Process Based Modelling of Future Variations in River Flows and Fluvial Sediment Supply to Coasts Due to Climate Change and Human Activities: Data Poor Regions

Thotapitiya Arachchillage Jeewanthi Gangani Sirisena

**PROCESS BASED MODELLING OF FUTURE VARIATIONS
IN RIVER FLOWS AND FLUVIAL SEDIMENT SUPPLY TO
COASTS DUE TO CLIMATE CHANGE AND HUMAN
ACTIVITIES: DATA POOR REGIONS**

Thotapitiya Arachchillage Jeewanthi Gangani Sirisena

**PROCESS BASED MODELLING OF FUTURE VARIATIONS
IN RIVER FLOWS AND FLUVIAL SEDIMENT SUPPLY TO
COASTS DUE TO CLIMATE CHANGE AND HUMAN
ACTIVITIES: DATA POOR REGIONS**

DISSERTATION

to obtain

the degree of doctor at the University of Twente,

on the authority of the rector magnificus,

Prof.dr.ir. A. Veldkamp,

on account of the decision of the doctorate board,

to be publicly defended

on Thursday the 10th of December 2020 at 10:45 hour

by

Thotapitiya Arachchillage Jeewanthi Gangani Sirisena

born on the 05th of October 1984

in Rathnapura, Sri Lanka.

This dissertation has been approved by:

Supervisor: Prof.dr. R. W. M. R. J. B. Ranasinghe

Co-supervisor: Asso.Prof.dr. S. Maskey

This research was conducted under the auspices of the Graduate School for Socio-Economic and Natural Sciences of the Environment (SENSE).

Cover photo credit: Creative Commons Attribution-Share Alike 4.0 International

ISBN: 978-90-365-5097-0

URL: <https://doi.org/10.3990/1.9789036550970>

Printed by: Veenman +, The Netherlands.

Copyright © 2020 by Thotapitiya Arachchillage Jeewanthi Gangani Sirisena. All rights reserved. No parts of this thesis may be reproduced, stored in a retrieval system or transmitted, in any form or by any means, without the prior permission in writing from the author.

Doctorate Board

Prof.dr. F. van der Meer	University of Twente - Chairman/secretary
Prof.dr. R. W. M. R. J. B. Ranasinghe	University of Twente / IHE Delft - Promotor
Asso.Prof.dr. S. Maskey	IHE Delft - Co-promotor
Prof.dr. M. S. Babel	Asian Institute of Technology, Thailand
Prof.dr. Z. Su	University of Twente
Asso.Prof.dr. D. C. M. Augustijn	University of Twente
Prof.dr. M. E. McClain	Delft University of Technology / IHE Delft
Prof.dr. K. P. P. Pathirana	University of Peradeniya, Sri Lanka

SUMMARY

One of the main, if not the main, source of sand to the coast is fluvial sediment supply. Any change in the sand supplied to the coast will disturb its equilibrium state, potentially leading to coastline recession (with a decrease in fluvial sediment supply) or coastline progradation (with an increase in fluvial sediment supply). Given ongoing human activities in basin areas (e.g., agriculture, hydropower dams, new/expanding human settlements) and climate change, many of the world's low elevation coastal zones are at risk of losing land and rich bio-diversity therein. In this context, hydrological model investigations are required to assess the impacts of climate change and relevant human activities on fluvial sediment supply to coasts. However, in data-poor areas, the standard approach of using a well-calibrated/ validated process-based hydrological modelling for impact assessment is challenging due to the limited availability of observed data.

The overarching objective of this study is to investigate how different modelling approaches and input data sources may influence projections of streamflow and fluvial sediment loads accounting for climate change and human activities, particularly in data-poor basins. In order to achieve this overarching objective, two case study sites were selected: Irrawaddy River Basin in Myanmar and Kalu River Basin in Sri Lanka. Compared to other major river systems in Southeast and South Asia, the main rivers of these two basins can be considered to be unregulated. However, future flow regimes in the two basins could change significantly due to proposed development activities. These changes can be further exacerbated due to impacts of the extreme weather conditions, which are quite frequently observed in these regions, and due to climate change effects.

The process-based hydrological model – Soil Water Assessment Tool (SWAT) was applied in a distributed setting (by dividing the basin into sub-basins and hydrological response units) to determine the best performing precipitation product(s) by simulating the streamflow in the Irrawaddy River Basin, Myanmar. The potential for using remote-sensing data (evapotranspiration) and available limited streamflow data in the calibration of the distributed hydrological model was rigorously investigated at the same basin. The validated SWAT model was then used to estimate changes in future streamflow and fluvial sediment supply to the coast under two scenarios: (a) climate change only, and (b) climate change and human activities. All simulations for the Irrawaddy basin were forced with General Circulation Models (GCMs) climate projection data for two Representative Concentration Pathways (RCP 2.6 and RCP 8.5). Future human activities were presented by six planned reservoirs on the Irrawaddy and tributary rivers. In order to identify the effect of spatial heterogeneity, the same methodology was applied at the Kalu River Basin, Sri Lanka, with some differences. Because the coarse resolution (> 1.1 degrees) of GCM data did not capture the seasonal variability of the precipitation here, Regional Climate Model (RCM) data for the same RCPs were used for the Kalu River Basin. Finally, the SWAT simulated fluvial

sediment loads were compared with corresponding projections obtained from a commonly used lumped empirical model (i.e., BQART model) to investigate the performance of two different modelling approaches.

The simulated streamflow in both basins shows that models forced with interpolated gauge data perform better, despite the low gauge density in the Irrawaddy River Basin than with other precipitation data products (without interpolated gauge data, PERSIANN-CDR and CHIRPS) tested in the study. The global precipitation products provide low annual precipitation compared to the in-situ precipitation data in the study areas. However, model simulations forced with those products also reproduce the observed streamflow with reasonable accuracy at a majority of the stations in the Irrawaddy River Basin. In terms of the model calibration, this study shows that hydrological model calibration with a single variable (either streamflow or evapotranspiration) leads to good performance with respect to the calibration variable but usually results in reduced performance in the other variable. In the multi-variable calibration using both streamflow and evapotranspiration, reasonable results are obtained in both variables.

SWAT model simulations forced with future projected climate data show that streamflow and fluvial sediment loads will increase in the Irrawaddy and Kalu basins by the end of the century. Due to the planned reservoirs in the Irrawaddy basin, seasonal streamflow is projected to change by -6% to 34% (on average), while sediment load may change by -9% to 37% (on average) at the basin outlet under RCP 8.5 during the end-century period. However, in terms of the annual sediment load, the projected reduction due to the planned reservoirs at the Irrawaddy basin outlet is minimal (-5%).

The comparison of sediment loads projected by SWAT (daily time step) and the lumped empirical BQART model (annual time step) showed different results for the Irrawaddy and Kalu basins. In the Irrawaddy basin, the SWAT model projected higher annual sediment load than the BQART model, whereas in the Kalu basin, BQART model projected higher sediment load than the SWAT model, under both climate change scenarios and both future periods considered. However, when the base period and future period estimates from the same model (either SWAT or BQART) were compared, the BQART model projected lower future increments than the SWAT model in both river basins. One major reason for this difference is the difference in size of the two basins. These results indicate that the BQART model might be more suitable for large basins (such as the Irrawaddy), whereas the SWAT model is suitable in both small and large basins.

ACKNOWLEDGEMENTS

Over the past five years, completion of this PhD was a biggest challenge to me. Many people helped and supported me along this long journey and without them, this would have been impossible to achieve. I want to express my sincere gratitude to all of them.

First, I would like to express my sincere gratitude to my promoter Professor Roshanka Ranasinghe for giving me this opportunity to work as a PhD student under his supervision. I am extremely grateful for your guidance, critical and motivate insights, patience, encouragement and understanding that played a vital role in this successful endeavour. Thank you for continuous support and motivating me throughout past five years to improve my work.

I extend my sincere thanks to my co-promoter Associate Professor. Shreedhar Maskey for his continuous guidance, critical and constructive comments and suggestions, in-depth knowledge, and advice. Many thanks for your critical evaluations and consistent inputs for every components of this study to thrive for the best possible outcomes. I would thank you for the continuous support given me to finalize my dissertation and research articles.

I am sincerely thankful to Professor M.S. Babel for his support on data collection. I gratefully acknowledge Dr. Ilyas Masih for giving his valuable time to guide me on hydrological modelling and to have fruitful discussions. A special thank goes to Associate Professor Assela Pathirana for helpful discussions we had and advices given to me.

Special thanks to all the members of the evaluation committee. It is an honour to have all of you assessing my dissertation. Thanks to all the scientific experts who reviewed the publications included in this dissertation.

I thank Netherlands Organization for International Cooperation in Higher Education (NUFFIC) for providing me a full scholarship and the Ministry of Infrastructure and Water, the Netherlands for providing the partial funds for this study. The model simulations were carried out on the Dutch national e-infrastructure with the support of SURF Cooperative. I gratefully acknowledge staff at SURFsara BV.

I am very much thankful to Eng. Mrs. Prema Hettiarachchi at the Department of Irrigation, Sri Lanka, Mr. Ajith Wijemannage at the Department of Meteorology, Sri Lanka, Dr. Karthigesu Raveenthiran at the Lanka Hydraulic Institute, Sri Lanka, and Dr. Erika Coppola at the International Centre for Theoretical Physics, Italy for providing required datasets for this study.

Janaka, you are the closest friend I met at IHE Delft from the beginning to the end. Of course, you are not just a friend to me, sometime, you were my teacher/ brother as I felt. You were there whenever I needed to talk or ask a help. Your insightful scientific inputs, great company, un-conditional support and help, encouragement, motivation, advices, and

non-scientific conversations throughout this long journey are highly appreciated. It helps me to make my stay in Netherlands more comfortable. I learnt many things from you. Thanks for everything.

Nila (my classmate), many thanks to you and family for your kindness and support given during difficult time I had. I am also grateful to all of my friends (Prasanthi, Suba, Kaushalya, Vasana, Laknath, Chathuri, Manori, Imalka, Ganga, Akalanka, Indika, and Nilupul) at Lanka Hydraulic Institute for their loving care and support given during my PhD time. Thanks to my batch mates (Aung, Jaya, Hiranya, Harshana, Ko, and Shweta), seniors (Bikesh and Maneesha), and juniors (Naditha and Shakthi) from AIT, Thailand, who supported me in many ways during last five years. Thanks very much Ms. Chandani Pathirana and family for great company and nice memories with lots of jokes, dinners, and BBQs, which made my life easier and enjoyable in Delft. I specially thank to all Sri Lankan friends, I met at Delft since 2016. Thanks you all for having good time and enjoyable moments, which made me feel like home. My appreciations go to endless colleagues and friends met in IHE Delft. Particularly, Clara, Mia, Carlos, Ruknul, Polpat, Tim, Varowit, Maria, Shahnoor, Adey, Jakia, Masserat, Emman, Chalachew, Mohan, Tarn, Tesfay, Abdi, Alex, Aklan, Miguel, Duoc, Vo, Ha, Aftab, Uwe, Mohanad, Aysun, Hieu, Dikman, Kelly, Milk, Swagatham, and Bahar, thanks for nice talks, memories, and friendship.

I would express my deepest gratitude to my beloved mother; you are my hero, strength and inspiration. Many thanks to my loving two sisters and their families for allowing me to continue my studies without any burden since you have covered up my absences. Thanks all for your unconditional love, care, and encouragement. I love you all!!!

TABLE OF CONTENT

SUMMARY	VII
ACKNOWLEDGEMENTS.....	IX
TABLE OF CONTENT	XI
1 INTRODUCTION.....	1
1.1 Background	1
1.2 Problem statement	2
1.3 Research objectives	4
1.4 Thesis outline	5
2 PREDICTING STREAMFLOW AND FLUVIAL SEDIMENT FLUXES TO THE COAST: A REVIEW.....	7
2.1 Introduction	7
2.2 Streamflow and fluvial sediment fluxes.....	8
2.3 Modelling streamflow and fluvial sediment fluxes.....	9
2.3.1 Data challenges and opportunities	11
2.3.2 Model calibration	13
2.4 Main drivers on future changes of streamflow and fluvial sediment supply	15
2.4.1 Climate change impacts on catchment hydrology	15
2.4.2 Human activities and their impacts	19
2.5 Conclusions	22
3 DATA AND METHODS	23
3.1 Introduction	23
3.2 Case study areas	24
3.2.1 Irrawaddy River Basin	24
3.2.2 Kalu River Basin	26
3.3 Methodological framework	29
3.4 Data used	31
4 EFFECTS OF DIFFERENT PRECIPITATION INPUTS ON STREAMFLOW SIMULATIONS	33
4.1 Introduction	33
4.2 Methods.....	35
4.2.1 Data	35
4.2.2 Model setup and calibration	36
4.3 Results and discussion: Irrawaddy River Basin	40
4.3.1 Comparison of precipitation datasets	40

4.3.2	Evaluation of simulated streamflow	43
4.3.3	Parameter uncertainty	46
4.4	Results and discussion: Kalu River Basin	49
4.4.1	Comparison of precipitation datasets.....	49
4.4.2	Evaluation of simulated streamflow	51
4.4.3	Parameter uncertainty	52
4.5	Comparison of results for the two basins: Irrawaddy vs Kalu.....	54
4.6	Conclusions.....	54
5	USE OF REMOTE-SENSING BASED EVAPOTRANSPIRATION DATA FOR HYDROLOGICAL MODEL CALIBRATION	57
5.1	Introduction.....	57
5.2	Data and methods.....	58
5.2.1	Study area.....	58
5.2.2	Datasets used.....	59
5.2.3	Model setup.....	60
5.2.4	Model calibration	61
5.2.5	Estimation of uncertainty in model parameters	62
5.3	Results.....	63
5.3.1	Model calibration with a single variable.....	63
5.3.2	Model calibration with multiple-variables.....	68
5.3.3	Parameter sensitivity and uncertainty	71
5.4	Discussion	75
5.5	Conclusions.....	76
6	SIMULATING STREAMFLOW AND SEDIMENT FLUXES TO THE COAST IN THE IRRAWADDY RIVER BASIN.....	79
6.1	Introduction.....	79
6.2	Methods.....	80
6.2.1	Selection of suitable GCM(s) and climate change scenarios.....	80
6.2.2	Bias correction of climate data	82
6.2.3	Model setup and scenarios	83
6.3	Results and discussion: Base period (1991-2005)	89
6.3.1	Representative GCM(s)	89
6.3.2	Bias corrected climatic variables	93
6.3.3	Evaluation of simulated sediment load forced with observed climate data (1991-2010).....	96
6.3.4	Simulated streamflow and sediment load using bias-corrected GCM data	99
6.4	Results and discussion: Future periods 2045-2065 and 2081-2100.....	101
6.4.1	Changes in future climate	101
6.4.2	Climate change-driven variations in future streamflow and sediment fluxes to the coast	103

6.4.3	The combined effect of climate change and reservoirs on streamflow and sediment fluxes to the coast	108
6.5	Conclusions	114
7	SIMULATING STREAMFLOW AND SEDIMENT FLUXES TO THE COAST IN THE KALU RIVER BASIN	117
7.1	Introduction	117
7.2	Data and methods	118
7.2.1	Climate models and climate change scenarios	118
7.2.2	Model setup and scenarios	120
7.3	Results and discussion: Base period (1991-2005)	121
7.3.1	Bias corrected climatic variables	121
7.3.2	Evaluation of simulated sediment load forced with observed climate data (1991-2000).....	123
7.3.3	Simulated streamflow and sediment load using bias-corrected RCM data...	124
7.4	Results and discussion: Future periods 2045-2065 and 2081-2099	127
7.4.1	Changes in future climate.....	127
7.4.2	Climate change-driven variations in future streamflow and sediment fluxes to the coast.....	128
7.5	Conclusions	133
8	COMPARISON OF DISTRIBUTED MODELLING VS LUMPED MODELLING IN SIMULATING FLUVIAL SEDIMENT SUPPLY TO THE COAST	135
8.1	Introduction	135
8.2	Methods.....	136
8.2.1	The BQART model description and input data.....	136
8.2.2	Comparison of projected sediment load at the basin outlet	139
8.3	Irrawaddy River Basin	139
8.3.1	Annual sediment fluxes to the coast simulated by BQART	139
8.3.2	Comparison of results obtained from SWAT and BQART models for the Irrawaddy basin outlet.....	140
8.4	Kalu River Basin	143
8.4.1	Annual sediment fluxes to the coast simulated by BQART	143
8.4.2	Comparison of model results obtained from SWAT and BQART for the Kalu River Basin.....	144
8.5	BQART projections with updated <i>E_h</i> values	146
8.6	Comparison of modelled results in the two basins.....	149
8.7	Concluding remarks	150
9	GENERAL CONCLUSIONS AND RECOMMENDATIONS	153
9.1	Introduction	153
9.2	General conclusions	154

9.3	Implications and future directions	157
ANNEXES		159
Annex A		159
A.1	Hydrological parameters used for model calibration.....	159
A.2	NSE of the best simulation in each iteration performed at each station	160
Annex B		161
B.1	Gridded average annual minimum temperature from ten different GCMs over the Irrawaddy River Basin from 1991 to 2005	161
B.2	Gridded average annual maximum temperature from ten different GCMs over the Irrawaddy River Basin from 1991 to 2005	162
B.3	Statistical performance of with and without bias-correction of precipitation data at each sub-basin	163
B.4	Statistical performance of with and without bias-correction of maximum temperature data at each station	165
B.5	Statistical performance of with and without bias-correction of minimum temperature data at each station	166
B.6	Average monthly precipitation over the Irrawaddy River Basin for future periods under two RCPs with base period values	167
B.7	Projected mean annual streamflow and sediment loads at Pyay in the Irrawaddy River Basin	168
Annex C		169
C.1	Gridded average annual temperatures from three RCMs over the Kalu River Basin from 1991 to 2005.....	169
C.2	Statistical performance of with and without bias-correction of precipitation data at each sub-basin	170
C.3	Statistical performance of with and without bias-correction of maximum and minimum temperature data at each station	171
C.4	Average monthly precipitation over the Kalu River Basin for future periods under two RCPs with base period values	172
REFERENCES		173
LIST OF FIGURES		193
LIST OF TABLES		197

INTRODUCTION

1.1 Background

Rivers are crucial contributors to the dynamic interaction between catchments and coasts by transferring water and sediment from land to the oceans. The sediment carried by rivers enriches coastal systems, which are shaped by river flows, fluvial sediments, waves and tides. Due to large-scale anthropogenic retentions of sediment, sand mining, socio-economic growth and climate change-driven impacts, the fluvial sediment supply to the coast has been fluctuating and has resulted in coastal erosion and destruction of coastal ecosystems in many places around the world. Presently, such problems are quite evident along many of the world's coasts, especially in Asia, USA and Africa (Besset et al., 2019; Luijendijk et al., 2018; Ranasinghe et al., 2019; Syvitski et al., 2009; Syvitski and Saito, 2007; Vörösmarty et al., 2009, 2003; Walling, 2006).

The global climate is changing. Relative to the 1986-2005 period, the global mean surface temperature is projected to increase by 0.3°C to 0.7°C (medium confidence) during the 2016-2035 period, whereas extreme precipitation and heatwaves over the tropical and mid-latitudes are projected to be more severe and frequent (IPCC, 2014). Furthermore, global mean sea level is projected to continue to rise during the 21st century, very likely at a greater rate than that is observed during 1971 to 2010 (Church et al., 2013). Impacts of climate change (CC) are not spatially uniform, and hence the hydrological cycle at basin scales will vary not only from basin to basin but also within large river basins. Such variations in

hydrological cycles at river basin scale can result in significant alteration of the fluvial sediment throughput from the river basin and the consequential sediment supply and river discharge to the coast.

On the other hand, during the past decades, intensive human activities such as land clearance, excessive agriculture, different land-use practices, water diversions and abstractions, reservoir/dam constructions, and sand-mining, have been carried out within river basins (Saito et al., 2007; Syvitski and Milliman, 2007; Syvitski et al., 2005; Vörösmarty and Sahagian, 2000; Walling, 2006; Zhao et al., 2014). For instance, dams and reservoirs play a major role in water resources management, particularly in terms of regulating water supply, hydropower generation and flood control. Many countries in the south and central Asian regions, Latin American countries such as Brazil, Paraguay, Venezuela, and Peru, Canada, Turkey and Russia are increasingly investing in harnessing unexploited hydro-power potential (Akpınara et al., 2011) as it is an attractive source of renewable energy. As a result, even though, there was a relative decrease in hydropower dam construction during 1990-2010, it has increased remarkably thereafter (Zarfl et al., 2014). Zarfl et al. (2014) reported that as of March 2014, there were 3700 hydropower dams either planned or under construction with more than 1MW capacity around the world. As a result, the sediment supply to many of the world's coasts and its delta systems has decreased substantially (Besset et al., 2019; Dunn et al., 2019; Ranasinghe et al., 2019; Saito et al., 2007; Syvitski et al., 2009; Syvitski and Saito, 2007).

1.2 Problem statement

The amount of fluvial sediment received by coasts has decreased globally, although soil erosion at basin scales has increased over the past few decades (Besset et al., 2019; Ranasinghe et al., 2019; Saito et al., 2007; Syvitski et al., 2005). Large-scale reservoir constructions and implementation of major water diversion systems are the primary reasons for this significant reduction of sand supply to coasts, whereas, socio-economic growth, urbanization and climate change impacts are the key drivers for the increased soil erosions at basin scales. Nearly half a billion people inhabit the world's deltas and estuaries, forming megacities in their vicinities (Syvitski and Saito, 2007; Woodroffe et al., 2006). These deltaic coasts are becoming highly vulnerable to subsidence, erosion and have also been exposed to frequent flooding (Besset et al., 2019; Syvitski et al., 2009; Vörösmarty et al., 2009). On the other hand, global climate change is also causing major problems, and its adverse effects are inevitable (IPCC, 2014). IPCC projections indicate that, the risks and vulnerabilities associated with climate change impacts in basins and coasts will increase globally due to high temperature, altered precipitation, extreme weather events and sea-level rise. Socio-economic growth and development activities that take place within the basins and coastal regions would further exacerbate these future risks and vulnerabilities.

South and Southeast Asian regions consist of some of the largest cities in the world (i.e., Dhaka, Delhi, and Bangkok), yet large areas are less urbanized. Only one-third of the total Asian populations live in urban areas. However, relative to other Asian regions, the highest growth rates of urban populations are recorded in the South and Southeast Asian regions (Hijioka et al., 2014). Economies of most of the countries in these regions are greatly dependent on agriculture and natural resources. Large areas of the South and Southeast Asian regions are annually exposed to many extreme climate events such as floods, droughts, tropical cyclones and heatwaves. Currently, these nations are identified to be among the most vulnerable areas to the impacts of global climate change (Kreft et al., 2015). According to long-term Climate Risk Index (CRI) analysis (Kreft et al., 2015), six countries in the South and Southeast regions are listed in the world's top 10 most vulnerable to the climate change-driven impacts between 1995 and 2014.

In this context, detailed hydrological investigations are required to assess the potential climate change and anthropogenic impacts on river/ coast systems. Process-based hydrological models when applied in distributed or semi-distributed settings, are capable of evaluating hydrological response at interior ungauged basins which is not possible with lumped parameter models (Wi et al., 2015). However, distributed hydrological modelling with high spatial and temporal resolutions is a challenging task due to scarcity, quality and uncertainties of data for model initialization, calibration, and validation. Data scarcity is particularly a problem in many river basins (Hrachowitz et al., 2013) of the South and Southeast Asia where sufficient data for model setup and calibration/validation do not exist (i.e., data-poor regions). In contrast, emerging reduced-complexity models that assess coastline changes employ empirical models such as BQART to compute fluvial sediment supply, in order to simulate the coastline projections over time scales of 50-100 years at a reasonable computational cost and time (Ranasinghe, 2020). However, significant variabilities in modelling techniques (i.e., model uncertainties) and modelling inputs (i.e., climatic variables and human activities) inevitably introduce uncertainties in coastline projections obtained from such coastline change models (Bamunawala et al., 2020). Therefore, it is important to be able to quantify the uncertainties associated with coastline change projections to facilitate risk-informed decision making by the coastal zone planners and managers. Computationally efficient reduced complexity models serve this purpose better than process-based modelling approaches that require a high level of input data and large computational power.

In this regard, this study attempts to explore the effective use of different modelling approaches in data poor regions to examine the impact of climate change and human activities on river/coast systems in terms of the streamflow and fluvial sediment supply. In particular, this study aims to address the following main research questions:

- 1) How does a hydrological model respond to and perform with respect to spatial scales and varied climatic input characteristics?

- 2) How can remote-sensing based evapotranspiration data and limitedly available streamflow data be effectively used to calibrate a process-based hydrological model in poorly gauged river basins?
- 3) How do streamflow and fluvial sediment load of a river basin vary with respect to climate change impacts and human activities in the 21st century?
- 4) How do sediment load projections by empirical models such as BQART compare with those by more distributed and process-based model such as SWAT in different basin conditions (e.g., basin size, reservoirs)? Do such empirical models perform better in some situations and worse in others?

1.3 Research objectives

The overarching objective of this study is to investigate how different modelling approaches and input data sources may influence projections of streamflow and fluvial sediment loads accounting for climate change and human activities, particularly in data-poor river basins.

The above overarching objective is achieved by investigating two selected study areas; the Irrawaddy River Basin in Myanmar (410,000 km², the largest river basin in Myanmar) and the Kalu River Basin in Sri Lanka (2,787 km², second-largest river basin in Sri Lanka). These two basins can be considered to broadly represent data-poor environments in the Southeast and South Asian regions as they encompass a broad range of spatial scales (very large to very small). Compared to the major rivers in the region, the main rivers of these basins are mostly unregulated in the present condition.

The specific objectives of the study are as follows:

- 1) Investigate the impacts of different model inputs (i.e., precipitation) on hydrological simulations of the study areas
- 2) Investigate the use of multi-variable calibration in a process-based hydrological model for data-poor basins by using Remote Sensing based evapotranspiration and limitedly available observed streamflow measurements
- 3) Determine the most representative climate forcing scenarios for the study areas
- 4) Assess potential changes in fluvial sediment supply to the coast under different climate change scenarios and human activities in the 21st century
- 5) Compare and contrast projections of fluvial sediment loads obtained from process-based modelling with those obtained under comparable forcing using an empirical fluvial sediment supply model

1.4 Thesis outline

This dissertation is structured into nine chapters, as summarized below:

Chapter 1 presents the research background and highlights the problem and research need on this topic in general and in particular in the data poor environment of river basins in South and Southeast Asia. It also introduces objectives and the research questions addressed in this study.

Chapter 2 provides a review of literature on predicting streamflow and fluvial sediment fluxes to the coast. Topics covered in the review include streamflow and sediment, modelling techniques and data requirement, and main drivers (i.e., climate change and human activities) of changes of streamflow and sediment loads.

Chapter 3 presents the case study sites (i.e., the Irrawaddy River Basin, Myanmar and Kalu River Basin, Sri Lanka) and detail methodological framework. It also summarizes the datasets used for this study.

Chapter 4 presents the effects of different precipitation inputs (i.e., observed and global products) on streamflow simulation in two study areas (i.e., the Irrawaddy and Kalu Basins). This chapter provides the details of the model setup with the Soil Water Assessment Tool (SWAT). Here, the best performing precipitation products(s) were selected by considering the model performances in reproducing the streamflow at the streamflow gauging stations.

Chapter 5 presents the use of observed streamflow data and remote-sensing (RS) based evapotranspiration data for hydrological model calibration. Here, single variable calibration (i.e., streamflow and RS based evapotranspiration separately) and multi-variable calibration (i.e., streamflow and RS based evapotranspiration together) were presented for the Chindwin Basin, which is a main tributary basin of the Irrawaddy Basin.

Chapter 6 presents the impacts of climate change and human activities on streamflow and fluvial sediment supply to the coast in the Irrawaddy River Basin, Myanmar for the base period (1991-2005) and two future periods (i.e., mid-century 2046-2065 and end-century 2081-2100).

Chapter 7 presents the impacts of climate change on streamflow and sediment load supply to the coast in the Kalu River Basin, Sri Lanka for the same future periods considered in the Irrawaddy River Basin.

Chapter 8 compares the distributed vs lumped model simulations for sediment loads. SWAT model projections of sediment loads obtained from Chapter 6 and 7 were compared with simulation results obtained from the BQART model in the two study areas for the base period (1991-2005) and future periods (2046-2065 and 2081-2100) considered.

Chapter 9 presents the general conclusions of this study and possible implications for future research.

2

PREDICTING STREAMFLOW AND FLUVIAL SEDIMENT FLUXES TO THE COAST: A REVIEW

2.1 Introduction

Streamflow and sediment are inter-connected through river networks and contribute to the dynamic stability of river/coast systems. They affect the morphodynamics of rivers, flood plains and deltas and carry various materials from land to the coast, which in turn support the coastal ecosystems. During the past few decades, global river systems have undergone significant changes due to climate change (i.e., increase/ decrease in rainfall intensity and volume, and increase in temperature) and a wide range of human activities such as land-use change, deforestation, damming of rivers, water diversion and abstraction, and sand-mining from river banks (Dunn et al., 2019; Ranasinghe et al., 2019; Syvitski and Milliman, 2007; Syvitski et al., 2005; Syvitski and Saito, 2007; Walling, 2009, 2006; Wu et al., 2017; Zhao et al., 2014). As a result, substantial variations of streamflow and sediment load can be observed in many river systems across the world. Recent studies have reported that many large rivers (i.e., Yellow River, Yangtze River, Chao Phraya River, Pearl River, and Nile River) show a considerable reduction of sediment supply to the coast due to reservoirs and land-use changes (Besset et al., 2019; Miao et al., 2011; Ranasinghe et al., 2019; Walling,

2009; Yang et al., 2015). Thus, it is essential to understand and evaluate the variability of streamflow and sediment load under different influencing factors. Such evaluations provide the basis for basin management and planning activities, flood/drought mitigation and adaptation measures, design of river structures, maintenance of water bodies (Zhao et al., 2014) coastal zone management and planning, and coastline projections.

The main objective of this review is to discuss the different modelling approaches used to compute the sediment and streamflow to the coast, and to gain insights into future forcing scenarios and their potential impacts on streamflow and fluvial sediment supply to the coast.

This chapter is organized as follows: Section 2.2 provides a brief introduction on streamflow and fluvial sediment fluxes. The modelling approaches used to compute these two variables are discussed in Section 2.3, in which different types of models, data requirements and model calibration approaches are reviewed. The main drivers (climate change and human activities) and their subsequent impacts on streamflow and fluvial sediment flux are discussed in Section 2.4.

2.2 Streamflow and fluvial sediment fluxes

Streamflow is invaluable to all animal and plant lives on Earth. The main influencing factor for streamflow is the amount of precipitation received within its basin (Perlman, 2016). Streamflow is also the transport agent for many nutrients, pesticides, fertilizers and sediment (Sitterson et al., 2017), which are generated from the watershed and transported to waterways through surface runoff. The streamflow rate and variation, and stream characteristics govern sediment deposition, erosion, and transport in the river, and consequently impacts on morphological changes and biodiversity of waterways and coastal systems.

Several inter-related factors affect soil erosion at basin scale. These include rainfall intensity, climatic variables (i.e., temperature and wind), land cover, land-use, topography, drainage network, runoff, soil characteristics (i.e., grain size and mineralogy), and land management practices (Morgan, 2005). Thus, the estimation of soil erosion at a basin scale is a complex undertaking. Not all the sediment eroded within basins will be transported through waterways to the coast. Some of the eroded sediment deposits in floodplains and other land surfaces and depressions. The sediment transportation through waterways is a function of two main processes known as degradation and deposition.

Sediment is a natural resource, which is vital for ecosystem functions and, enriching biodiversity (Hajigholizadeh et al., 2018). For instance, sediment deposition in areas such as deltas and flood plains enrich them for agriculture. On the other hand, soil erosion affects the environment and human life (Hajigholizadeh et al., 2018). For example, soil erosion reduces the useful life span of many hydraulic structures (i.e., dams, spillways, weirs) and the active storage of impound water resources such as rivers, reservoirs, and lakes. Despite

globally increasing soil erosion, the volume of sediment supply to the coastal zone is decreasing due to anthropogenic sediment retention (Ranasinghe et al., 2019; Syvitski, 2003; Syvitski et al., 2009). An estimation of sediment flux at global scale indicates that human activities over the past 50 years have accelerated the sediment flow through rivers by soil erosion (by 2.3 ± 0.6 GT per year) and have also reduced the sediment flux reaching the world's coasts by 1.4 ± 0.3 GT per year due to retentions within the reservoirs (Syvitski et al., 2005).

2.3 Modelling streamflow and fluvial sediment fluxes

A range of numerical models is available to compute the streamflow, sediment erosion and fluvial sediment load at different spatial and temporal scales, and the usability of these models are well documented in the literature. These models vary because of their complexity (methods and assumptions used), data requirements, scope of their application, and processes considered (De Vente et al., 2013; Gupta et al., 2015; Hajigholizadeh et al., 2018; Merritt et al., 2003; Pechlivanidis et al., 2011). Generally, a “best” model does not exist for all applications because each model development has its defined purpose(s). Therefore, the selection of a suitable model for a particular study/ research mainly depends on the objective(s) and the desired output of the study and the characteristics of the study area. However, there are a number of other factors that need to be considered in selecting an appropriate model for a given application (Hajigholizadeh et al., 2018; Merritt et al., 2003). These include:

- Data required for the model (input data with different spatial and temporal resolutions),
- Underlying model assumptions, model accuracy and validity,
- Model components, which reflect model capabilities,
- Affordability and ease of use with respect to available time and resources,
- Model output scales (spatial and temporal) and their form

Depending on adopted simplifications, processes simulated and data dependency, numerical models, in general, can be broadly classified as: (1) empirical, (2) conceptual, and (3) process- and/or physics-based. Table 2-1 presents the main characteristics of the three types of numerical models mentioned above.

Table 2-1. Characteristics of model types. Source: Devi et al. (2015) and Sitterson et al. (2017). References to the model listed in the table are (a) Devi et al. (2015), (b) Beven and Kirkby (1979), (c) Seibert and Vis (2012), (d) Johanson et al. (1980), (e) Abbott et al. (1986), (f) Neitsch et al. (2011), (g) Hamman et al. (2018), (h) Syvitski and Milliman (2007), (i) Williams and Berndt (1977), (j) De Vente and Poesen (2005), (k) Young et al. (1989), and (l) De Roo et al. (1996)

Description	Empirical	Conceptual	Process-/physics-based
Method	Non-linear relationship between inputs and outputs, Data-based or metric or black-box model	Simplified equations of physical processes	Physical laws and equations based on physical processes
Strengths	A limited number of parameters required, Fast simulation	Simple model structure	Incorporates spatial and temporal variability, usually applied in a distributed structure
Weakness	Little representation of features and processes of the system	Usually many calibration parameters	Usually requires a large number of inputs
Examples:			
Streamflow	Unit hydrograph for surface runoff, ANN rainfall-runoff model ^(a)	TOPMODEL ^(b) , HBV ^(c) , HSPF ^(d)	MIKE-SHE ^(e) , SWAT ^(f) , VIC-5 ^(g)
Sediment	BQART ^(h) , MUSLE ⁽ⁱ⁾ , PSIAC ^(j)	TOPMODEL, HSPF, AGNPS ^(k)	MIKE-SHE, SWAT, LISEM ^(l)

Hydrological models are the standard tool for studying the interactions of hydrological processes (i.e., streamflow, water quality, sediment and nutrient transport) and predicting river basin behaviour under different forcing scenarios (i.e., climate change, crop pattern changes, land-use change, water diversions, and different human activities). There are several published reviews on hydrological models (Beven, 2001; Clark et al., 2017; Devi et al., 2015; Fatichi et al., 2016; Jajarmizadeh et al., 2012; Pechlivanidis et al., 2011; Singh, 2018; Sitterson et al., 2017; Trambauer et al., 2013), which summarize the modelling capabilities, uncertainties, limitations, and new developments.

A comprehensive review presented by De Vente et al. (2013) emphasizes that modelling of sediment erosion and fluvial sediment load is strongly governed by the level of spatial and

temporal measures considered. De Vente et al. (2013) reviewed 14 models and more than 700 selected basins from the published literature. Another recent review by Hajigholizadeh et al. (2018) provided information on different types of currently available models, their characteristics, potential, and applicability to simulate the sediment erosion and transport phenomena at river basin scale.

2.3.1 Data challenges and opportunities

Watershed models are utilized to understand hydrological processes interactions and to predict system behavior under different forcing scenarios. Primary climatic data such as temperature and precipitation along with topography, and geological data, are the main types of data used to simulate hydrological phenomena within a given study area. Among these model inputs, precipitation is the fundamental variable to all hydrological modelling, as it is the primary source of water to generate the flow. On the other hand, hydrological processes such as evapotranspiration, precipitation, melting and freezing, condensation, and sediment erosion are intimately linked with surface temperature.

Accurate representation of precipitation capturing its spatial and temporal variability is essential for any hydrological model to simulate basin behavior reliably. Available gauged precipitation data are mostly inadequate to accurately represent the heterogeneity of precipitation in many river basins (Miao et al., 2015). Nowadays, however, there are several other precipitation products available to represent the amount of water received by watersheds, which include data derived from interpolating of in-situ measurements (e.g., APHRODITE, and CPC Unified), atmospheric model outputs with reanalysis (e.g., ERAInterim, NCEP-CFSR, and JRA-55), and remote sensing-based products (e.g., CHIRP, PERSIANN, CMORPH, GridSat, TRMM, GSMaP V5/6, and SM2RAIN-ASCAT). These products vary in spatial coverage (i.e., global and regional), spatial resolution ($0.05^{\circ} \times 0.05^{\circ}$ to $1^{\circ} \times 1^{\circ}$) and temporal resolution (hourly, daily, and monthly). Some of these products have been further developed by applying gauge-based corrections (e.g., CHIRPS, PERSIANN-CDR, CMORPH-CRT, and TMPA 3B42V7).

Many studies have investigated the impacts of different precipitation inputs on hydrological modelling in different parts of the world (e.g., Abera et al., 2016; Andreassian et al., 2001; Bárdossy and Das, 2006; Chen and Chen, 2018; Lopez et al., 2015; Masih et al., 2011; Massari et al., 2017; Miao et al., 2015; Moon et al., 2004; Moulin et al., 2008; Price et al., 2014; Segond et al., 2007; Thiemig et al., 2013; Toté et al., 2015; Tuo et al., 2016; Zhu et al., 2017). For instance, Beck et al. (2017) evaluated 22 global precipitation products, in which, 13 were assessed by comparing with daily in-situ gauge data. The remaining 9 products were evaluated in terms of streamflow simulation using the HBV model (the Hydrologiska Byråns Vattenbalansavdelning model) (Seibert and Vis, 2012). Their results have demonstrated significant biases among the precipitation products tested. Among the non-gauge corrected precipitation datasets: CHIRP V2.0, and MSWEP-ng V1.2 and V2.0 have produced the most accurate long-term mean precipitation due to the high-resolution

climatic datasets used therein. Seibert and Vis (2012) also noted that the gauge-corrected precipitation datasets (i.e., CPC Unified and MSWEP versions) performed best in the mid-latitude regions, where dense monitoring networks do exist. In contrast, their worst performance was observed in arid regions due to the impacts of highly localized and varied convective rainfall.

In South and Southeast Asia, where ground observations are particularly sparse and limited, there are only a handful of studies that have investigated the impacts of precipitation inputs on hydrological simulations. Table 2-2 summarizes the available studies undertaken within the South and Southeast Asian regions. It is also important to note that all precipitation products are not equally good or bad for all regions. Some products can be good/bad for even different parts of the same basin.

Table 2-2. Overview of the impacts of different precipitation inputs on hydrological simulations over South and Southeast Asia. Detailed information on each precipitation product can be found in Beck et al. (2017)

Precipitation products	Study area	Target variable and remarks	Reference
APHRODITE TRMM PERSIANN GPCP CHCHN2 NCEP/NCR	Dak Bla River Basin, Vietnam (2,560 km ²)	Streamflow <ul style="list-style-type: none"> • Use of APHRODITE performed very well at daily time scale, followed by GPCP in monthly time scale. • Due to different interpolation and assimilation algorithms, precipitation datasets have uncertainties, although these products are merged with ground data. 	Vu et al. (2012)
Gauge data TRMM-3B42V7	Mekong Basin (795,000 km ²)	Streamflow <ul style="list-style-type: none"> • Simulation with TRMM-3B42V7 produces better results than with gauge data • Grid-based TRMM data is less sensitive for selection of calibration period. Calibrated parameters from TRMM are stable and effective than that from gauge data 	Wang et al. (2016)
APHRODITE PERSIANN-CDR NCEP-CFSR	Kelantan & Johor River Basins in Malaysia (12,134 km ² and 1,652 km ²)	Streamflow <ul style="list-style-type: none"> • Simulations with APHRODITE data performed the best, but with under-estimation. • NCEP-CFSR overestimates the flow drastically. • PERSIANN-CDR shows acceptable results in Kelantan Basin but fails to reproduce the flow in Johor Basin. 	Tan et al. (2017)
CHIRP CHIRPS	Koshi Basin, Nepal (39,407 km ²)	Drought monitoring (SPI) <ul style="list-style-type: none"> • Comparable results were obtained from both products. 	Shrestha et al. (2017)

Precipitation products	Study area	Target variable and remarks	Reference
		<ul style="list-style-type: none"> • However, both products performed poorly in high elevation regions. 	
Gauge data TRMM-3B42V7 GPM-IMERG	Chindwin Basin, Myanmar (110,350 km ²)	Streamflow <ul style="list-style-type: none"> • TRMM-3B42V7 outperformed GPM-IMERG. • After bias correction, TRMM-3B42V7 based simulations performed better than gauge based simulations. 	Yuan et al. (2017)
Gauge data PERSIANN-CDR CHIRPS	Irrawaddy Basin, Myanmar (371,558 km ²)	Streamflow <ul style="list-style-type: none"> • Interpolated gauge data outperformed the other rainfall products. • CHIRPS and PERSIANN-CDR also showed acceptable results in most of the discharge gauge stations 	Sirisena et al. (2018) (part of this study)

2.3.2 Model calibration

Model calibration is the process of estimating model parameter values, which can accurately reproduce observed hydrological responses (i.e., streamflow, sediment load, groundwater levels, soil moisture) (Kumarasamy and Belmont, 2018; Yu, 2015). However, robust calibration of hydrological model is a challenging task (Yang et al., 2008), mainly due to the existence of different sources of uncertainties, such as natural, input data, model structure and parameters. Nevertheless, model calibration is essential to obtain reliable responses from distributed hydrological modelling (Beven, 2012).

