damage functions are derived as the ratio of the household contents/assets values

susceptible to damage to the total content value at different inundation depths. A total of 6 curves, considering 2 construction types (pucca such cement and kacha or mud-based) and 3 storey categories (single, double and multiple storeys in Figure 6-4 and Figure 5-3b), were validated against relevant published curves (e.g. Reese & Ramsay, 2010). Local survey data are complemented with socio-economic statistics and manually digitized by creating cluster polygons to scale up and spatially distribute residential assets and building types across the model domain (Figure 6-5a). To facilitate the risk computation, the exposure polygons are subsequently simplified into points that are scattered within each polygon with constant density. The economic value derived for each polygon is then distributed uniformly between its points. The final layer contains approximately 90,000 exposed elements located along the main rivers. The exposure distribution, values and damage functions are derived for present day and kept constant for future risk projections.

Figure 6-4 Examples of residential vulnerability curves (a) single storey (b) double storey (Data source: DHI et al., 2017). The curves are identical, but the total value of the content varies for the 2 building construction types (pucca and kacha).

6.3.8 Hazard-Exposure database and protection

The exposure layer is expanded with the discharge probabilities and the inundation maps produced in the flood hazard model. For each exposed element, water depth is extracted from each of the 80 inundation maps and associated with the corresponding peak discharge intensity of the direct upstream site. The river network is further divided into 892 sections with each one having an interval of 250 m. Each section represents a virtual embankment and each exposed element is associated with the nearest section. Economic exposure is then distributed along the river network to understand the relative economic importance of the virtual embankment sections. Figure 6-5b shows the quartiles of the normalized values of the asset exposed to 1,000-year event accumulated along each embankment section. For risk computation, each section can be associated with a design level of protection for current climate. By default, rural and urban zones are assumed to be protected for a 25- and 100-year discharge RPs, respectively. The level of protection can be varied locally for testing adaptation options.

Figure 6-5 Residential exposure in terms of (a) polygons and (b) normalized economic exposure quartiles as accumulated and distributed along the main river network for the 1,000-year flood

6.4 Results

6.4.1 Monsoon and annual maxima rainfall

Climate model outputs are used to identify projected changes in rainfall accumulation over the monsoon period and average annual maximum extremes. For each climate model, monsoon rainfall is accumulated over the months of June-July-August-September (JJAS) for control and projected periods, respectively, and change ratios between the two periods are estimated (Figure 6-6). Two climate models, CSIRO-MK3 RCP4.5 and IPSL-CM5A RCP8.5, are selected to illustrate the range of variation, in dryer or wetter monsoon, displayed by the model ensemble. The CSIRO-MK3 RCP4.5 projection show little change in the hills but has a decrease by up to 18% of monsoon rainfall volumes in the lower regions. The IPSL-CM5A RCP8.5 projection displays a similar gradient of variation from North to South but under overall wetter conditions with

above 20% volume increase in the northern hill regions and little variation in the lowest floodplains. All other RCP4.5 scenarios from the ensemble predict an increase of monsoon rainfall, suggesting that changes are more dependent of the GCM/RCM combination than the RCP scenario selected. Averaged at the basin scale, 7 out of 14 models indicate a monsoon precipitation increase above +5% (with a maximum increase of 33%) and 4 a decrease below -5% (with a maximum decrease of 36%). The south and east display a greater number of models (4 to 6) predicting a decrease ($<-5\%$) while the central and west show higher agreement (8 to 9 models) in monsoon rainfall increase (above 5%).

The annual maxima of daily rainfall are extracted from the climate models to produce an average variation of annual maxima between control and future periods (Figure 6-7). Despite a reduction in monsoon rainfall volume, the CSIRO-MK3 RCP4.5 scenario predicts an increase in average annual rainfall maximum across the full basin ranging from 5% in the south to up to 20% in the northern part of the basin. For the IPSL-CM5A RCP8.5 scenario, annual maxima are expected to increase by at least 20% across the whole basin and above 40% in the north-western part of the basin. There is higher agreement between climate models about a projected increase in daily rainfall annual maxima compared to the monsoon rainfall projections. On average, at the basin scale, 2 climate models predict a decrease ($>-35\%$ and $<-5\%$) and 10 predict an increase ($>+5\%$ and $<66\%$) in terms of daily annual maxima. The lower regions (around Dehradun and Haridwar), display the largest agreement between climate models towards an increase (12 out the 14 models).

Figure 6-6 Projected changes in monsoon rainfall during JJAS for scenarios of (a) CSIRO-MK3 RCP4.5 and (b) IPSL-CMSW RCP8.5 as well as the count of models predicting (c) decrease (>-36% and < -5%) and (d) increase (>5% and <33%).