Sivapalan et al. (2003) define an ungauged or poorly gauged basin as an area that lacks hydrological observations in terms of both quality and quantity to enable the computation of hydrological variables at appropriate spatial and temporal scales, and an acceptable level of accuracy for practical applications. The above definition implies that every river basin is ungauged to a certain extent. In most developing countries, the lack of data is a major problem for hydrological assessment (Immerzeel and Droogers, 2008; Wi et al., 2015). Research interests in hydrological simulations for ungauged or poorly gauged basins have increased recently, due to the availability of distributed modelling and sophisticated mathematical techniques used in model calibration. As an example, the Prediction in Ungauged Basin (PUB) initiative of the International Association was aimed at achieving reliable prediction in hydrological practice (Sivapalan et al., 2003).

The conventional method of hydrological model calibration is based on a comparison between simulated and observed hydrographs at available gauge locations. However, the use of one output variable for model calibration does not provide a robust representation of the hydrological behavior of a given area (Seibert and McDonnell, 2002). Model calibration has, in fact, become fairly complicated in distributed hydrological modelling because there

is a large number of spatially and temporally varying parameters involved in a typical hydrological model. In this regard, remote sensing (RS) data and auto-calibration algorithms have been utilized by researchers to overcome the above-mentioned limitation in model calibration. For instance, several studies have used remote sensing (RS) based evapotranspiration (ET) (e.g., Franco and Bonumá, 2017; Githui et al., 2012; Immerzeel and Droogers, 2008; López et al., 2017; Rientjes et al., 2013; Tobin and Bennett, 2017), soil moisture (e.g., Campo et al., 2006; Kunnath-Poovakka et al., 2016; Li et al., 2018; López et al., 2017; Rajib et al., 2016), snow cover and glacier mass balance (e.g., Finger et al., 2015, 2011), and land surface temperature (LST) (e.g., Corbari and Mancini, 2013) for hydrological model calibration.

The calibration process of a model can generally be classified into three broad categories; (1) manual, (2) automatic, and (3) combination of both manual and automatic methods. The manual calibration method, which is also known as the trial and error method, does not determine an exact point of termination for the calibration. Thus, the manual calibration method demands a lot of time and effort and also requires good knowledge and understating of hydrological processes involved. The automatic calibration method can perform thousands of simulations/trials within a relatively short time with several calibration parameters. This method requires numeric criteria to evaluate model performance automatically by the calibration algorithm. Such criteria have been developed by objective functions, which ultimately provides more consistent performance than the manual approach of model calibration (Boyle et al., 2000). However, this method does not entirely replace the manual approach because the automatic calibration cannot fully replicate human judgment. Therefore, model calibration is most successful when a combination of manual and automatic calibration processes are adopted (Pechlivanidis et al., 2011).

The automatic calibration process comprises of four major components; (1) the objective function (OF), also known as the performance measure, (2) optimization algorithm, (3) calibration parameters, constraints and termination criteria, and (4) calibration data. The objective function is a numerical measure of the difference between simulated and measured (observed) variables (Schaepli and Gupta, 2007). The most commonly used OFs in hydrological studies are the coefficient of determination (R^2) and the Nash-Sutcliffe Efficiency (NSE), which determine the relative variance of observed and simulated data (Nash and Sutcliffe, 1970). After evaluating several river basins in Australia, Gupta et al. (2009) showed that NSE has the ability to capture peak flows while underestimating the average flows. Optimization algorithms examine the response parameter space, which optimizes (minimize or maximize) the objective function value. Most of the optimization methods fall into either local or global search methods.

2.4 Main drivers on future changes of streamflow and fluvial sediment supply

Climate change and human activities are the main influencing drivers for changes in streamflow and fluvial sediment fluxes (Saito et al., 2007; Syvitski, 2003; Syvitski et al., 2005; Vörösmarty et al., 2003). Future climate projections provide information on several meteorological variables, primarily precipitation, and temperature, which are crucial to assess future changes in both streamflow and sediment fluxes at basin scale.

2.4.1 Climate change impacts on catchment hydrology

Climate models and scenarios

General Circulation Models (GCMs) simulate physical processes of the atmosphere, ocean, cryosphere and land surface. These models help to simulate both the past as well as a plausible future climate. However, uncertainties exist in GCM based future climate projections due to the inability of the models to accurately represent some physical process, such as cloud cover, radiation, water vapor and their feedback mechanisms. Currently, there are more than 30 GCMs developed by different research institutes around the world (Taylor et al., 2012).

The earth's climate system is highly sensitive to the concentration of the Green House Gases (GHGs) in its atmosphere. A better understanding of future changes in climate and their probable impact can be gained by considering the amount of GHGs in the atmosphere over the forthcoming years. The IPCC released a Special Report on Emission Scenarios (SRES) in 2000. In this report, four different future emission scenarios were presented; A1, A2, B1, and B2. Representative Concentration Pathways (RCPs) are the newly developed scenarios under Couple Model Inter-Comparison Project Phase 5 (CMIP5) that fed into the Fifth IPCC Assessment Report (AR5). Besides using socio-economic considerations, the RCPs are also based on projections of radiative forcing. The four RCPs in this assessment report are named according to the expected radiative forcing values by the year 2100 (relative to pre-industrial values) as follows:

- 1) RCP 2.6: Maximum radiative forcing at $\sim 3 \text{ W/m}^2$ by 2100 and decay thereafter
- 2) RCP 4.5: Balancing pathway without exceeding 4.5 W/m^2 and stable after 2100
- 3) RCP 6.0: Balancing pathway without exceeding 6 W/m^2 and stable after 2100
- 4) RCP 8.5: Rising radiative forcing to the level of 8.5 W/m^2 by 2100

Downscaling of GCM data

Because GCMs have relatively coarse spatial resolutions ($\sim 1^\circ - 3.5^\circ$ in horizontal), they show high biases (Chen et al., 2019). Such biased climatic data cannot be directly used in hydrological or water resources modelling at local scales (basin level) as they do not represent the local variabilities (Chen et al., 2019, 2013; Sharma et al., 2007; Smitha et al., 2018; Teutschbein and Seibert, 2012). Therefore, downscaling techniques are typically used to obtain more reliable climate variables at the regional level from the coarse resolution GCM data (Thiemeßl et al., 2011). Both dynamical and statistical downscaling techniques can be used to downscale the GCM data. In dynamical downscaling, Regional Climate Models (RCMs) are forced with coarser resolution GCM outputs and regional information (e.g., orography, and land-use) is taken into account to simulate local weather and climate information at a finer spatial resolution ($\sim 10\text{-}50$ km) (Smitha et al., 2018). In statistical downscaling, empirical relationships are established between large-scale GCM variables and local climate variables. These relationships are then used together with GCM data to derive projections of local climatic variables at a higher resolution.

Both downscaling methods have their strengths and limitations. Owing to their finer spatial resolution, RCMs could provide an improved representation of the non-stationarity of climate dynamics, and inter-annual variability of climatic variables derived from GCM simulations (Guyennon et al., 2013). However, dynamical downscaling is more complex and challenging to implement due to the high computational capacity and technical expertise required (Smitha et al., 2018). Furthermore, biases in parent GCM data will inevitably be inherited by the RCMs. On the other hand, statistical downscaling is easy to implement and computationally efficient. However, this method assumes that the relationship developed between modelled data and ground data for the base period will be valid for the future as well. This assumption is not strictly valid due to the non-linear and non-stationary nature of climate variabilities.

Currently, several RCMs are utilized for climate change impact studies at regional and local scales. These include RegCM4, WRF, REMO, PRECIS, RCA, RSM, CRCM, COSMO-CLM, ETA, and HIRHAM (more details in Giorgi (2019)). Statistical downscaling methods can be categorized as (1) transfer function (Wilby et al., 2002), (2) weather typing (Schoof and Pryor, 2001), and (3) weather generator (Zhang, 2005). The transfer function method establishes a linear or non-linear relationship between GCM outputs (predictors) and local climate data (predictands). Despite being easy to use, the main weakness of this method is that model can only explain the part of the observed climate variability (particularly in precipitation). The weather typing method groups the local climatic variables with respect to different atmospheric circulations. Therefore, there is a close link between local variables and large-scale circulations. However, this relationship is not stationary and, thus the reliability of this method is uncertain. The weather generator method involves perturbation of the parameter values with respect to relative changes in climate data. This method can produce sets of climate scenarios to study the impacts of climate and its variabilities.

Future projections

Future climate projections presented by in the IPCC AR5 show that global mean surface temperature is likely to increase by 0.3°-4.8° C by late 21st century (2081 - 2100) under four RCPs (relative to 1986-2005 period) (IPCC, 2014). Precipitation changes are not uniform (IPCC, 2014). More frequent and intense extreme precipitation are very likely to occur over mid-latitudes and wet tropical regions. Average precipitation over high latitudes and the equatorial Pacific regions are likely to increase by the end of this century under RCP 8.5 (Figure 2-1). In contrast, many mid-latitudes and subtropics are projected to be drier, while many mid-latitude wet regions are to be wetter. More intense and frequent extreme precipitation events are more likely to occur over mid-latitudes and wet tropics predominantly due to increases in global surface temperature (IPCC, 2014).

Figure 2-1. Changes in (a) average surface temperature (b) average precipitation for 2081 to 2100. The results are obtained from CMIP5 multi-model simulations and are relative to 1986 – 2005. The number of models used are indicated in the top right of each map. Source: IPCC (2014).

Apart from these investigations at the global level, many studies have investigated climate change-related aspects at the local/basin scales. In general, these investigations address the results at annual, seasonal or monthly time scale(s) using statistically downscaled or dynamically downscaled, bias-corrected GCM outputs. Table 2-3 summarizes the projected changes in precipitation and temperature in a few selected river basins in South and Southeast Asia. Many of these studies have focused on the mid-century (i.e., the 2050s) and the end-century (i.e., the 2080s) time horizons. The expected change in temperature show

clear indications of significant increments in the future. However, the characteristics of the projected changes in precipitation are not unidirectional. In many cases, the “dry regions get drier and wet regions to get wetter” (DGDWGW) paradigm as discussed by Hu et al. (2019) does appear to hold. For example, the Krishna Basin, India mostly belongs to the semi-arid region and annual precipitation is projected to decrease during 2009-2070 under RCP 4.5 and RCP 8.5 (Chanapathi et al., 2018). On the other hand, the Yang Basin, Thailand experiences two monsoons (north-east and south-west) and tropical cyclones from South-China sea, and an increase of precipitation is expected ($\sim >20\%$ in annual precipitation) (Shrestha and Lohpaisankrit, 2017). In general, most of the studies show that a higher increase in temperature/ precipitation is expected by the end of the century for RCP 8.5.

Table 2-3. Overview of bias-corrected future climate projections for selected studies in South and Southeast Asia. Note that the base period considered in the various studies may differ.

Climate Projections	Variables	Basin	Projection horizon and results	Reference
10 GCMs (RCP 2.6, 4.5, 6.0 and 8.5)	Precipitation Minimum and maximum temperature	Belu RB (Myanmar) 8,329 km ²	2010-2039, 2040-2069, and 2070-2099s Increase/decrease in annual precipitation by -1.78 - +9.14% Increases in minimum temperature by 0.64-5.27°C Increases in maximum temperature by 0.56-2.82°C	Aung et al. (2016)
3 GCMs (RCP 4.5 and 8.5)	Extreme Precipitation	Mahaweli RB (Sri Lanka) 10,448 km ²	2020s, 2050s, and 2080s Decrease/increases in annual precipitation by -0.5% - + 44%. Decrease in consecutive dry days and increase in wet days Decrease in monthly 5 days maximum precipitation	Imbulana et al. (2018)
3 GCMs (RCP 4.5 and 8.5)	Precipitation Minimum and maximum temperature	Yang RB (Thailand) 4,145 km ²	2020s, 2050s, and 2080s Increase in annual precipitation by 6.9% - 48.5% Increase in maximum temperature (0.05 – 3.8 °C) and minimum temperature (0.05 – 3.5 °C)	Shrestha and Lohpaisankrit (2017)
4 GCMs (RCP 2.6, 4.5, and 8.5)	Temperature	Lower Mekong Basin (Lao PDR, Thailand, Vietnam and Cambodia) ~600,000 km ²	2006-2049 and 2050-2093 Increase in mean annual temperature by 0.93 – 2.97 °C	Ruan et al. (2019)

Climate Projections	Variables	Basin	Projection horizon and results	Reference
5 RCMs (RCP 4.5 and 8.5)	Precipitation Temperature	Yarlung Tsangpo- Brahmaputra RB (India and Bangladesh) 530,000 km ²	2020-2035 Increase in basin average precipitation by 7.3-12.8% Increase in average temperature by 1.1-1.3 °C	Xu et al. (2019)
1 RCM (RCP 2.6, 4.5 and 8.5)	Precipitation Temperature	Headwaters of Yellow and Yangtze RBs (Tibetan Plateau, China) 259,600 km ²	2041-2060 Increase in annual precipitation by 0-70% Increase in temperature by 1-4 °C	Lu et al. (2018)
1 RCM (RCP 4.5 and 8.5)	Precipitation Temperature (mean, maximum and minimum)	Krishna RB (India) 258,948 km ²	2009-2040, 2043-2070, and 2073- 2100 Decrease and increase in mean annual precipitation (-13 % to +22 %) Increase in mean, maximum and minimum temperature (1.4-2.6 °C, 1.5-2.5 °C, and 1.7-2.6 °C, respectively)	Chanapathi et al. (2018)

These estimated changes in future climate are expected to alter hydrological regimes of the basins. For South and Southeast Asia, many studies have predicted a wide range of climate change driven impacts on streamflow (e.g., Ghimire et al., 2019; Lirong and Jianyun, 2012; Shrestha and Htut, 2016a; Shrestha and Lohpaisankrit, 2017; Thompson et al., 2013; Wang, 2015; Xu et al., 2019; Zhang et al., 2014), sediment erosion and load (e.g., Azim et al., 2016; Kim et al., 2017; Maharjan et al., 2014; Nilawar and Waikar, 2019; Shrestha et al., 2013; Zhou et al., 2017; Zhu et al., 2008), water quality (e.g., Whitehead et al., 2015), snow cover and glacier (e.g., Khadka et al., 2014; Lutz et al., 2014), evapotranspiration (e.g., Lu et al., 2018), water yield/ availability (e.g., Chanapathi et al., 2018; Deb et al., 2018; Shrestha et al., 2014), water scarcity (e.g., Gosling and Arnell, 2016) through numerous numerical model simulations and/ or empirical relationships.

2.4.2 Human activities and their impacts

Many studies have identified the intense pressure from human activities on the natural system, via interventions such as water diversion, reclamation, exploitation of groundwater resources, deforestation, land-use management, urbanization, and dam construction (Ranasinghe et al., 2019; Saito et al., 2007; Syvitski and Milliman, 2007; Syvitski et al., 2009, 2005; Walling, 2009, 2006), leading to the changes in streamflow, groundwater

resources, sediment load, soil erosion, biodiversity and eco-system, coastline position, and saline water intrusion (De Vente et al., 2013; Walling, 2009).

Impacts in past and present

Tan et al. (2015) evaluated effects of climate variability and land-use change on streamflow and evaporation in Johor River Basin in Malaysia for the period of 1975-2004 and found that climate variability driven influences on these two variables were higher than those resulting from land-use changes. Zhang et al. (2016) evaluated streamflow changes in Poyang Lake River Basin, China between 1955 and 2009 and found that climate change and human activities (land-use changes and reservoirs) had contributed 73.2% and 26.8%, respectively to observed changes in streamflow.

After construction of the Three Gorges Dams (TGD) along the Yangtze River in China, a 7% reduction of water flow during the period of 2003-2012 was observed, when compared with records over the previous 50 years (1950-2002) (Yang et al., 2015). Furthermore, Yang et al. (2015) have summarized that most of this reduction (60-70%) can be attributed to decreased precipitation, and the remainder can be attributed to the construction of reservoirs/dams, changes in water-soil conservation practices, and water consumption. They also estimated that about 65% of the declined sediment flux in the Yangtze River since 2003 resulted from the TGD. Fluvial sediment supply from Pearl River (China) to its coast has decreased by 71% during 1954-2013 due to human intervention such as damming and deforestation (Ranasinghe et al., 2019). Walling (2009) documented the driving factors, evidence and adaptations on sediment transport and erosion in the world's rivers. For example, the amount of annual sediment carried by Chao Phraya River in Thailand (draining from a basin of 110,569 km²) declined from 28 MT to 6 MT during the period 1960 to 1990. This sediment reduction is not only due to significant changes in the river flow but also due to sediment trapping caused by large (i.e., Bhumibol and Sirikit) and small dams and irrigation structures constructed on the tributaries of the main river.

In the past, large rivers such as the Yellow River, the Yangtze River, the Pearl River, the Red River, the Mekong River, the Chao-Phraya, and the Irrawaddy River in Southeast and East Asia together supplied total suspended sediments to the coast at a rate of ~2.5 GT per year. This has now decreased to about 1 GT per year, mainly due to human activities within the basin and coastal areas (Saito et al., 2007). Furthermore, Asian mega deltas are currently at risk of destruction due to declined sediment supply and relative sea-level rise (RSLR) (Besset et al., 2019; Saito et al., 2007). The Mekong Delta is now highly vulnerable to erosion as a result of decreased sediment supply to its coast, where not only do dams retain sediments but also massive sand mining activities in the delta contribute to a further reduction of the sediment supply to the coast, especially over the last decade (Anthony et al., 2015). As a result of development activities in basins and the ever-increasing socio-economic growth (Vörösmarty et al., 2009), most mega deltas and coasts are degrading and are exposed to frequent inundation, coastal erosion, extreme storm surges and loss of

ecosystems due to climate change impacts in the 21st century (Nicholls et al., 2007). Syvitski et al. (2009) studied 33 deltas to assess the impact of human activities on those areas. Their study has clearly illustrated a considerable reduction of sediment supply to deltas over the past 50 years. Based on their findings, during the past decade, 85% of deltas have experienced extreme flooding, inundating more than 260,000 km² of low-lying land. For example, deltas in Ganges, Mekong, Irrawaddy, Chao Phraya, Brahmani, Mahanadi, Krishana and Godavari have been exposed to substantial flooding in 2007-2008, resulting in loss of lives and innumerable damage to properties and ecosystems. A recent study by Besset et al. (2019) showed that in 38 world rivers (out of 54 rivers reviewed), sediment supply to the associated deltas has decreased by more than 20% between pre- and post-1970 periods. Notably, this decrease is more than 80% in Asian mega deltas (Chao Phraya, Red River, Pearl, Yellow River, and Krishna). Approximately 30% reduction in sediment supply is shown for the Ayeyarwaddy (Irrawaddy) Delta during 1974-2014 compared to pre-1970.

Impacts in future

Although many studies have investigated the future climate and associated impacts on hydrological processes in a basin, relatively few studies have assessed the combined (or relative) effect of climate change and human activities on the hydrological systems of the future. Human activities discussed in many of the literature are relevant for catchment hydrology included land-use change/urbanization (Kim et al., 2017; Maharjan et al., 2014; Marhaento et al., 2018; Pervez and Henebry, 2015; Sayasane et al., 2016; Trang et al., 2017; Vaighan et al., 2017; Zuo et al., 2016), existing or planned reservoirs (Mittal et al., 2016; Ngo et al., 2018; Piman et al., 2015; Shrestha et al., 2016).

Future land-use can be projected by the statistical method using historical data or modelling approach like CLUE-S (Conversion of land-use change and its effects at small regional extent - Verburg et al. (2002)) or assumed scenarios. For example, Sayasane et al. (2016) used historical land-use trends from 1997 to 2008 to produce future land-use in Nam Xong Basin, Lao PDR for 2011-2030. Their results revealed that with the combined effect of climate and land-use change, streamflow would reduce by 11.7-12.2%, particularly in the middle part of the basin. Shrestha and Htut (2016b) have used CLUE-S for projecting the future land-use in Bago River Basin, Myanmar. They found that climate change is the primary driver increasing the streamflow in the near future (i.e., 2020s). The combined effects of changes in climate and land-use were projected to result in a 68% increase in streamflow in the near future relative to 1990-2009 base period.

Mittal et al. (2016) analyzed individual and combined effects of climate change and dam construction on the hydrological flow regime in the Kangsabati River Basin, India. Results indicate that the impacts of reservoirs are larger than climate-induced effects on flow in this basin. Furthermore, the combined effects of climate and land-use were found to be significantly larger than their respective individual effects. Piman et al. (2015) incorporated 41 dams (8 existing, 11 under construction, and 22 proposed) to simulate flow alterations

and hydropower generation in the Mekong tributaries called 3S basins (Srepok, Sesan, and Sekong). They found that between 2010-2049, climate change and reservoirs may lead to ~3.8-8.5% decrease (compared to the base period: 1986-2005) in the annual flow under the A2 and B2 SRES scenarios.

2.5 Conclusions

This chapter presents different modelling approaches used to assess sediment load and streamflow generated from river basins, and main forcing scenarios and their potential impacts on the hydrological responses of basins.

Watershed models are utilized to understand hydrological processes, their interactions and to project system behaviour under different forcing scenarios. Among several model inputs, precipitation is the fundamental input variable for hydrological modelling. Due to limitations in-situ gauge data, reanalysis or remote sensing-based global precipitation products are being widely used in most of the recent hydrological studies. However, these global products do not always perform equally for all regions. Data availability, reliability and accessibility are limited in South and South-east Asian region. Therefore, it is essential to undertake future studies to identify the suitability of different global products before using them as alternative input datasets in hydrological modelling. Recent research findings highlight the importance of remote sensing-based products in hydrological model calibration. However, the suitability of those products for hydrological modelling is yet to be explored particularly in data-poor regions like South and South-east Asia.

Projections under different environmental changes (mainly due to varied climate and human activities) is a challenging task in hydrological modelling. Many studies show that impacts of climate change and human activities on landmasses are quite significant during the last few decades. GCM/RCM forced hydrological models that incorporate human activities (i.e., land-use changes, water diversions, and reservoirs) can quantify the potential impacts on streamflow and sediment loads from river basins. Further assessments and reviews are required to assess uncertainties associated with such projections of catchment responses, which is not discussed in this review.

3

DATA AND METHODS

3.1 Introduction

To achieve the objectives of this study (Section 1.3) the process-based hydrological model: Soil Water Assessment Tool (SWAT) was applied to two case study basins. The two case study basins broadly represent the substantial spatial heterogeneity (large and small scale) in data-poor Southeast and South Asian regions. The large basin selected here is the Irrawaddy (Ayeyarwady) River Basin in Myanmar, while the smaller basin is the Kalu River Basin in Sri Lanka. The climates of both countries are changing (Eriyagama and Smakhtin, 2010; GCCA, 2012; Imbulana et al., 2018; Kreft et al., 2015; Shrestha and Htut, 2016a), experiencing frequent flooding, drought, cyclones, storms, and sea-level rise. Both countries are also in a phase of rapid socio-economic growth, especially with foreign investors attracted to the underdeveloped potential for substantial hydropower generation in both countries (Kattelus et al., 2015). However, currently, the main rivers of both basins are mostly unregulated.

This chapter provides descriptions of the two case study areas (Section 3.2), the overall methodological framework adopted for this study (Section 3.3), and the data used including their sources (Section 3.4).

3.2 Case study areas

3.2.1 Irrawaddy River Basin

The Irrawaddy (Ayeyarwady) River Basin is mostly in Myanmar, with small parts located in Chinese (5%) and Indian (4%) territories, covering a total drainage area of about 410,000 km² (Figure 3-1). The main tributaries of the basin are Chindwin and Irrawaddy rivers. The Irrawaddy River, which is approximately 2100 km long, originates at the confluence of the Mali and N'Mai rivers and is augmented by the Chindwin at Pakokku. The Irrawaddy River, the most important commercial waterway in Myanmar discharges into the Andaman Sea, forming one of the two largest delta systems in Southeast Asia. The delta of the river originates about 120 km south of Pyay (Figure 3-1). The deltaic coastal zone is classified as a mud-silt tidal dominated system (Furuichi et al., 2009).

The basin has diverse topographic features, ranging from high mountainous terrain in its northern part to low-lying delta systems in the south. In the middle, there are plateaus (~500m above mean sea level (MSL)) and floodplains (Figure 3-1). Green forests and rain-fed crop cultivation comprise more than 65% of the basin area (Figure 3-2 (a)). Most of the croplands are located in the central valley and low-lying river flood plains, while dense forests are present in the northern hilly mountainous region. Myanmar is one of the most heavily forested countries in Southeast Asia, but the forest area has been decreasing at an annual rate of 0.3% (1990-2000) due to increased agricultural activities, fuelwood consumption, logging and increased plantations (Leimgruber et al., 2005). Acrisols, Cambisols and Gleysols are the dominant soil types in the study basin (Figure 3-2 (b)).

The population in the river basin in the year 2005 is reported to be around 37.2 million (Varis et al., 2012). The major agricultural and economical products of the area are rice and fishing, which extensively utilize the deltaic area of the basin (Driel and Nauta, 2014). The delta area contains rich fluvial sediments and natural habitats for various aquatic species (Taft and Evers, 2016).

Figure 3-1. Digital elevation map of Irrawaddy River Basin, Myanmar. (Digital Elevation Model used in the map was obtained from SRTM data (Jarvis et al., 2008)).

Myanmar has a tropical savanna climate. The basin experiences heavy rainfall from May to October and the dry season prevails from November to April. However, its mean annual rainfall is highly spatially variable, from about 500 mm in the central parts of the basin to 4000 mm in the northern mountainous regions. The average daily temperature varies from 21-34 °C in the summer and from 11-23 °C in the cold season. The annual average discharge is about 12,000 m³/s at the Pyay station (Figure 3-1). These annual average values presented here are estimates from observed precipitation, temperature, and streamflow data available for this study, which are described in Section 4.2.1. In the coastal zone, south-westerly waves dominate with significant wave heights ranging from 0.5 m to 2 m. This area experiences semi-diurnal tides with an annual average tidal amplitude as 1.5 m in western, 1.8 m in middle and 2.5 m in eastern deltaic coastline (Egbert and Erofeeva, 2002).

Myanmar's climate is changing considerably (Shrestha and Htut, 2016; GCCA, 2012). The country has experienced many natural hazards, such as frequent flooding, droughts, heatwaves, cyclones, storms and sea-level rise (GCCA, 2012). According to the Global Climate Risk Index (CRI), Myanmar is identified as the world's second most affected country in terms of extreme weather events that have occurred during 1995 - 2014 (Kreft et al., 2015). However, there are only a handful of climate change impact assessments focusing on Myanmar to date (Aung et al., 2016; Taft and Evers, 2016). Based on a statistical comparison between data collected in 19th and 20th centuries (periods of 1871-1879 and 1966-1996, respectively), it has been observed that the discharge of the Irrawaddy river has

significantly decreased over the last century (Furuichi et al., 2009). Socio-economic growth in Myanmar has accelerated over the last few decades. In the future (next 5 to 10 years), construction of large capacity reservoirs and other related diverse developments may disturb continuous sediment supply to Irrawaddy delta and its adjacent coastal region (Hedley et al., 2010).

Figure 3-2. Land-use (a) and Soil (b) maps of Irrawaddy Basin. (Source: Land-use map: European Space Agency (Arino et al., 2010) and Soil map (FAO, 2003)).

3.2.2 Kalu River Basin

The Kalu River Basin is the second largest river basin in Sri Lanka and receives high rainfalls leading to high river flows. The Kalu River (Kalu Ganga) originates from the Adam's peak range in South-central part of Sri Lanka and garners rainfall on the western slopes and falls out to the sea at Kaluthara after traversing about 129 km (Figure 3-3). The drainage area of the Kalu River is 2,787 km², and the river has steep gradients until Rathnapura and a very mild gradient in the lower part. The coastal zone adjacent to the Kalu river outfall comprises of a small tidal inlet system experiencing a 0.6 m oceanic tidal range.

The average annual rainfall in the basin is approximately 3800 mm, which is mainly driven by the south-west monsoon (May-Sep.). The average daily temperature in the basin is 25 °C. The middle and lower flood plain areas in the basin experience frequent floods due to heavy

rainfall during the southwest monsoon. These frequent floods greatly affect the socio-economic profile in Rathnapura and lower flood plain areas since these areas are highly populated and have a high potential for rice production. Much of the basin is utilized for rain-fed agriculture; paddy, rubber, tea and other crops (Figure 3-4 (a)), scattered throughout the whole basin. Clay rich Acrisol is the most dominant soil type found in the basin (Figure 3-4 (b)).

Sri Lanka is expected to be heavily affected by climate change, including an increase in land surface temperature, precipitation variability and its pattern, increase in extreme climatic events, and a rise in sea level. Average annual rainfall of the country has dropped by 144 mm from 1961 to 1990 compared to 1931-1960 (Chandrapala, 1996). The mean annual air temperature in Sri Lanka has increased at a rate of 0.016 °C per year for the same period (1961-1990) (Chandrapala, 1996). The HadCM3 GCM projections indicate that the average annual precipitation in Sri Lanka would increase by 14% and 5% under A2 and B2 scenarios, respectively during 2035-2065 (compared to 1961-1990) (De Silva et al., 2007). RegCM4 RCM simulations show an increase of precipitation over Sri Lanka by 39.6%, 35.5%, and 31.3% under A2, A1B, and B1 scenarios, respectively by 2080s compared to a baseline period of 1970-2000 (Ahmed and Suphachalasai, 2014). They also indicate that by the end of the 21st century, the mean annual temperature in Sri Lanka would increase by 3.6 °C, 3.3 °C, and 2.3 °C respectively under the same emission scenarios (compared to 1970-2000). The mean annual runoff of Sri Lanka is projected to increase by 31% (median value of 17 GCM projections) for RCP 8.5 during 2046-2075 (relative to 1976-2005) (Zheng et al., 2018).

Figure 3-3. Digital elevation map of the Kalu River Basin, Sri Lanka. (Digital Elevation Model used in the map was obtained from SRTM data (Jarvis et al., 2008))

Figure 3-4. Land-use (a) and Soil (b) maps of the Kalu River Basin, Sri Lanka. (Source: Land-use map: Survey Department of Sri Lanka and Soil map (FAO, 2003))

3.3 Methodological framework

The overall methodological framework adopted in this study is shown in Figure 3-5.

Figure 3-5. The overall methodological framework of the study. Abbreviations used in this figure are DEM: Digital Elevation Model, LU: Land-use, FDR: Flow Direction, FACC: Flow Accumulation, STR Link: Stream Link, RS: Remote sensing, ET: Evapotranspiration, GCMs: General Circulation Models, RCMs: Regional Climate Models, and RCP: Representative Concentration Pathways

To achieve Objective 1, catchment delineation and setting up of a distributed hydrological model for the study areas were undertaken with ArcSWAT software. The density of rain gauges is low in data-poor regions, and thus the available sparse data is unlikely to represent the precipitation over the entire basin area accurately. Therefore, the effects that differences

in input on hydrological model results were analysed by using observed and grid-based data obtained from several global precipitation products. Apart from the conventional calibration method used in hydrological modelling (using only streamflow data), remote sensing-based evapotranspiration (ET) was also utilized to calibrate the model. This model calibration procedure provides new insights on the use of ET and limited observed data to calibrate a hydrological model for a data-poor region (Objective 2).

GCMs/ RCMs outputs are the primary data sources for any climate change impact study. To achieve third objective of this study, the most representative climate model(s) among the available climate models were selected based on the statistical performance of climate data (i.e., precipitation, and maximum and minimum temperatures) and their capability to reproduce observed streamflow in the case study basins. Subsequently, precipitation and temperature data obtained from the selected GCMs/RCMs were bias-corrected. These bias-corrected data were then used to investigate climate change-driven variations in streamflow and fluvial sediment supply to coast over two twenty-year time slices: 2046-2065 and 2081-2100. All future model simulations undertaken in this study are based on the extreme IPCC emission scenario (RCP 8.5) and the low IPCC emission scenario (RCP 2.6).

Concerning the fourth objective of this study, dam construction across rivers was considered as the main human activity affecting future streamflow and fluvial sediment supply. Therefore, planned hydropower reservoirs in the two case study basins were identified and incorporated in the SWAT model to investigate their impacts on the hydrological response of the basin.

To achieve fifth objective, SWAT model results (i.e., fluvial sediment load) obtained under future conditions were compared with the projections obtained under similar conditions via the simplified BQART model presented by Syvitski and Milliman (2007). This comparison was made to gain novel insights on the necessity to undertake detailed (and time-consuming) hydrological modelling studies at a basin-scale to determine fluvial sediment load supply to coastal/ delta systems.

Detailed descriptions of these methods are given in Chapters 4 to 8, where the methods are applied.

3.4 Data used

The spatial, hydro-meteorological, and climate change projections data used in this study and their sources are shown in Table 3-1, Table 3-2, Table 3-3 and Table 3-4.

Table 3-1. Spatial data used in this study

S.N.	Data set	Resolution	Source
1	DEM	90m x 90m	SRTM (http://hydrosheds.cr.usgs.gov/index.php)
2	Land-use map	300m x 300m	European Space Agency (http://due.esrin.esa.int/globcover) and Department of Survey, Sri Lanka
3	Soil map	7km x 7km	FAO/UNESCO (http://www.fao.org/soils-portal/soil-survey/)

Table 3-2. Observed hydro-meteorological data. DM - Department of Meteorology; LHI- Lanka Hydraulic Institute; DI - Department of Irrigation. For Irrawaddy Basin, required data was collected from previous research studies carried out in Asian Institute of Technology, Thailand.

S.N.	Data set	Units	Frequency	Source
1	Temperature	°C	Daily	DM & LHI, Sri Lanka
2	Precipitation	mm	Daily	DM & LHI, Sri Lanka
3	Discharge	m ³ /s	Daily	DI & LHI, Sri Lanka
4	Relative Humidity	%	Monthly	DM, Sri Lanka
5	Wind Speed	Km/hr	Monthly	DM, Sri Lanka
6	Solar Radiation	MJ/m ²	Monthly	DM, Sri Lanka

Table 3-3. Global data. GLEAM- Global Land Evapotranspiration Amsterdam Model, G- Gauge, S-Satellite

S.N.	Data set	Data Source	Spatial Res.	Frequency	Source
1	Precipitation				
	PERSIANN-CDR	G, S	0.25°	Daily	http://chrs.web.uci.edu
	CHIRPS	G, S	0.05°	Daily	http://chg.ucsb.edu/data/
2	Evapotranspiration				
	GLEAM-ET	S	0.25°	Daily	https://www.gleam.eu/

Table 3-4. GCM and RCM data. All GCM data were obtained from ESGF at DOE LLNL (<http://pcmdi9.llnl.gov/>), and RCM data was obtained from ICTP, Italy.

S.N.	Model	Country	Modelling Center	Resolution
General Circulation Model Data				
1	CCSM4	USA	Community Climate System Model 4	1.25° x 0.94°
2	CSIRO-Mk3.6	Australia	Commonwealth Scientific and Industrial Research Organization/Queensland Climate Change Centre of Excellence	1.875° x 1.875°
3	GFDL-CM3	USA	Geophysical Fluid Dynamics Laboratory	2.5° x 2.0°
4	HadGEM2-AO	Korea / UK	National Institute of Meteorological Research/Korea Meteorological Administration	1.875° x 1.25°
5	HadGEM2-ES	UK	Met Office Hadley Centre	1.875° x 1.25°
6	IPSL-CM5A-MR	France	Institut Pierre-Simon Laplace	2.5° x 1.25°
7	MIROC5	Japan	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	1.4° x 1.4°
8	MRI-CGCM3	Japan	Meteorological Research Institute	1.1° x 1.1°
9	NorESM	Norway	Norwegian Climate Centre	2.5° x 1.875°
10	BCC-CSM1.1	China	Beijing Climate Center, China Meteorological Administration	2.8° x 2.8°
Regional Climate Model Data				
1	RegCM4/MIROC5	Italy	Oak Ridge National Laboratory	25km x 25km
2	RegCM4/MPI-M-MPI-ESM-MR	Italy	Oak Ridge National Laboratory	25km x 25km
3	RegCM4/NCC-NORES1-M	Italy	Oak Ridge National Laboratory	25km x 25km

4

EFFECTS OF DIFFERENT PRECIPITATION INPUTS ON STREAMFLOW SIMULATIONS¹

4.1 Introduction

Precipitation is the fundamental input variable for the hydrological modelling of river basins. The accuracy of hydrological model outcomes largely depends on the quality of the precipitation data used. One major challenge in hydrological modelling is the accurate representation of the spatial and temporal variations in precipitation over a river basin. Areal precipitation over a basin is usually estimated from in-situ gauge measurements. However, in many river basins, available gauged precipitation data are mostly inadequate to accurately represent the heterogeneity of precipitation (Miao et al., 2015). Nowadays, radar and satellite-based remotely sensed precipitation data are being widely used as alternative sources of precipitation inputs for hydrological simulations. There are several precipitation products available, which vary in spatial coverage (i.e., global and regional) and temporal

¹ This chapter is partially based on the published article: Sirisena, T. A. J. G., Maskey, S., Ranasinghe, R., Babel, S., 2018. Effects of different precipitation inputs on streamflow simulation in the Irrawaddy River Basin, Myanmar. *J. Hydrol. Reg. Stud.* 19, 265–278. <https://doi.org/10.1016/j.ejrh.2018.10.005>.

scales (hourly, daily, and monthly). These gridded precipitation data are available at various spatial resolutions, varying from $0.05^{\circ} \times 0.05^{\circ}$ to $1^{\circ} \times 1^{\circ}$. These products originate from interpolated in-situ measurements (APHRODITE, and CPC Unified), reanalysis products (ERAInterim, NCEP-CFSR, and JRA-55), and remote sensing (CHIRPS, PERSIANN, CMORPH, GridSat, TRMM, GSDMap V5/6, and SM2RAIN-ASCAT).

The main research questions addressed in this chapter are how different precipitation products perform with respect to streamflow simulation and how useful these products are in data-poor regions. To answer the above research questions, one of the most widely used hydrological model SWAT (Soil Water Assessment Tool) (Arnold et al., 1998; Neitsch et al., 2011) was used to simulate streamflow of two data-poor basins: Irrawaddy River Basin in Myanmar and Kalu River Basin in Sri Lanka. Out of the four precipitation datasets used, two datasets are derived from the available in-situ measurements (with and without interpolation), while the other two are satellite-based products. The reason for using two datasets from the same in-situ gauge measurements is due to the way precipitation input is handled in SWAT. In its default setting, SWAT assigns one precipitation gauging station to each sub-basin, which is closest to the basin's centroid, irrespective of the number of gauge stations available. This means that the same gauging stations may be assigned to more than one sub-basin while some gauging stations may not be assigned to any. As a result, for the same basin, if two SWAT hydrological models are configured with a different number of sub-basins, precipitation inputs to the models vary. One way to avoid this issue is to spatially interpolate the gauge observations over the basin using a fixed grid resolution and then to assign interpolated values to each sub-basin. The two remote sensing-based products used in this study are PERSIANN-CDR (Ashouri et al., 2015) and CHIRPS (Funk et al., 2015). PERSIANN-CDR is an abbreviation for Precipitation Estimation from Remote Sensing Information using Artificial Neural Network – Climate Data Record, and CHIRPS stands for Climate Hazard Group Infrared Precipitation with Station data. The main reason for choosing these two products was their reported success in recent studies (Ashouri et al., 2016; Casse and Gosset, 2015; Ceccherini et al., 2015; Guo et al., 2015; Le and Pricope, 2017; Shrestha et al., 2017; Zhu et al., 2017).

This chapter is organized as follows. Section 4.2 describes the data used, model setup and calibration of the SWAT model. In Section 4.3 and 4.4, results are presented for the two basins in terms of spatial and temporal variability of precipitation data, simulated discharge from those data, and uncertainty analysis. Section 4.5 discusses the comparison of model results for two basins. Finally, Section 4.6 concludes the output of this analysis.

4.2 Methods

4.2.1 Data

Spatial and hydro-meteorological data used in this analysis are summarized in Table 3-1, Table 3-2, and Table 3-3. The detailed descriptions of the data used for the two basins are presented below.

Irrawaddy River Basin, Myanmar

A 90 m x 90 m resolution STRM DEM was used for catchment delineation. Land cover information at 300 m x 300 m resolution for the year 2009 was obtained from the European Space Agency, and a soil map at 7 km x 7 km resolution was obtained from Food and Agriculture Organization (FAO, 2003). Topographic slope classification for the model followed the FAO (2003) slope class definitions: undulating land (0-8 % slope), hilly areas (8-30% slope), and mountainous areas (> 30% slope).

Observed daily temperature (minimum and maximum) data at the weather stations (Figure 4-1(a)) for the period from 2001 to 2010 were used. Furthermore, daily temperature data from 1990 to 2000 (obtained from previous studies) and monthly wind speed, and relative humidity data at five stations (Hkamti, Homalin, Mawlaik, Kalewa and Monywa) were also used in the simulations. Observed daily streamflow data are available for eight locations (Figure 4-1 (a)) from 1991 to 2010.

Four precipitation datasets were used in this analysis: (i) Gauge precipitation data, (ii) Interpolated Gauge data and two satellite-based (corrected with gauged precipitation) products: (iii) PERSIANN – CDR and (iv) CHIRPS (Table 3-3). Daily observed precipitation data from 19 weather stations (Figure 4-1 (a)) were used for the period from 2001 to 2010. With only 19 rain gauges available for this study, the gauge density is estimated at around 20,000 km² per station, which is a lot lower than a recommended gauge density in the WMO guidelines (WMO, 2008). Furthermore, precipitation data from 1990 to 2000 used in previous studies were also utilized due to limited availability of model calibration and validation data for this study. Gaps in the 1990-2000 dataset were filled with the Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE) data (Yatagai et al., 2012). In this study, the Inverse Distance and Elevation Weighted (IDEW) method was used to interpolate daily precipitation data from 19 gauges over a 25.5 km x 25.5 km uniform grid. Among the various interpolation methods discussed in the literature, IDEW method considers the combined effects of distance and elevation on the spatial variability of precipitation (Masih et al., 2011). This interpolation and aggregation over sub-basins were carried out using the tool Hykit, which was developed for grid-based interpolation in hydrological variables (Maskey, 2013). The corresponding parameter values were defined using the Jackknife cross-validation approach (Quenouille, 1956). In this method, the data from all stations,

excluding the current validation station are used for interpolation. Then, the interpolated precipitation at the current station is compared with the corresponding grid cell. The resulting interpolated precipitation values of grid cells were then averaged over the sub-basins. Gridded global data (PERSIANN-CDR and CHIRPS) were also averaged over each sub-basin.

Kalu River Basin, Sri Lanka

The same spatial data sources as for the Irrawaddy basin were used for this basin as well, except for land-use. The land-use data with 300 m x 300 m resolution was obtained from the Survey Department of Sri Lanka.

Here, observed daily temperature (minimum and maximum) data at three meteorological stations (Figure 4-1 (b)) for the period of 1990 to 2015 were used. Monthly wind speed, relative humidity, and solar radiation data from the same three stations were also used in the simulations. Observed daily streamflow data are available for three locations (Ellagawa, Millakanda, and Putupaula) (Figure 4-1 (b)) from 1991 to 2015. However, the streamflow data after the year 2000 are unreliable from Ellagawa and Putupaula due to rating curve errors. Therefore, only the 1990-2000 streamflow data were used.

Similar to the Irrawaddy River Basin, four precipitation datasets were used: (i) Gauge precipitation data, (ii) Interpolated Gauge data, and two global datasets: (iii) PERSIANN-CDR and (iv) CHIRPS. Daily observed precipitation data of the 25 rain gauge stations (Figure 4-1 (b)) were used from 1990 to 2015. A similar procedure as applied to Irrawaddy Basin was adopted here to obtain interpolated data for each sub-basin. Data from 25 stations were interpolated over a 5 km x 5 km grid and averaged over each basin. Global datasets were also averaged over each sub-basin.

The Kalu River Basin has high rain gauge density (110 km² per station). However, streamflow and temperature stations, and continuity of the available data in the Kalu RB are limited. Therefore, the Kalu RB can also be considered a data-poor region for hydrological studies.

4.2.2 Model setup and calibration

In catchment delineation, the threshold area that is used to define the origin of a stream must be specified (known as the stream definition in SWAT). A smaller value of stream definition will generate a more detailed stream network (i.e., more tributaries and outlets). Different model structures (i.e., number of sub-basins) were considered (by changing the stream definition value) to determine the most suitable model setup that can reproduce the streamflow of the Irrawaddy RB over 1991-2000. Finally, 750 km² was used as the stream definition value to define the stream network in the Irrawaddy RB. Based on the generated stream network and sub-basin outlets and manually introduced outlets, the study area of the Irrawaddy RB (371,558 km²) was delineated into 32 sub-basins (Figure 4-1 (a)). Based on

the defined thresholds for land-use, soil, and slope, the 32 sub-basins were further divided into 747 HRUs (Hydrological Response Units). Following a similar analysis of the stream definition at the Kalu River Basin, an area threshold of 5 km² was used therein. Based on the generated stream outlets and manually introduced outlet locations, the Kalu RB (2,787 km²) was divided into 15 sub-basins (Figure 4-1 (b)). These sub-basins were further divided into 161 HRUs (based on defined thresholds of land-use, soil, and slope for HRU generation).

Among the methods available in SWAT, Soil Conservation Services - Curve Number (SCS-CN) method was used to simulate surface runoff, and the variable storage method was adopted for routing the flow through channel networks. Potential evapotranspiration (PET) was calculated using the Hargreaves method (Neitsch et al., 2011), which requires fewer input data compared to other methods available in SWAT.

The first year of simulations (1990 (calibration run) and 2001 (validation run) in the Irrawaddy RB and 1990 in the Kalu RB) were used as warm-up period to initialize the model state variables such as soil moisture and groundwater. The Sequential Uncertainty Fitting algorithm version 2 (SUFI-2) (Abbaspour et al., 2007) in SWAT- Calibration and Uncertainty Programme (SWAT-CUP) (Abbaspour, 2015) was used for automatic model calibration and validation. Many successful applications of SUFI-2 can be found in literature (e.g., Abbaspour et al. (2015, 2007, 2004), Masih et al. (2011) and Shrestha et al. (2013)). Model parameters and their initial ranges for calibration were selected following the suggestions made in the studies mentioned above (see Table 4-1 for chosen parameter ranges). The calibration parameters represent the land cover, topographic conditions, soil properties, and groundwater process of the basin.

The Modified Nash-Sutcliffe Efficiency (MNSE) (Abbaspour, 2015) was used as the objective function to optimize the model calibration, which has been proven to perform better than NSE particularly in low flow regimes (Legates and McCabe Jr., 1999; Pushpalatha et al., 2012). The model was calibrated using different number of iterations, each with 500 simulations. After each iteration, the calibration program suggests a new set of parameter ranges for the next iteration. Parameter ranges for the subsequent iteration were selected by considering the suggested ranges by the calibration programme (SUFI-2) and the parameters' physically realistic upper and lower limits. The iteration process was terminated when no significant improvement in the model performance was observed between two successive iterations. Once a gauging station is calibrated, these parameters were fixed for all the sub-basins draining to that gauging station to proceed to the next downstream station for calibration. This procedure was repeated for each of the discharge gauging stations starting from the farthest upstream to the most downstream station. The calibrated parameter ranges from all sub-basins were then used for the validation period with 500 simulations. This method was repeated for the model simulations with the four different precipitation datasets.

Figure 4-1. Sub-basins and climatic stations used in this study (a) Irrawaddy River Basin, Myanmar and (b) Kalu River Basin, Sri Lanka

Table 4-1. Hydrological parameters used in model calibration. The prefixes a, v and r in the parameter name denote 'a value is added to the existing value', 'the existing value is replaced by a new one', and 'the existing value is increased or decreased relative to the existing value', respectively during calibration.

Parameter	Description	Scale	Default	Initial Range
a__CN2.mgt	SCS curve number, AMC (II)	HRU	HRU Specific	-8 - 10
v__GWQMN.gw	Threshold groundwater depth for return flow to occur (mm)	Basin	1000	0 - 1000
v__GW_DELAY.gw	Groundwater delay time (days)	Basin	31	0 - 150
v__ALPHA_BF.gw	Baseflow Alpha Factor (days)	Basin	0.048	0 - 1
v__CANMX.hru	Maximum canopy storage (mm)	Basin	0	0 - 1
v__CH_N2.rte	Manning's coefficient for the main channel	Basin	0.014	0.02 - 0.2
v__CH_K2.rte	Hydraulic conductivity of the main channel (mm/h)	Basin	0	0 - 100
r__SOL_AWC().sol	Available water capacity of a soil layer (mm H ₂ O / mm Soil)	HRU	Soil specific	-0.5 – 0.5
v__ESCO.hru	Soil evaporation compensation factor	HRU	0.95	0 - 1
v__SURLAG.hru	Surface runoff lag coefficient	HRU	2	0 - 10
v__EPCO.hru	Plant uptake compensation factor	HRU	1	0 - 1
r__OV_N.hru	Manning's coefficient for overland flow	HRU	HRU Specific	0 – 0.5
v__GW_REVAP.gw	Groundwater "revap" coefficient	Basin	0.02	0.02 - 0.2
v__REVAPMN.gw	Threshold water depth in a shallow aquifer for "revap" or percolation to occur (mm)	Basin	750	0 -1000

4.3 Results and discussion: Irrawaddy River Basin

4.3.1 Comparison of precipitation datasets

Monthly precipitation patterns of the four datasets (Figure 4-2) show that PERSIANN-CDR and IGP data yield the lowest and highest precipitation, respectively, throughout the ten years (2001 to 2010) considered. Monthly precipitation of PERSIANN-CDR and CHIRPS was lower than the IGP in each year, particularly during the months from June to August. The difference between GP and IGP is marginal (about 32 mm/year) in this case. The total precipitation of CHIRPS was relatively less than IGP data (170 mm/year), whereas PERSIANN-CDR showed the highest difference in total precipitation (235 mm/year).

Figure 4-2. Monthly precipitation of four precipitation datasets over the Irrawaddy River Basin

Variations in average annual precipitations over the sub-basins are presented in Figure 4-3. Precipitation based on IGP data varied from 1000 mm in the middle to 3400 mm in the northern part of the basin with a standard deviation of 622 mm. The highest spatial variation was observed with the GP data (750 mm to 4400 mm), with a standard deviation of 994 mm. PERSIANN-CDR precipitation varied from 1000 mm to 2700 mm (with a standard deviation of 357 mm), and CHIRPS precipitation varied between 800 mm to 3000 mm (with a standard deviation of 560 mm). PERSIANN-CDR and CHIRPS differed notably from IGP in the most upstream sub-basin areas, but those differences become smaller in downstream sub-basins.

Figure 4-3. Spatial distribution of average annual precipitation values for the four precipitation datasets considered (2001-2010). From left to right: GP (Gauge precipitation), IGP (Interpolated gauge precipitation), PERSIANN-CDR, and CHIRPS data.

Figure 4-4 shows the variations among the four datasets across the three main seasons (hot, monsoon, and cold) considered. Spatial variations of the four precipitation products are different for each season. The most upstream parts of the basin (sub-basins 1, 2 and 3) receive higher precipitation than other sub-basins during all seasons. During the hot season, GP, IGP, and CHIRPS precipitation values decrease towards the southern parts of the basin. PERSIANN-CDR data shows higher precipitation in the north-western and western parts of the basin during the same season. During the monsoon season (May to October), all the sub-basins receive more than 700 mm of precipitation in all the datasets used. During the same period, sub-basins 1, 2, and 3 receive more than 3500 mm/ year precipitation, which is also the highest for the entire Irrawaddy Basin. These computed precipitations of the basins mainly rely on Hkamti (Sub-basin 1) and Putao (Sub-basins 2 and 3) stations. Compared to IGP data, PERSIANN-CDR and CHIRPS data show less precipitation in the north-eastern and north-western parts of the basin. During the cold season (November to February), spatial variations in the total precipitation resulting from the IGP dataset are the least in all the sub-basins considered. The highest variability can be observed in CHIRPS precipitation over the basin. In terms of basin-wide seasonal precipitation, the highest precipitations during the hot (120 mm), monsoon (1927 mm), and cold (60 mm) seasons are observed in PERSIANN-CDR, IGP, and CHIRPS, respectively. Similarly, the lowest precipitation during the same seasons can be observed from IGP (70 mm), PERSIANN-CDR (1635 mm), and GP (49 mm), respectively.

Figure 4-4. Spatial distribution of seasonal variations of the four precipitation datasets (GP, IGP, PERSIANN-CDR, and CHIRPS) for the period 2001 to 2010

PERSIANN-CDR shows the lowest average annual rainfall over all the sub-basins. These results are consistent with findings of Miao et al. (2015), who found that, compared to the ground-based East Asia (EA) precipitation product, PERSIANN-CDR slightly underestimated the extreme rainfall events over China. Global products (PERSIANN-CDR and CHIRPS) produce lower rainfall compared to observed data, particularly in the high altitude regions of the Irrawaddy River Basin. Le and Pricope (2017) also showed that the CHIRPS dataset provides less accurate results for high altitude regions of the Nzoia Basin in Kenya. However, other studies on CHIRPS, which are also based in complex topographic regions (Funk et al., 2015; Katsanos et al., 2016; Shrestha et al., 2017) do not mention any issues in model performance. In general, the four datasets show considerably varied precipitation across the basin (Figure 4-3 and Figure 4-4). Given that precipitation is considered to be the primary forcing data for hydrological model simulation, such differences in precipitation inputs are expected to cause considerable variations in the outcomes of the hydrological simulations.

4.3.2 Evaluation of simulated streamflow

Comparison of the observed and model-simulated streamflow indicates that models based on observed precipitation (GP and IGP) outperform those based on global data sources (PERSIANN-CDR and CHIRPS) in both calibration (1991 - 2000) and validation (2002 - 2010) (Figure 4-5, Table 4-2 and Sirisena et al. (2018)). Models that utilize GP data slightly overestimate extreme events, whereas simulations with PERSIANN-CDR and CHIRPS perform relatively poorly during the high flow periods. Notably, for the year 2002, high flows were overestimated at the Katha, Sagaing, Monywa and Nyuang U stations. Simulated streamflow with the GP dataset at the Hkamti and Homalin stations showed better agreement with observed streamflow than with the other precipitation datasets. These two stations represent Sub-basins 1 and 7, respectively, each containing one rainfall gauging station. During the low flow period, simulations with all four datasets showed similar levels of accuracies. However, at the Katha and Sagaing stations, simulated streamflow with PERSIANN-CDR and CHIRPS were lower than the observed values. Models forced with CHIRPS precipitation adequately reproduced the observed streamflow at Homalin, Kalewa, Monywa, Nyaung U, and Pyay. Model simulations with four datasets reproduce the overall basin outflow at Pyay with reasonable accuracy (Figure 4-5).

Figure 4-5. Comparison of simulated and observed monthly streamflow of best simulation at Pyay during Calibration (1991-2000) and Validation (2002 - 2010) periods

Table 4-2 presents the statistical performance indicators (NSE, R^2 , and PBIAS) of the hydrological simulations (streamflow) at eight gauging locations for the calibration and validation periods. The highest NSE and R^2 and lowest PBIAS among the four cases are highlighted. For the calibration, R^2 varied within 0.8 to 0.96, while the NSE and PBIAS varied from 0.28 to 0.95 and -49.8% to 5.8%, respectively. All the models produced better results at Hkamti, Homalin, Kalewa, and Monywa gauging stations in the Chindwin River Basin than at the Katha and Sagaing stations located in the upper Irrawaddy River Basin.

According to the model evaluation criteria proposed by Moriasi et al. (2007) (see Section 4.2.2), performances of the models driven by GP and IGP were ‘very good’ in both calibration and validation at all stations, except the simulation with GP data at the Katha station that showed only ‘good’ performance. PERSIANN-CDR driven simulations showed varied performances at different stations. For example, the lowest NSE (0.28) and the highest PBIAS (-49.8%) were obtained at the Sagaing station, while the highest NSE (0.89) and the lowest PBIAS (1.8%) were observed at the Monywa station. Similarly, simulations with CHIRPS showed ‘satisfactory’ results at the Sagaing and Hkamti stations, whereas the model performances at the other stations were ‘very good’ in both calibration and validation. All the simulations show ‘very good’ results for streamflow simulation at Pyay and Nyaung U.

Table 4-2. SWAT model performance for calibration and validation periods. Bold values indicate the highest model performances.

Station	Calibration (1991 - 2000)				Validation (2002- 2010)			
	GP	IGP	P-CDR	CHIRPS	GP	IGP	P-CDR	CHIRPS
NSE								
Hkamti	0.93	0.86	0.59	0.73	0.85	0.93	0.55	0.74
Homalin	0.92	0.91	0.7	0.78	0.91	0.94	0.61	0.76
Kalewa	0.94	0.95	0.85	0.86	0.9	0.97	0.85	0.87
Monywa	0.92	0.95	0.89	0.91	0.75	0.95	0.93	0.91
Katha	0.69	0.91	0.35	0.75	0.56	0.9	0.12	0.76
Sagaing	0.82	0.83	0.28	0.58	0.81	0.89	0.42	0.72
Nyaung U	0.90	0.93	0.87	0.92	0.81	0.91	0.92	0.95
Pyay	0.94	0.93	0.86	0.91	0.91	0.96	0.89	0.93
R ²								
Hkamti	0.93	0.92	0.83	0.86	0.93	0.94	0.78	0.79
Homalin	0.93	0.93	0.84	0.87	0.94	0.95	0.83	0.77
Kalewa	0.94	0.96	0.89	0.92	0.95	0.97	0.91	0.92
Monywa	0.93	0.95	0.89	0.93	0.95	0.97	0.93	0.91
Katha	0.86	0.92	0.8	0.89	0.84	0.92	0.68	0.88
Sagaing	0.85	0.90	0.8	0.86	0.85	0.9	0.8	0.89
Nyaung U	0.95	0.95	0.9	0.94	0.94	0.96	0.93	0.95
Pyay	0.94	0.94	0.88	0.92	0.95	0.96	0.91	0.93
PBIAS								
Hkamti	-0.6	-22.6	-40.5	-26.1	20.9	-10.7	-42.5	-17.9
Homalin	-3.5	-10.7	-29.0	-21.7	1.1	-10.6	-37.9	8.2
Kalewa	-4.1	-5.5	-13.6	-15.4	8.9	-1.5	-16.2	-11.9
Monywa	0.7	1.6	1.8	-8.8	27.9	8.6	0.7	4.8
Katha	5.8	-4.9	-48.5	-29.1	9.3	-2.4	-50.1	-23.7
Sagaing	-11.1	-19.7	-49.8	-38.2	-1.1	-9.1	-44.2	-30.0
Nyaung U	5.8	2.3	-11.2	-10.5	22.7	8.3	-3.9	2.0
Pyay	-0.1	4.3	-7.4	-7.7	13.5	4.9	-4.1	1.7

PERSIANN-CDR had the lowest total precipitation compared to the other datasets; thus, the simulations driven with PERSIANN-CDR data tended to underestimate high streamflow and demonstrate weaker model performance in terms of NSE and PBIAS. During the monsoon season, both PERSIANN-CDR and CHIRPS yielded less precipitation over the eastern and northern parts of the basin. Thus simulations with those datasets significantly underestimate the high flows at Hkamti, Katha and Sagaing stations than at the other stations. During the hot and cold seasons, all the models showed reasonable agreements with the observed streamflow. However, R^2 values were greater than 0.8 at all the gauging stations for both the calibration and validation periods. Despite overestimating the high flows at all the gauging stations, simulations forced with the GP dataset satisfactorily reproduced the observed flow in the entire study area. Although the average rain gauge density of Irrawaddy RB is approximately 20,000 km² per station, which is very low compared to the minimum requirement stated in the WMO guidelines (5,750 km² per station for interior plains), the models driven by IGP managed to reproduce the measured streamflow at all the stations with good accuracy. This indicates that the interpolation of gauge data may lead to an improved representation of precipitation over the basin. In most cases, PERSIANN-CDR and CHIRPS also showed good agreement with observed streamflow in terms of NSE and R^2 , however, their biases were higher than the biases of simulations forced with IGP. In general, CHIRPS driven simulations performed better than simulations forced with PERSIANN-CDR. Therefore, the CHIRPS product can be utilized as an alternative source of rainfall inputs for hydrological studies in the Irrawaddy River Basin. Tuo et al. (2016) have also suggested CHIRPS data as a favourable choice for data-scarce Alpine regions. Apart from that, Le and Pricope (2017) concluded that the use of CHIRPS data with the SWAT model significantly improved the streamflow volume estimation, but not the satisfactory efficiency criteria, for the Nzoia Basin, Kenya. Further, as discussed by Faridzad et al. (2018), despite having limitations and uncertainties, the bias-corrected PERSIANN-CDR data provides valuable information for hydrological simulation in remote and high altitude areas.

4.3.3 Parameter uncertainty

During the model calibration, 14 selected hydrological parameters were adjusted and converged to different optimal intervals to reproduce streamflow at eight gauging stations. While noting that sensitivities of the parameters can be basin specific, five globally sensitive hydrological parameters have been selected to discuss these results (Figure 4-6). The Curve Number (CN2) corresponds to the land-use type and predominantly affects surface runoff generation. The four precipitation inputs used in this study led to different best fit CN2 values (a_CN2 varies -7 to 7) and ranges. For the simulations with GP, fitted parameter values significantly deviated from those obtained through simulations with the other three precipitation inputs. Hence, a common pattern for fitted CN2 values could not be identified for all sub-basins. GW_QMN is an important parameter related to baseflow. During low flow periods, groundwater contribution to streamflow can be significant. There is an

apparent variability in these fitted parameters for most of the sub-basins, where the highest variability for this parameter (v_GWQMN from 81 to 874) was observed in the sub-basins corresponding to the Katha station. Compared to CN2, the variability of the fitted GW_QMN for the four models at each sub-basin was high. The base flow recession factor (ALPHA_BF) can vary between 0 and 1. The sub-basins corresponding to the Hkamti, Homalin and Nyaung U stations resulted in nearly equal best fit ALPHA_BF for all precipitation datasets. SOL_AWC is related to the available water capacity in the soil, which is calculated based on water content at field capacity and water content at permanent wilting point. The best-fitted parameters (i.e., relative changes of the initial value of SOL_AWC) varied from -0.49 to 0.23. Fitted parameter values for ESCO, which is relevant for soil evaporation, varies between default SWAT limits (0 - 1) for the precipitation inputs considered.

Figure 4-6. Uncertainty analysis of five selected model parameters. The initial parameter ranges are indicated by blue lines and fitted values in red dots for the four models with different precipitation inputs, v- denotes replacement of the existing value; a- denotes adding a fixed value to the existing value and r- denotes the relative change of the existing value. G- Gauge precipitation, I- Interpolated gauge precipitation, P- PERSIANN-CDR, and C-CHIRPS. Corresponding parameter changes in sub-basins for each stations: Hkamti - 1, Homalin - 6 and 7, Kalewa- 15, Monywa - 16,17,18,19 and 20, Katha - 2,3,4,5,6,9,10 and 11, Sagaing - 12, 13, 14 and 22, Nyaung U - 21,23,24,25,26,27,28,29 and 30 and Pyay - 31,32.

4.4 Results and discussion: Kalu River Basin

4.4.1 Comparison of precipitation datasets

The observed data products (GP and IGP) show that all sub-basins in the Kalu River Basins receive more than 2245 mm of precipitation annually (Figure 4-7). The highest and lowest variations of precipitation were observed with GP data (2740-4510 mm with a standard deviation of 551 mm) and PERSIANN-CDR data (2245-2450 mm with a standard deviation of 86 mm), respectively. These precipitations imply that PERSIANN-CDR underestimates the precipitation over the basin. The total precipitation of CHIRPS is also relatively low (505 mm/yr – the difference between IGP and CHIRPS data). The difference between GP and IGP data for cumulative precipitation of 25 years (1991-2015) is marginal (approximately 88 mm/year). The average annual precipitations of the global precipitation products are considerably lower compared to the GP and IGP data, thus only GP and IGP data were further analyzed and used for streamflow simulation in this basin.

Figure 4-7. Spatial distribution of average annual precipitation values for the four precipitation datasets. (GP (Gauge precipitation), IGP (Interpolated gauge precipitation), PERSIANN-CDR, and CHIRPS) considered (1990-2015).

In Sri Lanka, a hydrological year is divided into four main seasons based on monsoon rainfall variations: Inter monsoon 1 (March to April), Southwest monsoon (May to September), Inter monsoon 2 (October to November), and Northeast monsoon (December to February). Spatial variations of the two selected precipitation products (i.e., GP and IGP) are different for each season (Figure 4-8). From May to October (during SW monsoon and

Inter monsoon 2), all the sub-basins receive higher precipitation than the rest of the year. Since the Kalu River Basin is located in the Southwest monsoon belt, some parts of the basin receive more than 2000 mm of rainfall from May to September. The most-upstream parts of the basin (Sub-basins 1, and 6) receive higher precipitation than other sub-basins during all the seasons except NE monsoon. In terms of basin-wide seasonal precipitation, the highest precipitations during the Inter monsoon 1 (672 mm), SW monsoon (2429 mm), Inter monsoon 2 (1038 mm) and NE monsoon (684) are observed in GP data. Similarly, the lowest precipitation during the same seasons is also observed with the GP dataset. These are, respectively, 399, 1171, 629, and 364 mm.

Figure 4-8. Spatial distribution of seasonal variations of the two selected precipitation datasets (GP and IGP) for the period 1990 to 2015. SW: South-west and NE: North-east

4.4.2 Evaluation of simulated streamflow

The model based on IGP data generally outperformed that based on GP data (Figure 4-9 and Table 4-3), but with only marginal differences in the performance indicators. Both models (with GP and IGP) produced better results ('very good') at Ellagawa and Putupaula, which are located in the main river. However, at Putupaula, low flow conditions are underestimated in model simulations with IGP inputs. Both models underestimated the streamflow at Millakanda. The reason for this underestimation at Millakanda is likely the inadequate rainfall input from both datasets, particularly in sub-basins 4, 8, and 9 throughout the year (Figure 4-8) due to uneven distribution of rainfall stations in the Millakanda drainage area. The average rain gauge density of the basin is 110 km² per station, which is within the minimum requirement as per WMO guidelines (2,500 km² per station for Mountains and 5,750 km² per station for interior plains). Thus, both GP and IGP datasets result in nearly equal performance in streamflow simulation (Table 4-3).

Figure 4-9. Comparison of simulated and observed monthly streamflow of the best simulations at three stations during the calibration period (1991-2000). Red and blue lines indicate the observed and simulated data.

Table 4-3. SWAT model performance for calibration period (1991-2000)

Station	NSE		R ²		PBIAS	
	GP	IGP	GP	IGP	GP	IGP
Ellagawa	0.81	0.84	0.84	0.89	-2.2	-10.4
Millakanda	0.53	0.58	0.77	0.86	-28.5	-26.1
Putupaula	0.81	0.85	0.86	0.88	13.9	6.9

4.4.3 Parameter uncertainty

Similar to the uncertainty analysis done for the Irrawaddy basin in Section 4.3.3, five global parameters were selected to analyze the parameter uncertainty (Figure 4-10). Overall, in the sub-basins corresponding to Putupaula gauging station, the best-fitted parameter values and their ranges significantly differ from those at the other two stations. The best-fit for a_{CN2} values vary between 1 and 6. For the simulations with GP, fitted values for Ellagawa (Putupaula) is lower (higher) than that of IGP. However, those values for Millakanda are almost equal. Compared to CN2, GW_QMN has higher variability in sub-basins corresponding to Ellagawa (v_{GWQMN} from 0 to 1900) and Putupaula (v_{GWQMN} from 1300 to 3000) stations. However, all sub-basins show nearly equal best-fitted values for model simulations with GP and IGP. It can also be seen that the higher the GW_QMN, the lower the low flows are, which is clearly shown in the simulated flow at Putupaula (Figure 4-9). All sub-basins resulted in nearly equal v_{ALPHA_BF} values (~ 0.5) except for sub-basins corresponding to the Putupaula station. The absolute value for available water capacity in the soil layer (a_{SOL_AWC}) does not show considerable differences for both precipitation datasets. For example, at Ellagawa, a_{SOL_AWC} is 0.19 and 0.18 in simulation with GP and IGP, respectively. The soil evaporation factor (ESCO) is always more than 0.5 for both precipitation datasets at all stations.

Figure 4-10. Uncertainty analysis of five selected model parameters for the Kalu River Basin. The initial parameter range is indicated by the blue line and fitted values in red dots for the two models with different precipitation inputs, v- denotes replacement of the existing value; a- denotes adding a fixed value to the existing value and r- denotes the relative change of the existing value. GP- Gauge precipitation, IGP- Interpolated gauge precipitation. Corresponding parameter changes in sub-basins for each of the stations: Ellagawa – 1 to 7, Millakanda – 8 to 11, and Putupaula – 12 to 15.

4.5 Comparison of results for the two basins: Irrawaddy vs Kalu

While there are some similarities between the two case study basins (i.e., tropical environment, data-poor in terms of hydro-meteorology data [i.e., precipitation, temperature, and streamflow]), their spatial scales are more than two orders of magnitude different. Both study basins are located in the tropical belt. However, the two climatic conditions in the two basins are significantly different from one another. The Irrawaddy basin has three main seasons: hot, monsoon, and cold. The Kalu basin has four main seasons; Inter monsoon 1, Southwest monsoon, Inter monsoon 2, and Northeast monsoon. The average annual precipitation within the Irrawaddy basin varies from 500 mm (in the mid-altitudes) to 4000 mm (in the high altitudes). In the Kalu basin, annual precipitation varies from 2500 mm to 4500 mm. The global precipitation products (PERSIANN-CDR and CHIRPS) showed varied performance over the two basins. In general, these products poorly represent the precipitation over the Kalu basin. The above diverse performances indicate that the spatial resolution of global precipitation products is a crucial factor requiring consideration where small-scale river basins are concerned.

In general, streamflow simulations with Interpolated gauge data show a good agreement with observed streamflow data in both the basins. It is noteworthy that, in the small Kalu River Basin, the difference in each statistical indicator between simulations with gauge data and interpolated gauge data is minimal. This is because the Kalu RB has a higher gauge network density (110 km² per station on average) compared to the Irrawaddy RB (~ 20,000 km² per station on average). However, in the Irrawaddy RB, simulated streamflow at few stations (e.g., Hkamti and Homalin) showed better performance when the simulations are forced with gauge data than interpolated gauge data.

4.6 Conclusions

This chapter investigated the agreement/ disagreement between different precipitation data sources and the reliability of the streamflow modelled with these data sources for the Irrawaddy River Basin in Myanmar and Kalu River Basin in Sri Lanka. The four precipitation data sets used in this study are in-situ gauge data without interpolation (GP) and with interpolation (IGP), PERSIANN-CDR, and CHIRPS. All streamflow simulations were undertaken with the process-based model SWAT. Conclusions are presented here in terms of the spatial and temporal distribution of the precipitation datasets and their impacts on streamflow simulation in the two basins.

The precipitation datasets are different both in magnitude and spatial/ temporal distributions over the study areas. The global datasets (PERSIANN-CDR and CHIRPS) shows lower annual and seasonal precipitation compared to the in-situ gauge data in both basins. The annual cumulative precipitation of both GP and IGP datasets are almost equal.

The rain gauge density over the larger Irrawaddy River Basin is very low (20,000 km² per station on an average) compared to the smaller Kalu River Basin (110 km² per station on an average). Despite the low density of rain gauges in the Irrawaddy River Basin, in general, streamflow simulations forced by interpolated gauge precipitation data showed a good agreement with observed streamflow data for all the stations in the basin. SWAT simulations forced with CHIRPS and PERSIANN-CDR produced streamflow that compared well with the in-situ at a majority of the stations in the Irrawaddy basin. For the Kalu River Basin, SWAT simulations forced with interpolated gauge precipitation data outperformed those with in-situ gauge data (with SWAT default setting).

Different precipitation inputs lead to different best-fitted model parameter values and ranges at different sub-basins. Overall, it was found that differences in precipitation datasets have considerable impacts on model performance, parameter estimation and uncertainty in streamflow simulations.

The in-situ gauge data used in Irrawaddy River Basin is available only for 20 years. Since the CHIRPS and PERSIANN-CDR products have longer periods of records (more than 35 years), they can be valuable assets for hydrological applications requiring long data records in data-poor basins. Another potential application of the global data is the development of a merged superior quality product that combines gauged data and one or more global data products.

5

USE OF REMOTE-SENSING BASED EVAPOTRANSPIRATION DATA FOR HYDROLOGICAL MODEL CALIBRATION²

5.1 Introduction

The conventional method of hydrological model calibration is primarily based on the comparison between simulated and observed hydrographs at a few locations or just at the outlet of the study basin (Anderton et al., 2002). Many river basins are ungauged in terms of streamflow measurements, and available streamflow gauges are not always uniformly distributed over the basin to represent existing hydrological variability. Moreover, streamflow measurements are point data, and calibrating with only point data at the basin outlet does not guarantee that other water balance components such as evapotranspiration and storage change are simulated accurately. Fenicia et al. (2007) also recognized that model calibration with one variable might lead to over-parameterization. One way to overcome

² This chapter is based on submitted paper “Hydrological model calibration with streamflow data and remote sensing based evapotranspiration data at a data poor basin”, Special Issue: Remote Sensing in Hydrology and Water Resources Management.

this problem is to calibrate using multi-variables, e.g., streamflow, evapotranspiration, snow cover, and at multi-sites, e.g., using streamflow data from various streams (or sub-basins) within the river basin (Beven, 2012; Daggupati et al., 2015; Molina-Navarro et al., 2017; Zhang et al., 2008).

In the last few decades, earth observations (radar and satellite-based data) and reanalysis products have improved the data availability for hydrological modelling. Consequently, the use of two or more variables in hydrological model calibration has received considerable attention. For example, several studies have used remote-sensing (RS) based evapotranspiration (ET) (Franco and Bonumá, 2017; Githui et al., 2012; Immerzeel and Droogers, 2008; López et al., 2017; Rientjes et al., 2013; Tobin and Bennett, 2017), soil moisture (Campo et al., 2006; Kunnath-Poovakka et al., 2016; Li et al., 2018; López et al., 2017; Rajib et al., 2016), snow cover and glacier mass balance (Finger et al., 2015, 2011), and satellite-based Land Surface Temperature (LST) (Corbari and Mancini, 2013) for hydrological model calibration.

Despite the aforementioned studies employing RS based ET data, the use of evapotranspiration in hydrological model calibration is still rare. This study, therefore, focusses on the multi-variable calibration of a hydrological model, using observed streamflow and RS based evapotranspiration data together. The main objective here is to evaluate the calibration performance of a hydrological model based on single variable calibration with streamflow and RS based evapotranspiration separately, and multi-variable calibration with streamflow and RS based evapotranspiration together.

This chapter is organized as follows. Section 5.2 describes the study area and data used, and model setup, model calibration and uncertainty analysis procedures. In the results and discussion (Section 5.3), model calibration with single and multiple-variables, and parameter sensitivity and uncertainty are discussed, which is followed by conclusions in Section 5.5.

5.2 Data and methods

5.2.1 Study area

The Chindwin basin, which is a major sub-basin of the Irrawaddy basin is used in this study. It is located in the north-western part of Myanmar and has the drainage area of 110,926 km² and river length of 1,100 km. The elevation in the basin varies from about 3,800 m above mean sea level (MSL) in northern forest mountainous region to about 100 m above MSL in the southern part (Figure 5-1 (a)). More than 80% of the Chindwin basin area is forest. Rest of the basin is primarily covered by cropland, sparsely vegetated or bare lands, and water bodies. According to the FAO soil map (FAO, 2003), Acrisols and Cambisols are the dominant soil types found in this river basin (Figure 5-1 (b)).

The Chindwin basin experiences subtropical and tropical climates (Yuan et al., 2017). Based on the available meteorological data for the period of 2001 to 2010, mean annual rainfall in the basin varies from 3900 mm (Hkamti station in the northern part) to 770 mm (Monywa station in the southern part), and annual average temperature varies from 17 °C to 40 °C (Figure 5-1(c)). The area average annual runoff is ~1200 mm at the basin outlet (Monywa Station). The basin has a complex topography and spatially varied climatic condition.

Figure 5-1. Chindwin River Basin, Myanmar (a) location and topography, and (b) land-use (top) and soil type (bottom), and (c) climate

5.2.2 Datasets used

The geo-spatial data used in this study include: (1) 90 m resolution Digital Elevation Model (DEM) from the Shuttle Radar Topography Mission (SRTM) digital topographic data (Jarvis et al., 2008), (2) 300 m resolution land-use dataset in 2009 from the European Space Agency (Arino et al., 2010), and (3) 7 km resolution soil data from the UN Food and Agriculture Organization (FAO, 2003). The precipitation data used in this study comprised spatially interpolated daily precipitation data from 2001 to 2010. Other meteorological data (for the same period) used included: temperature, relative humidity, solar radiation, and wind speed, and daily streamflow data at four stations (Hkamti, Homalin, Kalewa, and Monywa). Model calibration was carried out at the above mentioned four stations (Figure 5-1 (a)). More information on model forcing data can be found in (Sirisena et al., 2018).

The RS based ET data were obtained from the Global Land Evaporation Amsterdam Model (GLEAM) (Martens et al., 2017; Miralles et al., 2011). GLEAM version 3.0b (GLEAM_v3.0b) is driven only by satellite-based data (radiation, air temperature, precipitation, surface soil moisture, vegetation optical depth) spanning 13 years (2003–2015) at daily time scale with a spatial resolution of $0.25^\circ \times 0.25^\circ$ (Table 3-3). Actual evapotranspiration presented in GLEAM is estimated as the sum of different terrestrial evaporation components such as transpiration, bare-soil evaporation, interception loss, open-water evaporation, and snow sublimation (Miralles et al., 2011). The GLEAM ET data for the study area indicates that, the monthly average evapotranspiration over the basin varies from 46 mm (minimum) in January to 121 mm (maximum) in July (Figure 5-2 (a)). The average annual evapotranspiration over the basin is 1009 mm with a standard deviation of 24 mm. The annual evapotranspiration generally decreases from upstream to downstream ranging from 1106 mm to 790 mm (Figure 5-2 (b)). The highest evapotranspiration occurs in the Hkamti Sub-basin (Sub-basin 1) where most of the land cover is forest. The most downstream of the basin is used for residential, agricultural and mining activities.

Figure 5-2. Inter-annual variability of GLEAM ET data over the Chindwin Basin for the period of 2003 – 2010 (a) and average annual evapotranspiration of each sub-basin (b)

5.2.3 Model setup

The SWAT modelling software was used to build a hydrological model of the basin. SWAT requires topographic, land-use, soil and weather data to run hydrological simulations. The DEM data were used for stream network generation and basin delineation, which is needed to set up a SWAT model. The land-use, soil data, and slope classification derived from DEM were used for creating Hydrological Response Units (HRUs) with the delineated sub-basins.

Here the basin was subdivided into nine sub-basins (Figure 5-2 (b)), and 202 HRUs. The Hargreaves method (Neitsch et al., 2011), which requires only temperature data, was used to estimate potential evapotranspiration. Surface runoff was estimated using the Soil Conservation Services – Curve Number (SCS-CN) method, and channel routing was based on the variable storage method. SWAT simulations were performed at a daily time step for the period from 2001 to 2010, with a warm-up period of one year to allow the model to establish a stable initial state.

5.2.4 Model calibration

Model calibration was carried out for streamflow and actual evapotranspiration on a monthly time step using Sequential Uncertainty Fitting Algorithm (SUFI-2), which is a calibration and uncertainty analysis tool available within the SWAT-CUP program (Abbaspour, 2015).

Monthly time series of streamflow from four gauging stations and the GLEAM based evapotranspiration from nine sub-basins are used for calibration. Based on the availability of data, calibrations for streamflow and evapotranspiration were performed for 2002 – 2010 and 2003 – 2010 periods, respectively. Selection of model parameters for calibration was based on their sensitivity to streamflow and evapotranspiration. The initial ranges of the 22 parameters selected for calibration are presented in Annex A. Model calibration was carried out in several iterations, and each iteration consisted of 2000 simulations with parameter sets generated using the Latin Hypercube Sampling technique (Abbaspour et al., 2004). To go from one iteration to the next, SUFI-2 suggests new ranges for parameter values based on their performance in the current iteration. Occasionally, SUFI-2 suggested parameter ranges needed to be adjusted when they were beyond the acceptable parameter ranges of SWAT. The Modified Nash-Sutcliffe Efficiency (MNSE, Abbaspour et al. (2004)) was used as an objective measure of model calibration performance or objective function. When there is no significant improvement in the MNSE between two successive iterations (< 0.02), the calibration process is terminated.

The four streamflow gauging stations (used for calibration) are in series, from upstream to downstream: Hkamti, Homalin, Kalewa and Monywa (Figure 5-1 (a)). The drainage area for these stations are from sub-basin 1 for Hkamti (27,439 km²), 1 and 2 for Homalin (43,370 km²), 1 to 4 for Kalewa (73,495 km²), and 1 to 9 for Monywa (110,926 km²) (Figure 5-2 (b)). The calibration was carried out one station at a time starting from upstream to downstream. Once the calibration is done for one gauging station, the parameters of the sub-basins included in the current calibration were fixed to their best-fitted values, and the calibration for the next station downstream was done.

Two calibration schemes were used in this study: single variable calibration and multi-variable calibration. In the single variable calibration, the model was calibrated for streamflow and evapotranspiration separately. In multi-variable calibration, the calibration was carried out for streamflow and evapotranspiration together using a multi-variable

objective function. The multi-variable objective function, here referred to as overall MNSE, is defined as the weighted sum of the MNSEs concerning streamflow and evapotranspiration.