Figure 6-7 Projected changes in average annual maxima of daily rainfall for scenarios of (a) CSIRO-MK3 RCP4.5 and (b) for IPSL-CMSW RCP8.5 scenario as well as the count of models predicting a decrease (>-35% and <-5%), (d) as count of models predicting an increase (>+5% and <66%).

6.4.2 Extreme discharge estimation and projections

A manual calibration of the hydrological model (i.e. NAM) was performed by comparing the simulated and observed annual peaks for the 1980-2015 period. Figure 6-8 shows the simulated produced by the hydrodynamic model and observed peak discharges

at the upstream and downstream gauges. After quality control, 3 years record, presenting excessive ($>60\%$) deviations between rainfall and discharge observations, were removed from the historical dataset. As an example, an event in year 2011 displays the highest rainfall values uniformly across the full basin while no large discharge event has been recorded for the year. Of the remaining years, an average positive bias of 15-30% in the simulated peaks is considered acceptable to account for the differences between the observations, representing a peak value averaged over a 24-hour window, and the instantaneous nature of the peak discharge simulations (Figure 6a). The regional calibration approach is validated at the catchment outlet in Haridwar with a mean relative error in peak discharge prediction of 1.9% (Figure 6b). The overall calibration of the NAM model is judged satisfactory for the simulation of high peak flows associated with extreme rainfall events under present and future climate.

Figure 6-8 Simulated versus historical annual peak discharges for (a) calibration at mountain gauges, and (b) validation of the regional calibration approach in Haridwar. The discharge for the year 2013 is back estimated at $21,519 \text{ m}^3/\text{s}$ (Agrawal, 2017) without the Tehri Dam (not modelled).

Continuous rainfall-runoff and hydrodynamic simulations are performed for the 32 years of observations and downscaled climate projections. In each scenario, annual maximum series are extracted at 120 discharge nodes. To perform the RFFA, we split the basin into 2 geographical regions (north-east NE and south-west SW) with expected similarities in terms of discharge regime. The two regions are tested for homogeneity, discordancy and goodness-of-fit using the Hosking and Wallis tests (Hosking & Wallis, 2005) using the sampling of variability of L-moment ratios based on Monte-Carlo simulation of 1,000 replications of a region. To minimize dependencies, which may influence the test result, two subsets of 7 to 9 sites from different tributaries are picked to represent each region. The tests results are summarized in Table 6-2. Heterogeneity measures of 0.81 (NE) and 0.60 (SW) and at-site discordancy measures below critical levels are produced from the site subsets, confirming the homogeneous characteristics of the 2 regions selected.

Goodness of fit is evaluated, according to the test of Hosking & Wallis (2005), for the generalized logistic (GLO), generalized extreme value (GEV), generalized normal (lognormal), Pearson type III (PE3), and generalized Pareto (GPA) distributions. In this test, and for an acceptably homogeneous region, for a distribution to be valid, the goodness of fit measure can be approximated by a standard normal distribution. The distribution then is accepted at the 10% significance level corresponding to a Z score absolute value below 1.645. From the goodness-of-fit tests, the GLO is judged acceptable for the NE region, and the GLO, GEV, GNO and PE3 for the SW region. The GLO distribution is subsequently used for regional parameter estimation in both regions. The two regional distribution parameters are estimated from all sites in each region, and for each site quantiles for the 80 RPs are estimated.

Table 6-2 Results of discordancy, heterogeneity and goodness of fit for regional flood frequency analysis according to the tests of Hosking and Wallis (2005)

Region	Sites	Discordancy			Heterogeneity H1	Goodness-of-fit				
		Critical	Min	Max		GLO	GEV	GNO	PE3	GPA
NE	9	2.49	0.43	2.1	0.81	-0.96	-2.02	-2.52	-3.42	-4.68
SW	7	1.92	0.18	1.58	0.6	1.16	0.16	-0.29	-1.12	-2.34

To illustrate the sensitivity of the RFFA approach, we compared the quantile estimates derived from the RFFA using GLO distribution to those derived from at-site fit of a GEV distribution (based on the L-moments), widely used and often preferred in hydrology to model extreme rainfall or flood events (e.g. Sinclair & Ahmad, 1988; Morrison et al., 2002; Falter et al. 2015). The results are shown at four locations (Figure 6-9) and across the full basin for the 25- and 100-year RPs (Figure 6-10). At the four locations selected, the GLO and GEV distributions appear suitable to describe the heavy tailed maximum discharge simulated. Differences between the 2 approaches are minimal (10% or less) for the 25-year RP but more pronounced for the 100-year and larger RPs. At the scale of the basin, the pattern shown at the 4 locations is confirmed with an increasing difference between RFFA and at-site estimation procedures for increasing RP. We can also identify a spatial pattern of the differences in peak magnitudes between the two approaches, with the regional GLO distributions producing higher peaks in the upstream and eastern rivers and lower intensities in the west and downstream reaches. The RFFA approach is expected to produce more efficient quantile estimates, especially for larger RPs where at-site estimates have large uncertainties.