The multi-variable calibration requires a weight to be defined for each variable. Different approaches have been tried in a number of previous studies to specify weights to the multi-variable objective function. For example, Abbaspour et al. (2007) and Rostamian et al. (2008) applied weights inversely proportional to the variance of the observed data used in calibration, and Rientjes et al. (2013) and Rode et al. (2007) used the coefficient of variation, i.e., standard deviation divided by the mean, instead of the variance. However, assigning equal weights is by far the most commonly adopted approach (e.g., Franco and Bonumá (2017) and Rajib et al. (2016)), probably due to the lack of sufficient justification for other approaches. Here, different weight combinations varying from 0 to 1 (with the sum of the two weights equals to 1) with an interval of 0.05 were tested. It was found that the respective weights for streamflow and ET within 0.4 - 0.75 and 0.6 - 0.25 resulting in reasonable model performances for both streamflow and evapotranspiration. Therefore, here too equal weights were adopted for the two main variables calibrated in each station.

Although, only MNSE was used for the objective function, the performance of calibrated results in terms of other commonly used efficiency criteria such as NSE (Nash-Sutcliffe Efficiency), PBIAS (Percentage of bias), and R^2 (Coefficient of determination) was also assessed.

5.2.5 Estimation of uncertainty in model parameters

Model input data, model structure, parameters, and calibration data are the main sources of model prediction uncertainty (Pechlivanidis et al., 2011; Yang et al., 2008). In the SUFI-2 approach used in this study, all sources of model prediction uncertainties are expressed by parameter uncertainty (Abbaspour, 2015; Abbaspour et al., 2004). Various parameters such as CN2, GW_DELAY, ESCO, and EPCO. related to streamflow and evapotranspiration computations were used for model calibration (22 parameters listed in Annex A). Based on the global sensitivity analysis (Abbaspour, 2015), the five most sensitive parameters with respect to simulating streamflow and evapotranspiration separately were selected to analyze the uncertainty of parameters in each iteration.

SUFI-2 uses the Latin Hypercube Sampling technique (LHS), which generates possible sets of parameter values from the given parameter ranges. To determine the extent of uncertainty associated with each parameter, the normalized uncertainty scoring method (Kumar and Merwade, 2009; Rajib et al., 2016) was applied, in which the parameter values are normalized between 0 and 100 using Eq. 5-1.

$$P_n = \left[\frac{P_b - L_l}{U_l - L_l} \right] \times 100 \quad \text{Eq. 5-1}$$

where P_n is the normalized uncertainty score of a parameter of one simulation, P_b is the parameter value of the same simulation, and U_l and L_l are upper and lower limits of the corresponding parameter, respectively. The minimum and maximum of the normalized scores represent the uncertainty range associated with that particular parameter. The larger the range of uncertainty scores, the higher the parameter uncertainty.

5.3 Results

5.3.1 Model calibration with a single variable

Note that all the model performance analysis reported in this study are based on monthly time series data. When adopting the single variable calibration approach, in general, model performance with respect to a variable, which is calibrated against (e.g., streamflow) improves while the performance with respect to another variable (e.g., Evapotranspiration) decreases (Figure 5-3). However, here the calibration with streamflow alone resulted in a reasonable performance in both streamflow and evapotranspiration (on the monthly time series data). This is particularly true with respect to R^2 . For example, in the 5th iteration of Hkamti station, the NSE of streamflow varies between 0.74 and 0.94, whereas, the NSE of evapotranspiration varies between 0.30 and 0.55. At the same station and same iteration, PBIAS of streamflow and evapotranspiration varies between -20.0 % and -6.7%, and -5.2% and -15.6%, respectively, while R^2 varies between 0.82 and 0.95 for streamflow, and between 0.8 and 0.85 for evapotranspiration. In contrast, calibration with evapotranspiration alone shows considerably low performance for streamflow. For the same example mentioned above, in the calibration with evapotranspiration alone, the NSE of streamflow ranges between -0.51 and 0.19, and NSE of evapotranspiration varies between 0.32 and 0.72. Similarly, PBIAS of streamflow and evapotranspiration vary between -60% and -12.9%, and -15.6% and -5.2%, respectively, whereas R^2 varies between 0 and 0.31 in streamflow, and 0.8 and 0.85 in evapotranspiration.

However, when calibration is carried out at successive stations (starting at Hkamti, then Homalin, Kalewa, and ending at Monywa), the variability of performance reduces considerably for both variables (streamflow and evapotranspiration, Figure 5-3). This is not surprising because the upstream station is already calibrated for streamflow and evapotranspiration separately. In successive iterations, model simulations show approximately similar performance for both variables for calibration with evapotranspiration alone, but always with better values for evapotranspiration than for streamflow. However, in both calibration approaches, NSE is better for streamflow compared to evapotranspiration. For example, in the 5th iteration of Homalin, NSE of streamflow varies from 0.91 to 0.95, and from 0.55 to 0.7 for single variable calibration with streamflow and evapotranspiration, respectively (Figure 5-3 (a)). For the same iteration at the same station, the weighted NSE of evapotranspiration (from Sub-basin 1 and 2) varies between 0.27 and 0.41, and between 0.67 and 0.72 in the two calibration approaches

(streamflow alone and evapotranspiration alone), respectively. In contrast, streamflow shows higher bias: -15% to -11 % and -28% to 21% for calibration with streamflow and evapotranspiration, respectively, whereas the bias of evapotranspiration changes between -14% and -9%, and between -5% and 4%, respectively (Figure 5-3 (b)). However, R^2 is greater than 0.77 for streamflow, and evapotranspiration in both calibration approaches (Figure 5-3 (c)), implying that both variables preserve the temporal characteristics of observed data.

Figure 5-3. Model performance of each iteration in single variable calibration (a) NSE and (b) PBIAS, and (c) R^2 . Left and right columns respectively show the results of calibration with streamflow alone and evapotranspiration alone for each efficiency indicator. The names in the sub-plots refer to the streamflow gauging stations from upstream to downstream. Each station refers to the different sub-basins: Hkamti – 1, Homalin – 1 and 2, Kalewa – 1 to 4, and Monywa – 1 to 9. The indicators of evapotranspiration represent comparisons of area weighted average evapotranspiration of simulated and observed data. In axis labels, Q and ET denote streamflow and evapotranspiration, respectively.

When considering the best performing simulation in the last iteration for both single variable calibrations, results with streamflow alone show better performance in dry seasons (low flows) than in monsoon seasons (high flows) Figure 5-4 (a). Notably, the flows at Hkamti and Homalin are underestimated during the high flow period (June to August). This mismatch in high flows may be due to the poor spatial representation of rainfall over the sub-basins. The model calibration with evapotranspiration alone underestimates the high flows and overestimates the low flows, which is similar for all stations for the entire simulation period.

In the calibration with evapotranspiration alone, comparison of GLEAM ET and simulated ET (Figure 5-4 (b)) shows the seasonal pattern of evapotranspiration well matched in all the sub-basins. However, in terms of the magnitude or bias, the model estimated ET is lower than GLEAM ET during the dry period (December to February). In contrast, the model estimated ET is higher than GLEAM ET in sub-basins 6, 8, and 9 during the monsoon period. The calibration with streamflow alone underestimates evapotranspiration in all sub-basins during the dry period, and overestimates it during the monsoon period, particularly in sub-basins 1, 6, 8, and 9. Overall, calibration only streamflow alone appears to be capable of reproducing the observed evapotranspiration (in the case the GLEAM ET) at an acceptable level.

In successive calibration iterations, an increase in the NSE of the calibration variable is not always accompanied by a deterioration in the performance of the other variable. For example, in the calibration with streamflow alone, the NSE of evapotranspiration increased when the NSE of streamflow also increased, and subsequently decreased in next iteration(s) for all stations except Kalewa (Annex A). Similar results were obtained in calibration with evapotranspiration alone (Annex A). This may be because different parameter combinations are able to increase the performances of both variables together as well as one at a time.

Figure 5-4. Comparison of simulated and observed (a) streamflow and (b) evapotranspiration for the best simulation of the last iteration for each single variable calibration approach and multi-variable calibration approach for four stations and nine sub-basins.

5.3.2 Model calibration with multiple-variables

In the multi-variable calibration approach using streamflow and GLEAM ET, successive iterations improve the performance of evapotranspiration predictions compared to that of streamflow at all stations except the Hkamti station (Figure 5-5). For example, in the final iteration of Homalin, Kalewa, and Monywa, the NSE of streamflow varies between 0.86 and 0.92, 0.92 and 0.96, and 0.95 and 0.97, respectively. In the same simulations, the NSEs of evapotranspiration for these stations vary between 0.46 to 0.66, 0.53 to 0.63, and 0.63 to 0.67, respectively (Figure 5-5 (a)). In addition, PBIAS of evapotranspiration varies between -6 % and +7%, indicating under and over-estimations of evapotranspiration in all three stations mentioned above. However, the model always underestimated streamflow except at the Monywa station (Figure 5-5 (b)). With respect to R^2 , the model calibrations show good performance (> 0.77) for both streamflow and evapotranspiration at all the stations (Figure 5-5 (c)). This implies that simulated streamflow and evapotranspiration adequately capture

the temporal variability in the observed data. Compared to the single variable calibration, the multi-variable calibration also reduces the biases in both streamflow and evapotranspiration.

In successive iterations, the NSE of streamflow shows an increase in most of the cases, whereas that of evapotranspiration shows a decrease. However, these decreases are small, e.g., from 0.62 to 0.61 in Kalewa station, and from 0.68 to 0.64 in Monywa station (Annex A). Model performances from the best simulation of each station are presented in Table 5-1. Overall, in each performance indicator of streamflow, there is no significant difference among the four stations. Among all sub-basins, the least accurate performances of evapotranspiration are for the sub-basin 6 even for calibration only with evapotranspiration, which can be explained with uncertainty in GLEAM ET. These results imply that multi-variable calibration is able to reproduce the observed streamflow better than evapotranspiration. However, the model simulated the reasonably good estimation of ET as well.

Overall, the multi-variable calibration with streamflow and GLEAM ET showed reasonably good streamflow estimations ($NSE > 0.85$) but understandably did not result in streamflow performances any better than that obtained from the single variable calibration with streamflow only (Figure 5-4 (a), Table 5-1 and Annex A). On the other hand, this multi-variable calibration showed still sounds better for evapotranspiration as that from the single variable calibration with evapotranspiration only and better than the single variable calibration with streamflow only (Figure 5-4 (b)).

Figure 5-5. Model performance of each iteration in the multi-variable calibration (a) NSE (b) PBIAS (c) R^2 . Similar to Figure 5-3, performances of evapotranspiration are evaluated via area-weighted average evapotranspiration for each corresponding streamflow station.

Table 5-1. Model performance for monthly streamflow and evapotranspiration of the Chindwin River Basin. Results represent the overall best model simulation in the last iteration of each calibration at each station and sub-basin. A: Model calibration with streamflow only, B: Model calibration with evapotranspiration only, and Model calibration with both streamflow and evapotranspiration. The best statistical performance among the streamflow stations and the evapotranspiration at sub-basin levels indicates in bold for each calibration approach.

Variable	Station/ sub-basin	NSE			PBIAS %			R ²		
		A	B	C	A	B	C	A	B	C
Streamflow	Hkamti	0.93	0.16	0.86	-9.2	-21.8	-17.4	0.95	0.22	0.91
	Homalin	0.94	0.66	0.91	-11.2	-23.1	-17.5	0.95	0.85	0.95
	Kalewa	0.97	0.62	0.96	-3.5	-16.2	-8.5	0.97	0.83	0.97
	Monywa	0.98	0.70	0.97	1.4	-3.7	-1.7	0.98	0.80	0.97
Evapotranspiration	Sub-basin 1	0.36	0.74	0.57	-12.8	-0.4	3.9	0.84	0.82	0.73
	Sub-basin 2	-0.08	0.55	0.26	-16.9	-9.1	-13.9	0.87	0.85	0.88
	Sub-basin 3	0.36	0.59	0.39	-12.5	-4.9	-11.2	0.84	0.80	0.84
	Sub-basin 4	0.27	0.30	0.32	-13.5	3.1	-11.5	0.86	0.77	0.86
	Sub-basin 5	0.76	0.67	0.78	3.5	-6.8	2.8	0.81	0.81	0.83
	Sub-basin 6	-0.61	0.09	-0.48	23.9	9.3	21.7	0.81	0.82	0.80
	Sub-basin 7	0.72	0.80	0.79	5.3	-7.8	2.3	0.74	0.86	0.80
	Sub-basin 8	-0.98	0.47	-0.73	37.3	-2.9	34.3	0.65	0.68	0.66
	Sub-basin 9	-0.17	0.24	-0.20	28.0	-14.2	30.3	0.47	0.44	0.50

5.3.3 Parameter sensitivity and uncertainty

The most sensitive model parameters for streamflow and evapotranspiration were found to be different. Figure 5-6 shows the five most sensitive model parameters of each variable (streamflow and evapotranspiration) with the respective MNSE values. GW_DELAY, RCHRG_DP, ALPHA_BF, SLSOL, and LAT_TIME are the five most sensitive parameters for streamflow, and SOL_BD, SOL_Z, ESCO, EPCO, and SOL_AWC are the five most sensitive parameters for evapotranspiration (refer Annex A for definitions of parameters). The variability of MNSE for evapotranspiration calibration was found to be less than that for streamflow based calibration. In the multi-variable calibration, weighted average MNSE

shows less variability than both single variable streamflow and evapotranspiration calibrations.

Sensitive parameters for streamflow are mostly related to the base flow (or groundwater flow) except the SLSOL, which is related to the subsurface lateral flow. In the calibration with evapotranspiration alone, all parameters are related to soil properties except EPCO, which is the plant uptake compensation factor (Neitsch et al., 2011). The parameter values resulting in a reasonable MNSE (> 0.5) are scattered within their initial ranges (for initial ranges, please refer to Annex A). This shows that many combinations of parameter values can reproduce similar outputs.

Figure 5-6. Parameter values or absolute changes versus objective function MNSE for each iteration with 2000 simulations. Calibration with a single variable; blue dots represent calibration based on streamflow, red dots represent calibration based on evapotranspiration and black dots for multi-variable calibration. Y-axis represents MNSE value ranging from 0 to 1 and the X-axis represents the changes of parameter value or absolute change of a corresponding parameter. 'v_' denotes replacement of the existing parameter value (ex. $v_{GW_DELAY.gw}$), 'a_' denotes adding a fixed value to existing value (ex. $a_{SOL_BD.sol}$). First five parameters are corresponding to streamflow and last five to evapotranspiration.

Figure 5-7. Normalized uncertainty scores of selected parameters out of 22 parameters used. Each box plot contains 2000 simulations for the last iteration of multi-variable calibration.

For the multi-variable calibration, the range of uncertainty of each parameter was examined in terms of normalized uncertainty scores (ranges from 0 to 100) using Eq. 5-1 (Figure 5-7). The uncertainty scores presented there were calculated from the last iteration of multi-variable calibration. The analysis shows that uncertainty scores vary greatly among different parameters and different stations for the same parameter. Parameters, which are most sensitive to streamflow, show higher uncertainty than the parameters sensitive to evapotranspiration with the exception of SOL_BD. However, among the five most sensitive parameters for streamflow, SLSOIL and LAT_TIME show considerably less uncertainty at all the stations, while only ESCO, one of the most five sensitive parameters for evapotranspiration, shows considerably less uncertainty. Furthermore, the uncertainty ranges for SOL_AWC is the smallest at Homalin and Kalewa stations, whereas they are larger in Hkamti and Monywa stations.

5.4 Discussion

The results presented in this chapter is another application among a few studies that have used GLEAM ET data to support hydrological model calibration in data-scarce Chindwin River Basin in Myanmar. This study has to limit for calibration due to insufficient data for validation, which is a prevalent limitation in many data-scarce basins (Winsemius et al., 2009). In general, under the three calibration approaches used, streamflow shows the best and worst performance in calibration only with streamflow and evapotranspiration, respectively, and vice versa for the calibration performance for evapotranspiration. Both variables show slightly lower performance in multi-variable calibration than the individual calibrations with streamflow and ET. In some of the sub-basins (e.g., Sub-basins 2 to 4), simulated ET does not properly represent the GLEAM-ET during dry seasons (Figure 5-4 (b)) under all three calibration approaches. In contrast, Sub-basins 6, 8, and 9 overestimate the ET during high flow periods (June to September) for the calibrations with streamflow and multi-variable calibration. These differences may be attributed to the precipitation over the basins. Similar findings were obtained in a study on the Karkheh River Basin in Iran by Rientjes et al. (2013). They found that streamflow and ET obtain good performances when the variables are calibrated separately. However, for model calibration with both streamflow and ET, simulated ETs of most of the sub-basins show good agreement with SEBS-ET (Satellite-based surface energy balance system – actual evapotranspiration). Immerzeel and Droogers (2008) also could not find any improvement in streamflow simulation under the model calibration with satellite-based evapotranspiration from time series of MODIS images of the Upper Bhima River Basin in south India. López et al. (2017) also found that model calibration with GLEAM ET and Soil moisture data shows a reasonable streamflow estimation (with NSE values from 0.5 to 0.75), but a better model performance was obtained when it was calibrated with in-situ streamflow data.

Tobin and Bennett (2017) concluded that although there is no performance improvement in streamflow simulation, GLEAM ET data can be used to constrain the evapotranspiration parameters in the SWAT model. They considered 16 major SWAT parameters, in which five are attributed to evapotranspiration (ESCO, EPCO, CANMX, GW_REVAP, and REVAPMN, refer to Annex A for details). ESCO and CANMX are identified as the most sensitive parameters for model calibration. Immerzeel and Droogers (2008) found that actual ET is more sensitive to the groundwater (GW_REVAP) and meteorological (monthly rainfall increment - RFINC) parameters than soil (SOL_AWC) and land-use parameters (Maximum plant leaf area index- BLAI). In our analysis, SOL_BD, SOL_Z, ESCO, EPCO, and SOL_AWC are to be the most sensitive parameters for evapotranspiration. Furthermore, Winsemius et al. (2009) suggested that satellite-based ET and soil moisture information would be required to reduce the parameter uncertainty and constrain the model parameters within physically realistic ranges in hydrological model calibration.

Even though we discussed only the parameter uncertainty, there are other sources of uncertainty in hydrological modelling, such as input data, model structure, and observed

data (Pechlivanidis et al., 2011; Yang et al., 2008). Precipitation, the primary input data used in this analysis was derived from interpolated gauge data of six stations, which are not well distributed over the basin. Therefore, we believe that precipitation data contributes to prediction uncertainty. In terms of observed streamflow data, Harmel et al. (2009) stated that the typical uncertainty in measured streamflow as $\pm 7 - 23\%$. Di Baldassarre and Montanari (2009) stated that the average error of the measured streamflow data was found to be 25.6 % for the Po River, Italy. With respect to ET, the accuracy of remote sensing-based products may vary significantly over the different regions due to climatic variability, topography, and land cover (Campo et al., 2006). For example, Trambauer et al. (2014) have compared eight different ET products over the African continent and summarized that some products show good consistency among them in some areas and diverge in other areas of the continent. Another analysis by Tobin and Bennett (2017) showed that simulated ET matches with GLEAM-TMPA better than GLEAM-CMORPH. Therefore, these RS based ET products may possess considerable biases. Thus, further information is required to analyze and discuss the uncertainty in model outputs.

5.5 Conclusions

This chapter evaluated the use of measured streamflow and Remote Sensing (RS) based evapotranspiration (ET) data to calibrate a hydrological model of the Chindwin Basin, Myanmar, which is one of the main tributaries of the Irrawaddy River. The hydrological model used was SWAT and two calibration approaches were tested: single variable and multiple variable calibration. RS based ET data were obtained from the Global Land Evaporation: Amsterdam Model (GLEAM ET), and 9 years of measured streamflow were obtained at four gauging stations in the basin.

Results indicate that GLEAM ET data, together with streamflow data, offers good potential for hydrological model calibration in the study region as the simulation results show a good performance for streamflow (with an NSE > 0.85 on monthly time series), while maintaining a reasonable performance for evapotranspiration (with an NSE > 0.61). Moreover, the results of single variable calibration with GLEAM ET indicate that even in the absence of streamflow data (i.e., in an ungauged basin), the model would have produced streamflow NSE values of greater than 0.69 for three out of four stations with PBIAS varying between -2.6 % and -23 %. The exception was the Hkamti station with NSE of 0.16 and PBIAS of -22%. It is noted that the Hkamti station is the uppermost station of the four and so its calibration is independent of the other three stations. Whereas the other three (Homalin, Kalewa, and Monywa) are all downstream of Hkamti and in series. Hence, their calibration results are influenced by the calibration results of upstream station(s).

The analysis of calibration parameters suggests that parameter sensitivity and values change among different calibration set-ups, and that the uncertainty ranges of parameters differ

among different parameters and different stations. Results also showed that different sets of parameter values could produce similar results.

There is room for further research on the multi-variable calibration of process-based hydrological models using both globally available observations such as evapotranspiration, snow cover, and soil moisture data and traditionally used streamflow data. Such a calibration approach could lead to better representation of hydrological responses, particularly, ungauged basins, as this approach would enable reasonable parameter estimations across such basins.

6

SIMULATING STREAMFLOW AND SEDIMENT FLUXES TO THE COAST IN THE IRRAWADDY RIVER BASIN

6.1 Introduction

Climate change is now an unequivocally accepted phenomenon (IPCC, 2014) and future climate is uncertain. Impacts of climate change are not uniform in time and space, and hence the hydrologic responses at basin scales vary. On the other hand, the continued increase of human activities in river basins (e.g., dams, sand mining, deforestation, agriculture, and urbanization) also affect hydrological responses in a river basin. This chapter investigates the impacts that climate changes and human activities might have on the 21st century streamflow and fluvial sediment loads in the Irrawaddy River Basin (Irrawaddy RB). The analysis is carried out for a base period (1991-2005) and two future periods: mid-century (2046 - 2065) and end-century (2081 – 2100) under different RCPs.

This chapter is structured as follows: Section 6.2 describes the methods used, which includes GCM selection, bias correction of climate data, SWAT model setup and scenarios for future

streamflow and sediment estimation. Sections 6.3 and 6.4 presents results for the base and future periods, respectively. Section 6.5 presents the conclusions of the investigation.

6.2 Methods

6.2.1 Selection of suitable GCM(s) and climate change scenarios

The future climatic data (precipitation, and minimum and maximum temperature) were obtained from 10 GCMs (details are in Table 3-4). The climatic projections obtained via different GCMs are likely to vary among models. These variabilities are mainly driven by the differences in inputs, structure, boundary conditions, pathways, initial conditions associated with the respective models (Jalota et al., 2018). The average annual precipitation over the Irrawaddy RB during the base period (1991-2005) varies significantly among the GCMs considered (Figure 6-1). Particularly, CCSM4, GFDL-CM3, IPSL-CM5A-MR, MRI-CGCM3, and Nor-ESM1-M show less than 1500 mm of annual precipitation over the basin. Furthermore, observations show that the most northern and middle parts of the basin receive more than 3500 mm and less than 1500 mm annual precipitation, respectively (Figure 4-3). Therefore, these GCMs underestimate the precipitation in the northern parts of the Irrawaddy RB. Average annual maximum and minimum temperatures do not show significant difference among GCMs (Annex B). All GCMs underestimate the minimum and maximum daily temperature in the entire basin. For example, in the northern parts of the basin, the observed maximum and minimum daily temperature ranges are 26-30 °C and 15-19 °C, respectively. However, the same temperature values obtained from the selected GCMs vary between 15-24 °C and 5-13 °C, respectively.

Figure 6-1. Gridded average annual precipitation from 1991 to 2005. (a) CCSM4, (b) CSIRO-Mk3.6, (c) GFDL-CM3, (d) HadGEM2-AO, (e) HadGEM2-ES, (f) IPSL-CM5A-MR, (g) MIROC5, (h) MRI-CGCM3, (i) NorESM, and (j) BCC-CSM1.1. Data were obtained from <http://pcmdi9.llnl.gov/>. The GCMs have different spatial resolutions (Table 3-4).

The most representative climate models were selected by following the approach shown in Figure 6-2, which uses GCM outputs and observations for the base period (1991-2005). First, the climatic variables from each model were compared with the observed data at different time scales (daily, monthly and annual) in each sub-basin. Here, spatially interpolated gauge precipitation (IGP) data (Section 4.2.1) were used as the observed data. Secondly, data from the selected GCMs (i.e., precipitation and temperature) were used to force the previously calibrated SWAT setup (refer Section 4.2 and Sirisena et al. (2018)), and the model performance in terms of simulating streamflow was evaluated at eight gauging stations.

Figure 6-2. Procedure adopted in this study for GCM selection for streamflow simulation in the Irrawaddy River Basin

With regard to the future climate scenarios, two RCPs (Representative Concentration Pathways): RCP 2.6 and RCP 8.5 were selected. RCP 2.6 represents a GHG (Green House Gas) mitigation scenario targeting a low radiative forcing level ($\sim 3\text{W/m}^2$) before 2100, and start declining by 2100. RCP 8.5 represents the pathway with the highest radiative forcing ($> 8.5\text{ W/m}^2$) by 2100 and keeps increasing thereafter (Moss et al., 2010). Thus, this study investigates the impacts of both low and high radiative forcing scenarios on the hydrological response at the basin scale. The analysis was carried out for two future periods: mid-century (2046-2065) and end-century (2081-2100).

6.2.2 Bias correction of climate data

The selected GCM data (precipitation and temperature) were bias-corrected using the mean-based method (Lenderink et al., 2007; Schmidli et al., 2006; L. Wang et al., 2016) applied on a monthly basis. The methods adopted for precipitation and temperature are shown in Eq. 6-1 and Eq. 6-2, respectively.

$$X'_M(i) = X_M(i) \times \frac{\mu_O}{\mu_M} \quad \text{Eq. 6-1}$$

$$X'_M(i) = X_M(i) + \mu_O - \mu_M \quad \text{Eq. 6-2}$$

where, i is a day in the month, μ_O and μ_M are monthly means of observed and model (GCM) data for the base period, respectively. X_M is the raw daily model data and X'_M is the bias-corrected daily data.

For the future periods (2046-2065 (mid-century) and 2081-2100 (end-century)), $\frac{\mu_O}{\mu_M}$ for precipitation and $\mu_O - \mu_M$ for temperature are taken from the base period (1991-2005) at monthly basis and applied the above equations (Eq. 6-1 and Eq. 6-2) to correct the biases in GCM data.

6.2.3 Model setup and scenarios

Suspended sediment modelling

The amount of sediment yield from a given basin area is related to the complex interaction among topography, climate, soil, land-use, drainage networks and sediment characteristics. SWAT estimates the soil erosion, caused by rainfall and runoff within each basic computational unit (called Hydrological Response Units; HRUs), using the Modified Universal Soil Loss Equation (MUSLE, Eq. 6-3) (Neitsch et al., 2011).

$$sed = 11.8 \cdot (Q_{surf} \cdot q_{peak} \cdot area_{hru})^{0.56} K_{USLE} \cdot C_{USLE} \cdot P_{USLE} \cdot LS_{USLE} \cdot CFRG \quad Eq. 6-3$$

where, sed is the sediment yield (tons), Q_{surf} is the surface runoff (mm), q_{peak} is the peak runoff (m^3/s), $area_{hru}$ is the area of Hydrological Response Unit (HRU, ha), K_{USLE} , C_{USLE} , P_{USLE} , and LS_{USLE} are USLE soil erodibility factor, cover and management factor, support practice factor, and topographic factor, respectively, and $CFRG$ is the coarse fragment factor.

The sediment transport model used in SWAT consists of two processes (deposition and degradation) that determine the magnitude of sediment generated within a river reach. The amount of sediment deposition or degradation depends on several factors such as the maximum sediment concentration transported with river flow (Eq. 6-4, according to Bagnold's Equation (Neitsch et al., 2011)), flow velocity, flow rate, soil cover and erodibility of the reach.

$$conc_{sed,ch,mx} = c_{sp} \cdot v_{ch,pk}^{spexp} \quad Eq. 6-4$$

where, $conc_{sed,ch,mx}$ is the maximum sediment concentration transported by water (ton/m^3), c_{sp} is the sediment transport coefficient, $v_{ch,pk}$ is the peak velocity in the river (m/s), and $spexp$ is the exponent to the velocity.

When the maximum sediment concentration that can be carried by the water flow is less than the sediment concentration of the reach, sediment deposition (Eq. 6-5) occurs and vice versa for sediment degradation (Eq. 6-6).

$$sed_{dep} = (conc_{sed,ch,i} - conc_{sed,ch,mx}) \cdot V_{ch} \quad Eq. 6-5$$

$$sed_{deg} = (conc_{sed,ch,mx} - conc_{sed,ch,i}) \cdot V_{ch} \cdot K_{CH} \cdot C_{CH} \quad Eq. 6-6$$

where, sed_{dep} and sed_{deg} are the deposited and reentrained sediment amount in the reach, respectively (tons), $conc_{sed,ch,i}$ is the sediment concentration of the reach at the initial time (ton/m³), $conc_{sed,ch,mx}$ is the maximum sediment concentration, which can be carried by water (ton/m³), V_{ch} is the water volume in the reach (m³), K_{ch} is the erodibility factor of the channel, and C_{CH} is the cover factor of the channel.

The amount of sediment (in tons) flowing out from a river reach (Eq. 6-7) is calculated based on the sediment amount (in tons – based on the initial amount of suspended sediment in the reach, deposited and degraded sediments), and volume of outflows.

$$sed_{out} = sed_{ch} \cdot \frac{V_{out}}{V_{ch}} \quad Eq. 6-7$$

where, sed_{out} is the amount of sediment outflow from the reach (tons), sed_{ch} is the suspended sediment load in the reach (tons), and V_{out} is the outflow volume (m³).

The SWAT model that performed best in streamflow simulation during calibration and validation periods (discussed in Section 4.3) was used to compute the sediment load at different locations in the basin. Erosion and sediment transportation are mainly governed by temperature, precipitation, and streamflow. In SWAT, some calibration parameters directly affect both streamflow and sediment process. Hence, only the sediment related calibration parameters were selected (Table 6-1) to calibrate the sediment load generated from the basin. Monthly sediment data from three stations (Kalewa, Sagaing and Pyay) were obtained from previous studies (Furuichi et al., 2009; IFC, 2017; Imbulana, 2018). Those data were derived from streamflow-sediment load rating curves. The model parameters for monthly sediment loads were calibrated manually for the 1991-2010 period. However, continuous datasets were not available for all the three stations. Kalewa data is only available for 1991-1997 and 2002-2010 periods, while the Sagaing and Pyay are available for 1991 – 2007, and 1991-1996 periods, respectively.

Table 6-1. Parameters used for sediment load calibration

Parameter	Description	Scale	Default	Initial Range
v_CH_EROD.rte	Channel erodibility factor	Reach	0	0 – 1
v_CH_COV2.rte	Channel cover factor	Reach	0	0 – 1
v_SPCON.rte	Liner parameter for calculating the maximum amount of sediment that can be re-entrained during channel sediment routing	Reach	0.0001	0.0001 – 0.002
v_USLE_P.mgt	USLE support practice factor	HRU	HRU	0 - 1
v_USLE_C.plant.dat	USLE cover factor	plant	plant	0.001 – 0.3

With reservoirs

Apart from the climate-driven changes, human-induced activities influence the changes in the hydrological regime of the river basin. Such activities include dam construction, infrastructure development, changes in land-use due to crops and deforestation, and sand mining. In this study, reservoir construction is considered as the main human activity affecting sediment supply to the coast (Syvitski et al., 2005; Vörösmarty et al., 2003; Yang et al., 2015, 2014).

By 2010, there were 20 reservoirs planned to be constructed in the Irrawaddy RB mainly for hydropower generation (Figure 3 in Kattelus et al. (2015)). The estimated power production of these planned reservoirs varies between 24 MW and 4,100 MW. For this study, six of the planned reservoirs (capacity > 500 MW) were incorporated into the model to assess the future changes in streamflow and sediment loads due to reservoirs (Figure 6-3).

Figure 6-3. Approximate locations of the planned reservoirs (Capacity > 500 MW) in the Irrawaddy River Basin considered in this study.

The SWAT model includes a reservoir module to assess the effects of reservoir operation on runoff and sediment load. The model computes the water balance in a reservoir as:

$$V = V_{stored} + V_{flowin} - V_{flowout} + V_{pcp} - V_{evap} - V_{seep} \quad \text{Eq. 6-8}$$

where, V is the volume of water in the reservoir at the end of the time step (m^3), V_{stored} is the stored water volume at the beginning of the time step (m^3), V_{flowin} is the volume of water entering during the time step (m^3), $V_{flowout}$ is the volume of water released from the reservoir during the time step (m^3), V_{pcp} is the volume of precipitation falling on the reservoir (m^3), V_{evapo} is the volume of evaporated water from the reservoir during the time step (m^3), and V_{seep} is the volume of water loss by seepage during the time step (m^3).

The volume of precipitation falling in the reservoir and volume of water lost via evaporation are calculated based on the relevant sub-basin precipitation and evapotranspiration,

respectively, while also taking into account the surface area of the reservoir. Seepage loss is calculated based on the hydraulic conductivity and surface area of the reservoir (Neitsch et al., 2011). The hydraulic conductivity of the soil under reservoir was given based on the hydraulic conductivity of dominant soil type in the respective sub-basin.

The detailed information regarding the planned reservoirs (e.g., storage capacity, volume and surface area related to the spillway) is not known or not available for this study. There are four main parameters required by SWAT to simulate reservoir operations: (1) RES_ESA (reservoir surface area when the reservoir is filled to the emergency spillway), (2) RES_EVOL (volume of water needed to fill the reservoir to the emergency spillway), (3) RES_PSA (reservoir surface area when the reservoir is filled to the principal spillway), and (4) RES_PVOL (volume of water needed to fill the reservoir to the principal spillway). The storage capacity of the reservoir was determined using monthly streamflow data of 20 years (1991-2010), assuming the condition that over the long-term total inflow to the reservoir minus losses equals total outflow. The Sequent Peak Algorithm (SPA, Thomas and Fiering, 1963 cited in Lele, 1987) was used to determine the capacity. The cumulative sum of the difference between inflow and water demand (withdrawals) are calculated to develop the mass curve of this net outflow (inflow – withdrawals). The withdrawal is taken as the 80% of average inflow in each month. The mass curve comprises peaks (local maxima) and trough (local minima). For any given peak (P_i), the next following peak, that is higher than (P_i), is identified as a sequent peak. The required reservoir capacity is then obtained by taking the maximum of the difference between the sequent peak and the lowest trough during the entire analysis period.

Since these reservoirs are mainly planned for hydropower generation, it was assumed that 80% of the average streamflow is released from the reservoir in a given month. The required maximum storage capacities were derived from the model as described above and the corresponding surface areas were calculated based on elevation-area-capacity curve developed from the SRTM DEM having 90 m x 90 m spatial resolution (Figure 3-1). It was assumed that RES_PVOL is 90% of RES_EVOL, and corresponding RES_PSA was calculated from the area-capacity curves. The reservoir details, thus, derived are summarized in Table 6-2.

There are four approaches available in SWAT to calculate the volume of outflow from reservoirs: observed daily outflow, observed monthly outflow, average annual release rate for uncontrolled reservoirs, and controlled outflow with target release (Neitsch et al., 2011). Here the outflow was estimated by the average annual release rate for uncontrolled reservoirs as there is a lack of data for these planned reservoirs (Brauer et al., 2015; Vigiak et al., 2016). This method requires a daily maximum spillway release rate when the water volume is between emergency spill volume and maximum spill volume. In reservoir operation, reservoir release can be given as the minimum or maximum or both minimum and maximum release on a monthly basis (Neitsch et al., 2011). This study considered only the minimum water release condition by assigning a constant value for all months in a year.

The average annual release rate and minimum release were estimated by assuming a 10% failure of outflow from the reservoir (outflow over spillway < specified minimum release) for the entire future simulation period (2046-2100). This method of reservoir outflow estimation (average annual release rate for uncontrolled reservoirs) has been successfully applied by Vigiak et al. (2015) for streamflow and sediment simulation in the Danube River Basin, which drains to the Black Sea. Furthermore, Brauer et al. (2015) also used this method to simulate the streamflow in the Canadian Basin, USA. However, Jalowska and Yuan (2018) recommended this method to use for sediment modelling, only if data is not available for controlled outflow with target release method.

The median diameter of particle size (RES_D50) was set as 10.5 μm (medium size silt), which is the average suspended particle size found by Robinson et al., (2007) for the Irrawaddy RB. Initial and equilibrium sediment concentrations (RES_SED and RES_NSED, respectively) of the reservoir play a vital role in sedimentation as particle settling is a function of the concentration and time. Therefore, different trapping efficiencies of a reservoir were assumed to define these values (here, RES_SED and RES_NSED are equal). Trapping efficiency (TE) is the percentage of incoming sediment, which remains in the reservoir. Based on previous studies (Eizel-Din et al., 2010; Kummu and Varis, 2007; Lewis et al., 2013; Maneux et al., 2001; Shrestha et al., 2016; Yang et al., 2014), two TE scenarios (50%, and 95%) were assumed here to derive the equilibrium sediment concentration. In both TE cases, the same TE was initially assumed for all six reservoirs. Then, TE was calculated for every year from the simulated sediment inflow and outflow from the reservoir, and subsequently, an average TE was calculated for the simulation period (2046 to 2100). When this average TE of each reservoir is equal to assumed TE (50% or 95%), simulation results were analyzed to investigate the effects of reservoir construction on sediment load and streamflow at the basin outlet.

Table 6-2. Basic characteristics of the planned reservoirs considered in this study. ES – Emergency Spillway

No.	Reservoir name	Basin area (km^2)	Volume at ES ($\times 10^6 \text{ m}^3$)	Surface area at ES (km^2)
1	Thamanthi	43,370	17,711	880
2	Shweli	13,090	2,186	221
3	Yeywa	28,910	2,600	67
4	Mawlaik	73,490	11,168	1,012
5	Myitsone	48,170	13,282	353
6	Shwe Sar Yay	105,700	8,597	505

Scenarios for future streamflow and sediment load estimation

Future streamflow and sediment load were projected under two scenarios: (a) Climate change (CC) only, and (b) Climate change and human activities (CC + HA). These projections were derived using bias-corrected future climate data (for 2045-2065 and 2080-2100) to force the calibrated SWAT model (see Section 4.3).

Three different model simulations were carried: (1) GCM data-driven simulations for the base period (1991-2005) with climate change only, (2) GCM data-driven simulations for future periods with climate change only, and (3) GCM data-driven simulations for future periods with climate change and planned six reservoirs.

6.3 Results and discussion: Base period (1991-2005)

6.3.1 Representative GCM(s)

Performance of climate data

Different GCMs show different distributions of daily precipitation over sub-basins for the base period (1991-2005) (Figure 6-4). For example, in Sub-basin 1, the occurrence of dry days (0 mm/day) was 36% in the in-situ observations, whereas with the GCM data the number of dry days varies between 28% and 52%. Both HadGEM2-AO and HadGEM2-ES show nearly 35% of dry day occurrence in the basin. In sub-basin 21, these GCMs show 47% and 48% occurrence of dry events, which are slightly higher compared to that shown in the observed data (39%). The most significant differences between observed and GCM precipitation is found for precipitation amounts less than 5 mm/day, and the least difference is observed for high precipitation events (> 50 mm/day). For the dry events (0 mm/day), HadGEM2-AO and HadGEM2-ES show good agreement with observed data in each sub-basin. For high precipitation events (> 50mm/day), all GCMs except BCC-CSM1.1 show a similar probability of occurrence as observed data. The lowest differences between GCM and observed data for 1-50 mm/day precipitation show in CSIRO Mk3.6, GFDL CM3, HadGEM2-AO, and HadGEM2-ES data (Figure 6-4).

Figure 6-4. Distribution of daily precipitation of ten CMIP5 GCMs compared with observed data at selected sub-basins over the base period (1991-2005). Red line indicates observed data. Model/data comparisons are shown for the most upstream (Sub-basins 1 and 2), middle (Sub-basins 21 and 22), and most downstream (Sub-basins 31 and 32) parts of the Irrawaddy River Basin.

In terms of monthly precipitation, five GCMs (CCSM4, CSIRO Mk3.6, GFDL-CM3, HadGEM2-AO, and HadGEM2-ES) show reasonably good agreement with observed precipitation data over the base period with R^2 values greater than 0.5 in more than 24 sub-basins. The highest underestimation of precipitation is observed in IPSL-CM5A-MR

(< - 37% of bias in all 32 sub-basins), followed by GFDL-CM3 (varying -9% to 71% of bias over the sub-basins). In contrast, BCC-CSM1.1 overestimates the precipitation in 15 out of 32 sub-basins with more than 20% of PBIAS. MIROC5 shows more than 20% of PBIAS in 10 sub-basins. High biases of GCMs are observed during the monsoon period (May to September). In terms of NSE, only three GCMs (CSIRO-Mk3.6, GFDL-CM3, and HadGEM2-ES) show more than 0.5 of NSE approximately in half of the entire basin. Aung et al. (2016) also found overestimation of high rainfall events by CCSM4 and BCC-CSM1.1 models in the Bago River Basin, Myanmar.

The monthly averaged minimum temperature (Tmin) values from all GCMs are in good agreement with the observed data ($R^2 > 0.74$) at 14 stations (Figure 4-1). Monthly averaged maximum temperatures (Tmax) of CSIRO Mk3.6, GFDL-CM3, HadGEM2-AO, HadGEM2-ES, and MIROC5 also show good agreement with data ($R^2 > 0.5$) in most of the stations (12 out of 14 stations). In terms of PBIAS, only HadGEM2-AO and MRI-CGCM3 show low bias ($-20\% < \text{PBIAS} < 20\%$) in most of the stations for Tmin and Tmax. However, all GCMs except IPSL-CM5A-MR show very low NSE (< 0) for Tmax in all the stations. The IPSL-CM5A-MR model shows more than 0.2 of NSE in three stations (Meiktila, Minbu, and Monywa, Figure 4-1). In contrast, all the GCMs except GFDL-CM3 show acceptable NSE for most of the stations for Tmin.

In summary, GCM data show varied performance in terms of precipitation, and temperature (daily minimum and maximum) over the base period (1991-2005). Daily precipitation occurrences and performance statistics indicate that CSIRO-Mk3.6, GFDL-CM3, HadGEM2-AO, and HadGEM2-ES perform well in the Irrawaddy RB, both in terms of monthly precipitation and monthly average of daily minimum and maximum temperature.

Performance of GCM forced streamflow simulations

Monthly streamflow from SWAT model simulations forced with data from the different GCMs were evaluated against observations during the base period at eight gauging stations. Figure 6-5(a) shows that best results are obtained with CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES at all eight stations with $\text{NSE} > 0.32$. The model forced with IPSL-CM5A-MR shows the poorest performance with $\text{NSE} < -0.06$ at all the stations. Models forced with BCC-CSM1.1 and MIROC5 show better performances at six upstream stations (Hkamti, Homalin, Kalewa, Monywa, Katha, and Sagaing) than most downstream stations (Nyaung U and Pyay). The model forced with HadGEM2-AO data reproduce the streamflow with lower PBIAS ($-21\% < \text{PBIAS} < 3\%$) at all stations, followed by HadGEM2-ES with varying PBIAS between -14.7% and -38.2% (Figure 6-5 (b)). Most of the GCMs lead to an underestimated modelled streamflow at all stations with some exceptions. For example, MIROC5 overestimates the flow at Sagaing, Katha, Nyaung U, and Pyay, and BCC-CSM1.1 overestimates the flow at Nyaung U and Pyay. MIROC5 and BCC-CSM1.1 also show the highest overestimation of monthly precipitation over the Irrawaddy RB, which can be directly attributed to the over-estimation of streamflow at different stations. Except for the

model simulations with CCSM4, IPSL-CM5A-MR, and MRI-CGCM3, all other GCM data forced simulations showed $R^2 > 0.4$ at all eight stations.

The uncertainties in simulated streamflow stem from different sources, primarily the GCM projections and the model parameters. Among the 10 GCMs considered, CSIRO-Mk3.6, HadGEM2-AO, and HadGEM2-ES outperform the other GCMs in simulating streamflow at eight stations.

According to the above comparisons of climate variables (i.e., precipitation and maximum and minimum temperatures) and GCM data-driven streamflow estimations over 1991-2005, three GCMs (viz. CSIRO-Mk3.6, HadGEM2-AO, and HadGEM2-ES) were selected for further model applications (i.e., for simulating streamflow and sediment loads) in Chapter 6 and 8.

Figure 6-5. NSE (a) and PBIAS (b) of simulated streamflow forced with GCM data

6.3.2 Bias corrected climatic variables

There are considerable biases in GCM climatic data (Section 6.3.1). For example, CSIRO Mk3.6 data underestimates the monthly precipitation in the upstream part of the basin, while overestimating it in the downstream part of the basin. In contrast, HadGEM2-AO data underestimates the precipitation in downstream and overestimates it in the upstream part of the basin (except Sub-basins 2 and 3). HadGEM2-ES data underestimates the precipitation in all sub-basins (Figure 6-6 and detailed information in Annex B). All three GCMs underestimate the minimum and maximum temperatures across the Irrawaddy RB for the entire period considered (1991-2005) (Figure 6-7 and Annex B).

After performing bias correction (Section 6.2.2), monthly observed precipitation and bias-corrected GCM precipitation show reasonable agreement with some exceptions. (Figure 6-6 and Annex B). The NSE and R^2 in most of the sub-basins are greater than 0.5. The mean monthly bias over the entire period is zero for all the sub-basins, which is by virtue of the mean-based bias-correction applied here. Similar to the precipitation data, both minimum and maximum temperatures show reasonably good performance compared with observed monthly mean temperatures after bias correction (Figure 6-7 and Annex B). NSEs of bias-corrected minimum and maximum temperatures are greater than 0.87 and 0.25, respectively in all the stations. It is also noted that bias correction preserved the temporal characteristics of both minimum and maximum temperatures of all the stations ($R^2 > 0.87$ and 0.37, respectively).

Figure 6-6. Monthly precipitation of observed and GCMs (without and with bias correction) for the selected sub-basins during 1991-2005. In the legend, Raw denotes without bias correction and BC denotes with bias correction. The NSE values of GCM precipitation (CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES) are shown in three subsequent columns for without (Raw) and with (BC) bias correction data. Statistical performances of all sub-basins are tabulated in Annex B. The three selected sub-basins represent the up-, mid-, and downstream of the Irrawaddy River Basin, respectively.

Figure 6-7. Monthly mean minimum temperature (T_{min} in shaded three plots) and maximum temperature (T_{max} in the bottom three plots) of observed and GCM data for the selected stations during 1991-2005. In the legend, Raw denotes without bias correction and BC denotes with bias correction. The NSE values of GCM temperatures (CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES) are shown in three subsequent columns for without (Raw) and with (BC) bias correction data. Statistical performances of all stations are tabulated in Annex B. The three selected stations represent the upstream (Putao), middle-stream (Mandalay), and downstream (Pyay) of the Irrawaddy River Basin, respectively.

6.3.3 Evaluation of simulated sediment load forced with observed climate data (1991-2010)

These model simulations were undertaken with the best-performing SWAT model in terms of streamflow (discussed in Section 4.3) for 1991-2010, which is same as the streamflow calibration and validation period (discussed in Section 4.3). In terms of sediment load, model calibrations at Kalewa and Pyay show good model performance with NSE of 0.92 and 0.84, and PBIAS of 5% and -15%, respectively. At Sagaing station, these indicators are 0.71 and -17%, respectively. Figure 6-8 shows that the model underestimates the sediment load during the high flow period, while it overestimates the sediment load during the low flow period at Sagaing station. At Kalewa station, the model underestimates few of the peaks during the high flow period (July to September). These mismatches can be attributed to the uncertainties in precipitation data, streamflow simulation, parameterization, and also the observed data used in calibration. In general, simulated results at all three stations preserve the temporal variability of observed data with $R^2 > 0.75$.

Figure 6-8. Observed and simulated monthly sediment load at three stations: Kalewa (top), Sagaing (middle), and Pyay (bottom) for the calibration period (1991 – 2010).

Figure 6-9 shows the spatial variability in the simulated average annual sediment yield from each of the sub-basins, together with the coefficient of variation, for the period of 1991 to 2010. Computed average annual erosion rates vary between 2 t/ha/yr and 51 t/ha/yr. The most northern and north-western parts of the basin show high rates of erosion with an average of 35 t/ha/yr. These areas are high steep-sloped mountainous regions and receive the highest precipitation each year. Most downstream sub-basins (sub-basins 31 and 32) also have high sediment erosion (> 37 t/ha/yr). Most of these low-lands are utilized for agriculture and receive more than 2500 mm of annual precipitation (Figure 4-3). The middle part of the basin (dry zone) shows the lowest soil loss as this area has very mild slopes and receives low precipitation during the monsoon period. Sub-basin 16 shows the highest coefficient of variation (107%). It is also the sub-basin with the highest rate of sediment erosion (> 50 t/ha/yr) during 1996-2010. This high erosion is related to the high amount of precipitation (> 3300 mm/yr) received by this sub-basin during the calibration period.

Figure 6-9. The model simulated (a) average annual sediment yield and (b) coefficient of variation of sediment yield at sub-basin level for the period of 1991-2010 in Irrawaddy River Basin.

The simulated basin average sediment yield is found to be 22 t/ha/yr, which is higher than the global mean of 15 t/ha/yr (Adwubi et al., 2009). However, the variation of global sediment yield presented by Walling and Webb (1996) shows that the sediment yield in the

Irrawaddy RB could vary between 2 t/ha/yr to 51 t/ha/yr. Furthermore, Garzanti et al. (2016), who investigated the sources of heavy minerals, and bedload sand in the basin to estimate the sediment contribution of different tributaries of the Irrawaddy RB, estimated a basin average sediment yield and erosion rate of ~ 10 t/ha/yr and ~ 0.3 mm/yr, respectively. Sediment loads and erosion rates have also been computed for other large basins in previous studies. Galy and France-Lanord (2001) calculated the erosion rates (based on Al-Si mass balance) in Brahmaputra ($583,000 \text{ km}^2$) and Ganges ($1,060,000 \text{ km}^2$) River Basins to be 2.9 mm/yr, and 2.1 mm/yr, respectively. Maharjan et al. (2014) showed that the sediment yield in the Nam Ou Basin ($26,180 \text{ km}^2$) in Mekong River Basin, was less than 20 t/ha/yr for their base period of 1980 to 2000. The soil erosion rate in the Loess Plateau, China was shown to range between 0 and 80 t/ha/yr (at sub-basin levels) during 1980 to 1990 (Zhang et al., 2017). Betrie et al. (2011) found that most areas of the Blue Nile Basin have soil erosion rates ranging between 1 to 20 t/ha/yr, while the erosion rate in cultivated lands therein exceeds 150 t/ha/yr. It must be noted that basin-scale soil erosion depends on several factors such as precipitation, climate, geology, topography, land cover, surface runoff, slope, characteristic of grain size, chemical composition, mineralogy, and hydraulic characteristics of channels (Morgan, 2005). Therefore, sediment yield at the sub-basin level can vary significantly, and a definite reason(s) cannot be identified for the high computed sediment erosion in the Irrawaddy RB. Furthermore, not all of this sediment eroded from the basin is transported to the basin outlet due to deposition in the waterways and other trapping mechanisms.

The SWAT simulations for the period 1991-2010 shows a sediment load of $269 \pm 49 \times 10^6$ t/yr at the Pyay station, with an average of $265 \pm 41 \times 10^6$ t/yr at Pyay from 1991 to 1996. In previous studies focusing on the sediment load in this basin, Robinson et al. (2007) calculated a sediment load of $364 \pm 60 \times 10^6$ t/yr by revisiting the 19th-century sediment load estimation (261×10^6 t/yr) presented by Gordon (1885). Furuichi et al., (2009) computed a mean annual sediment load of $325 \pm 57 \times 10^6$ t/yr at Pyay from 1966 to 1996 based on 31 years of streamflow measurements and a streamflow-sediment rating curve derived from suspended sediment concentrations at Pyay. At the Magway station, located 168 km upstream of Pyay, the average sediment load determined by the Directorate of Water Resources and Improvement of River Systems (DWIR), Myanmar is 125×10^6 t/yr for the period of 1990 to 2010 (IFC, 2017). For the same period, sediment load at Chauk, located further 93 km upstream of Magway is 154×10^6 t/yr (IFC, 2017). Syvitski and Milliman (2007) have calculated 30- year average suspended sediment load in the Irrawaddy River Basin as 258.6×10^6 t/yr. However, sediment load received by Irrawaddy river delta has decreased by $\sim 30\%$ during 1974-2015 compared to pre-1970s (Besset et al., 2019). Simulated sediment loads at Pyay vary from the results presented in previous studies. The discrepancy between sediment loads computed in the present study and those reported in the above mentioned data-based studies could be due to many reasons, including different measurement locations, the variability of sediment transport in the river, seasonality effects

on measurements (wet or dry seasons), cross-sectional variations (which leads to changes in water level-streamflow relationship), and differences in sampling methods (IFC, 2017).

The SWAT simulation undertaken here shows that approximately half of the total sediment load (55% of total) is generated from Chindwin Basin, where the average annual load is $149 \pm 27 \times 10^6$ t/yr. The Upper Irrawaddy (at outlet sub-basin 29) generates 37% of the total load. These results are consistent with the findings of previous studies (Garzanti et al., 2016; Stamp, 2015). Garzanti et al. (2016)'s analysis showed that approximately 50% of the sediment load in the Irrawaddy RB originates from Chindwin basin, while 35% of sediment originates from Mali and N'Mali headwaters and the remaining (<15%) is contributed by other sub-basins. Stamp (2015) also found that nearly half of the sediment load in the Irrawaddy RB is received from the Chindwin Basin.

6.3.4 Simulated streamflow and sediment load using bias-corrected GCM data

Comparison of GCM data forced simulated future changes (discussed in Section 6.4) in streamflow and sediment loads was undertaken with respect to the model simulations forced with GCM data for the base period (1991-2005). The bias-corrected precipitation and temperature data of the three selected climate models: (i.e., CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES, presented in Section 6.3.1) were used to simulate streamflow and sediment load for the base period using above described calibrated SWAT model setup (Section 6.3.3).

Streamflow

The simulated streamflow for the base period show good agreement with the seasonal variation of observed data with an R^2 of more than 0.5 being achieved at all eight gauging stations, except in the simulations forced with CSIRO Mk3.6 data. As an illustration, simulation results are further discussed below for the Pyay station (Figure 6-10 (a)). Models forced with all the three selected GCMs overestimate the high flows at Pyay during most of the years in the base period, among which the simulation forced with CSIRO Mk3.6 shows the highest differences with observed data. In the observed data, peak streamflow at Pyay generally occur in August (Figure 6-10 (a)), whereas streamflow simulated with CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES show the peak flow occurrence in September, August and July, respectively. Simulated mean annual streamflow over the base period at Pyay are 476 ± 85 , 460 ± 55 , and $457 \pm 41 \times 10^9$ m³ in the models forced with CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES, respectively. The mean annual streamflow values from observed data and the calibrated SWAT model over the same period are 379 ± 51 , and $391 \pm 42 \times 10^9$ m³, respectively.

Sediment load

The simulated sediment load over the base period show similar variation to streamflow (Figure 6-10 (b)) at Pyay. The simulated mean annual sediment loads for the base period at Pyay are 316 ± 87 , 294 ± 49 , and 291 ± 41 million tons in the simulations forced with CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES, respectively. The model calibration estimates the load of 275 ± 49 Million tons for the base period, which is less than the long-term (1966-1996) average of observed data (325 ± 57 million tons, Furuichi et al. (2009)). Similar to the streamflow, simulations forced with bias-corrected GCM data result in a basin sediment load that is higher than the observed and the results of the calibrated SWAT model forced with observed climate data. These discrepancies in streamflow and sediment load estimation may be attributed to the uncertainties in GCM data, model parameters, model structure, and bias correction method.

Figure 6-10. Simulated (a) streamflow, and (b) sediment load at Pyay with bias-corrected GCM data (CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES) for the base period (1991-2005) in the Irrawaddy River Basin. The observed streamflow and sediment loads are presented in thick pink color line. Model simulations were carried out with the calibrated SWAT model for both streamflow and sediment load.

6.4 Results and discussion: Future periods 2045-2065 and 2081-2100

6.4.1 Changes in future climate

Precipitation

The changes in precipitation in the future are not unidirectional depending on climate model, RCP, and the time periods considered. The Irrawaddy RB is projected to have a significantly increased monsoon precipitation (May to September) (Annex B), with the exception of CSIRO Mk3.6 of the three GCMs considered, which project a decrease in the monsoon precipitation during the mid-century (2046-2065) period. All three models project decreased precipitation in December to February in the mid-century under RCP 2.6 (compared to the base period). Only HadGEM2-AO and HadGEM2-ES show an increase of mean monthly precipitation in all months except December during 2046-2065 and 2081-2100 for RCP 8.5. The maximum increment in precipitation is projected with HadGEM2-AO during June (78 mm) and July (142 mm) for RCP 2.6 and RCP 8.5, respectively. The largest reduction of precipitation is projected with CSIRO Mk3.6 data for the month of May with 47 mm and 50 mm for RCP 2.6 and RCP 8.5, respectively.

Mean annual precipitation is projected to increase and decrease over the different parts of the basin (Figure 6-11). Upper and lower parts of the basin are projected to experience more changes than the middle part (dry zone). The percentage changes of each GCM precipitation projection were calculated with respect to their base precipitation (1991 - 2005). North-eastern parts of the basin are projected to experience the highest increment of precipitation (more than 10%) for both RCPs by HadGEM2-AO and HadGEM2-ES. In contrast, the highest decrease of precipitation (19%) is projected over the western parts of the basin for CSIRO Mk3.6 data, particularly for the mid-century period. During the end-century, precipitations from three GCMs are projected to vary between 7 % and 12% for RCP 2.6 and 8% to 31% for RCP 8.5 (compared to the base period). Similar to these findings, a recent study also shows that the upper Irrawaddy Basin (north and north-eastern parts of the study area) may experience an increase of precipitation of 16-20% in the 2040s and 21%-28% in 2080s (compared to their base period of 1975 to 2005) (Ghimire et al., 2019). Over the Belu River Basin (a small basin adjacent to the eastern part of the Irrawaddy RB), Myanmar, the average precipitation is projected to vary with no clear trends (-1.78% – 9.14%). The peak rainfall of that basin is also projected to vary by -3.4% – 23.2% during August compared to the base period 1976-2005 (Aung et al., 2016). Considering the entirety of Myanmar, precipitation is projected to increase by 6%-23% across the country during the 2041-2070 period compared to a base period of 1980-2006 (Horton et al., 2017). IPCC projections indicate that average precipitation over Myanmar may increase by 0-10% for RCP 2.6 and 10-20% for RCP 8.5 during the end-century (2081-2100) compared to the AR5 base period 1986-2005 (Figure SPM 7, IPCC, 2014).

Temperature

In general, the selected GCMs show an increase in temperature over the basin for all RCPs. The spatial variation of the temperature increment is minimal. The GCM projections for RCP 2.6 project average maximum temperature increases of 0.9-2.2 °C and average minimum temperature increases of 0.4-2.0 °C compared to the base period. For RCP 8.5, both maximum and minimum temperature are projected to increase by 2.1-5.1 °C and by 1.9-6.0 °C, respectively. During end-century (2081-2100), the highest increments of maximum and minimum temperature are projected with CSIRO Mk3.6 (by 5.1 °C) and HadGEM2-ES (by 6.0 °C) for RCP 8.5, respectively. For the same period under RCP 8.5, the lowest increments of both temperatures are projected with HadGEM-AO by 4.2 °C and 4.3 °C, respectively. All increases mentioned above are relative to the base period of 1991- 2005.

In Balu River Basin, Myanmar, the minimum temperature changes are almost double as compared to changes in maximum temperature (Aung et al., 2016). For example, in the 2080s, minimum (maximum) temperature increases by 5.27 °C (2.82 °C) for RCP 8.5 (compared to the base period 1976-2005). In Bago River Basin in Myanmar, outcomes of six GCM models show an increase of average temperature by 1.5 °C and 3 °C for RCP 4.5 and RCP 8.5 by 2070-2099, respectively when compared to the base period (1975-2009) values (Shrestha and Htut, 2016a). Similar increases in temperature are projected for the entirety of Myanmar by 2041-2070 with average annual temperature projected to rise by 1.3-2.7 °C over Myanmar compared to the period of 1980 to 2006 (Horton et al., 2017). By the end of 21st century, the increase of average surface temperature in Myanmar is projected to be 1- 1.5 °C and 3-5 °C for RCP 2.6 and RCP 8.5, respectively compared to 1986 - 2005 (Figure SPM 7, IPCC, 2014).

Figure 6-11. Percentage change of precipitation under two RCPs (RCP 2.6 on the left and RCP 8.5 on the right) of the three selected GCMs (from left to right CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES), relative to the base period (1991 – 2005) over each sub-basin of the Irrawaddy River Basin. In each RCP plot, two future periods are presented: 2046-2065 (top) and 2081-2100 (bottom).

6.4.2 Climate change-driven variations in future streamflow and sediment fluxes to the coast

All future changes in streamflow and sediment loads for mid-century (2046-2065) and end-century (2081-2100) periods were computed relative to the base period (1991-2005) (Section 6.3.4). As the focus here is on the streamflow at the basin outlet and sediment fluxes to the coast, this section presents results obtained at Pyay.

Streamflow

In general, similar to the projected increment in precipitation over the basin, streamflow at Pyay may also increase, particularly during the monsoon period (May to October) of both mid- and end-century periods considered (Figure 6-12). The variability of projected monthly mean streamflow at Pyay is more significant for RCP 8.5 (-36% to 93%) compared to RCP 2.6 (-43 % to 55%) over mid- and end-century periods. The most substantial increment of streamflow at Pyay (93% in May) is projected in simulations forced with HadGEM2-ES (under RCP 8.5) during end-century (2081-2100), while the most considerable reduction of

the streamflow (43 % in May) is projected in the simulation forced with CSIRO Mk3.6 (under RCP 2.6) during mid-century (2046-2065).

The mean high flows (during monsoon period) are projected to vary considerably, ranging from -8% to 1% and from -2% to 6% for RCP 2.6 during the mid and end century periods, respectively. Similarly, changes in monsoonal mean high flows are projected to vary from -5% to 10% and 9% to 25% for RCP 8.5 during mid- and end-century periods considered, respectively. During the low flow periods (November to April), changes in the mean flow are projected to vary between -13% and 4% and -3% and 5% for RCP 2.6 and between -5% and 10% and -1% and 24% for RCP 8.5 during mid- and end-century periods, respectively. During the monsoon period, projections obtained with HadGEM2-ES have the highest mean flow increment (25%) for RCP 8.5 during the end-century. For the same GCM inputs, the largest reduction of 8% of the mean flow is projected during mid-century for RCP 2.6. Similarly, during the non-monsoon periods, the HadGEM2-AO forced simulation shows the largest increase of 24% under RCP 8.5 during the end-century period and simulation forced with CSIRO Mk3.6 shows the largest decrease (13%) under RCP 2.6 during the mid-century. CSIRO Mk3.6 and HadGEM2-ES driven simulations project the occurrence of peak flow in September and July, respectively, which is in line with the historical timing of peak flows. The projection with HadGEM2-AO forcing indicates that the peak flow would occur in July, one month earlier than during the base period.

Similar projections, albeit with some variation, have been reported for other basins in the region. A study on Upper Irrawaddy Basin showed that the peak flows (during June to September) would increase (< 50%) while experiencing reductions during October to November (< 25%) for both RCP 4.5 and RCP 8.5 (Ghimire et al., 2019). That study also indicated that the flows from January to April might also experience considerably higher relative changes as well (w.r.t. base period of 1975-2014). Shrestha et al. (2013) found that intra-annual (monthly) flows are projected to vary between -62% to 105% in Nam Ou Basin in Lao PDR during 2041-2070. Agarwal et al., (2014) found that average monthly flows in Koshi River Basin (Nepal) would increase for three emission scenarios (B1, A1B, and A2) with a shift in the peak flow from the month of July (during the base period) to August (during the future period). It should be noted that these studies have used different scenarios, climate models, and methods of downscaling/bias correction.

Figure 6-12. Percentage change in projected mean monthly streamflow at Pyay relative to the base period (1991-2005) for simulations forced with the three different GCM data. Top panel shows the mid-century period (2046-2065) and the bottom panel shows the end-century period (2081-2100). Each panel includes the results of simulations forced with three GCMs (CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES) under both RCP 2.6 (filled circles) and RCP 8.5 (asterisks).

The mean annual precipitation and streamflow variations of Irrawaddy RB have a similar trend (Figure 6-13). However, the streamflow variation (in magnitude) is always higher than that of precipitation. During the end-century period, all simulations project streamflow to increase by 8% - 17 % and 9% - 45% for RCP 2.6 and RCP 8.5, respectively. In contrast, simulations forced with CSIRO Mk3.6 project reductions in the streamflow by 6% and 3% during the mid-century period for RCP 2.6 and RCP 8.5, respectively, while, HadGEM2-AO and HadGEM2-ES forced simulations project increments of 6% - 20% (RCP 2.6) and 15% - 25% (RCP 8.5) for the same period. Projections reported in previous studies of the Irrawaddy RB show variations that are similar to those obtained in this study. For example, Ghimire et al. (2019)'s mean decadal streamflow projections for the Upper Irrawaddy basin indicate an increase of 21% (22.7%) during 2021-2030 and 33% (41.8%) during 2091-2100 compared to 1975-214 under RCP 4.5 (RCP 8.5). In another study focusing on Bago River Basin in Myanmar, Shrestha and Htut (2016a) projected that the annual streamflow would

increase by 46.8% under RCP 8.5 during 2070-2099 compared to the baseline period (1990-2009).

Figure 6-13. Percentage change of projected mean annual flow (left) and sediment load (right) at Pyay relative to the base period (1991-2005) under RCP 2.6 and RCP 8.5 computed using the three selected GCM data as forcing. Q is Streamflow and rf is precipitation. Each panel (left and right) show results for RCP 2.6 (top) and RCP 8.5 (bottom) and the 3 selected GCMs (CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES). In each plot, light color bar shows the result relevant to the mid-century period (2046-2065), whereas dark color bar shows results relevant to end-century (2081-2100). In the left panel, streamflow changes are in the primary axis (left Y-axis) and precipitation changes are in the inverse secondary axis (right Y-axis). Similarly, in the right panel, sediment load changes are in the primary axis, and streamflow changes are in the inverse secondary axis.

Sediment load

The projected changes in mean monthly sediment load at Pyay follow a similar trend to that of streamflow projections (Figure 6-14). The mean monthly sediment load projections vary between -58 % and 117 % and -20% and 112% for RCP 2.6 during the 2046-2065 and 2081-2100 periods, respectively. Similarly, for RCP 8.5, the projected change in the mean monthly sediment load is between -51% to 104% and -47% to 273% for mid- and end-century periods, respectively. The highest projected increase (273%; for RCP 8.5) and decrease (58%; for RCP 2.6) of sediment loads are obtained with HadGEM2-AO (in February during 2081-2100) and CSIRO Mk3.6 (in May during 2046-2065), respectively.

It should be noted that the projected monthly percentage changes in sediment load are greater than the corresponding percentage changes in streamflow.

During the monsoon period, mean sediment load changes ranging from -10% to 8% for RCP 2.6 and from -7 % to 37% for RCP 8.5 are projected. Similarly, the sediment load in non-monsoonal months is projected to change between -21% and 8% under RCP 2.6, while between 8% and 51% under RCP 8.5. The mean annual sediment load is projected to increase in all the RCPs and periods, except for the simulations forced with CSIRO Mk3.6 data during the mid-century (Figure 6-13). On average, the projected increases are 11% (20%) during the mid-century and 22% (52%) over the end-century period for RCP 2.6 (RCP 8.5).

Figure 6-14. Percentage changes in projected mean monthly sediment load at Pyay relative to the base period (1991-2005) for simulations forced with the three different GCM data. Top panel shows the mid-century period (2046-2065) and the bottom panel shows the end-century period (2081-2100). Each panel includes the results of simulations forced with three GCMs (CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES) under both RCP 2.6 (filled circles) and RCP 8.5 (asterisks).

6.4.3 The combined effect of climate change and reservoirs on streamflow and sediment fluxes to the coast

Streamflow

For simulations with reservoirs, the relative changes of streamflow and sediment loads are calculated with reference to each climate scenario. The simulation results show that the streamflow at Pyay is similar for both trapping efficiencies (TE=50%, and 95%) (Annex B), because streamflow does not depend on sediment retention/outflow. The seasonal and annual changes in streamflow at Pyay are presented in Table 6-3 for the different climate scenarios with 95% trapping efficiency in all six reservoirs. The streamflow projections show a reduction in mean monsoonal flow (7% for RCP 2.6 and 6.1% for RCP 8.5) at Pyay. In contrast, non-monsoonal streamflow are projected to increase by 36.5% and 34% (on average) for RCP 2.6 and RCP 8.5, respectively. As discussed in Section 6.4.2, except for RCP 2.6 with HadGEM2-AO forcing, climate change-driven impacts are projected to increase the monsoon streamflow with all GCMs and for both RCPs considered. The reservoirs store water during the monsoon period, which causes a reduction of the downstream flow. On the other hand, reservoir operational release plays a significant role in the non-monsoonal period, as the operational release is specified here as a constant minimum release (Section 6.2.3). Therefore, the simulated low flow projections during the Nov-Apr period is greater with reservoirs than without (Table 6-3).

Similar projections (with some variations) are also reported in other basins in the region. A similar study carried out in the Sesan River Basin (Vietnam) with seven reservoirs in operation indicates that compared to the base period (2002-2012), streamflow may increase during the dry period but decreases during the wet period under both RCP 4.5 and RCP 8.5 during 2010-2100 (Ngo et al., 2018). Thus, simulation results for the Irrawaddy River Basin are consistent with results obtained for the Sesan River Basin. However, the same study by Ngo et al. (2018) shows an increase of both wet and dry period flows in the Srepok River Basin (Vietnam), where five cascade reservoirs exist. The mean annual flows are projected to decrease by 2-3% (compared to without reservoirs condition) in Sesan River under RCP 4.5 and RCP 8.5 during 2010-2100, and no changes are projected in the Srepok River for the same conditions. Furthermore, a study presented by Mittal et al. (2016) indicates that the flow variability in the Kangsabati River Basin (India) would reduce due to reservoir operations. This is due to the fact that high flows during flood events are buffered by the reservoirs while increasing the pre-monsoon flows via flow regulations.

Table 6-3. Changes in projected seasonal streamflow at Pyay during the end-century period (2081-2100) under RCP 2.6 and RCP 8.5 with/without reservoirs. Monsoon period is from May to October and Non-monsoon period is from November to April. Results related to reservoirs scenarios are with 95% trapping efficiency at all reservoirs. The simulation without reservoirs (Section 6.4.2) is considered as the reference to compute relative changes of projections obtained with reservoirs. It was assumed that all the reservoirs are full at their maximum level at the beginning of all simulations.

RCPs	GCMs	Monsoon Period (May to Oct) (m ³ /s)	Relative change due to reservoirs (%)	Non- Monsoon Period (Nov- Apr) (m ³ /s)	Relative change due to reservoirs (%)
Reference condition: Without reservoir (CC only) (Section 6.4.2)					
RCP 2.6	CSIRO Mk3.6	26,626		5,933	
	HadGEM-AO	27,834		5,635	
	HadGEM-ES	27,592		6,317	
RCP 8.5	CSIRO Mk3.6	27,265		5,587	
	HadGEM-AO	35,055		7,195	
	HadGEM-ES	33,214		6,961	
Scenario: CC + Reservoirs					
RCP 2.6	CSIRO Mk3.6	24,826	-6.8	7,979	34.5
	HadGEM-AO	25,660	-7.8	8,063	43.1
	HadGEM-ES	25,835	-6.4	8,334	31.9
RCP 8.5	CSIRO Mk3.6	25,412	-6.8	7,684	37.5
	HadGEM-AO	33,140	-5.5	9,484	31.8
	HadGEM-ES	31,227	-6.0	9,272	33.2

Sediment load

The mean seasonal and annual sediment loads also follow the same variations of streamflow projections. The sediment load at Pyay does not change due to different trapping efficiencies of the reservoirs. However, output sediment load from the Chindwin Basin shows a considerable reduction compared to the projections without reservoirs. For example, with 95% TEs of all six reservoirs, the mean annual sediment load is projected to decrease from -27% to -24% and from -27% to -20% for RCP 2.6 and RCP 8.5, respectively. In contrast, sediment reduction due to the three planned reservoirs in the upper Irrawaddy Basin is not as high as the Chindwin Basin. This reduction at the outlet of Sub-basin 29 varies only from 3.2% to 3.8% under both RCPs. Two of these reservoirs (out of three) are located far upstream in the basin and the Yeywa reservoir (Sub-basin 26) is the nearest one to basin

outlet (Figure 6-3). The reservoir retention effect has been neglected during the routing process to the outlet.

Table 6-4 shows the mean seasonal and annual sediment load variation at Pyay by the end-century period with 95% trapping. During the monsoon period, the mean sediment load is projected to reduce by 11.2% and 9.5% for RCP 2.6 and RCP 8.5, respectively, due to reservoirs. On the other hand, during the non-monsoon period, the mean sediment load is projected to increase up to 52.4%. Even though a higher sediment reduction appears at the outlet of Chindwin Basin (Sub-basin 28), the mean annual sediment load at the Pyay is projected to vary from -5.9% to -4.9% and from -5.7% to -4.2% for RCP 2.6 and RCP 8.5, respectively. It is observed that relative changes in seasonal sediment load are always higher than that for streamflow. For example, the mean monsoon sediment load is more than five times the same for the non-monsoon period during 2081-2100, whereas the comparable streamflow projections show almost three times.

Table 6-4. Changes in projected seasonal and annual sediment load at Pyay during the end-century period (2081-2100) under RCP 2.6 and RCP 8.5 with/without reservoirs. Monsoon period is from May to October and Non-monsoon period is from November to April. Results related to reservoirs scenarios are with 95% trapping efficiency at all reservoirs. The simulation without reservoirs (Section 6.4.2) is considered as the reference to compute relative changes of projections obtained with reservoirs.

RCP scenario	GCMs	Monsoon period (May to Oct) (MT)	Relative change due to reservoirs (%)	Non-monsoon period (Nov-Apr) (MT)	Relative change due to reservoirs (%)	Annual (MT)	Relative change due to reservoirs (%)
RCP 2.6	CSIRO Mk3.6	318		39		357	
	HadGEM-AO	334		35		370	
	HadGEM-ES	326		42		367	
RCP 8.5	CSIRO Mk3.6	339		35		374	
	HadGEM-AO	461		55		515	
	HadGEM-ES	424		49		473	
RCP 2.6	CSIRO Mk3.6	281	-11.4	55	39.4	336	-5.8
	HadGEM-AO	294	-12.1	53	52.4	348	-5.9
	HadGEM-ES	292	-10.2	58	36.0	349	-4.9
RCP 8.5	CSIRO Mk3.6	302	-10.8	51	43.6	353	-5.7
	HadGEM-AO	422	-8.5	72	31.9	494	-4.2
	HadGEM-ES	385	-9.1	67	36.1	452	-4.4

To investigate the relationship between trapping efficiency (TE) and the projected differences in sediment load at the basin outlet, the mean annual sediment load in the main reaches was analyzed. For example, Figure 6-15 shows sediment load projections from simulations forced with CSIRO Mk3.6 under RCP 8.5 for the 2081-2100 period. Due to the high amount of sediment trapping within three reservoirs in the cascade system, a considerable reduction of sediment load at the outlet of the Chindwin Basin is expected. However, model results show only 15 MT/yr of sediment reduction with 95% TE compared to 50% TE (161 MT/yr with 50% TE and 146 MT/yr with 95% TE). This limited reduction in sediment volume for 45% increase TE implies that the river channels would erode and generate sediment load when the river reaches are starved of sediment due to reservoir trapping. It is also interesting to note that an increase of trapping efficiency from 50% to 95% has no effect on the sediment load at Pyay. This can be explained as follows: the area of sub-basins 30 and 31 (just downstream of the Chindwin and Irrawaddy confluence) is 49,000 km². Most of this land area is utilized for agriculture, which generates a higher rate of sediment erosion, and thus a very high sediment load (512 MT/yr), which completely overshadows the 15MT/yr difference between the 50% and 95% TE cases. When the sediment carrying capacity of the river is less than the amount of sediment introduced to the river, excess sediment is deposited along the riverbed or flood plains. Thus, in both simulations shown in Figure 6-15, the sediment load at Pyay is governed by the sediment carrying capacity in the river reach from the confluence to the outlet, which does not change in the two cases. Therefore, the computed sediment load at Pyay is identical in the 50% and 95% TE cases.

Figure 6-15. Projected mean annual sediment load in the reservoir reaches (just downstream of reservoirs) from simulations with CSIRO Mk3.6 under RCP 8.5 with 50% trapping efficiency (left) and 95% trapping efficiency (right). All the values are in Million Tons per year (MT/yr). The green area is the Upper Irrawaddy Basin and the beige area is the Chindwin Basin. The planned reservoir locations are shown by red triangles. Black color arrows represent the flow direction.

The ranges of projected decreases in sediment load at the basin outlet Pyay under RCP 8.5 for the end of century period (2081-2100), even with a 95% TE, is significantly lower than that projected for other large basins in the region. For example, Shrestha et al. (2016) indicated that the sediment outflow from the Nam Ou Basin, Lao PDR (drainage area of 26,181 km²) would reduce considerably as the number of reservoirs increases. That study indicates a decrease of sediment outflow by 44% to 80% only with the most upstream reservoir (capacity of 1,469 MCM) and by 66% to 89% with five reservoirs (cumulative capacity of 2,400 MCM) within the cascade system at Nam Ou Basin. Yang et al. (2015) indicated that the mean sediment flux (mean discharge) in the Yangtze River Basin, China (drainage area of 1.8 million km²) has reduced by 71% (7%) during 2003-2012 (post-dam period) compared with the 1950-2002 (pre-dam period, where the three-gorges dams (TGDs, capacity of 39,300 MCM) were completed in 2003). The total sediment reduction is attributed to the TGDs (65%), other dams of 64,000 MCM cumulative capacity (10%), precipitation decline (14%), soil conservation (10%), and water abstraction (1%). Ranasinghe et al. (2019) showed that in Pearl River, China (drainage area of 450,000 km²), fluvial sediment supply to the coast has reduced by 71% (compared to natural condition)

during 1954-2013 due to excessive human activities such as dam constructions, river flow diversions and deforestation. Increased streamflow due to climate change during the 21st century would only reduce 1% of this sediment deficit by 2100. According to the global sediment fluxes estimation by Syvitski et al. (2005), the sediment supplied to the world's coast has reduced by 1.4 ± 0.3 billion tons per year because of anthropogenic retention during 1960 to 1995.

The summary of projected mean annual streamflow and sediment load at Pyay discussed in Sections 6.3.4, 6.4.2, and 6.4.3 is shown in Table 6-5 and Table 6-6. The results of the present study suggest that future climate and reservoirs affect the streamflow regime and sediment outflux of the basin. However, these impacts can be dominated by reservoir operations as mentioned by Ngo et al. (2018). Reservoirs have greater impacts than climate change on sediment outflow (Ranasinghe et al., 2019; Shrestha et al., 2016) and natural flow regime (Mittal et al., 2016). Furthermore, Mittal et al. (2016) have concluded that the combined effects of climate change and reservoirs are considerably higher than their individual effects.

Table 6-5. Projected mean annual streamflow and sediment loads at Pyay from the three GCMs for the base period (1991-2005) and mid-century periods (2046-2065). Q is streamflow and Qs is sediment load (highlighted). CC means Climate change.

GCM	Base Period (1991-2005)		RCP	Projections for the mid-century period (2046-2065)			
	Q (m³/s)	Qs (MT/yr)		CC only		CC + reservoirs	
				Q (m³/s)	Qs (MT/yr)	Q (m³/s)	Qs (MT/yr)
CSIRO Mk3.6	15,088	316	RCP 2.6	14,148	370	14,223	273
			RCP 8.5	14,569	386	14,647	285
HadGEM2-AO	14,597	294	RCP 2.6	17,439	383	17,555	363
			RCP 8.5	16,791	365	16,894	344
HadGEM2-ES	14,501	291	RCP 2.6	15,296	317	15,396	299
			RCP 8.5	18,100	407	18,230	387

Table 6-6. Projected mean annual streamflow and sediment loads at Pyay from the three GCMs for the base period (1991-2005) and end-century periods (2081-2100). *Q* is streamflow and *Qs* is sediment load (highlighted). CC means Climate change.

GCM	Base Period (1991-2005)		RCP	Projections for the end-century period (2081-2100)			
	Q (m³/s)	Qs (MT/yr)		CC only		CC + reservoir	
				Q (m³/s)	Qs (MT/yr)	Q (m³/s)	Qs (MT/yr)
CSIRO Mk3.6	15,088	316	RCP 2.6	16,333	357	16,433	336
			RCP 8.5	16,492	374	16,593	353
HadGEM2-AO	14,597	294	RCP 2.6	16,834	370	16,946	348
			RCP 8.5	21,193	515	21,367	494
HadGEM2-ES	14,501	291	RCP 2.6	16,982	367	17,100	349
			RCP 8.5	20,183	473	20,294	452

6.5 Conclusions

This chapter assessed the impact of climate change and human activities on streamflow and sediment load simulation in the Irrawaddy River Basin, Myanmar. SWAT model simulations for the base period (1991 - 2005), and two future periods: mid-century (2046-2065) and end-century (2081-2100) are presented. Data from 10 GCMs were initially considered in this study and three most representative GCM models (CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES) for the Irrawaddy RB were selected based on the performance of GCM climate variables (precipitation, and minimum and maximum temperatures) and performance of SWAT hydrological simulations forced with GCM data. The data from the three selected GCMs were corrected for biases using the mean bias correction method and used to force a series of SWAT models. The SWAT model was set up for sediment and reservoir simulation, taking into account six planned reservoirs in the basin. Model simulations were undertaken with only climate change forcing and with climate change forcing together with planned reservoirs.

Sediment load calibration (SWAT model forced with observed data) at three stations (Kalewa, Sagaing and Pyay) shows good agreement with observed data (1991-2010). Model simulations forced with bias-corrected GCM data from CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES for the base period (1991-2005) overestimate the observed streamflow at

Pyay station, particularly during high flow period (July to September). Similar to the streamflow, simulated sediment load at Pyay is also higher than the observed sediment load.

Results show that changes in climate variables (precipitation and temperature) alter the streamflow and sediment fluxes in the basin. However, the projected changes in sediment fluxes are not consistent among the climate models used in this study. In general, streamflow and sediment load are projected to increase during the monsoon period compared to non-monsoonal months. The projected changes in sediment loads are always higher than the variations in streamflow.