Figure 6-9 Weibull plotting position of simulated annual maxima of discharge for historical observations and climate projections (CSIRO-MK3 RCP4.5 in red and IPSL-MK3 RCP8.5 in blue) with RFFA GLO distribution (plain line) and at-site GEV distribution (dashed line) at locations of (a) Haridwar, (b), Karanprayag, (c) Uttarkashi, and (d) Joshimat.

Figure 6-10 Percentage variation of discharge levels between GLO (L-moments RFFA) and GEV (L-moments at-site) distributions for (a) 25-year RP and (b) 100-year RP.

Figure 6-11 shows the changes in extreme discharge are estimated for the current and projected climates from the RFFA GLO distribution quantiles. The CSIRO-MK3 RCP4.5 model generally tends to predict a decrease of the 25-year (-20%) and 100-year (-10%) discharges in southern and eastern reaches and no change or increase in the northern reaches. This scenario exemplifies the difference that can be expected from the analysis of average annual maxima of rainfall and extreme discharge. Here, the same scenario predicts an increase in average rainfall annual maxima (Figure 5) but lower discharge extremes, potentially impacted by the spatial and temporal redistribution of extreme rainfall and by the monthly variation of quantile change factors at the beginning and the end of the monsoon periods when historical flooding occurred.

Figure 6-11 Projected changes in 25-year and 100-year discharges for (a-b) CSIRO-MK3 RCP4.5 scenario, (c-d) IPSL-CM5A RCP8.5 scenario, and (e-f) the count of models predicting an increase (>5%) in discharge.

The IPSL-CM5A RCP8.5 produces more uniform and extreme results across the basin with a predicted increase between 50 and 100% for the 25-year and between 75% and 120% for the 100-year discharge peaks. On average, the 25-year and the 100-year are predicted to increase by 40% and 60% respectively across the basin and scenarios, indicating that the lower probability event magnitudes are expected to increase more than the more frequent events. While there is no full agreement between all the climate models, the majority (at least 10 out of 14) indicates an increase (>5%) of discharge extremes across the full basin with 11 models predicting an increase in the high exposure downstream reaches.

6.4.3 Future impacts

Figure 6-12 shows the risk metrics produced by the present and future discharges estimated from the RFFA and at-site statistics. Residential LEP curves are produced for observed and climate projections using the extreme discharge levels produced by both RFFA GLO (Figure 6-12a) and at-site GEV (Figure 6-12b) distributions. Losses are established assuming 25-year and 100-year levels of protection for the current climate at rural and urban zones respectively. The method used to estimate extreme discharge levels has little impact on climate scenarios producing losses larger than losses estimated for current observations. However, larger differences are seen for the 3 climate projections predicting lower losses than under current climate conditions. This model behaviour is attributed to the larger differences in discharge quantiles given by the GEV distribution for probabilities above the 100-year RP for those projections and at locations with critical exposure (e.g. Haridwar in Figure 6-9a).

Figure 6-12 Residential LEP curves for observations and climate projections using discharge extreme probabilities from (a) RFFA GLO, and (b) at-site GEV; (c) Quartiles of changes in loss return period of losses predicted by the ensembles of climate projections, and (d) boxplot of AAL for the ensembles of climate projections using both GLO and GEV distributions for estimating discharge extremes.

Changes of probability for the same loss levels are produced for the ensemble of climate projections and for both extreme discharge estimation methods (Figure 6-12c). The model ensembles indicate that the 30-year and 100-year loss events, under current climate,

could become as frequent as the 10-year and 30-year events or lower, respectively, for half or more of the climate projections. The impact of the extreme discharge estimation method is minimal in the first and second quartiles of the projection's ensemble. The differences in the third quartile for probabilities above the 100-year RP are attributed to the much lower level of losses generated from the 3 dryer projections for which the GEV distribution gives much lower discharge peaks.

The estimated AAL grouped by RCP is shown in Figure 10d. The median AAL is projected to increase by 3, 4 and nearly 6 times for the RCP26, RCP4.5 and RCP8.5 scenarios respectively. Again, the extreme discharge estimation methods show little influence on the results. On the other hand, the AAL presents large variations for the same RCP scenario. For example, the EC-EARTH RCP26 scenario projects an AAL equal to 0.7 of the AAL value under current climate while the same emission scenario MPI-ESM-LR RCP26 predicts a 5-fold increase. Furthermore, the predicted AAL for both RCP26 emission scenarios are higher and smaller than the highest and smallest AAL, respectively, predicted by the 6 RCP4.5 emission scenarios.