The changes in both seasonal streamflow and sediment load are considerably affected by the planned reservoirs. Reservoirs act as buffer storage during high flows, which in turn reduce peak flows. Besides, reservoirs release a minimum flow throughout the year, which results in an increase in river flow during the low flow period. Seasonal changes in sediment load follow the same changes of streamflow. In terms of mean annual streamflow and sediment loads, projected increases are 10%-46% and 12%-68% (compared to base period estimates), respectively during the end-century period (2081-2100) under RCP 8.5 with planned reservoirs. The same projections with climate change alone (i.e., no reservoirs) are 9%-45% and 18%-75%, respectively for 2081-2100 under RCP 8.5.

It should be noted that the sediment load at the basin outlet may depend on factors other than climate change and reservoirs. One such factor, which is not considered in the present study, is changes in future land-use. Different land-use practices can affect the rate and magnitude of soil erosion and sediment yield of a basin and the streamflow (Pokhrel, 2018; Rodriguez-Lloveras et al., 2016). Therefore, as a future direction, a study combining the potential effects of climate, land-use and other human activities (i.e., water diversions, damming) are recommended.

7

SIMULATING STREAMFLOW AND SEDIMENT FLUXES TO THE COAST IN THE KALU RIVER BASIN

7.1 Introduction

This chapter investigates the impacts that climate change might have on 21st century streamflow and sediment load in the Kalu River Basin, Sri Lanka. The analysis is carried out for a base period (1991-2005) and two future periods: mid-century (2046 - 2065) and end-century (2081 – 2099) under different RCPs.

This chapter is structured as follows: Section 7.2 describes the methods adopted, which includes analysis of the projected climate data, bias correction of climate data, SWAT model set-up, and scenarios for future streamflow and sediment load estimation. Sections 7.3 and 7.4 present the results for the base period and future periods, respectively. Section 7.5 presents the conclusions of the investigations.

7.2 Data and methods

7.2.1 Climate models and climate change scenarios

Climate data for Kalu River Basin were obtained from three RegCM4 RCMs (details in Table 3-4) because coarser-resolution GCM data could not capture the seasonal variability of precipitation within the basin. Similar to the GCM data discussed for Irrawaddy River Basin, three RCMs data also show a significant difference in climate data over the basin (Figure 7-1 and Annex C). Average annual precipitation from the RCMs during the base period (1991-2005) is significantly higher than the average annual precipitation from the observed data over the basin (3600 mm, Section 4.4.1) (Figure 7-1). The RCM data based on MIROC5 and MPI-ESM-MR data show the highest annual precipitation over the basin (7090 mm and 6630 mm, respectively), while the RCM data based on NCC-NORES1-M data show 4490 mm of annual precipitation.

The RCM outputs show varied distributions of daily precipitation over sub-basins for the base period (1991-2005) (Figure 7-2). For example, in sub-basin 1, while the observed data shows 17% dry days (that is percentage days over 1991-2005 with 0 mm precipitation), the three RCMs (MIROC5, MPI-ESM-MR, and NCC-NORES1-M) show 1%, 1% and 3% of dry days, respectively. In sub-basin 10, the dry day occurrences are 15% in the observed data, and 1%, 1%, and 2% in the three RCM data. For heavy precipitation (here considered as greater than 50 mm/day), average differences in the probability of occurrence between observed and RCM data are small in Sub-basin 1 (<4%) and Sub-basin 10 (<9%). In contrast, when compared with observed data, medium precipitation (here considered as between 5 and 50 mm/day) of RCM data shows the highest computed difference (21% in Sub-basin 1 and 22% in Sub-basin 10) in the probability of occurrence. The analysis of the three RCMs and observed precipitation data for 1991-2005 (Figure 7-2) indicates that MIROC5 data deviates most from the observed data.

The daily maximum and minimum temperatures over the Kalu River Basin during the base period (1991-2005) do not vary significantly among the RCMs (Annex C). All RCMs underestimate the maximum daily temperature in the entire basin. For example, the observations show that maximum daily temperature is 31-34 °C, while RCMs show 27- 28 °C. The RCM estimates of minimum temperatures are almost similar to observations in the basin except in the northern part, where the RCM estimates show 2°C lower temperature than observed values (minimum temperature).

Figure 7-1. Gridded average annual precipitation from 1991 to 2005. (a) RegCM4/MIROC5, (b) RegCM4/MPI-M-MPI-ESM-MR, and (c) RegCM4/NCC-NORESM1-M. Data were collected from ICTP, Italy (Table 3-4).

Figure 7-2. Distribution of daily precipitation of three RegCM4 RCMs compared with observed data at selected sub-basins over the base period (1991-2005). Red line indicates the observed data. Data comparisons are shown for most upstream (Sub-basins 1 and 2), middle (Sub-basins 6 and 8), and most downstream (Sub-basin 10 and 14) parts of the Kalu Basin. These basins represent the individual grids covered the entire basin from upstream to downstream.

7.2.2 Model setup and scenarios

Suspended sediment modelling

Similar to the method adopted for the Irrawaddy River Basin, the best-performing SWAT model for streamflow simulation (Section 4.4) was used to further calibrate the model for sediment load at the Kalu RB. However, the available sediment load observations (time series data) is not sufficient enough for a comprehensive model calibration for fluvial sediment loads. Nevertheless, based on few yearly sediment values (in 1976, 1984, 1991, and 2001) published by CCD (2006), model parameters (Table 6-1) were adjusted manually to obtain a reasonably calibrated model for 1991-2000 period.

Calibration with one average value of sediment load (average of four years of annual values) does not represent a robust model calibration. Thus, the projected variability of the sediment loads was assessed by considering parameter uncertainty. Among the five parameters selected for calibration (Table 6-1), three parameters (SPCON, CH_COV1, and CH_COV2) are related to the sediment transport in the river reach and remaining two parameters (USLE_P and USLE_C) are related to the soil erosion within the basin. It was found that among these five parameters, the erosion related parameters are less sensitive to the estimated sediment load at the basin outlet compared to the parameters related to sediment transport in the river. Therefore, parameter uncertainty assessment was carried out only for the sediment transport parameters (i.e., SPCON, CH_COV1, and CH_COV2). The input values of these parameters were varied within a $\pm 50\%$ range (i.e., -50%, -25%, +25%, and +50%) of the respective calibrated magnitudes. New simulations were carried out with these new parameter combinations for the uncertainty assessment.

Model scenarios and simulations

RCM data (precipitation, and maximum and minimum temperatures) were bias-corrected using mean-bias correction method (details in Section 6.2.2). Future streamflow and sediment loads were projected under climate change only. These projections were derived using model simulations forced with bias-corrected climate data in the calibrated SWAT model.

Similar to the Irrawaddy River Basin, mainly three different model simulations were carried out in this study: (1) calibration for sediment load (using observed data as model forcing), (2) GCM forced for a base period with climate change only, and (3) GCM forced for future periods with climate change only. Projection uncertainty in sediment load due to parameters was also assessed.

7.3 Results and discussion: Base period (1991-2005)

7.3.1 Bias corrected climatic variables

In general, none of the RCM data reproduced the seasonal variation of precipitation (i.e., inter-annual variability) adequately (Figure 7-3). MIROC5 and MPI-ESM-MR data show considerably higher biases than NCC-NorESM1-M data. After bias correction, monthly precipitation data still do not show good agreement with observed precipitation ($NSE < 0$) in many of the sub-basins (e.g., sub-basin Annex C). Thus, the mean bias correction procedure does not appear to preserve the temporal characteristics of observed precipitation adequately ($0.1 < R^2 < 0.31$). Compared to the precipitation data, after applying the bias correction, minimum and maximum monthly mean temperatures show good agreement with observed data (Figure 7-4).

Figure 7-3. Monthly precipitation of observed and RCMs (without and with bias correction) for the selected sub-basins during 1991-2005. In the legend, Raw denotes without bias correction and BC denotes with bias correction. The NSE values of RCM precipitation (MIROC 5, MPI-ESM-MR and NCC-NorESM1-M) are shown in three subsequent columns for without (Raw) and with (BC) bias correction data. Statistical performances of all sub-basins are tabulated in Annex C. The three selected sub-basins represent the up-, mid-, and downstream of the Kalu River Basin, respectively.

Figure 7-4. Monthly mean minimum temperature (T_{min} in shaded 3 three plots) and maximum temperature (T_{max} in bottom three plots) of observed and RCMs for three stations during 1991-2005. In the legend, Raw denotes without bias correction and BC denotes with bias correction. The NSE values of RCM temperatures (MIROC5, MPI-ESM-MR, and NCC-NorESM1-M) are shown in three columns subsequently for without (Raw) and with (BC) bias correction data. Statistical performances of three stations are tabulated in Annex C.

7.3.2 Evaluation of simulated sediment load forced with observed climate data (1991-2000)

Model simulations were carried out with the best-performing SWAT model setup in streamflow computations (discussed in Section 4.4) for 1991-2000 that is similar to the streamflow calibration period (discussed in Section 4.4). In terms of sediment load, model calibration at the basin outlet shows a good agreement with annual observations (Figure 7-5). For the year 1991, the model marginally underestimates the sediment load, where the simulated and observed annual sediment loads are 0.658 and 0.672×10^6 tons, respectively. The average annual sediment load at Kalu river outlet is estimated as $0.78 \pm 0.19 \times 10^6$ t/yr by the model, whereas the averaged value of four-year observations is $0.70 \pm 0.09 \times 10^6$ t/yr. All the observations (four-yearly values) are within the maximum and minimum sediment load projections for the 1991-2000 period. According to the records presented by CCD (2006), the total basin sediment supply during the 1976-2001 period is about 10 Million m^3 (70 tons/ha/yr).

Figure 7-5. Annual sediment load at the Kalu River Basin outlet. Blue line indicates the sediment load computed with calibrated parameters, and the shaded area indicates the range between maximum and minimum values of the projected sediment load. Red dots represent the observed annual sediment loads of four different years (1976, 1984, 1991 and 2001).

The simulated average sediment yield over the calibration period (1991-2000) ranges between 39 to 80 t/ha/yr (Figure 7-6 (a)), and the basin averaged value is 59 t/ha/yr. This value is considerably higher than the global average (15 t/ha/yr). The highest soil loss is in sub-basin 6, 7 and 11, where rubber and tea are the dominant crops. Compared to the Irrawaddy River Basin, estimated mean yield does not vary significantly over the simulation period (as shown in Figure 7-6 (b)). Dissanayake and Rupasinghe (1996) showed that soil losses due to tobacco, carrot and chilies cultivation in mild slope terrain in Sri Lanka are as high as 70 t/ha/yr, 18 t/ha/yr, and 38 t/ha/yr, respectively, and also that soil loss in the tea

cultivation is as 52.6 t/ha/yr. The estimated sediment yield in the upper part of the largest river basin in Sri Lanka (Mahaweli basin) is high as 10 – 70 t/ha/yr (Hewawasam, 2010). The same study found that the short-term sediment yield of the basin may vary between 1.3 – 21 t/ha/yr based on the river monitoring sediment load in tributaries. Therefore, sediment yield simulated here for the Kalu River Basin is in a reasonable agreement with previous studies in Sri Lanka.

Figure 7-6. The model simulated (a) average annual sediment yield, and (b) coefficient of variation of sediment yield at sub-basin level for the base period (1991-2000) in Kalu River Basin

7.3.3 Simulated streamflow and sediment load using bias-corrected RCM data

Comparison of future changes in streamflow and sediment loads were undertaken with respect to the model simulations forced with GCM data for the base period (1991-2005). The bias-corrected precipitation and temperature data of three selected RegCM4 regional climate models (i.e., MIROC5, MPI-ESM-MR, and NCC-NORES1-M, presented in Table 3-4) were used to simulate streamflow and sediment load for the base period using above described calibrated SWAT model (Section 7.3.2).

Streamflow

The simulations forced with bias-corrected RCMs data show a reasonable performance of the streamflow. For example, Figure 7-7 (a) shows the comparison of simulated and observed streamflow at the most downstream station of the basin: Putupaula. Models forced with all three RCMs underestimate as well as overestimate the streamflow, particularly during May to June (early Southwest monsoon) and October to November (inter-monsoon 2). Simulated mean annual streamflow over the base period (1991-2005) at Putupaula are 5.2 ± 1 , 5.2 ± 1.3 , and $5.3 \pm 1.1 \times 10^9 \text{ m}^3$ in the models forced with MIROC5, MPI-ESM-MR, and NCC-NORES1-M, respectively. These estimations are almost nearly equal to the observed and SWAT simulated streamflow for 1991-2000 of 5.5 ± 0.9 , and $5.7 \pm 1.0 \times 10^9 \text{ m}^3$, respectively.

Sediment load

A similar variation is also observed in the base period sediment load estimation at the basin outlet, 20 km downstream of Putupaula gauging station (Figure 7-7 (b)). Different parameter combinations lead to changes in a certainty range of the sediment predictions (minimum and maximum of the predictions). The annual sediment loads obtained from the simulations with calibrated parameters show reasonable agreement with two observations (year 1991 and 2001, Figure 7-7(c)). The simulated mean annual sediment load from three RCMs (MIROC5, MPI-ESM-MR, and NCC-NORES1-M) at the basin-outlet over the base period (1991-2005) are 0.63 ± 0.20 , 0.66 ± 0.26 , and $0.64 \pm 0.19 \times 10^6$ tons, respectively. These predictions underestimate the observed and SWAT simulated (forced with observed climate data) sediment load of $0.78 \pm 0.19 \times 10^6$ t/yr (for 1991-2000), and $0.70 \pm 0.09 \times 10^6$ t/yr (average of four-year observations (1976, 1984, 1991, and 2001) at the basin outlet, respectively.

Figure 7-7. Simulated (a) monthly streamflow at Putupaula, and (b) monthly, and (c) annual sediment load at basin outlet with bias-corrected RegCM4 RCM data (MIROC 5, MPI-M-MPI-ESM-MR, and NCC-NORES1-M) for the base period (1991-2005) in the Kalu River Basin. Thick pink color line in figure (a) represents the observed streamflow at Putupaula. Model simulations were carried out with the previously calibrated SWAT model for both streamflow and sediment load. The grey area in the plots (b) and (c) presents the maximum and minimum sediment-load prediction range (monthly and annual). The “*” in the plot (c) represents the observed annual sediment loads in year 1991 and 2001. Solid lines in each plot present the results obtained from the simulation with the calibrated parameter set.

7.4 Results and discussion: Future periods 2045-2065 and 2081-2099

7.4.1 Changes in future climate

Precipitation

Similar to the Irrawaddy RB, the changes in precipitation in the future are not unidirectional in the Kalu RB, depending on RCPs, climate models used and periods considered. The southwest (SW) monsoon and inter-monsoon bring high amounts of precipitation over the basin. Hence, the basin is projected to experience significantly increased monsoon precipitation (May to September) for RCP 8.5 by the end of the century (Annex C). For example, RegCM4/NORES-M projections indicate increments in monsoon precipitation of the sub-basins by 22% -120% during end-century (2081-2099) under RCP 8.5. Except for RegCM4/MIROC5, all the RCMs preserve the two peaks (in May and October) for RCP 2.6. The projections of RegCM4/MIROC5 indicate a shift in peak precipitation from May to June during the end-century period. This shift in monsoonal period implies a delay of southwest monsoon. Under RCP 8.5, all RCMs project a shift in the SW monsoon peak from May to June during the end of the century, while only RegCM4/MIROC5 project the same shift during the mid-century period. During the SW monsoon (May to Sep.), the maximum variation of monthly precipitation (34 – 1038 mm) is projected for RCP 8.5 during the end-century period. The minimum variation (-56 - 80 mm) of the same is projected for RCP 2.6 during the mid-century period. Similarly, for the Inter-monsoon 2 period (Oct. - Nov), maximum (23 - 282 mm during end-century) and minimum (-24 - 58 mm during mid-century) variations of precipitations are projected for RCP 8.5 and 2.6, respectively.

All models show an increase of average annual precipitation over the basin except the RegCM4/MPI-ESM-MR which shows a decrease of precipitation in the most downstream part of the basin (Sub-basin 14 and 15) (Figure 7-8). Lowest and highest increases in precipitation are projected within the eastern and coastal parts of the basin, respectively. During the end-century period, the mean annual precipitation in the basin is projected to increase by 6% - 10% and 39% - 52% for RCP 2.6 and RCP 8.5, respectively (compared to the base period: 1991-2005). However, an IPCC multi-model analysis shows that the mean annual precipitation over Sri Lanka would increase by 0% - 10% (RCP 2.6) and 10% - 20% (RCP 8.5) compared to 1986-2005 (Figure SPM 7, IPCC, 2014). Another study has shown that annual rainfall is likely to change by -0.5% - 44% compared to 1971-2000 over the Mahaweli River Basin (Sri Lanka), which is the largest basin in the country (Imbulana et al., 2018). The projected change of annual precipitation over Sri Lanka is +11% (median from 42 GCMs) for 2046-2070 compared to 1976-2005 under RCP 8.5 (Zheng et al., 2018). Relative to these prior studies, the changes in mean annual precipitation of Kalu River Basin projected in this study appear to be higher than those projected for adjacent basins and Sri Lanka as a whole.

Figure 7-8. Percentage change of precipitation under RCP 2.6 (left) and RCP 8.5 (right) of three RegCM4 RCMs (from left to right MIROC5, MPI-M-MPI-ESM-MR, and NCC-NORESM1-M) with respect to the base period (1991 – 2005) over each sub-basin of the Kalu River Basin. In each RCP plot, two future periods are presented: 2046-2065 (top) and 2081-2099 (bottom).

Temperature

All the selected models show an increase in average annual maximum and minimum temperatures. The minimum temperature increase is greater than the same for maximum temperature. During the mid-century (2046-2065), the projected maximum and minimum temperature increments compared to the base period (1991-2005) are 0.6-1.6 °C and 0.6-1.8 °C, respectively for RCP 2.6. Similarly, the same increments for RCP 8.5 are 1.4-3.3 °C and 1.4-3.3 °C. By the end of the century (2081-2100), the temperature is projected to rise by 2.3-3.3 °C (maximum temperature) and 2.6-3.3 °C (minimum temperature) for RCP 8.5. Similar to these findings, the average surface temperature over Sri Lanka is projected to rise by 0.5-1 °C and 3-4 °C for RCP 2.6 and RCP 8.5, respectively during 2081-2100 (compared to the period of 1986-2005) (Figure SPM 7, IPCC, 2014). The annual average temperature over Sri Lanka is projected to increase by 2 °C during 2046-2070 for RCP 8.5, which is the median value of 42 GCMs outputs (Zheng et al., 2018).

7.4.2 Climate change-driven variations in future streamflow and sediment fluxes to the coast

All future changes in streamflow and sediment loads for mid-century (2046-2065) and end-century (2081-2099) periods were computed relative to the base period (1991-2005) (Section 7.3.3). This section presents the results (streamflow and sediment load) obtained at the basin outlet.

Streamflow

The projected relative changes of mean streamflow are higher for RCP 8.5 than RCP 2.6 (Figure 7-9). The mean monthly streamflow at the basin outlet is projected to increase

between -26% and 71% during the mid-century and between -9% and 68% during the end of the century for RCP 2.6. For RCP 8.5, these values during mid- and end-century periods vary between -47% to 76% and -44% to 452%, respectively. Similarly, all simulations indicate a 2nd peak of streamflow in October under both RCPs, which is in line with the historical timing of peak flows. Furthermore, simulations forced with RegCM4/MIROC5 show a shift in the 1st peak flow month from May to June under both RCPs. The model projections from the other two RCMs (RegCM4/MPI-ESM-MR and RegCM4/NORES1-M) show mixed results for the shift in the peak flow month. For example, both RCMs have a projected peak in the month of June during the end of the century for RCP 8.5. The results from RegCM4/MPI-ESM-MR show a peak in June and other RCMs show a peak in May during the end of the century for RCP 2.6.

The mean annual streamflow is projected to increase in both future periods under both RCPs (Figure 7-10). Projections show an increase by 5%-13% (14-22%) during the mid-century and 9%-20% (67-87%) during end-century for RCP 2.6 (RCP 8.5). The projected variations in annual streamflow are always higher for RCP 8.5 than RCP 2.6.

Figure 7-9. Percentage change in projected mean monthly streamflow at the basin outlet relative to the base period (1991-2005) for simulations forced with the three RegCM4 RCM data. Top panel shows the mid-century period (2046-2065) and the bottom panel shows the end-century period (2081-2099). Each panel shows the results of simulations forced with three RegCM4 RCMs (MIROC5, MPI-M-MPI-ESM-MR, and NCC-NORES1-M) under both RCP 2.6 (filled circles) and RCP 8.5 (asterisks).

Figure 7-10. Percentage change in projected mean annual flow (left) and sediment load (right) at basin outlet relative to the base period (1991-2005) under RCP 2.6 and RCP 8.5, computed using the three RegCM4 RCM data as forcing. Q is Streamflow and rf is precipitation. Each panel (left and right) shows results for RCP 2.6 (top) and RCP 8.5 (bottom) and the three RegCM4 RCMs (MIROC5, MPI-M-MPI-ESM-MR, and NCC-NORESM1-M). In each subplot, the light color bar shows the result relevant to the mid-century period (2046-2065), whereas the dark color bar shows the result relevant to the end-century (2081-2099). In the left panel, streamflow changes are in the primary axis (left Y-axis), and precipitation changes are in the inverse secondary axis (right Y-axis). Similarly, in the right panel, sediment load changes are in the primary axis and streamflow changes are in the inverse secondary axis.

Sediment load

Uncertainties in sediment load projections are higher in future periods than in the base period for both RCPs considered (Figure 7-11 and Figure 7-12). This is likely due to the projection uncertainties of RCMs for future periods. The maximum and minimum projections ranges are higher for RCP 8.5 during the end-century period due to the larger increments in precipitation and streamflow (discussed in Section 7.4.1 and Section 7.4.2). The highest uncertainty of the sediment load projections is observed during the high flow months (April- June and October) of the end-century period (0.002-2.79 million tons during April- June and 0.01-1.3 million tons in October).

Figure 7-11. Average monthly sediment load projections for RCP 2.6. Three colors represent the three RCMs. Solid lines indicate the projected average monthly sediment loads for each future period (2046-2065 and 2081-2099) and dotted lines show the same values for the base period (1991-2005), simulated with calibrated parameter set. The maximum and minimum projection ranges are shown in the representative colors of each RCM for the base period and in grey for the future periods.

Figure 7-12. Average monthly sediment load projections for RCP 8.5. Three colors represent the three RCMs. Solid lines indicate the projected average monthly sediment loads for each future period (2046-2065 and 2081-2099) and dotted lines show the same values for the base period (1991-2005), simulated with calibrated parameter set. The maximum and minimum projection ranges are shown in the representative colors of each RCM for the base period and in grey for future periods.

The projected variation of fluvial sediment is greater than that of streamflow (Figure 7-13). The mean monthly sediment load at basin outlet is projected to vary between -39% and 128% during mid-century and from 19% to 158% during the end-century for RCP 2.6 compared to the base period. Similarly, simulation results show that sediment load varies

between 63% and 217% during mid-century and between 57% and 922% increase during end-century for RCP 8.5. Peak months of sediment load are similar to that of streamflow peaks in all cases. The only exception for this behavior is projected with RCP 8.5 inputs of RegCM4/MIROC5 data during the end-century period (2081-2099), in which the sediment peak occurs in April, while the streamflow peak occurs in June. During 2081-2099, MIROC5 data-driven SWAT simulations show seven (out of 228) high sediment loads (> 0.5 million tons/ month) and high streamflow ($> 800 \text{ m}^3/\text{s}$). Out of these sediment peaks, only one is projected to occur in April with four peaks in May (and the remaining two in October). The high sediment load in April (2 million tons/ month) is projected in 2099, which is the reason underlying the shifting of the average monthly sediment peak over 2081- 2099 to April. If 2099 is omitted from the averaging, peaks of both streamflow and sediment loads will occur in the month of May.

Similar to the annual streamflow variation, climate change is projected to increase the sediment load of the Kalu RB (Figure 7-10). On average, the mean annual sediment load is projected to increase by 16% (37%) and 26% (142%) for RCP 2.6 (RCP 8.5) during mid- and end-century periods, respectively.

Figure 7-13. Percentage change in projected mean monthly sediment load at the basin outlet relative to the base period (1991-2005) simulations of individual RegCM4 RCM. Top panel shows the mid-century period (2046-2065), and the bottom panel shows the end-century period (2081-2099). Each panel shows the results of three RegCM4 RCMs (MIROC5, MPI-M-MPI-ESM-MR, and NCC-NORES1-M) under RCP 2.6 and 8.5.

In general, an increase/ decrease in streamflow will have a similar effect on the sediment load at monthly, seasonally, and annual time scales. These variations in sediment load are always higher than the projected changes in streamflow. Similar findings were observed in a study carried out in the Nam Ou Basin (Lao PDR) (Shrestha et al., 2013). In that study, - 27% to 160% variation in sediment loads are projected for -17% to 66% changes in annual streamflow for five GCMs and three emission scenarios. Similarly, the average annual runoff in headwaters of the Yinma RB (China) is projected to increase by 88% and 48% during 2021-2050 for RCP 4.5 and RCP 8.5, respectively, leading to 237% and 133% respective increments of sediment yields for RCP 4.5 and 8.5 (Zhou et al., 2017).

7.5 Conclusions

This chapter assessed the impact of climate change on streamflow and sediment load simulations in the Kalu River Basin, Sri Lanka. SWAT model simulations for the base period (1991 - 2005), and two future periods: mid-century (2046-2065) and end-century (2081-2099) are presented. For this analysis, required climate data (precipitation and temperatures) to force the SWAT model were obtained from three Regional Climate Models (RCMs), which were corrected for biases using the mean bias correction method.

Model calibration was first undertaken with a SWAT model forced with observed precipitation and temperature data over the 1991-2000 period, achieving a reasonable agreement between the limited available annual observed sediment loads and modelled sediment loads at the basin outlet. SWAT model simulations forced with the bias-corrected RCM data (precipitation, and maximum and minimum temperatures) projected the streamflow and sediment load to an acceptable level (with some over-estimation) for the base period (1991-2005). Uncertainty assessment for the sediment loads computed for the base period shows that different parameter combinations and RCM ensembles may lead to differences in maximum and minimum ranges of predicted sediment loads in each year.

In general, streamflow and sediment load are projected to increase during the Southwest monsoon period compared to other periods (Inter-monsoons and Northeast monsoon). Simulations for RCP 8.5 shows the highest uncertainty in the projected monthly sediment load. The projected changes in sediment load are proportionally higher than the projected changes in streamflow. During the end-century (2081-2099) under RCP 8.5, all simulations project an increase in streamflow and sediment load by 67-87% and 128-145%, respectively.

8

COMPARISON OF DISTRIBUTED MODELLING VS LUMPED MODELLING IN SIMULATING FLUVIAL SEDIMENT SUPPLY TO THE COAST

8.1 Introduction

Fluvial sediment supply is one of the main sources of sediment received by coasts. Sediment transport from catchment to coast is a complex process and is affected by geology, climate, geography and human activities of the basin (Syvitski and Milliman, 2007). Based on the contemporary trend in fluvial sediment supply, Syvitski et al. (2005) indicate that despite the generally increased catchment (basin) erosion, sediment supply to the coast is decreasing. To understand this complex phenomenon of sediment erosion and transport process at the basin scale, several numerical models have been developed. Some of them are Area Relief Temperature sediment delivery model (ART, Syvitski (2003)), BQART model (Syvitski and Milliman, 2007), Annualized Agricultural Non-Point Source Pollution Model (AnnAGNPS, Bingner and Theurer (2001)), SWAT (Neitsch et al., 2011), Limburg

Soil Erosion Model (LISEM, De Roo et al. (1996)), Pan-European Soil Erosion Risk Assessment (PESERA, Kirkby et al. (2008)), SPATIally Distributed Scoring model (SPADS, De Vente et al. (2008)), Pelletier (Pelletier, 2012), WATEM–SEDEM (Rompaey et al., 2001) and WBMsed (Cohen et al., 2013).

As discussed in Section 1.2, the common usage of empirical lumped parameter sediment load in reduced complexity models of coastline change to enable fast computations may however compromise the accuracy of results obtained thereof. This chapter compares the sediment load estimations from a process-based model (i.e., SWAT) applied in a distributed setting (by dividing a basin into sub-basins and further into hydrological response units) and a lumped empirical model (i.e., BQART model) to provide insights on the appropriateness of using the latter in reduced complexity models of long term coastline change. The comparison for the same future conditions considered in Chapters 6 and 7, for the Irrawaddy and Kalu River Basins.

This chapter is structured as follows: Section 8.2 describes the BQART model and compares the two modelling approaches used here (SWAT and BQART). Section 8.3 and Section 8.4 discuss the results obtained from BQART model and present the comparison of the results obtained from the two modelling approaches, under the same conditions, for Irrawaddy and Kalu River Basins, respectively. A discussion on the BQART modelling approach is presented in Section 8.5. Comparison of results for the two case study basins is given in Section 0, with conclusions given in Section 8.7.

8.2 Methods

8.2.1 The BQART model description and input data

Many coastal studies have used the BQART model presented by Syvitski and Milliman (2007) to project annual fluvial sediment supply to the coast (ex. Balthazar et al., 2013; Bamunawala et al., 2020, 2018b, 2018a). BQART was developed using data from 488 global river basins (Syvitski and Milliman, 2007) and it estimates the long-term average annual suspended sediment load using the following equations.

$$Q_s = \omega B Q^{0.31} A^{0.5} R T \quad \text{for } T \geq 2^\circ\text{C} \quad \text{Eq. 8-1}$$

where Q_s is the sediment load in kg/s or MT/yr with $\omega = 0.02$ or 0.0006 respectively, B is the lithology and human impact index, Q is the annual streamflow from the basin (km^3/yr), A is the basin area (km^2), R is the relief of the basin (km), T is mean annual temperature of the basin ($^\circ\text{C}$).

The term ‘B’ accounts for geology and human activities, which is defined as the following;

$$B = IL(1 - T_E)E_h \quad \text{Eq. 8-2}$$

where, I is glacial erosion factor ($I \geq 1$), L is the basin-wide lithology factor, T_E is reservoir trapping efficiency, and E_h is the human-induced erosion factor.

The term I is defined as

$$I = 1 + 0.09A_g \quad \text{Eq. 8-3}$$

where, A_g is the percentage of ice coverage area in the basin.

Currently, the main rivers in the two study areas considered in this thesis are more or less in pristine condition. However, for the future periods, there are a number of planned reservoirs in the Irrawaddy basin, and in Chapter 6, six large planned reservoirs were considered to analyze their impacts on streamflow and sediment transport using the SWAT model. In the SWAT model, each reservoir and its trapping efficiency are represented individually. In BQART model, the trapping efficiency is defined for the entire basin, because it is a lumped model. Therefore, for application in the BQART model, the basin-wide TE from the six reservoirs were estimated using the method proposed by Vörösmarty et al. (2003) (from Eq. 8-4 to Eq. 8-6). Vörösmarty et al. (2003) developed the basin-wide trapping efficiency model for large reservoirs (> 500 MCM) by considering 633 reservoirs data across the world. This basin-wide trapping (TE_{basin}) is derived by considering the geographical locations of the considered reservoirs and the sediment residence time from 236 regulated river basins. Figure 8-1 shows the schematic diagram of a representative basin as considered by Vörösmarty et al. (2003) in this derivation.

Figure 8-1. Vörösmarty et al. (2003)'s representation of a basin for estimating basin-wide sediment trapping for large reservoirs. Source - Vörösmarty et al. (2003).

$$\Delta\tau_{reg,j} = \frac{\sum_1^n V_i}{Q_j} \left(eg. \frac{(V_2+V_3+V_4+V_5)}{Q_B} \right) \quad \text{Eq. 8-4}$$

$$TE_{reg,j} = 1 - \frac{0.05}{\sqrt{\Delta\tau_{reg,j}}} \quad \text{Eq. 8-5}$$

$$TE_{basin} = \frac{\sum_1^m TE_{reg,j} Q_j}{Q_m} \quad Eq. 8-6$$

where, $\Delta\tau_{reg,j}$ is the residence time of reservoir areas of j^{th} regulated sub-basin of the basin (j is A, B, and C here), V_i is the operational volume of i^{th} reservoir in j , Q_j is discharge at regulated sub-basin j , $TE_{reg,j}$ is approximated trapping efficiencies of j^{th} sub-basin, TE_{basin} is the discharge-weighted trapping efficiency of the basin based on discharge, Q_m is discharge at basin outlet, n is number of reservoirs in each regulated sub-basin j , and m is number of regulated sub-basins in the basin

For the Irrawaddy RB, different TE_{basin} values were calculated for each GCM under RCP 2.6 and RCP 8.5 for the two future periods considered: 2046-2065 (mid-century) and 2081-2100 (end-century). As there are no planned reservoirs for the Kalu basin, reservoir effects are not considered in the fluvial sediment load estimations. Furthermore, a zero-trapping efficiency was considered while implementing the BQART model for both river basins to represent only the climate-driven impacts on fluvial sediment supply explicitly. The calculation of TE_{basin} (Eq. 8-6) is based on the volume of reservoirs, discharge from reservoirs and discharge at the basin outlet. The average basin-wide trapping efficiency (TE_{basin}) in Irrawaddy RB computed from Eq. 8-6 is 42% based on three GCMs and two RCPs. Vörösmarty et al. (2003) calculated the basin-wide trapping efficiencies (TE_{basin}) of 236 Basins using 633 large reservoirs, which includes some Asian River Basins such as the Mekong (0-20%), Chao-Pharya (20-40%), Ganges and Brahmaputra (0-20%), Krishna (80- 100%), Yangetz Basin (60-80%), and Indus (40-60%). The number of large reservoirs within each of these basins vary from 3 to 20. Furthermore, large reservoirs (633) and small reservoirs ($> 40,000$) in the world contribute 30% and 23% of sediment trapping, respectively (Vörösmarty et al., 2003). Considering this wide range of computed trapping efficiencies, the above calculated TE_{basin} of the Irrawaddy RB appears to be reasonable.

Table 8-1 summarizes the input parameters of the BQART model. The river discharge (Q) values were obtained from the SWAT simulation results (presented in Chapter 6 and 7) over the base period, and mid- and end-century periods for RCP 2.6 and RCP 8.5. The mean temperature (T) over the basins was obtained from the three selected GCMs/RCMs (discussed in Chapters 6 and 7) for the same RCPs. The human-induced erosion factor (E_h) in Eq. 8-2 is based on land-use, socio-economic situation and population. The suggested optimum range of E_h is $0.3 \leq E_h \leq 2.0$ (Syvitski and Milliman, 2007). In the SWAT simulations for future periods, it is assumed that the prevailing land-use condition will remain invariant throughout the modelling period and the inclusion of planned reservoirs is the only future human activity considered. Thus, for future simulations with the BQART model, human-induced erosion factor (E_h) is assumed to remain constant throughout the 21st century (Table 8-1).

Table 8-1. Summary of model input parameters. * obtained from Syvitski and Milliman (2007). ** indicates the average basin-wide trapping (T_E) for the entire Irrawaddy basin obtained from different GCMs (CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES), RCPs (RCP 2.6 and RCP 8.5) and two periods (2046-2065 and 2081-2100), but this value changes for each case (depending on GCM, RCP and periods considered), *** E_h represents the current condition obtained from Syvitski and Milliman (2007).

Parameter	Irrawaddy Basin	Kalu Basin
Lithology factor (L)*	1.0	0.5
Sediment Trapping (T_E)	0.42**	0
Human-induced erosion factor (E_h) ***	1	2
Area (A in km ²)	371,558	2,787
Relief of the basin (R in km)	5.7	2.25

8.2.2 Comparison of projected sediment load at the basin outlet

The projected sediment loads from two numerical models (SWAT and BQART) were compared based on the mean annual sediment load for the base period (1991-2005) and under both RCPs considered for mid- and end-century periods. For the Kalu River Basin, the SWAT model results from uncertainty analysis were also incorporated for this comparison.

8.3 Irrawaddy River Basin

8.3.1 Annual sediment fluxes to the coast simulated by BQART

The BQART projected sediment loads at the basin outlet under different scenarios are given in Table 8-2. The projected mean annual sediment loads for RCP 8.5 are higher than that of for RCP 2.6 during both periods. By the end of the century under RCP 8.5, sediment supply to the coast is projected to increase by 35% (relative to the base period) when the future changes are only driven by climate change. In comparison, the sediment supply is projected to decrease by 21% due to the combined effect of climate change and reservoirs. The projected sediment load by BQART model varies between 319 and 356 MT/yr and between 326 and 412 MT/yr for mid-century and end-century, respectively under the assumed zero trapping condition (i.e., no reservoirs). These values are projected to reduce to 179-210 MT/yr and 189-247 MT/yr for same two periods, respectively, when the reservoirs are considered (with basin-wide trapping efficiencies). Due to the combined effects of climate change and reservoirs, the average reduction of sediment supply is 41% for both future

periods relative to that due to climate change alone. It is evident that the basin-wide trapping (TE_{basin}) is the main influencing factor (average $T_E = 0.42$, Table 8-1) for this reduction.

Table 8-2. BQART projected mean annual sediment load in Million tons per year at the Irrawaddy basin outlet. Numbers shown in parentheses are the standard deviations of the computed annual sediment loads for each period.

GCM inputs	Base period	RCP 2.6		RCP 8.5	
		Mid-Century	End-Century	Mid-Century	End-Century
Without reservoir trapping (CC only)					
CSIRO Mk3.6	300 (13)	323 (13)	341 (9)	341 (10)	386 (20)
HadGEM2-AO	307 (10)	337 (9)	334 (14)	352 (15)	412 (14)
HadGEM2-ES	290 (9)	319 (12)	326 (7)	356 (14)	409 (15)
With reservoir trapping (CC + Reservoirs)					
CSIRO Mk3.6		181 (8)	194 (5)	198 (6)	228 (12)
HadGEM2-AO		199 (5)	191 (8)	204 (9)	247 (9)
HadGEM2-ES		179 (6)	189 (4)	210 (9)	233 (9)

8.3.2 Comparison of results obtained from SWAT and BQART models for the Irrawaddy basin outlet

The SWAT derived base period and future projections of sediment loads at the Irrawaddy RB outlet are consistently higher than that obtained from BQART model for all three GCMs considered (Figure 8-2). For the base period (1991-2005), simulated mean sediment loads from SWAT and BQART are 365-388 MT/yr and 290-307 MT/yr, respectively. BQART predictions for the base period is 20% (on average) lower compared to SWAT predictions. Syvitski and Milliman (2007) have calculated 30-year average sediment yield in the Irrawaddy RB as 258.6 MT/yr with different input parameters (e.g., $A = 405,963 \text{ km}^2$, $R = 4.8 \text{ km}$ and $T = 22 \text{ }^\circ\text{C}$), which is not too different from the BQART results obtained here, considering the level of aggregation in the model. During the end-century period, on average, BQART projections are 27% (25%) and 56% (55%) lower compared to SWAT projections under RCP 2.6 (RCP 8.5) without and with reservoirs, respectively. Due to the six planned reservoirs in the Irrawaddy RB, the average sediment load at its outlet is projected to decrease by 4.7 % (RCP 2.6) and 2.1 % (RCP 8.5) by the SWAT simulations

for the period 2081-2100, while under the same conditions, BQART projects decrease of 42.7% and 41.3% for RCP 2.6 and RCP 8.5, respectively.

In general, the BQART model projections show smaller increments with climate change only and higher reduction of sediment loads when reservoirs are considered (compared to the base period model estimations) compared to the corresponding SWAT derived projections, with the exception for the SWAT simulation driven by CISRO Mk3.6 (Figure 8-3). On average, with climate change alone, SWAT and BQART model projections indicate increases of sediment load by 22% and 12% under RCP 2.6, respectively during the end-century period, while under RCP 8.5, SWAT and BQART project 47% and 35% increment of sediment loads, respectively. In contrast, with planned reservoirs, BQART model projects sediment load reductions of 36% and 21% during end-century period for RCP 2.6 and RCP 8.5, respectively, while SWAT projections indicate increases of sediment loads by 16% and 44% under the same two RCPs respectively (compared to the base period model estimates). Such directional changes in the projections obtained from the two different models are a cause for concern.

There could be several reasons for these large mismatches between the two models. The BQART model uses the mean annual streamflow, and so does not differentiate the inter-annual variability in sediment load. The SWAT model, on the other hand, runs at a daily time step, thus accounts for both high and low flows conditions. SWAT simulations provide the total sediment load at the basin outlet for a given year based on the sediment erosion within the basin and sediment routing through the river reaches (Section 6.2.3). On the other hand, BQART computes the sediment load as a linear function of the basin temperature. Furthermore, the mean annual temperatures used in BQART are not bias-corrected and these raw GCM temperatures may underestimate the basin-wide temperature as discussed in Section 6.3.1. All these factors may have contributed to the lower sediment load estimates given by the BQART. A large difference (up to 53% different) in sediment load projections obtained from the two models can be seen in simulations that account for planned reservoirs. This is likely due to the estimated basin-wide trapping efficiency used in the BQART model as opposed to reservoir specific TEs used in SWAT. Based on the calculated basin-wide trapping efficiency (Section 8.2.1), approximately 42% of the sediment load is expected to be trapped by the reservoirs. At present, there is no data available to verify this value for the Irrawaddy basin.

Figure 8-2. Comparison of the mean annual sediment projections (Millions Tons (MT)) at the Irrawaddy basin outlet obtained from SWAT and BQART models. Panel 1 and Panel 2 show the estimates of sediment loads for the base period (1991-2005) and two future periods (2046-2065 and 2081-2100) under two RCPs (RCP 2.6 and 8.5), respectively. The shaded area in Panel 2 represents the results under CC + Reservoirs scenario.

Figure 8-3. Comparison of the relative changes in mean annual sediment projections for future periods (2046-2065 and 2081-2100) compared to the base period model estimates at the Irrawaddy basin outlet using SWAT and BQART models. The shaded area in each plot represents results under CC + Reservoirs scenario. The positive changes (+ %) mean that sediment load is projected to increase in the future compared to base period, while negative changes (- %) mean that sediment load is projected to decrease.

8.4 Kalu River Basin

8.4.1 Annual sediment fluxes to the coast simulated by BQART

The BQART projected sediment load at the Kalu basin outlet is shown in Table 8-3. Similar to the Irrawaddy RB, projected mean annual sediment load for RCP 8.5 is higher than that for RCP 2.6 during both periods considered, except MIROC5 associated simulations under RCP 8.5 in mid-century. By the end of the century, sediment supply to the coast is projected to increase by 5% and 32% (relative to the base period) under RCP 2.6 and RCP 8.5, respectively under climate change (i.e., no reservoirs). The projected sediment load by BQART model varies between 2.81 and 3.06 MT/yr and between 2.83 and 3.66 MT/yr for mid-century and end-century, respectively under the assumed zero trapping condition (i.e., no reservoirs).

Table 8-3. BQART projected mean annual sediment load in million tons per year (MT/yr) at the Kalu basin outlet under zero trapping condition (i.e., no reservoirs). Numbers shown in parentheses are the standard deviations of the computed annual sediment loads for each period.

RegCM4 RCM inputs	Base period	RCP 2.6		RCP 8.5	
		Mid-Century	End-Century	Mid-Century	End-Century
MIROC5	2.73 (0.18)	2.92 (0.19)	2.90 (0.21)	3.04 (0.31)	3.54 (0.45)
MPI-ESM-MR	2.72 (0.24)	2.81 (0.22)	2.89 (0.25)	3.06 (0.30)	3.66 (0.49)
NCC-NORES1-M	2.75 (0.19)	2.81 (0.21)	2.83 (0.28)	2.94 (0.30)	3.65 (0.40)

8.4.2 Comparison of model results obtained from SWAT and BQART for the Kalu River Basin

A comparison of the above BQART results with results obtained under the same conditions using SWAT is shown in Figure 8-4. Clearly, the BQART projections of sediment load at the outlet are up to an order of magnitude larger than that of SWAT simulations. For the base period, SWAT and BQART respectively models simulate 0.63-0.66 MT/yr and 2.72-2.75 MT/yr of sediment load with the inputs from 3 RegCM4 RCMs. During the end-century period, on average, BQART projections are 258% and 129% higher compared to SWAT under RCP 2.6 and RCP 8.5, respectively.

In general, SWAT shows higher increments (relative to the base period model estimates) of sediment loads under both RCPs for both periods (Figure 8-5). For example, SWAT and BQART project the increase of sediment load by 25% and 5% (average of 3 RCMs) under RCP 2.6, respectively during the end-century period. For RCP 8.5, the SWAT and BQART projected increases (compared to the base period model estimates) are 145% and 32%, respectively. The lower BQART projected change in sediment load relative to the base period is likely due to its low sensitivity to streamflow, which is projected to increase by 67% - 87% under RCP 8.5 by the end of the century. Such large increases in streamflow will, however, have significant implications on increasing the SWAT projected sediment loads.

One explanation for the large differences between the sediment load projected by the two models could be the use of the aggregated quantity human-induced erosion factor E_h in BQART. This factor is based on countrywide GNP/ capita, and hence using the value for all of Sri Lanka, following Syvitski and Milliman (2007), a E_h value of 2 was used in the calculations for the Kalu River Basin. However, as the Kalu River Basin contains large areas with low-income communities, this value should, in fact, be different for the Kalu RB.

Figure 8-4. Comparison of the mean annual sediment projections (Million tons (MT)) at the Kalu basin outlet obtained from SWAT and BQART models. Panel 1 and 2 show the estimated sediment loads for the base period (1991-2005) and two future periods (2046-2065 and 2081-2099) under two RCPs (RCP 2.6 and RCP 8.5), respectively. Simulations were carried out with the three different RCMs presented along the X-axis. The uncertainty band in each color represents the range of results from SWAT simulations. The black color bar presents the average annual load with respect to calibrated parameters of SWAT. “●” shows the BQART results associated with each RCM.

Figure 8-5. Comparison of the relative changes of mean annual sediment projections for future periods (2046-2065 and 2081-2099) compared to the base period model estimates at the Kalu basin outlet using SWAT and BQART models. The three RegCM4 RCMs used are presented along the X-axis. The uncertainty band in each color represents the range of results from SWAT simulations. The black color bar presents the percentage change for simulation with calibrated parameters of SWAT. “●” shows the BQART results associated with each RCM. The positive changes (+ %) mean that sediment load is projected to increase in the future compared to the base period, while negative changes (- %) mean that sediment load is projected to decrease.

8.5 BQART projections with updated E_h values

The parameter ‘B’ in the BQART model represents the geology and human activities in the basin. The human-induced erosion factor (E_h) is one of the main influencing factors, for B, and is linearly correlated with B, and consequently with the fluvial sediment load computed by the BQART model. Syvitski and Milliman (2007) have derived the E_h factor based on land-use, socio-economic situation and population. However, recent studies by Balthazar et al., (2013) and Bamunawala et al. (2020, 2018a, 2018b) have shown that the human footprint index (HFPI) presented by Wildlife Conservation Society-WCS and Center for International Earth Science Information Network-CIESIN-Columbia University (2005) can be a better representation of the anthropogenic influences on fluvial sediment load estimation via the BQART model. The HFPI was developed based on several global datasets; population,

urban areas, land-use, navigable waterways, roads, electrical infrastructure (Sanderson et al., 2002).

As a further test of the SWAT and BQART projected fluvial sediment loads, here the BQART projections were re-calculated using HFPI and re-compared with the corresponding SWAT projections. To do this, HFPI values, which range from 0 to 100 need to be rescaled to the global range of E_h ($0.3 \leq E_h \leq 2.0$) estimated by Syvitski and Milliman (2007) for use in BQART. HFPI values across the Irrawaddy and Kalu River Basins were obtained from $0.25^\circ \times 0.25^\circ$ resolution data (Wildlife Conservation Society-WCS and Center for International Earth Science Information Network-CIESIN-Columbia University, 2005) and rescaled. Subsequently, the basin average rescaled HFPI value was used with BQART to re-compute the fluvial sediment load at the outlets of the two basins. The comparison of projected sediment loads from SWAT and BQART (with the two E_h factors; one derived from HFPI and one following Syvitski and Milliman (2007)) with climate change only (i.e., no reservoirs) is shown in Table 8-4. With the HFPI based E_h , BQART projects lower sediment loads in both basins compared to previous BQART estimations. This is because the HFPI based human-induced erosion factors (E_h) for the two basin areas are almost half of the E_h values that were derived according to Syvitski and Milliman (2007) (Table 8-1).

Table 8-4. Projected average annual sediment loads in Million tons per year (MT/yr) for the Irrawaddy and Kalu basins under RCP 2.6 and RCP 8.5, without reservoirs. A: Estimated load from SWAT simulations (shaded values), B: Estimated load from BQART model with human-induced erosion factor: $E_h = 1$ for the Irrawaddy Basin and $E_h = 2$ for the Kalu Basin obtained from Figure 7 in Syvitski and Milliman, (2007), and C: Estimated load from BQART model with human-induced erosion factor $E_h = 0.64$ for the Irrawaddy Basin and $E_h = 0.93$ for the Kalu Basin obtained from Human Foot Print Index published by (Wildlife Conservation Society-WCS and Center for International Earth Science Information Network - CIESIN - Columbia University, 2005). SWAT model results for both basins are from simulations with the calibrated parameter set presented in Chapters 6 and 7.

GCM/RCM inputs	RCP	Mid-Century			End-Century		
		A	B	C	A	B	C
Irrawaddy River Basin							
CSIRO Mk3.6	RCP 2.6	370	323	207	443	341	218
	RCP 8.5	386	341	218	454	386	247
HadGEM2-AO	RCP 2.6	483	337	215	461	334	214
	RCP 8.5	455	352	225	618	412	264
HadGEM2-ES	RCP 2.6	397	319	204	458	326	209
	RCP 8.5	495	356	228	572	409	262
Kalu River Basin							
MIROC5	RCP 2.6	0.76	2.92	1.36	0.76	2.90	1.35
	RCP 8.5	0.88	3.04	1.41	1.45	3.54	1.65
MPI-ESM-MR	RCP 2.6	0.77	2.81	1.31	0.87	2.89	1.35
	RCP 8.5	0.97	3.06	1.42	1.69	3.66	1.70
NORESM1-M	RCP 2.6	0.71	2.81	1.31	0.79	2.83	1.32
	RCP 8.5	0.80	2.94	1.37	1.61	3.65	1.70

8.6 Comparison of modelled results in the two basins

The sediment load projections by SWAT and BQART models are different in the two river basins. In Irrawaddy RB, SWAT simulations project higher sediment load than the BQART model and vice versa in the Kalu RB. For example, according to human-induced erosion factor (E_h) obtained from Syvitski and Milliman (2007), BQART underestimates the SWAT projected sediment load by 20% in the Irrawaddy RB and over-predicts that in the Kalu RB by 325% for the base period (1991-2005). During the end-century period under RCP 8.5, BQART model underestimates the SWAT projected sediment load by 25% in the Irrawaddy RB and overestimates by 129% in the Kalu RB. During the same period and under the same RCP, the amount of projected sediment supply is further reduced in the Irrawaddy RB due to proposed reservoirs, where the BQART underestimates the SWAT projected sediment load by 55%. Compared to the base period (1991-2005) model estimations, in general, BQART projections show lower increment than SWAT projected increments in the Irrawaddy and Kalu River Basins without reservoirs (i.e., climate change only).

When adopting the human-induced erosion factor (E_h) derived from the human foot print index, BQART underestimates the SWAT projected sediment load by 48% in the Irrawaddy RB and over-predicts that in the Kalu RB by 97% for the base period (1991-2005). During the end-century period under RCP 8.5, BQART underestimates the SWAT projected sediment load by 71% in the Irrawaddy RB and overestimates by 7% in the Kalu RB. These results indicate that using the HFPI based E_h increases the under predictions by BQART in the Irrawaddy basin, but decreases the over-predictions in the Kalu basin.

The BQART model does not provide the information on sediment erosion, transport, and deposition in the flood plains, as it only estimates sediment delivery rate at river station at/near sea level (Syvitski and Milliman, 2007). The BQART empirical equation was developed based on 488 global river dataset having a broad span of basin size (160 km² – 5,853,804 km²) with high accuracy in calibration ($R^2 = 0.96$ for 292 basins) and validation ($R^2 = 0.94$ for 196 basins) (Syvitski and Milliman, 2007). However, a recent analysis by De Vente et al. (2013) summarized that non-linear regression models like BQART might provide more accurate results than what distributed models such as SWAT would for sediment yield in basins larger than 10,000 km². Nevertheless, a study of the Blue Nile and Atbara river systems showed that BQART is not well suited for capturing highly spatially varied sediment yields ranging thousands of ton/km²/year (Balthazar et al., 2013). Spatially distributed models demand more input data and high calibration efforts as well. However, the SWAT model (categorized as a process-based model) is more suitable for assessing environmental change scenarios such as changes in climate, land-use and management practices (Neitsch et al., 2011). On the other hand, lumped empirical models such as BQART are more suitable for assessing sediment yield in large basins (De Vente et al., 2013). Therefore, both models have their own advantages and disadvantages in sediment load estimation for a selected region under different environmental conditions.

8.7 Concluding remarks

This chapter aimed to evaluate the estimation of fluvial sediment supply to the coasts using a distributed process-based model (SWAT) and an empirical lumped model (BQART) in the Irrawaddy and Kalu River Basins. Similar to the SWAT model simulations described in Chapters 6 and 7, the BQART model simulations were undertaken with and without reservoirs over the two future periods considered (i.e., 2046-2065 and 2081-2100) for the RCP 2.6 and 8.5.

Results show very significant differences between the sediment loads projected by the two models in the two basins. In the Irrawaddy River Basin, SWAT simulations project higher sediment loads than the BQART model with the three selected GCMs. In contrast, SWAT simulations project lower sediment loads than BQART in the Kalu River Basin with the three RCMs. Compared to the base period (1991-2005) model estimates, the BQART shows lower increment than SWAT increments in both Irrawaddy and Kalu River Basins with climate change alone (i.e., no reservoirs). Based on these estimations of sediment load by BQART in two basins, it can be concluded that BQART model projections are more in line with SWAT derived projections at the large Irrawaddy RB than at the small Kalu RB.

In the SWAT simulations, computed changes in sediment load follow a similar trend as streamflow and in general, percentage changes in sediment load are always greater than the percentage changes in streamflow. Changes in streamflow do not result in similar proportional changes in sediment yield in the BQART model, because of the power function of streamflow and sediment load ($Q_s \propto Q^{0.31}$). Within the BQART model, the impact of reservoirs on sediment loads is introduced as a basin-wide trapping efficiency (TE_{basin}). Computation of this TE_{basin} accounts for reservoir locations within the basin and their volumes, and the discharge of the respective sub-basin outlets (Section 8.2.1; Eq. 8-4 to Eq. 8-6). The percentage sediment reduction in the BQART model is directly proportionate to the trapping efficiency factor adopted because it does not account for eroded or deposited sediment loads along river canals and floodplains. In contrast, the SWAT uses different trapping efficiency for each reservoir, which can be calculated separately for each of the reservoirs in the basin. The sediment generation and routing processes are also simulated downstream of the reservoir(s) by SWAT. Therefore, in general, trapping efficiency is more sensitive for fluvial sediment load estimates computed by BQART compared to those computed by SWAT.

Both SWAT and BQART model projections possess uncertainties due to the inherent uncertainties in projected future climatic inputs (precipitation and temperature) and other variables such as human-induced erosion factor, and model calibration parameters. An aggregated global model such as BQART does not always guarantee equally good results in all regions, as it is not explicitly calibrated specifically for individual study regions. SWAT model, as a standard practice, is calibrated to the specific basin, thus, the quality of SWAT model results also depend on quality/ quantity of data available for calibration. On

the other hand, reservoir simulation in the SWAT model requires detailed information on reservoirs such as operational capacity, high flood level, operation practices, and sediment data. Some of this information has to be approximated/ assumed due to the lack of actual reservoir design/ operation details. Thus, both model approaches adopt certain approximations, which in turn have implications on the reliability of the projected sediment loads.

9

GENERAL CONCLUSIONS AND RECOMMENDATIONS

9.1 Introduction

The preceding chapters of this dissertation presented a detailed investigation of the how different modelling approaches and input data sources may influence simulating streamflow and sediment fluxes to the coast in data-poor regions, taking into account model calibration, and plausible variations in natural and anthropogenic impacts. In order to achieve this main objective of this research study, a process-based model SWAT is applied at two data-poor case study sites; the large Irrawaddy River Basin in Myanmar and the small Kalu River Basin in Sri Lanka. The relative merits of using a process-based distributed versus lumped empirical models to derive projections of fluvial sediment supply to the coast were also investigated in order to provide insights on the appropriateness of using the latter in reduced complexity models of long-term coastline change. This final chapter presents the general conclusions of the overall study (Section 9.2) and provides suggestions and recommendations for future research on this topic (Section 9.3).

9.2 General conclusions

Hydrological responses of a river basin (i.e., streamflow and sediment fluxes to the coast) under projected climate change and human activities in data-poor regions can be investigated through process-based modelling at different spatial scales. Such modelling approaches, in general, consist of several key steps, which include the selection of suitable input data sources, model calibration and validation for reference base period, and application of the calibrated model to simulate future responses using projected climate model inputs.

Different precipitation products for streamflow simulation

Precipitation is one of the fundamental input variables for hydrological modelling and, hence the quality of precipitation data plays a crucial role in achieving reliable model outputs. In this study, four different precipitation products (i.e., Gauge data with and without interpolation, PERSIANN-CDR, and CHIRPS) were used in a process-based hydrological model: Soil Water Assessment Tool (SWAT) for simulating streamflow. The suitability of these precipitation products for streamflow simulation in data-poor basins was assessed considering their spatial and temporal variability, and model performance, so that best-suited precipitation product at each study site can be determined.

Detailed analysis of the selected precipitation data products indicated that the global precipitation products (PERSIANN-CDR and CHIRPS) yield lower precipitation volumes at both case study river basins (Irrawaddy RB and Kalu RB) compared to the in-situ precipitation data. Such low precipitation estimations were particularly observed during the monsoon season(s) (May to October), in which the PERSIANN-CDR data showed the lowest cumulative estimation. When different precipitation products (gauge data with or without interpolation and global products) are used in the hydrological model to simulate streamflow, simulations with interpolated gauge data outperformed the simulations forced with other precipitation products at most of the gauging stations, in both basins. However, global precipitation products (PERSIANN-CDR and CHIRPS) also produced acceptable performances in streamflow estimation in the larger Irrawaddy Basin. Different precipitation inputs lead to differences in model performances, best-fitted model parameters, and uncertainty in model predictions. Even though the global precipitation products have a bias towards lower precipitations, they can be valuable assets for hydrological applications requiring long data records in data-poor basins. Another potential application of the global data is the development of a merged superior quality product that combines gauged data and one or more global data products.

Hydrological model calibration with ET and streamflow

Here, the use of remote sensing (RS) based hydrological variables for calibrating the SWAT model was investigated. The Global Land Evaporation: the Amsterdam Model actual Evapotranspiration (GLEAM-ET) and available streamflow data were used to examine two methods of model calibration; (i) single variable calibration, and (ii) multi-variable calibration in a selected part of the Irrawaddy River Basin.

Model calibration with multiple-variables (measured streamflow and GLEAM-ET) resulted in good model performance for monthly streamflow ($NSE > 0.85$) and evapotranspiration ($NSE > 0.61$). Single variable calibration with GLEAM-ET indicated that the model could reproduce the streamflow with an NSE value greater than 0.69 at three of the four stations considered within the Irrawaddy River Basin. The only exception was observed at the farthest upstream gauge station, which resulted in NSE value of 0.16. The analysis of calibration parameters suggested that parameter sensitivity and values change among different calibration set-ups, and that the uncertainty ranges of parameters differ among the different parameters and the different stations. Results also showed that different sets of parameter values could produce similar results. In general, the results of this investigation point towards the possibility of using RS based hydrological variables such as evapotranspiration for successful hydrological model calibration, particularly in ungagged basins.

Projections of streamflow and sediment load under climate change and human activities

The impact of climate change and human activities (here represented only by planned reservoirs) on streamflow and sediment load simulation in the two case study river basins were investigated via SWAT model simulations for the base period (1991 - 2005), and two future periods: mid-century (2046-2065) and end-century (2081-2100). Data from 10 GCMs were initially considered and the three most representative GCMs were selected based on the performance of GCM climate variables (precipitation, and minimum and maximum temperatures) and performance of SWAT hydrological simulations forced with GCM data. For Irrawaddy River Basin, the best performing GCMs were CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES. Coarser-resolution GCM data could not capture the seasonal variability of precipitation within the small Kalu River Basin, therefore, dynamically downscaled projections of the RCMs (RegCM4/MIROC5, RegCM4/MPI-M-MPI-ESM-MR, and RegCM4/NCC-NORES-M1-M) were used in all computations therein. The GCM/RCM data were corrected for biases and used to force a series of SWAT models. For the Irrawaddy RB, the SWAT model was set up for sediment and reservoir simulation, taking into account six planned reservoirs in the basin. Model simulations were undertaken with only climate change forcing (RCP 2.6 and RCP 8.5) and with climate change forcing together with planned reservoirs. There are no documented planned reservoirs for the Kalu

RB, and hence all simulations were undertaken with climate change forcing only (RCP 2.6 and RCP 8.5).

The computed sediment yields at two case study basins (22 t/ha/yr in the Irrawaddy RB, 59 t/ha/yr in the Kalu RB) are larger than the global average value (15 t/ha/yr in the globe).

The projected precipitation data of GCMs/ RCMs show higher variability among the models than projected temperature values. Thus, consistency among GCMs or RCMs projections was not observed in both basins. These variabilities in key climatic inputs (precipitation and temperature), in turn, resulted in hydrological projections with significant uncertainties. Applying a bias correction does not always guarantee a good model performance in the entire basin, and it does not consider the non-stationarity of future climatic variables. In general, when compared with the base period (1991-2005), the Irrawaddy and Kalu River Basins will be warmer and wetter by the end of the 21st century. Consequently, future streamflow and sediment fluxes to the coast are projected to increase in both basins by the end of the 21st century under both RCPs considered (RCP 2.6 and RCP 8.5). However, the simulated results forced with different GCMs/RCMs climate projections show a difference in the projections for the mid- and end-century periods (2046-2065 and 2081-2100). Further, the projected proportional changes in sediment loads are more significant than that with respect to streamflow.

The combined effect of changes in climate conditions and human activities (i.e., reservoir constructions) has considerable impacts on the hydrological responses in the Irrawaddy River Basin. Compared to the model projections without reservoirs, seasonal variations (monsoon and non-monsoon) of sediment fluxes and streamflow to the coast with reservoirs are projected to be considerably higher. Reservoir operational rules adopted in this study have remarkable effects on its projected streamflow and sediment loads. Apart from uncertainties due to the model inputs (i.e., projected climatic data), assumptions made regarding reservoir operation may add to the uncertainty in the streamflow and sediment load projections.

Comparison of distributed model vs lumped model for determining fluvial sediment supply to the coast

The use of a process-based distributed model and an empirical lumped parameter model to assess fluvial sediment supply from river basins to the coast was analyzed by comparing sediment loads estimated from SWAT and BQART models.

SWAT projections of sediment loads were higher than that of the BQART in the Irrawaddy River Basin and vice versa in the Kalu River Basin. However, compared to the base period model estimates, BQART projections show lower increments in sediment load projections than SWAT increments in both Irrawaddy and Kalu Basins under the influence of climate change. The BQART model results largely depend on accurate representation of anthropogenic activities (human-induced erosion factor and reservoir trapping efficiency)

and average temperature as they have a linear relationship with the computed sediment load. When reservoirs are included, sediment projections for Irrawaddy RB from these two models show higher inter-model differences (55%) than without reservoir condition (25%) (for RCP 8.5, by the end-century period). The BQART model requires a single estimate of basin-wide relative reservoir-trapping efficiency, which depends on reservoir storage, reservoir outflow and flows at the basin outlet. Therefore, the estimation of a representative basin-wide relative trapping efficiency is crucial for BQART model applications that accounts for reservoir impacts.

Projections obtained from both models contain uncertainties due to the inherent uncertainties in projected future climatic inputs (precipitation and temperature) and other variables such as human-induced erosion factor, and model calibration parameters. An aggregated global model such as BQART does not always guarantee equally good results in all regions, as it is not explicitly calibrated for individual study regions. As a standard practice, SWAT model is calibrated to the specific basin, and the quality of model results also depend on the quality/ quality of data available for calibration. On the other hand, reservoir simulation in the SWAT model requires detailed information on reservoir geometry, operation, and sediment data, some of which may have to be approximated/ assumed due to the lack of data.

9.3 Implications and future directions

Global precipitation products can be used as additional data sets that cover more prolonged periods than some of the in-situ measurements. Hence, they can be used to determine the hydrological responses of a river basin. This study analyzed only two global precipitation products over two river basins. Therefore, other freely available precipitation products (e.g., MSWEP, TMPA 3B42 V7, and CMORPH-CRT V1, Beck et al. (2017)) can be examined for these study locations. Apart from GLEAM ET, other global remote-sensing based data products may be further explored and analyzed for their appropriateness in hydrological model calibration. Such global datasets include remote-sensing based evapotranspiration products such as MODIS16 (Running et al., 2017), soil moisture content such as ESA CCI (Dorigo et al., 2017) and AMSR-E (Njoku et al., 2003). Integration of those RS based data and in-situ streamflow observations may be further investigated for better simulation of hydrological responses of the study areas.

Use of actual reservoir data/ details (e.g., reservoir storage capacity, full supply level, spillway capacity, and reservoir operational data) would improve the estimation of future changes in streamflow and sediment fluxes. Furthermore, the currently available reservoir simulation methods in SWAT is not fully capable of representing complex dynamics of sediment and flow controls. A detailed analysis may be carried out by integrating SWAT with models dedicated to reservoir operation to assess the effect of plausible water allocation and reservoir operation scenarios.

Land-use change is a common phenomenon in many parts of the world. Due to increased demands of the growing population (e.g., food, water and houses), adverse effects from land-use changes are inevitable. Streamflow and sediment yield are highly dependent on the land-use pattern within the basin. However, this study did not consider the effects of land-use changes, assumed it to be invariant in all future simulation periods. Dynamical land-use modelling approaches such as Conversion of Land-Use Change and its Effects at Small Regional Extent (CLUE-S, Verburg et al. (2002)) may be used to project the land-use in future periods. The combined effects of climate change, land-use and reservoirs can be analyzed for better projections of streamflow and fluvial sediment quantity from the river basins.

In this study, SWAT and BQART model applications projected widely different results at two spatially heterogeneous river basins. Therefore, to gain more insights on the relative merits of computing fluvial sediment supply to the coast using process-based distributed vs lumped models, more such comparisons are recommended for different sizes of basins located in different climatic zones around the world.

There are two main sources of uncertainties associated with the model estimations/projections: model uncertainties (i.e., model structure and model parameters) and input uncertainties (i.e., model input data). In this study, in the case of SWAT model, the model parameter sensitivity and predictive uncertainty are assessed using a commonly used tool: SUFI-2 (Sequential Uncertainty Fitting, Abbaspour (2015)). These results are discussed in Chapter 4 and 5, when the SWAT model was calibrated with various precipitation inputs and with the remote sensing-based evapotranspiration. When the hydrological model (in this case SWAT) is run with multiple precipitation datasets (model inputs), the ensemble of model realizations with respect to these input datasets can be interpreted as input uncertainty. However, in this study, the motivation was more to evaluate these precipitation products for streamflow simulation, comparing against available measurements, than to use them as ensemble inputs. In the case of future projections under climate change, the climate projection data from different global circulation models serve as multiple inputs (ensembles) of precipitation and temperature to the SWAT and BQART models and also constitute a major source of uncertainty, which is illustrated by the differences in model results with respect to these different inputs (Chapter 6, 7, and 8). In the future projections, because the hydrological model cannot be calibrated for the future periods, the same model calibrated for the base period is used but the projection results are presented in terms of the relative change (from the base period values). A more comprehensive assessment of uncertainty in the projections could be carried out, which is recommended for future studies, in the Monte Carlo framework (e.g., recent study by Bamunawala et al. (2020)) incorporating both model and input uncertainties.

ANNEXES

Annex A

A.1 Hydrological parameters used for model calibration

Parameter	Description	Scale	Default	Initial Range
a__CN2.mgt	SCS curve number, AMC (II)	HRU	HRU Specific	-10 - 9
v__GWQMN.gw	Threshold groundwater depth for return flow to occur (mm)	Basin	1000	0 - 5000
v__GW_DELAY.gw	Groundwater delay time (days)	Basin	31	0 - 500
v__ALPHA_BF.gw	Base flow Alpha Factor (days)	Basin	0.048	0 - 1
v__GW_REVAP.gw	Groundwater "revap" coefficient	HRU	0.02	0.02 - 0.2
v__REVAPMN.gw	Threshold water depth in shallow aquifer for "revap" or percolation to occur (mm)	HRU	750	0 - 1000
v__SHALLST.gw	Initial depth of water in the shallow aquifer (mm H ₂ O)	Basin	1000	0 - 5000
v__RCHRG_DP.gw	Deep aquifer percolation fraction	Basin	0.05	0 - 1
v__CH_N2.rte	Manning's coefficient for main channel	Basin	0.014	0.01 - 0.3
v__ALPHA_BNK.rte	Base flow Alpha Factor for bank storage (days)	Basin	0	0 - 1
a__SOL_AWC().sol	Available water capacity of a soil layer (mm H ₂ O / mm Soil)	HRU	Soil specific	0 - 0.8
a__SOL_Z().sol	Depth from soil surface to bottom of layer (mm)	HRU	Soil layer specific	0 - 3000
a__SOL_BD().sol	Moist bulk density of soil layer (Mg/m ³ or g/cm ³)	HRU	Soil specific	0 - 0.8
a__SOL_K().sol	Saturated soil conductivity of layer (mm/hr)	HRU	Soil specific	0 - 200
v__ESCO.hru	Soil evaporation compensation factor	HRU	0.95	0 - 1
v__SURLAG.hru	Surface runoff lag coefficient	HRU	2	0 - 24
v__EPCO.hru	Plant uptake compensation factor	HRU	1	0 - 1
v__SLSUBBSN.hru	Average slope length (m)	HRU	HRU Specific	10 - 120
v__LAT_TTIME.hru	Lateral flow travel time (days)	HRU	0	0 - 180

Parameter	Description	Scale	Default	Initial Range
v__CANMX.hru	Maximum canopy storage (mm)	Basin	0	0 - 10
v__SLSOIL.hru	Slope length for lateral subsurface flow (m)	HRU	0	0 - 150
v__CH_K2.rte	Hydraulic conductivity of main channel (mm/h)	Basin	0	0 - 100

Note: *a* means ‘value added’, *v* means ‘a replacement’ and *r* means ‘relative change’ to existing initial parameter values.

A.2 NSE of the best simulation in each iteration performed at each station

Note: The scales of two axis in each plot are not identical

Annex B

B.1 Gridded average annual minimum temperature from ten different GCMs over the Irrawaddy River Basin from 1991 to 2005

B.2 Gridded average annual maximum temperature from ten different GCMs over the Irrawaddy River Basin from 1991 to 2005

B.3 Statistical performance of with and without bias-correction of precipitation data at each sub-basin

Sub-basin	Without bias correction			With Bias correction		
	CSIRO-Mk3.6	HadGEM2-AO	HadGEM2-ES	CSIRO-Mk3.6	HadGEM2-AO	HadGEM2-ES
NSE						
Sub_1	0.50	0.50	0.59	0.78	0.77	0.81
Sub_2	0.56	0.51	0.50	0.8	0.82	0.84
Sub_3	0.59	0.41	0.37	0.8	0.86	0.87
Sub_4	0.62	0.54	0.70	0.64	0.71	0.75
Sub_5	0.67	0.53	0.74	0.68	0.74	0.79
Sub_6	0.65	0.53	0.73	0.65	0.73	0.77
Sub_7	0.62	0.44	0.58	0.69	0.69	0.76
Sub_8	0.67	0.33	0.62	0.66	0.68	0.74
Sub_9	0.66	0.35	0.72	0.64	0.72	0.76
Sub_10	0.67	0.37	0.75	0.66	0.73	0.78
Sub_11	0.52	0.62	0.69	0.55	0.66	0.68
Sub_12	0.38	0.32	0.48	0.03	0.35	0.46
Sub_13	0.67	0.30	0.74	0.66	0.73	0.77
Sub_14	0.54	0.58	0.72	0.43	0.66	0.70
Sub_15	0.44	0.27	0.50	0.26	0.32	0.55
Sub_16	0.22	0.09	0.40	0.18	0.28	0.48
Sub_17	0.40	0.24	0.50	0.23	0.32	0.54
Sub_18	-0.18	0.46	0.47	0.33	0.44	0.48
Sub_19	0.10	0.46	0.46	0.17	0.44	0.47
Sub_20	-1.84	0.39	0.47	0.38	0.45	0.54
Sub_21	0.54	0.45	0.64	0.30	0.54	0.62
Sub_22	0.47	0.39	0.61	0.18	0.49	0.58
Sub_23	-2.30	0.32	0.37	0.12	0.34	0.38
Sub_24	-2.64	0.28	0.34	0.08	0.30	0.35
Sub_25	-1.75	0.34	0.38	0.12	0.37	0.39
Sub_26	0.34	0.55	0.63	0.37	0.57	0.63
Sub_27	-0.71	0.39	0.41	0.26	0.40	0.41
Sub_28	-1.18	0.45	0.50	0.4	0.47	0.48
Sub_29	-1.21	0.42	0.46	0.31	0.41	0.42
Sub_30	-0.80	0.42	0.45	0.32	0.45	0.44
Sub_31	-0.85	0.51	0.52	0.52	0.52	0.58
Sub_32	0.59	0.59	0.55	0.60	0.54	0.48

Sub-basin	Without bias correction			With Bias correction		
	CSIRO-Mk3.6	HadGEM2-AO	HadGEM2-ES	CSIRO-Mk3.6	HadGEM2-AO	HadGEM2-ES
R²						
Sub_1	0.64	0.51	0.61	0.80	0.78	0.82
Sub_2	0.68	0.61	0.69	0.81	0.82	0.84
Sub_3	0.68	0.53	0.55	0.81	0.87	0.88
Sub_4	0.65	0.60	0.72	0.68	0.73	0.76
Sub_5	0.71	0.62	0.76	0.72	0.77	0.81
Sub_6	0.67	0.62	0.74	0.70	0.75	0.78
Sub_7	0.71	0.49	0.61	0.73	0.72	0.77
Sub_8	0.70	0.50	0.63	0.71	0.72	0.76
Sub_9	0.68	0.59	0.73	0.68	0.74	0.77
Sub_10	0.70	0.61	0.75	0.71	0.76	0.79
Sub_11	0.61	0.65	0.71	0.62	0.68	0.71
Sub_12	0.48	0.41	0.51	0.36	0.45	0.52
Sub_13	0.70	0.61	0.75	0.71	0.75	0.79
Sub_14	0.61	0.65	0.74	0.58	0.70	0.73
Sub_15	0.57	0.38	0.53	0.51	0.51	0.63
Sub_16	0.49	0.34	0.48	0.47	0.48	0.57
Sub_17	0.57	0.39	0.54	0.51	0.51	0.62
Sub_18	0.60	0.58	0.61	0.54	0.58	0.60
Sub_19	0.51	0.58	0.58	0.48	0.58	0.59
Sub_20	0.55	0.52	0.55	0.55	0.54	0.61
Sub_21	0.63	0.55	0.67	0.53	0.52	0.67
Sub_22	0.61	0.53	0.64	0.48	0.59	0.64
Sub_23	0.48	0.43	0.48	0.44	0.50	0.48
Sub_24	0.44	0.40	0.44	0.42	0.47	0.45
Sub_25	0.51	0.45	0.49	0.45	0.42	0.48
Sub_26	0.59	0.62	0.69	0.56	0.63	0.69
Sub_27	0.61	0.53	0.58	0.52	0.50	0.57
Sub_28	0.61	0.55	0.60	0.57	0.53	0.60
Sub_29	0.60	0.53	0.58	0.54	0.50	0.57
Sub_30	0.62	0.55	0.59	0.54	0.53	0.58
Sub_31	0.64	0.64	0.68	0.62	0.61	0.66
Sub_32	0.64	0.64	0.60	0.63	0.61	0.57

B.4 Statistical performance of with and without bias-correction of maximum temperature data at each station

Stations	Without bias correction			With bias correction		
	CSIRO-Mk3.6	HadGEM2-AO	HadGEM2-ES	CSIRO-Mk3.6	HadGEM2-AO	HadGEM2-ES
NSE						
Putao	-5.59	-6.17	-8.03	0.32	0.48	0.46
Hkamti	-1.95	-4.89	-6.95	0.49	0.61	0.75
Myitkyina	-5.21	-3.87	-4.86	0.25	0.51	0.44
Homalin	-2.51	-5.25	-7.31	0.46	0.50	0.65
Bhamo	-6.0	-2.49	-3.41	0.54	0.67	0.7
Katha	-2.39	-4.68	-6.47	0.42	0.43	0.48
Lashio	-3.98	-1.4	-2.27	0.37	0.5	0.56
Hakha	-15.33	-12.16	-8.54	0.45	0.38	0.38
Monywa	-2.75	-1.94	-3.76	0.83	0.67	0.75
Mandalay	-3.14	-3.14	-4.55	0.66	0.62	0.67
Meiktila	-2.25	-0.74	-2.11	0.81	0.63	0.68
Taunggyi	-1.53	-6.28	-4.9	0.59	0.58	0.5
Minbu	0.13	-0.03	-0.94	0.89	0.82	0.81
Pyay	-1.21	-1.26	-3.52	0.81	0.76	0.74
R ²						
Putao	0.35	0.45	0.42	0.38	0.49	0.47
Hkamti	0.60	0.67	0.66	0.59	0.65	0.75
Myitkyina	0.43	0.49	0.45	0.37	0.53	0.47
Homalin	0.60	0.58	0.56	0.57	0.57	0.66
Bhamo	0.71	0.76	0.76	0.63	0.71	0.72
Katha	0.55	0.60	0.61	0.51	0.52	0.54
Lashio	0.62	0.64	0.64	0.52	0.58	0.60
Hakha	0.56	0.68	0.66	0.54	0.54	0.51
Monywa	0.58	0.68	0.72	0.84	0.70	0.76
Mandalay	0.56	0.70	0.70	0.70	0.67	0.70
Meiktila	0.71	0.56	0.60	0.82	0.67	0.70
Taunggyi	0.61	0.46	0.41	0.67	0.64	0.58
Minbu	0.81	0.67	0.70	0.90	0.83	0.82
Pyay	0.71	0.53	0.51	0.83	0.78	0.76

B.5 Statistical performance of with and without bias-correction of minimum temperature data at each station

Stations	Without bias correction			With bias correction		
	CSIRO-Mk3.6	HadGEM2-AO	HadGEM2-ES	CSIRO-Mk3.6	HadGEM2-AO	HadGEM2-ES
NSE						
Putao	-0.78	-0.67	-0.97	0.88	0.87	0.87
Hkamti	0.36	0.63	0.60	0.95	0.96	0.96
Myitkyina	-0.84	0.40	-0.10	0.94	0.95	0.95
Homalin	0.30	0.76	0.64	0.95	0.96	0.94
Bhamo	-0.81	0.69	0.31	0.94	0.95	0.95
Katha	0.20	0.65	0.32	0.88	0.91	0.91
Lashio	0.84	0.61	0.81	0.95	0.96	0.96
Hakha	-1.93	-2.7	-1.18	0.92	0.92	0.91
Monywa	-0.74	-0.05	-0.8	0.96	0.95	0.95
Mandalay	-0.49	0.05	-0.65	0.91	0.94	0.93
Meiktila	-1.26	-0.29	-1.34	0.94	0.92	0.89
Taunggyi	0.27	-0.79	0.19	0.89	0.9	0.90
Minbu	0.37	0.61	0.02	0.95	0.94	0.92
Pyay	-0.92	-0.26	-0.38	0.90	0.89	0.9
R²						
Putao	0.80	0.82	0.82	0.88	0.87	0.87
Hkamti	0.94	0.93	0.94	0.95	0.96	0.96
Myitkyina	0.94	0.93	0.94	0.94	0.95	0.95
Homalin	0.95	0.93	0.94	0.95	0.96	0.94
Bhamo	0.93	0.92	0.93	0.94	0.95	0.95
Katha	0.88	0.88	0.88	0.88	0.91	0.91
Lashio	0.88	0.80	0.83	0.95	0.96	0.96
Hakha	0.91	0.84	0.88	0.92	0.92	0.91
Monywa	0.92	0.92	0.94	0.96	0.95	0.95
Mandalay	0.91	0.92	0.91	0.92	0.94	0.93
Meiktila	0.87	0.88	0.86	0.94	0.92	0.89
Taunggyi	0.91	0.88	0.91	0.90	0.90	0.90
Minbu	0.87	0.90	0.91	0.95	0.94	0.93
Pyay	0.81	0.86	0.90	0.91	0.89	0.91

B.6 Average monthly precipitation over the Irrawaddy River Basin for future periods under two RCPs with base period values.

B.7 Projected mean annual streamflow and sediment loads at Pyay in the Irrawaddy River Basin

Simulations forced with three GCMs under RCP 2.6 and RCP 8.5 for two future periods (mid-century [2046-2065] and end-century [2081-2100]).

Variable	Time period	RCP 2.6					
		CSIRO Mk3.6		HadGEM2-AO		HadGEM2-ES	
		TE = 50%	TE = 95%	TE = 50%	TE = 95%	TE = 50%	TE = 95%
Streamflow (m ³ /s)	Mid-century	14,223	14,223	17,555	17,555	15,396	15,396
	End-century	16,433	16,433	16,946	16,946	17,100	17,100
Sediment load (Million tons)	Mid-century	273	273	363	363	299	299
	End-century	336	336	348	348	349	349
RCP 8.5							
Streamflow (m ³ /s)	Mid-century	14,647	14,647	16,894	16,894	18,230	18,230
	End-century	16,593	16,593	21,367	21,367	20,294	20,294
Sediment load (Million tons)	Mid-century	285	285	344	344	387	387
	End-century	353	353	494	494	452	452

Annex C

C.1 Gridded average annual temperatures from three RCMs over the Kalu River Basin from 1991 to 2005

Top row presents the minimum temperature and bottom row presents the maximum temperature.