These results illustrate the large variability of results principally attributed to the GCM/RCM model prediction. The range of variation is also extensive for RCP8.5 emission scenario with AAL predicted to increase between 1.6 to 8.4 depending on the GCM/RCM combination.

6.4.4 Structural adaptation

The flood risk modelling framework can be used to efficiently screen for climate change adaptation strategies at the scale of the basin. In this study, adaptation is achieved by identifying design protection levels for the smallest number of embankment sections

required to maintain future losses within the range of losses associated with the current climate. This is essentially determining what level of adaptation is required to maintain the status quo with respect to losses.

To illustrate the concept, the IPSL-CM5A RCP4.5 scenario with an AAL 3.5 times higher than the current climate is selected as scenario to prepare for. The 250 m river sections of the Exposure-Hazard database are ordered decreasingly according to the exposure value they serve to protect. Different lengths of the re-ordered river sections are chosen for upgrading to a higher protection level under the current climate. In this example, 5, 12, 25, 62 and 125 km of upgraded river sections with uniform 250, 500 and 1,000-year protection levels are chosen.

For each length of upgraded river, and each level of protection, LEP curves are established and compared with the LEP curve for current climate for return period above 25-year (no losses are expected below the 25-year threshold as per current climate protection). The LEP changes reported here assume that the exposed elements driving the most frequent losses (i.e. below the 25-year RP under climate projection) are not adapted (Scenario A) or fully adapted (Scenario B). Those exposure elements are usually located in rural areas scattered along the rivers. Due to their low value accumulation at the local scale, they are not identified as the most cost-effective river reaches to protect. However, their accumulation at the scale of the basin can influence the LEP and ALL results by producing limited but chronic losses. There, alternative adaptation options (e.g. building proofing, re-settlement) should be identified, particularly if minimizing AAL variations are considered in planning.

Figure 6-13 shows the results of the different adaptation strategies. Benefits are visible for RPs up to the 75, 150 and 300-year loss levels respectively for the 250, 500 and

1,000-year protection upgrades. Maintaining projected losses within a 10-30% increase would require upgrading the most critical 62 km (Scenario A) or 25 km (Scenario B) of river reaches. Full adaptation (loss change below the 10% increase) would require protecting twice the length of river sections with benefits visible only up to the 50, 100 and 150-year losses for the 250, 500 and 1,000-year protection level respectively.

Figure 6-13 Changes in losses under current climate and IPSL-CM5A RCP4.5 scenario for different lengths of rivers (5 to 125 km) upgraded to 250, 500 and 1,000-year protection levels under current climate. **Scenario A:** no adaptation of critical zones; **Scenario B:** adaptation of critical zones. Critical zones comprise scattered rural zones producing losses below the 25-year RP under climate change.

The results illustrate the advantage of a regional risk-based approach to identify economic benefits produced by local adaptation strategies. They allow to identify convergence of regional mitigation strategies based on both spatial distribution of structure upgrade and design level of protection for the upgrade. These results can be further used to establish the most viable option between an additional upgrade of 37 km of river in

Scenario A or alternative measures required to reduce flood exposure or vulnerability in scattered rural zone in Scenario B.

6.5 Discussion

6.5.1 Data quality and flood hazard model

The flood hazard and risk models have been developed with the best datasets available in the region at the time of the study. However, inundation predictions are still subject to significant uncertainties originating from the data available. Hydrometric data is limited, and its quality can be questioned; particularly in the hills. Discharge estimates in the hills lack sufficient spatial and temporal resolution, and estimates based on the rating curve method can be altered by morphological changes occurring over the monsoon season or during a single flood event. Therefore, to compensate for the low spatial resolution of ground-based observations, weather variables have been complemented with climate model outputs, satellite observations and orographic corrections. Despite this approach, convective processes and orographic influences might have very localized effects that are not necessarily captured in the final data produced. Despite these limitations, the hazard model reproduces historical discharge observations with enough accuracy, particularly in the downstream and most exposed locations (for instance, Haridwar) where accuracy is most important.

The quality of the terrain model varies greatly across the study domain and, despite the correction applied, a higher accuracy and homogeneous dataset complemented with cross-sections and water level observations using a consistent benchmark, would enhance the calibration of the model and accuracy of results. The hydrodynamic model structure, relying on a fixed description of river bed geometry, is not designed to capture the frequent

morphological changes occurring in the river. Those processes can have non-negligible consequences in expected water levels and inundation probabilities (Guan et al., 2015; Oliver et al., 2018).

6.5.2 Future rainfall and discharge extremes

From the 14 climate models, 6 indicated an increase ($>5\%$) and 3 a decrease ($< -5\%$) in monsoon rainfall across the basin. Large variations exist between models and across the basin with some presenting drier conditions in the higher mountain ranges and wetter conditions in the foothills (e.g. EC-EARTH) and others showing opposite trends (MPI-ESM-LR). The differences between CORDEX-SA model outputs over the Himalayas were previously illustrated by Choudhary & Dimri (2017).

The agreement between climate models on the direction of change for extreme rainfall is greater than the model agreement for monsoon rainfall, with the basin average of 10 models indicating an increase and 2 models a decrease in the annual rainfall maxima. Within the basin, the higher agreements are reached for the centre and particularly the southern region, with up to 12 of the models predicting an increase. These results are aligned with the findings of Wijngaard et al (2017), who showed an overall increase in extreme precipitation for the Upper Ganga basin for all 8 GCM investigated and Singh et al. (2016) that established full agreement between downscaled GCM towards an increase in sub-daily rainfall extremes over Roorkee (south of Haridwar).

Discharge extremes show relatively good agreement between models towards an increase (11 out of 14 on average) with larger variations between GCM/RCM models rather than RCP scenarios. The lower probability discharges are expected to increase more (e.g. 100-year with 60% increase) than the more frequent ones (e.g. 25-year with 40%

increase). These results are again similar to the results of Wijngaard et al (2017) that showed increase in 50-year discharge between 53% and 74% across the full Upper Ganga basin (Nepal side) in the near future (2035-2064) for 2 climate scenarios.

The extreme discharge probabilities appear to be little sensitive to the estimation method (at-site or RFFA) and distribution (GLO or GEV) for estimates below the 100-year RP. However, they are expected to be much more sensitive to the statistical downscaling method applied. The CFQM method applied here specifically account for changes in extreme precipitation and is usually better at preserving extremes compared to change factor methods based on mean precipitation only or bias correction methods (Sunyer et al., 2015). However, the correction factors for extreme quantiles is derived from relatively few values originating from climate models not able to describe the full complexity of the mountainous weather systems. It is important to remember that projections of precipitation extremes are affected by high level of uncertainties originating from climate models, downscaling techniques and natural variability (Kundzewicz et al., 2014; Nicholls and Seneviratne 2015), particularly in the complex terrains of the Himalayas.

Further studies should be aimed at identifying the sensitivity of the extreme discharge prediction to different statistical modelling approaches in the study area or, more generally, at improving the representation of the complex orographic effects and convective storms in dynamic climate models.

6.5.3 Risk model and future risks

Extreme discharge variations between the climate projections propagate into significant differences in damages predictions. The climate models tend to agree into an overall increase on average 4 to 5 times higher than annual average losses predicted under

current climate but with large variations in magnitude between climate models. Again, the methods for estimating discharge quantiles seemed to have little influence on the results except for the experiments showing decrease in losses. In this study, the 100-year residential loss is up to 1.5 time higher than current day losses. The result is in the same order of magnitude of the 100-year direct loss increase predicted by Hallegate et al. (2010) for Mumbai for the 2080. However, loss variations are hardly comparable between studies due to the specific risk profile of each region and the different assets, climate models, and future periods considered. Here, the risk analysis should be further expanded to integrate other classes of assets relevant for the basin economy (e.g. agriculture) and population and their related socio-economic vulnerabilities.

In this application, the event structure assumed a spatially uniform RP and direct association of the same RP to describe the inundation scenario and damage probability. Such approach can lead to an overestimation of the risk cumuli over larger spatial scale (Thiessen et al., 2015; Schneeberger et al., 2017). However, the large exposure concentration in the downstream reaches and the strong event correlation within the area is expected to produce negligible errors in risk metrics compared to the variations in losses produced by the climate scenarios (see Oliver et al., 2019).

Water depth alone, as used here to describe flooding intensity, do not capture fully the hydrological risks, particularly in the hilly regions of Uttarakhand. In this steep terrain, flooding can be associated with scouring, erosion and debris flow, frequently combined with landslides dam break (Wasson et al., 2013) and Glacier Lake Outburst Flows (Rana et al., 2013; Das et al., 2013). Therefore, the overall risks predicted in this study might be underestimated for the mountains but the relative changes between scenarios is believed to

provide a solid measure of the significance of climate change projected impacts at the full basin scale.

6.5.4 Further considerations for adaptation

The flood risk modelling is used to efficiently test structural adaptation strategies at the full basin scale. The simulations performed allow to quickly identify protection levels under current climate and the spatial coverage required to reduce residential losses close to present levels for any future condition. The approach is based on spatial relationships between exposed elements and embankment sections and a subsequent classification of the accumulated economic value of protection. Also, the adaptation approaches investigated account only for reduction of absolute economic damages associated with residential assets. Active risk management and adaption requires to integrate other critical infrastructure and economic sectors such as agriculture and infrastructure or socio-economic exposure and vulnerabilities.

Finally, the derived information for adaptation can help screen priority intervention areas and design protection level to be sought for further analysis within a comprehensive cost-benefit analysis CBA framework. The risk modelling framework could be extended further and could easily integrate additional information (e.g. construction costs, varying protection levels, changes in exposure and vulnerabilities) that could support more detailed CBA or optimization procedures (see for example Dittes-Li, 2017; Wang et al., 2015).

6.6 Summary

This study presents a flood risk modelling framework adapted for climate change impact assessment. The modelling framework has been applied to the Upper Ganga River

in Uttarakhand, India, to investigate residential economic risks in the medium-term future (2045-2065) and identify possible structural adaptation strategies to mitigate future risk at the basin scale.

The climate models provided good agreement on the direction of change for extreme rainfall with the basin average of 10 models indicating an increase but larger variation on the magnitude of the increase. Discharge extremes showed relatively good agreement between models towards an increase (11 out of 14 on average) with larger variations between GCM/RCM models rather than RCP scenarios. Extreme discharges variations between climate scenarios propagated into significant differences in damages predictions. The climate models tend to agree into an overall increase on average 4 to 5 times higher than annual average losses predicted under current climate. Structural adaptation strategies, considering the level and locations of protection upgrade required to minimize future losses of an average climate scenario, were tested at the full basin scale. A cost-efficient strategy could consist in upgrading 25 km of the most economically exposed river section to a 500-year protection level.

The modelling approach was found useful and efficient to screen priority intervention areas and design protection level to be sought for further analysis within a comprehensive cost-benefit analysis framework. It could also be extended further to integrate additional information (e.g. construction costs, varying protection levels, changes in exposure and vulnerabilities) and more detailed optimization procedures.

CHAPTER 7 Conclusion

7.1 Summary of study

The objective of this work was the development and application of three different frameworks for flood risk assessments. The different approaches proposed allowed to address some of the limitations of traditional flood risk management, namely, the reciprocal influences of morpho-dynamics and dike failure on hazard and risks patterns, the spatial coherency of regional events and future flood risk simulation and adaptation at the regional scale. The approaches were developed to ensure a computationally efficient modelling system suitable to represent the dynamics and uncertainties of the different risk modelling components (hazard, vulnerability and risk) forced by data intensive and novel continuous simulation approaches or ensembles of climate models. Each of the three frameworks and studies carried out was developed to answer independent research questions.

7.1.1 How river morphological dynamics impact dike failure, flood hazards and risks over different time-scales?

An efficient probabilistic hazard and risk modelling approach using continuous simulations was developed to capture uncertainty and variability of river channel conveyance over time and failure of dikes. The approach was applied in the Koshi River, Nepal to investigate changes in river bed aggradation and their consequences for present day and near future (2-year and 5-year time windows) and using continuous simulation of 1,000 year of discharge.

The study investigated potential changes in: (i) dike failure locations and frequencies as produced from local changes in river morphology and accounting for uncertainties in changes prediction and river roughness, (ii) probabilistic inundation extents accounting for the uncertainty in the selection of the flood hazard footprint extracted from a pre-run catalogue of 2,295 deterministic flood events, and, (iii) the distribution of flood losses established for the loss distribution and frequencies of the ensemble of flooding scenarios produced by the modelling chain.

In the context of the Koshi River, the variations produced by the different scenarios supported the general conclusion that river bed aggradation has a non-negligible impact on losses, particularly for high frequency events, which might be critical for proper cost-benefit analysis and decision-making. The study also demonstrated that, for rivers protected by embankments, loss frequencies can be expected to occur below the design criteria of the protection scheme in place. The use of continuous simulations and a probabilistic dike breach model illustrated significant differences in risk metrics when compared with a binary treatment of dike breach or the direct association of peak discharge and loss frequencies as traditionally applied in flood risk analysis.

In summary, the consideration of the dynamics and variability of the full flood hazard system, comprising river-dike-floodplain, and the application of continuous simulation improved greatly the quantification of flood risks and shall be considered for impact-based mitigation solutions. The modelling framework and the approach proposed have the potential to be transferred to many river systems where dike failure potential or changes in channel conveyance, originating from sedimentation or debris blockage of bridges and structures, which are frequently occurring during flood events, should be accounted for.

7.1.2 How risk metrics vary between spatially coherent and continuous simulations and traditional flood risk assessment methods when applied to regional scales?

This study presented an efficient probabilistic flood hazard and risk modelling chain to produce exhaustive and spatially coherent discharge events at the regional scale. The chain relied on the generation of 5,000 years of continuous weather variables synthetically derived from a multi-site weather generator. The long-term time series allowed to produce continuous discharge and inundation maps. Different event sets were produced from the continuous and spatially coherent data and different degrees of simplification of its underlying structure (e.g. spatial and discharge variability) to investigate the significance of its different components. Catalogues of inundation maps corresponding to each event set were combined and used for damage modelling. The model was applied to investigate the impact of spatial variability in the risk modelling chain and risk cumuli for agriculture and residential economic risks, downstream of four river basins in Uttarakhand, India.

To develop the model chain, three different multisite weather generators were tested to identify their suitability in reproducing discharge extremes. A k-nearest neighbour type was found more suitable for the reproduction of extreme discharge in the downstream area and preserving well the spatial rainfall distribution. The continuous climatic and hydrologic simulations were used to investigate risk metrics derived from the continuous and spatially coherent event set and from the application of T-year return periods events uniformly at the regional scale. From a discharge event perspective, preserving the spatial coherency at the regional scale led to a spreading of local T-year event distributions (and their possible losses) on both sides of a regionally uniform T-year RP. The specificity of the exposure distributions and the correlations between local events magnitude translated

into smaller differences (4%) in losses at high RPs (above 50-year) but larger differences (20%) at low RPs (5-year).

Most importantly, this study illustrated the redistribution of losses in a spatially coherent event set with a shift in the minimum RP generating losses from 5-year (assuming a uniform T-year event set) to 3-year corresponding to the de-correlated events occurring at individual locations. These variations (both positive and negative) led to negligible differences between the average annual losses derived from the spatially coherent and continuous event set and appropriate uniform T-year events but larger differences in the standard deviation of annual losses. The study also showed that, when using traditional flood risk analysis approaches, the number and choice of the T-year RPs should be made with care. The use of too few or not adequate RPs could lead to large errors in the regional averaged risk metrics.

7.1.3 How future flood impacts can be predicted and cost-effectively mitigated at the regional scale?

The study proposed a flood risk modelling framework adapted for climate change impact assessment. The modelling framework relied on: (i) the continuous simulation of a semi-distributed hydrological model forced with present and future weather data, downscaled using quantile perturbation factors, (ii) the continuous hydraulic simulation of the hydrological results, (iii) Regional Flood Frequency Analysis of the discharge simulations generated by the hydraulic model, (iv) a catalogue of flood hazard footprints distributed between regularly spaced river segments and for a dense number of local return period discharge, (v) a database of peak discharge, water level and exposure elements coupled to 6 classes of damage functions, (vi) a risk model allowing to establish scenario

losses based on resampling of the hydraulic simulation and exposure-hazard database accounting for a current or future design protection level for 892 river sections. The modelling framework was applied to the Upper Ganga River in Uttarakhand, India, to investigate residential economic risks in the medium-term future (2045-2065) and identify possible structural adaptation strategies at the basin scale.

The climate models provided good agreement on the direction of change for extreme rainfall with the basin average of 10 models indicating an increase but large variation on the magnitude of the increase. Discharge extremes showed relatively good agreement between models towards an increase (11 out of 14 on average) with larger variations between GCM/RCM models rather than RCP scenarios. Extreme discharges variations between climate scenarios propagated into significant differences in damages predictions. The climate models tend to agree into an overall increase on average 4 to 5 times higher than annual average losses predicted under current climate. Structural adaptation strategies, considering the level and locations of protection upgrade required to minimize future losses of an average climate scenario, were tested at the full basin scale. A possible strategy could consist in upgrading 25 km of the most economically exposed river section to a 500-year protection level.

The modelling approach was found useful and efficient to screen priority intervention areas and design protection level to be sought for further analysis within a comprehensive cost-benefit analysis framework. It could also be extended further to integrate additional information (e.g. construction costs, varying protection levels, changes in exposure and vulnerabilities) and more detailed optimization procedures.

7.2 Future works

The objectives to develop and apply methodological frameworks able to answer the research questions was realized with three different approaches. The overall research investigated the dynamics and structure of flood hazard events and their consequences in flood risk analysis. It is important at this stage to remember that other components of risk, namely exposure and vulnerability are also variable in time and space and their dynamics should be captured together with the hazard dynamics investigated in this work. The fact that each question necessitated a different approach illustrates the pragmatism required for the modelling exercise. Depending on the context and use of the model, the principles of parsimony and pragmatism shall dictate the approach to ensure efficiency and usability of the model and results. The three methodological approaches, while suitable to the study objectives, also displayed limitations and need for future work and are discussed below.

7.2.1 Probabilistic Flood Risk Analysis Considering Morphological Dynamics and Dike Failure

The modelling framework developed in this study allowed to account for variability and uncertainty of river channel conveyance using local probability distribution to represent evolution of river bed elevation and channel conveyance. The use of distributions without direct simulation of the sedimentation processes allows to generate a much larger number of simulations. However, the parametrization of such probability functions to predict future states of the river bed relies on additional morphological studies.

The stochastic breaching model, based on fragility curves, considered three failure mechanisms (overtopping, piping and micro-instability) predominant in some river systems. However, other processes can occur, for example, in braided rivers, where

migrating channel can attack the toe of the structure leading to collapse. While the modelling framework can be parametrized and relate one-dimensional dynamic model outputs (water level, velocity, duration) to failure probabilities, more research is needed to establish fragility curves for other types of failure mechanisms. Similarly, some of the breaching processes might require more accuracy and advanced formulation in 2 or 3 dimensions of the breaching mechanisms and flow characteristics. Advanced physical based models allow to carry such investigations, but their application is limited to localized and scenario-based simulations.

Finally, inundations are determined from a catalogue of exhaustive breach scenarios at any locations along the river. This approach might not be suitable in floodplains where the reciprocal influence between river, dike and floodplain is important, where several layers of flood defences are present or at larger scale. Under such circumstances, simplified approaches (e.g. Courage, 2013) or the application of fast inundation models (see Vorogushyn et al., 2010; Falter et al. 2015) could be investigated, but the computational cost associated is beyond the reach of applicable for large scale flood risk assessment of dike breach scenarios particularly under continuous simulation.

7.2.2 A probabilistic risk modelling chain for analysis of regional flood events

A continuous modelling chain was developed for analysing the limitation of traditional flood risk analysis practice on deriving risk metrics at larger scale. The modelling chain allowed to quantify the uncertainty in the spatial distribution of discharge, roughness and vulnerability parameters.

The study highlighted some of the challenges in the different components of the modelling chain yet to be addressed. As an example, the use of multisite weather generators

presents many advantages to produce regional and local scale events compared to methods based on multivariate frequency analysis of discharge. However, the approach introduces additional uncertainty in the modelling chain and the suitability of multi-site weather generators to represent extreme hydrological events at both the local and regional scale still need further attention.

In theory, the modelling framework could have been enhanced to capture the stochasticity of dike failure in the modelling chain. The approach would have been feasible because of the simplified inundation model suitable to describe the narrow floodplains of Uttarakhand. Instead a simple binary treatment of the flood defences was applied because of the limited defence data available and the scope and duration of the study itself. The applicability of a continuous approach coupled with a dynamically coupled stochastic failure component still need to be demonstrated at this scale.

7.2.3 Impacts and risk-based adaptation to future floods at the regional scale

A flood risk modelling framework for climate change impact assessment relying on statistical downscaling of weather variables was applied to the Upper Ganga Basin, India. Projections of precipitation and subsequent discharge extremes are affected by high level of uncertainties originating from climate models, downscaling techniques and natural variability, particularly in the complex terrains of the Himalayas. The CFQM method applied accounts for changes in extreme precipitation. However, the correction factors for extreme quantiles are derived from relatively few values produced by climate models not able to describe the full complexity of the mountainous weather systems. Further studies should be aimed at identifying the sensitivity of the extreme discharge prediction to different statistical modelling approaches in the study area or, more generally, at improving

the representation of the complex orographic effects and convective storms in dynamic climate models.

To describe the loss, the event structure assumed a spatially uniform RP and direct association of the same RP to describe the inundation scenario and damage probability. For simplicity purpose and considering the limited impacts of spatial events on the risk metrics established earlier in the Upper Ganga, this approach was judged sufficient. However, this simplification of the event structure can lead to an overestimation of the risk cumuli over larger spatial scale. A better representation of the risks could be achieved using long-term and continuous simulation of weather variables using multi-site weather generators integrating projected climate changes.

The flood risk modelling is used to efficiently test structural adaptation strategies at the full basin scale and screen for adaptation strategies. The risk modelling framework could be extended further and could easily integrate additional information including: cost of construction and maintenance, plans and policies designed to reduce vulnerability and exposure. The different components could be easily added to the modelling framework to support the design of detailed and optimal mitigation strategies.

7.3 Concluding remarks

The research work proposed different modelling approaches to investigate specific limitations of current practice of flood hazard and risk modelling and analyses. Different modelling approaches have been designed to specifically address the research questions. From this work, it is possible to envision an ideal and generic modelling framework for flood risk assessment that would comprises (i) long-term continuous and spatially coherent event set produced from, present or future, synthetic rainfall or discharge, (ii) a

probabilistic river channel model able to describe different levels of uncertainties associated with the river (sedimentation, roughness, conveyance), (iii) a stochastic structure behaviour model, to capture the uncertainty associated with flood defence flow control system performance, (iv) an efficient inundation model or an extensive catalogue of flood events, (v) a probabilistic damage model able to merge the uncertainties of the hazard, exposure and vulnerability models. The research demonstrated that integrated approaches, which can model the complexity and uncertainties of flood hazard and risk, are nowadays applicable. As researchers produce more accurate and efficient approaches to model the different components of the risk chain, and as data availability and computational power increase, the application of integrated approaches shall become more widely used to better support the design of risk management strategies for the public and private sectors.

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