C.2 Statistical performance of with and without bias-correction of precipitation data at each sub-basin

Sub-basins	Without bias correction			With bias correction		
	MIROC5	MPI-ESM-MR	NCC-NORESML-M	MIROC6	MPI-ESM-MR	NCC-NORESML-M
NSE						
Sub-1	-4.97	-7.76	-2.03	-0.38	-0.55	-0.21
Sub-2	-2.84	-2.6	-1.21	-0.05	0	-0.16
Sub-3	-4.81	-7.42	-1.85	-0.25	-0.44	-0.05
Sub-4	-3.8	-3.67	-1.15	0.07	-0.03	0.03
Sub-5	-10.22	-6.55	-1.36	-0.72	-0.69	-0.01
Sub-6	-10.84	-6.88	-1.48	-0.75	-0.74	-0.04
Sub-7	-18.16	-11.73	-3.98	-0.33	-0.38	0
Sub-8	-3.28	-3.2	-0.97	0.06	-0.07	0.03
Sub-9	-19.35	-12.41	-4.26	-0.37	-0.43	-0.02
Sub-10	-19.14	-12.35	-4.17	-0.31	-0.39	0.04
Sub-11	-18.44	-11.81	-4.05	-0.27	-0.28	0.11
Sub-12	-17.76	-11.35	-3.87	-0.27	-0.29	0.11
Sub-13	-11.75	-7.31	-1.62	-0.58	-0.52	0.1
Sub-14	-2.4	-0.69	-1.38	-0.18	0.01	-0.05
Sub-15	-2.9	-0.84	-1.47	-0.07	0.09	-0.01
R ²						
Sub-1	0.14	0.07	0.05	0.12	0.13	0.20
Sub-2	0.00	0.00	0.14	0.23	0.20	0.18
Sub-3	0.15	0.07	0.06	0.17	0.17	0.27
Sub-4	0.09	0.03	0.09	0.24	0.21	0.26
Sub-5	0.01	0.01	0.03	0.09	0.12	0.25
Sub-6	0.00	0.01	0.03	0.10	0.13	0.26
Sub-7	0.01	0.02	0.02	0.14	0.16	0.25
Sub-8	0.09	0.03	0.08	0.22	0.18	0.24
Sub-9	0.01	0.02	0.02	0.14	0.15	0.25
Sub-10	0.01	0.01	0.02	0.15	0.15	0.27
Sub-11	0.00	0.01	0.02	0.15	0.18	0.30
Sub-12	0.00	0.01	0.02	0.15	0.17	0.30
Sub-13	0.00	0.01	0.02	0.12	0.17	0.31
Sub-14	0.00	0.01	0.01	0.19	0.27	0.28
Sub-15	0.00	0.02	0.01	0.22	0.30	0.28

C.3 Statistical performance of with and without bias-correction of maximum and minimum temperature data at each station

Station	Maximum Temperature					
	Without bias correction			With bias correction		
	MIROC5	MPI-ESM-MR	NCC-NORESM1-M	MIROC6	MPI-ESM-MR	NCC-NORESM1-M
	NSE					
Rathnapura	-13.35	-12.49	-9.54	0.66	0.66	0.52
Agalawatta	-16.55	-15.22	-12.15	0.67	0.61	0.43
Bombuwala	-36.2	-32.16	-37.77	0.44	0.54	0.41
R ²						
Rathnapura	0.53	0.45	0.56	0.67	0.68	0.58
Agalawatta	0.63	0.54	0.58	0.68	0.63	0.52
Bombuwala	0.00	0.38	0.00	0.54	0.59	0.51
Minimum Temperature						
NSE						
Rathnapura	-8.52	-8.11	-13.02	0.51	0.53	0.49
Agalawatta	-0.57	-0.07	-1.71	0.40	0.53	0.46
Bombuwala	-1.21	-1.09	-0.63	0.14	0.38	0.36
R ²						
Rathnapura	0.47	0.54	0.23	0.61	0.61	0.59
Agalawatta	0.37	0.53	0.31	0.44	0.54	0.48
Bombuwala	0.14	0.27	0.21	0.18	0.37	0.36

C.4 Average monthly precipitation over the Kalu River Basin for future periods under two RCPs with base period values

REFERENCES

- Abbaspour, K.C., 2015. SWAT-Calibration and uncertainty programs (CUP). <https://doi.org/10.1007/s00402-009-1032-4>
- Abbaspour, K.C., Johnson, C.A., van Genuchten, M.T., 2004. Estimating uncertain flow and transport parameters using a Sequential Uncertainty Fitting procedure, in: *Vadose Zone Journal*. pp. 1340–1352. <https://doi.org/10.2136/vzj2004.1340>
- Abbaspour, K.C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., Kløve, B., 2015. A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. *J. Hydrol.* 524, 733–752. <https://doi.org/10.1016/j.jhydrol.2015.03.027>
- Abbaspour, K.C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., Zobrist, J., Srinivasan, R., 2007. Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. *J. Hydrol.* 333, 413–430. <https://doi.org/10.1016/j.jhydrol.2006.09.014>
- Abbott, M.B., Bathurst, J.C., Cunge, J.A., O’Connell, P.E., Rasmussen, J., 1986. An introduction to the European Hydrological System - Systeme Hydrologique Europeen, “SHE”, 1: History and philosophy of a physically-based, distributed modelling system. *J. Hydrol.* 87, 45–59. [https://doi.org/10.1016/0022-1694\(86\)90114-9](https://doi.org/10.1016/0022-1694(86)90114-9)
- Abera, W., Brocca, L., Rigon, R., 2016. Comparative evaluation of different satellite rainfall estimation products and bias correction in the Upper Blue Nile (UBN) basin. *Atmos. Res.* 178–179, 471–483. <https://doi.org/10.1016/j.atmosres.2016.04.017>
- Adwubi, A., Amegashie, B.K., Agyare, W.A., Tamene, L., Odai, S.N., Quansah, C., Vlek, P., 2009. Assessing sediment inputs to small reservoirs in Upper East Region, Ghana. *Lakes Reserv. Res. Manag.* 14, 279–287. <https://doi.org/10.1111/j.1440-1770.2009.00410.x>
- Agarwal, A., Babel, M.S., Maskey, S., 2014. Analysis of future precipitation in the Koshi river basin, Nepal. *J. Hydrol.* 513, 422–434. <https://doi.org/10.1016/j.jhydrol.2014.03.047>
- Ahmed, M., Suphachalasai, S., 2014. Assessing the Costs of Climate Change and Adaptation in South Asia. Manila, Philippines.
- Akpınara, A., Kömürcüb, M.I., Kankal, M., 2011. Development of hydropower energy in Turkey : The case of Coruh river basin. *Renew. Sustain. energy Rev.* 15, 1201–1209. <https://doi.org/10.1016/j.rser.2010.10.001>
- Andreassian, V., Perrin, C., Michel, C., Sanchez, I.U., Lavabre, J., 2001. Impact of imperfect rainfall knowledge on the efficiency and the parameters of watershed models. *J. Hydrol.* 250, 206–223.
- Anthony, E.J., Brunier, G., Besset, M., Goichot, M., 2015. Linking rapid erosion of the Mekong River delta to human activities. *Sci. Rep. Nat. Publ. Gr.* 5, 1–12. <https://doi.org/10.1038/srep14745>
- Arino, O., Perez, J.R., Kalogirou, V., Defourny, P., Achard, F., 2010. Globcover 2009, in: *ESA Living Planet Symposium*. Bergen, Norway.

- Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling and assesment Part I: Model development. *JAWRA J. Am. Water Resour. Assoc.* 34, 73–89. <https://doi.org/10.1111/j.1752-1688.1998.tb05961.x>
- Ashouri, H., Hsu, K.L., Sorooshian, S., Braithwaite, D.K., Knapp, K.R., Cecil, L.D., Nelson, B.R., Prat, O.P., 2015. PERSIANN-CDR: Daily precipitation climate data record from multisatellite observations for hydrological and climate studies. *Bull. Am. Meteorol. Soc.* 96, 69–83. <https://doi.org/10.1175/BAMS-D-13-00068.1>
- Ashouri, H., Nguyen, P., Thorstensen, A., Hsu, K.-L., Sorooshian, S., Braithwaite, D., 2016. Assessing the efficacy of high-resolution satellite-based PERSIANN-CDR precipitation product in simulating streamflow. *J. Hydrometeorol.* 17, 2061–2076. <https://doi.org/10.1175/JHM-D-15-0192.1>
- Aung, M.T., Shrestha, S., Weesakul, S., Shrestha, P.K., 2016. Multi-model Climate Change Projections for Belu River Basin , Myanmar under Representative Concentration Pathways. *J Earth Sci Clim Chang.* 7, 0–13. <https://doi.org/10.4172/2157-7617.1000323>
- Azim, F., Shakir, A.S., Habib-ur-Rehman, Kanwal, A., 2016. Impact of climate change on sediment yield for Naran watershed, Pakistan. *Int. J. Sediment Res.* 31, 212–219. <https://doi.org/10.1016/j.ijsrc.2015.08.002>
- Balthazar, V., Vanacker, V., Girma, A., Poesen, J., Golla, S., 2013. Human impact on sediment fluxes within the Blue Nile and Atbara River basins. *Geomorphology* 180–181, 231–241. <https://doi.org/10.1016/j.geomorph.2012.10.013>
- Bamunawala, J., Dastgheib, A., Ranasinghe, R., Spek, A. van der, Maskey, S., Duong, T.M., Murray, A.B., Barnard, P.L., Sirisena, T.A.J.G., 2020a. A holistic, reduced-complexity modelling approach to project the evolution of inlet-interrupted coastlines over the 21st century. *Front. Mar. Sci.* 7:542, 1–20. <https://doi.org/10.3389/fmars.2020.00542>
- Bamunawala, J., Dastgheib, A., Ranasinghe, R., Spek, A. Van Der, Murray, A.B., Barnard, P.L., Duong, T.M., Sirisena, T.A.J.G., 2020b. Probabilistic application of an integrated catchment-estuary-coastal system model to assess the evolution of inlet-interrupted coasts over the 21 st century. *Front. Mar. Sci.* Under Revi, 1–30.
- Bamunawala, J., Maskey, S., Duong, T., van der Spek, A., 2018a. Significance of Fluvial Sediment Supply in Coastline Modelling at Tidal Inlets. *J. Mar. Sci. Eng.* 6, 1–12. <https://doi.org/10.3390/jmse6030079>
- Bamunawala, J., Ranasinghe, R., van der Spek, A., Maskey, S., Udo, K., 2018b. Assessing Future Coastline Change in the Vicinity of Tidal Inlets via Reduced Complexity Modelling. *J. Coast. Res.* 85, 636–640. <https://doi.org/10.2112/si85-128.1>
- Bárdossy, A., Das, T., 2006. Influence of rainfall observation network on model calibration and application. *Hydrol. Earth Syst. Sci. Discuss.* 3, 3691–3726. <https://doi.org/10.5194/hessd-3-3691-2006>
- Beck, H.E., Vergopolan, N., Pan, M., Levizzani, V., van Dijk, A.I.J.M., Weedon, G., Brocca, L., Pappenberger, F., Huffman, G.J., Wood, E.F., 2017. Global-scale evaluation of 22 precipitation datasets using gauge observations and hydrological modeling. *Hydrol. Earth Syst. Sci.* 21, 1–23. <https://doi.org/10.5194/hess-2017-508>
- Besset, M., Anthony, E.J., Bouchette, F., 2019. Multi-decadal variations in delta shorelines and their relationship to river sediment supply: An assessment and review. *Earth-*

- Science Rev. 193, 199–219. <https://doi.org/10.1016/j.earscirev.2019.04.018>
- Betrie, G.D., Mohamed, Y.A., Van Griensven, A., Srinivasan, R., 2011. Sediment management modelling in the Blue Nile Basin using SWAT model. *Hydrol. Earth Syst. Sci.* 15, 807–818. <https://doi.org/10.5194/hess-15-807-2011>
- Beven, K., 2001. How far can we go in distributed hydrological modelling? *Hydrol. Earth Syst. Sci.* 5, 1–12. <https://doi.org/10.5194/hess-5-1-2001>
- Beven, K.J., 2012. *Rainfall-runoff modelling: The primer*, 2nd ed. Wiley-Blackwell.
- Beven, K.J., Kirkby, M.J., 1979. A physically based, variable contributing area model of basin hydrology. *Hydrol. Sci. Bull.* 24, 43–69. <https://doi.org/10.1080/02626667909491834>
- Bingner, R.-R., Theurer, F., 2001. AnnAGNPS: Estimating sediment yield by particle size for sheet and rill erosion, in: *Sediment: Monitoring, Modeling, and Manag- Ing*, 7th Federal Interagency Sedimentation Conference. Subcommittee on Sedimen- Tation Interagency Advisory Committee on Water Data,. Reno (pp. I-1 I-7).
- Boyle, D.P., Gupta, H. V., Sorooshian, S., 2000. Toward improved calibration of hydrologic models: Combining the strengths of manual and automatic methods. *Water Resour. Res.* 36, 3663–3674. <https://doi.org/10.1029/2000WR900207>
- Brauer, D., Baumhardt, R.L., Gitz, D., Gowda, P., Brauer, D., Baumhardt, R.L., Gitz, D., Gowda, P., Mahan, J., 2015. Characterization of trends in reservoir storage , streamflow , and precipitation in the Canadian River watershed in New Mexico and Texas. *Lake Reserv. Manag.* ISSN 31, 64–79. <https://doi.org/10.1080/10402381.2015.1006348>
- Campo, L., Caparrini, F., Castelli, F., 2006. Use of multi-platform, multi-temporal remote-sensing data for calibration of a distributed hydrological model: An application in the Arno basin, Italy. *Hydrol. Process.* 20, 2693–2712. <https://doi.org/10.1002/hyp.6061>
- Casse, C., Gosset, M., 2015. Analysis of hydrological changes and flood increase in Niamey based on the PERSIANN-CDR satellite rainfall estimate and hydrological simulations over the 1983-2013 period. *IAHS-AISH Proc. Reports* 370, 117–123. <https://doi.org/10.5194/piahs-370-117-2015>
- CCD, 2006. *Gazette exrtordinary of the Democratic Socialist Republic of Sri Lanka* 2006.
- Ceccherini, G., Amezttoy, I., Hernandez, C.P.R., Moreno, C.C., 2015. High-resolution precipitation datasets in South America and West Africa based on satellite-derived rainfall, enhanced vegetation index and digital elevation model. *Remote Sens.* 7, 6454–6488. <https://doi.org/10.3390/rs70506454>
- Chanapathi, T., Thatikonda, S., Raghavan, S., 2018. Analysis of rainfall extremes and water yield of Krishna river basin under future climate scenarios. *J. Hydrol. Reg. Stud.* 19, 287–306. <https://doi.org/10.1016/j.ejrh.2018.10.004>
- Chandrapala, L., 1996. Long-term Trends of Rainfall and Temperature in Sri Lanka, in: Y. P. Abrol, S.G. and G.B.P. (Ed.), *Climate Variability and Agriculture*. Narosa Publishing House, New Delhi, India, pp. 153–162.
- Chen, A., Chen, D., 2018. Assessing reliability of precipitation data over the Mekong River Basin: A comparison of ground-based , satellite , and reanalysis datasets. *Int. J. Climatol.* 1–21. <https://doi.org/10.1002/joc.5670>

- Chen, J., Brissette, F.P., Chaumont, D., Braun, M., 2013. Finding appropriate bias correction methods in downscaling precipitation for hydrologic impact studies over North America. *Water Resour. Res.* 49, 4187–4205. <https://doi.org/10.1002/wrcr.20331>
- Chen, J., Brissette, F.P., Zhang, X.J., Chen, H., Guo, S., Zhao, Y., 2019. Bias correcting climate model multi-member ensembles to assess climate change impacts on hydrology. *Clim. Change* 153, 361–377. <https://doi.org/10.1007/s10584-019-02393-x>
- Church, J.A., Clark, P.U., Cazenave, A., Gregory, J.M., Jevrejeva, S., Levermann, A., Merrifield, M.A., Milne, G.A., Nerem, R.S., Nunn, P.D., Payne, A.J., Pfeffer, W.T., Stammer, D., Unnikrishnan, A.S., 2013. Sea Level Change, in: Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J.B., A. Nauels, Y. Xia, V.B. and P.M.M. (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Clark, M.P., Bierkens, M.F.P., Samaniego, L., Woods, R.A., Uijlenhoet, R., Bennett, K.E., Pauwels, V.R.N., Cai, X., Wood, A.W., Peters-Lidard, C.D., 2017. The evolution of process-based hydrologic models: Historical challenges and the collective quest for physical realism. *Hydrol. Earth Syst. Sci.* 21, 3427–3440. <https://doi.org/10.5194/hess-21-3427-2017>
- Cohen, S., J.Kettner, A., Syvitski, J.P.M., Fekete, B.M., 2013. WBMsed, a distributed global-scale riverine sediment flux model: Model description and validation. *Comput. Geosci.* 53, 80–93.
- De Roo, A.P.J., Wesseling, C.G., Ritsema, C.J., 1996. Lisem: A Single-Event Physically Based Hydrological and Soil Erosion Model for Drainage Basins. I: Theory, Input and Output. *Hydrol. Process.* 10, 1107–1117. [https://doi.org/10.1002/\(SICI\)1099-1085\(199608\)10:8<1107::AID-HYP415>3.0.CO;2-4](https://doi.org/10.1002/(SICI)1099-1085(199608)10:8<1107::AID-HYP415>3.0.CO;2-4)
- De Silva, C.S., Weatherhead, E.K., Knox, J.W., Rodriguez-Diaz, J.A., 2007. Predicting the impacts of climate change-A case study of paddy irrigation water requirements in Sri Lanka. *Agric. Water Manag.* 93, 19–29. <https://doi.org/10.1016/j.agwat.2007.06.003>
- De Vente, J., Poesen, J., 2005. Predicting soil erosion and sediment yield at the basin scale: Scale issues and semi-quantitative models. *Earth-Science Rev.* 71, 95–125. <https://doi.org/10.1016/j.earscirev.2005.02.002>
- De Vente, J., Poesen, J., Verstraeten, G., Govers, G., Vanmaercke, M., Van Rompaey, A., Arabkhedri, M., Boix-Fayos, C., 2013. Predicting soil erosion and sediment yield at regional scales: Where do we stand? *Earth-Science Rev.* 127, 16–29. <https://doi.org/10.1016/j.earscirev.2013.08.014>
- De Vente, J., Poesen, J., Verstraeten, G., Rompaey, Anton Van Govers, G., 2008. Spatially distributed modelling of soil erosion and sediment yield at regional scales in Spain. *Glob. Planet. Change* 60, 393–415.
- Deb, P., Babel, M.S., Denis, A.F., 2018. Multi-GCMs approach for assessing climate change impact on water resources in Thailand. *Model. Earth Syst. Environ.* 4, 825–839. <https://doi.org/10.1007/s40808-018-0428-y>
- Devi, G.K., Ganasri, B.P., Dwarakish, G.S., 2015. A Review on Hydrological Models. *Aquat. Procedia* 4, 1001–1007. <https://doi.org/10.1016/j.aqpro.2015.02.126>
- Di Baldassarre, G., Montanari, A., 2009. Uncertainty in river discharge observations: a

- quantitative analysis. *Hydrol. Earth Syst. Sci.* 13, 913–921. <https://doi.org/10.5194/hess-13-913-2009>
- Dissanayake, C.B., Rupasinghe, M.S., 1996. Environmental impact of mining , erosion and sedimentation in Sri Lanka. *Intern. J. Environ. Stud.* 51, 35–50.
- Dorigo, W., Wagner, W., Albergel, C., Albrecht, F., Balsamo, G., Brocca, L., Chung, D., Ertl, M., Forkel, M., Gruber, A., Haas, E., Hamer, P.D., Hirschi, M., Ikonen, J., de Jeu, R., Kidd, R., Lahoz, W., Liu, Y.Y., Miralles, D., Mistelbauer, T., Nicolai-Shaw, N., Parinussa, R., Pratola, C., Reimer, C., van der Schalie, R., Seneviratne, S.I., Smolander, T., Lecomte, P., 2017. ESA CCI Soil Moisture for improved Earth system understanding: State-of-the art and future directions. *Remote Sens. Environ.* 203, 185–215. <https://doi.org/10.1016/j.rse.2017.07.001>
- Driel, W.F., Nauta, T.A., 2014. Vulnerability and Resilience Assessment of the Ayeyarwady Delta , Myanmar Full assessment report Delta Alliance Report No 10. Bay of Bengal Large Marine Ecosystem (BOBLME) Project, Global Water Partnership (GWP) and Delta Alliance, Delft-Wageningen, The N.
- Dunn, F.E., Darby, S.E., Nicholls, R.J., Cohen, S., Zarfl, C., Fekete, B.M., 2019. Projections of declining fluvial sediment delivery to major deltas worldwide in response to climate change and anthropogenic stress. *Environ. Res. Lett.* 14. <https://doi.org/10.1088/1748-9326/ab304e>
- Egbert, G.D., Erofeeva, S.Y., 2002. Efficient inverse modeling of barotropic ocean tides. *J. Atmos. Ocean. Technol.* 19, 183–204. [https://doi.org/10.1175/1520-0426\(2002\)019<0183:EIMOBO>2.0.CO;2](https://doi.org/10.1175/1520-0426(2002)019<0183:EIMOBO>2.0.CO;2)
- Eizel-Din, M.A., Bui, M.D., Rutschmann, P., Failer, E., Grass, C., Kramer, K., Hussein, A.S., Saghayroon-Elzein, A., 2010. Trap efficiency of reservoirs on the Nile River. *River Flow* 1111–1117.
- Eriyagama, N., Smakhtin, V., 2010. Observed and projected climatic changes, their impacts and adaptation options for Sri Lanka: A review, in: National Conference on Water, Food Security and Climate Change. pp. 99–117.
- FAO, 2003. The Digital soil map of the world (Version 3.6). FAO/UNESCO, Rome, Italy.
- Faridzad, M., Yang, T., Hsu, K., Sorooshian, S., Xiao, C., 2018. Rainfall frequency analysis for ungauged regions using remotely sensed precipitation information. *J. Hydrol.* 563, 123–142. <https://doi.org/10.1016/j.jhydrol.2018.05.071>
- Fatichi, S., Vivoni, E.R., Ogden, F.L., Ivanov, V.Y., Mirus, B., Gochis, D., Downer, C.W., Camporese, M., Davison, J.H., Ebel, B., Jones, N., Kim, J., Mascaro, G., Niswonger, R., Restrepo, P., Rigon, R., Shen, C., Sulis, M., Tarboton, D., 2016. An overview of current applications , challenges , and future trends in distributed process-based models in hydrology. *J. Hydrol.* 537, 45–60. <https://doi.org/10.1016/j.jhydrol.2016.03.026>
- Franco, A.C.L., Bonumá, N.B., 2017. Multi-variable SWAT model calibration with remotely sensed evapotranspiration and observed flow. *Brazilian J. Water Resour.* 22, 1–14. <https://doi.org/http://dx.doi.org/10.1590/2318-0331.011716090>
- Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., Michaelsen, J., 2015. The climate hazards infrared precipitation with stations - a new environmental record for monitoring extremes. *Sci. Data* 2, 150066. <https://doi.org/10.1038/sdata.2015.66>

- Furuichi, T., Win, Z., Wasson, R.J., 2009. Discharge and suspended sediment transport in the Ayeyarwady River, Myanmar: Centennial and decadal changes. *Hydrol. Process.* 23, 1631–1641. <https://doi.org/10.1002/hyp>
- Galy, A., France-Lanord, C., 2001. Higher erosion rates in the Himalaya: Geochemical constraints on riverine fluxes. *Geology* 29, 23–26. [https://doi.org/10.1130/0091-7613\(2001\)029<0023:HERITH>2.0.CO;2](https://doi.org/10.1130/0091-7613(2001)029<0023:HERITH>2.0.CO;2)
- Garzanti, E., Wang, J.G., Vezzoli, G., Limonta, M., 2016. Tracing provenance and sediment fluxes in the Irrawaddy River basin (Myanmar). *Chem. Geol.* 440, 73–90. <https://doi.org/10.1016/j.chemgeo.2016.06.010>
- GCCA, 2012. Myanmar Climate Change Alliance [WWW Document]. URL <http://www.gcca.eu/national-programmes/asia/gcca-myanmar> (accessed 6.13.16).
- Ghimire, U., Babel, M.S., Shrestha, S., Srinivasan, G., 2019. A multi-temporal analysis of streamflow using multiple CMIP5 GCMs in the Upper Ayerawaddy Basin, Myanmar. *Clim. Change*. <https://doi.org/10.1007/s10584-019-02444-3>
- Giorgi, F., 2019. Thirty Years of Regional Climate Modeling: Where Are We and Where Are We Going next? *J. Geophys. Res. Atmos.* 124, 5696–5723. <https://doi.org/10.1029/2018JD030094>
- Gordon, R., 1885. The Irawadi river, in: Royal Geographical Society (London) Proceedings (New Series) . 7. pp. 292–331.
- Gosling, S.N., Arnell, N.W., 2016. A global assessment of the impact of climate change on water scarcity. *Clim. Change* 134, 371–385. <https://doi.org/10.1007/s10584-013-0853-x>
- Guo, H., Chen, S., Bao, A., Hu, J., Gebregiorgis, A.S., Xue, X., Zhang, X., 2015. Inter-comparison of high-resolution satellite precipitation products over Central Asia. *Remote Sens.* 7, 7181–7211. <https://doi.org/10.3390/rs70607181>
- Gupta, K., Sharma, G., Jethoo, A., Tyagi, J., Gupta, N., 2015. A critical review of hydrological models. II Roorkee, *Water Resour. River Eng.* 1, 17–19.
- Gupta, H. V., Kling, H., Yilmaz, K.K., Martinez, G.F., 2009. Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *J. Hydrol.* 377, 80–91. <https://doi.org/10.1016/j.jhydrol.2009.08.003>
- Guyennon, N., Romano, E., Portoghesi, I., Salerno, F., Calmanti, S., Petrangeli, A.B., Tartari, G., Copetti, D., 2013. Benefits from using combined dynamical-statistical downscaling approaches - Lessons from a case study in the Mediterranean region. *Hydrol. Earth Syst. Sci.* 17, 705–720. <https://doi.org/10.5194/hess-17-705-2013>
- Hajigholizadeh, M., Melesse, A.M., Fuentes, H.R., 2018. Erosion and sediment transport modelling in shallowwaters: A review on approaches, models and applications. *Int. J. Environ. Res. Public Health* 15. <https://doi.org/10.3390/ijerph15030518>
- Hamman, J.J., Nijssen, B., Bohn, T.J., Gergel, D.R., Mao, Y., 2018. The variable infiltration capacity model version 5 (VIC-5): Infrastructure improvements for new applications and reproducibility. *Geosci. Model Dev.* 11, 3481–3496. <https://doi.org/10.5194/gmd-11-3481-2018>
- Harmel, R.D., Smith, D.R., King, K.W., Slade, R.M., 2009. Estimating storm discharge and water quality data uncertainty: A software tool for monitoring and modeling

- applications. *Environ. Model. Softw.* 24, 832–842. <https://doi.org/10.1016/j.envsoft.2008.12.006>
- Hedley, P.J., Bird, M.I., Robinson, R.A.J., 2010. Evolution of the Irrawaddy delta region since 1850. *Geogr. J.* 176, 138–149. <https://doi.org/10.1111/j.1475-4959.2009.00346.x>
- Hewawasam, T., 2010. Effect of land use in the upper Mahaweli catchment area on erosion , landslides and siltation in hydropower reservoirs of Sri Lanka Effect of land use in the upper Mahaweli catchment area on erosion , landslides and siltation in hydropower reservoirs of S. *J.Natn.Sci.Foundation Sri Lanka* 38, 3–14. <https://doi.org/10.4038/jnsfsr.v38i1.1721>
- Hijioka, Y., Lin, E., Pereira, J.J., Corlett, R.T., Cui, X., Insarov, G.E., Lasco, R.D., Lindgren, E., Surjan, A., 2014. Aisa, in: Barros, V.R., C.B. Field, D.J. Dokken, M.D. Mastrandrea, K.J. Mach, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L.W. (Ed.), In *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1327–1370. <https://doi.org/10.1029/2006GB002898>.Barros
- Horton, R., Mel, M. De, Peters, D., Lesk, C., Bartlett, R., Helsing, H., Bader, D., Capizzi, P., Martin, S., Rosenzweig, C., 2017. *Assessing Climate Risk in Myanmar*. New York, NY, USA.
- Hrachowitz, M., Savenije, H.H.G., Blöschl, G., McDonnell, J.J., Sivapalan, M., Pomeroy, J.W., Arheimer, B., Blume, T., Clark, M.P., Ehret, U., Fenicia, F., Freer, J.E., Gelfan, A., Gupta, H.V., Hughes, D. a., Hut, R.W., Montanari, A., Pande, S., Tetzlaff, D., Troch, P.A., Uhlenbrook, S., Wagener, T., Winsemius, H.C., Woods, R. a., Zehe, E., Cudennec, C., 2013. A decade of Predictions in Ungauged Basins (PUB)—a review. *Hydrol. Sci. J.* 58, 1198–1255. <https://doi.org/10.1080/02626667.2013.803183>
- Hu, Z., Chen, X., Chen, D., Li, J., Wang, S., Zhou, Q., Yin, G., Guo, M., 2019. “Dry gets drier, wet gets wetter”: A case study over the arid regions of central Asia. *Int. J. Climatol.* 39, 1072–1091. <https://doi.org/10.1002/joc.5863>
- IFC, 2017. *Baseline Assessment Report: Geomorphic and Sediment Transport*. Washington DC.
- Imbulana, K.A.N.D., 2018. *Assessment of Climate Change Impacts on River Hydrology and Morphology and Resulting Socio-Economic Vulnerability : A Case Study of the Chindwin River Basin in Myanmar*. Asian Institute of Technology, Thailand.
- Imbulana, N., Gunawardana, S., Shrestha, S., Datta, A., 2018. Projections of extreme precipitation events under climate change scenarios in Mahaweli River Basin of Sri Lanka. *Curr. Sci.* 114, 1495–1509. <https://doi.org/10.18520/cs/v114/i07/1495-1509>
- Immerzeel, W.W., Droogers, P., 2008. Calibration of a distributed hydrological model based on satellite evapotranspiration. *J. Hydrol.* 349, 411–424. <https://doi.org/10.1016/j.jhydrol.2007.11.017>
- IPCC, 2014. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, p. 151.

- Jajarmizadeh, M., Harun, S., Salarpour, M., 2012. A review on theoretical consideration and types of models in hydrology. *J. Environ. Sci. Technol.* 5, 249–261. <https://doi.org/10.3923/jest.2012.249.261>
- Jalota, S.K., Vashisht, B.B., Sharma, S., Kaur, S., 2018. Climate Change Projections, in: Jalota, S.K., Vashisht, B.B., Sharma, S., Kaur, S. (Eds.), *Understanding Climate Change Impacts on Crop Productivity and Water Balance*. Elsevier Inc., London, UK, pp. 55–83. <https://doi.org/10.1016/C2015-0-05656-8>
- Jalowska, A.M., Yuan, Y., 2018. Evaluation of SWAT Impoundment Modeling Methods in Water and Sediment Simulations. *J. Am. water Resour. Assoc.* 1–19. <https://doi.org/10.1111/1752-1688.12715>
- Jarvis, A., Reuter, H.I., Nelson, A., Guevara, E., 2008. Hole-filled SRTM for the globe Version 4, available from the CGIAR-CSI SRTM 90m Database (<http://srtm.csi.cgiar.org>) [WWW Document].
- Johanson, R., Imhoff, J., Davis, H., 1980. Users manual for hydrological simulation program-Fortran (HSPF), U.S. Environmental Protection Agency, Washington, D.C., EPA/600/9-80/015.
- Katsanos, D., Retalis, A., Michaelides, S., 2016. Validation of a high-resolution precipitation database (CHIRPS) over Cyprus for a 30-year period. *Atmos. Res.* 169, 459–464. <https://doi.org/10.1016/j.atmosres.2015.05.015>
- Kattelus, M., Rahaman, M.M., Varis, O., 2015. Hydropower development in Myanmar and its implications on regional energy cooperation. *Int. J. Sustain. Soc.* 7, 42–66. <https://doi.org/10.1504/IJSSOC.2015.068071>
- Khadka, D., Babel, M.S., Shrestha, S., Tripathi, N.K., 2014. Climate change impact on glacier and snow melt and runoff in Tamakoshi basin in the Hindu Kush Himalayan (HKH) region. *J. Hydrol.* 511, 49–60. <https://doi.org/10.1016/j.jhydrol.2014.01.005>
- Kim, Y. Do, Kim, J.M., Kang, B., 2017. Projection of runoff and sediment yield under coordinated climate change and urbanization scenarios in Doam dam watershed, Korea. *J. Water Clim. Chang.* 8, 235–253. <https://doi.org/10.2166/wcc.2016.068>
- Kirkby, M.J., Irvine, B.J., Jones, R.J.A., Govers, G., Team, P., 2008. The PESERA coarse scale erosion model for Europe. I. Model rationale and implementation. *Eur. J. Soil Sci.* 59, 1293–1306.
- Kreft, S., Eckstein, D., Dorsch, L., Fischer, L., 2015. Global climate risk index 2016 Who Suffers Most From Extreme Weather Events? Weather-related Loss Events in 2014 and 1995 to 2014. Germanwatch e.V., Bonn, Germany.
- Kumar, S., Merwade, V., 2009. Impact of watershed subdivision and soil data resolution on swat model calibration and parameter uncertainty. *J. Am. Water Resour. Assoc.* 45, 1179–1196. <https://doi.org/10.1111/j.1752-1688.2009.00353.x>
- Kumarasamy, K., Belmont, P., 2018. Calibration Parameter Selection and Watershed Hydrology Model Evaluation in Time and Frequency Domains. *Water* 10, 1–20. <https://doi.org/10.3390/w10060710>
- Kummu, M., Varis, O., 2007. Sediment-related impacts due to upstream reservoir trapping, the Lower Mekong River. *Geomorphology* 85, 275–293. <https://doi.org/10.1016/j.geomorph.2006.03.024>

- Kunnath-Poovakka, A., Ryu, D., Renzullo, L.J., George, B., 2016. The efficacy of calibrating hydrologic model using remotely sensed evapotranspiration and soil moisture for streamflow prediction. *J. Hydrol.* 535, 509–524. <https://doi.org/10.1016/j.jhydrol.2016.02.018>
- Le, A.M., Pricope, N., 2017. Increasing the accuracy of runoff and streamflow simulation in the Nzoia Basin, Western Kenya, through the incorporation of satellite-derived CHIRPS Data. *Water* 9, 1–15. <https://doi.org/10.3390/w9020114>
- Legates, D.R., McCabe Jr., G.J., 1999. Evaluating the use of “Goodness of Fit” measures in hydrologic and hydroclimatic model validation. *Water Resour. Res.* 35, 233–241. <https://doi.org/10.1029/1998WR900018>
- Leimgruber, P., Kelly, D.S., Steininger, M.K., Brunner, J., Müller, T., Songer, M., 2005. Forest cover change patterns in Myanmar (Burma) 1990–2000. *Environ. Conserv.* 32, 356–364. <https://doi.org/10.1017/s0376892905002493>
- Lele, S., 1987. Improved algorithms for reservoir capacity calculation incorporating storage dependent losses and reliability norm. *Water Resour. Res.* 23, 1819–1823.
- Lenderink, G., Buishand, A., Van Deursen, W., 2007. Estimates of future discharges of the river Rhine using two scenario methodologies: Direct versus delta approach. *Hydrol. Earth Syst. Sci.* 11, 1145–1159. <https://doi.org/10.5194/hess-11-1145-2007>
- Lewis, S.E., Bainbridge, Z.T., Kuhnert, P.M., Sherman, B.S., Henderson, B., Dougall, C., Cooper, M., Brodie, J.E., 2013. Calculating sediment trapping efficiencies for reservoirs in tropical settings: A case study from the Burdekin Falls Dam, NE Australia. *Water Resour. Res.* 49, 1017–1029. <https://doi.org/10.1002/wrcr.20117>
- Li, Y., Grimaldi, S., Pauwels, V.R.N., Walker, J.P., 2018. Hydrologic model calibration using remotely sensed soil moisture and discharge measurements: The impact on predictions at gauged and ungauged locations. *J. Hydrol.* 557, 897–909. <https://doi.org/10.1016/j.jhydrol.2018.01.013>
- Lirong, S., Jianyun, Z., 2012. Hydrological Response to Climate Change in Beijiang River Basin Based on the SWAT Model. *Procedia Eng.* 28, 241–245. <https://doi.org/10.1016/j.proeng.2012.01.713>
- Lopez, M.G., Wennerstorm, H., Norden, L.-A., Seibert, J., 2015. Location and density of rain gauges for the Estimation of Spatial varying precipitation. *Phys. Geogr.* 97, 167–179. <https://doi.org/10.1111/geoa.12094>
- López, P.L., Sutanudjaja, E.H., Schellekens, J., Sterk, G., Bierkens, M.F.P., 2017. Calibration of a large-scale hydrological model using satellite-based soil moisture and evapotranspiration products. *Hydrol. Earth Syst. Sci.* 21, 3125–3144. <https://doi.org/10.5194/hess-21-3125-2017>
- Lu, W., Wang, W., Shao, Q., Yu, Z., Hao, Z., Xing, W., Yong, B., Li, J., 2018. Hydrological projections of future climate change over the source region of Yellow River and Yangtze River in the Tibetan Plateau: A comprehensive assessment by coupling RegCM4 and VIC model. *Hydrol. Process.* 32, 2096–2117. <https://doi.org/10.1002/hyp.13145>
- Luijendijk, A., Hagenaars, G., Ranasinghe, R., Baart, F., Donchyts, G., Aarninkhof, S., 2018. The State of the World’s Beaches. *Sci. Rep.* 8, 1–11. <https://doi.org/10.1038/s41598-018-24630-6>

- Lutz, A.F., Immerzeel, W.W., Shrestha, A.B., Bierkens, M.F.P., 2014. Consistent increase in High Asia's runoff due to increasing glacier melt and precipitation. *Nat. Clim. Chang.* 4, 587–592. <https://doi.org/10.1038/nclimate2237>
- Maharjan, M., Babel, M.S., Maskey, S., 2014. Reducing the basin vulnerability by land management practices under past and future climate: a case study of the Nam Ou River Basin, Lao PDR. *Hydrol. Earth Syst. Sci. Discuss.* 11, 9863–9905. <https://doi.org/10.5194/hessd-11-9863-2014>
- Maneux, E., Probst, J.L., Veyssy, E., Etcheber, H., 2001. Assessment of dam trapping efficiency from water residence time: Application to fluvial sediment transport in the Adour, Dordogne, and Garonne River basins (France). *Water Resour. Res.* 37, 801–811. <https://doi.org/10.1029/2000WR900195>
- Marhaento, H., Booij, M.J., Hoekstra, A.Y., 2018. Hydrological response to future land-use change and climate change in a tropical catchment. *Hydrol. Sci. J.* 63, 1368–1385. <https://doi.org/10.1080/02626667.2018.1511054>
- Martens, B., Miralles, D.G., Lievens, H., Van Der Schalie, R., De Jeu, R.A.M., Fernández-Prieto, D., Beck, H.E., Dorigo, W.A., Verhoest, N.E.C., 2017. GLEAM v3: Satellite-based land evaporation and root-zone soil moisture. *Geosci. Model Dev.* 10, 1903–1925. <https://doi.org/10.5194/gmd-10-1903-2017>
- Masih, I., Maskey, S., Uhlenbrook, S., Smakhtin, V., 2011. Assessing the impact of areal precipitation input on streamflow simulations using the SWAT model. *J. Am. Water Resour. Assoc.* 47, 179–195. <https://doi.org/10.1111/j.1752-1688.2010.00502.x>
- Maskey, S., 2013. HyKit: A Tool for grid-based interpolation of hydrological variables, User's Guide (Version 1.3).
- Massari, C., Crow, W., Brocca, L., 2017. An assessment of the accuracy of global rainfall estimates without ground-based observations. *Hydrol. Earth Syst. Sci.* 21, 4347–4361. <https://doi.org/10.5194/hess-2017-163>
- Merritt, W.S., Letcher, R.A., Jakeman, A.J., 2003. A review of erosion and sediment transport models. *Environ. Model. Softw.* 18, 761–799. [https://doi.org/10.1016/S1364-8152\(03\)00078-1](https://doi.org/10.1016/S1364-8152(03)00078-1)
- Miao, C., Ashouri, H., Hsu, K.-L., Sorooshian, S., Duan, Q., 2015. Evaluation of the PERSIANN-CDR Daily Rainfall Estimates in Capturing the Behavior of Extreme Precipitation Events over China. *J. Hydrometeorol.* 16, 1387–1396. <https://doi.org/10.1175/JHM-D-14-0174.1>
- Miao, C., Ni, J., Borthwick, A.G.L., Yang, L., 2011. A preliminary estimate of human and natural contributions to the changes in water discharge and sediment load in the Yellow River. *Glob. Planet. Change* 76, 196–205. <https://doi.org/10.1016/j.gloplacha.2011.01.008>
- Miralles, D.G., Holmes, T.R.H., De Jeu, R.A.M., Gash, J.H., Meesters, A.G.C.A., Dolman, A.J., 2011. Global land-surface evaporation estimated from satellite-based observations. *Hydrol. Earth Syst. Sci.* 15, 453–469. <https://doi.org/10.5194/hess-15-453-2011>
- Mittal, N., Bhawe, A.G., Mishra, A., Singh, R., 2016. Impact of human intervention and climate change on natural flow regime. *Water Resour. Manag.* 30, 685–699. <https://doi.org/10.1007/s11269-015-1185-6>

- Moon, J., Srinivasan, R., Jacobs, J.H., 2004. Stream flow estimation using spatially distributed rainfall in the Trinity River Basin, Texas. *Trans. ASAE* 47, 1445–1452. <https://doi.org/10.13031/2013.17624>
- Morgan, R.P.C., 2005. *Soil erosion and Conservation*, 3rd ed. Blackwell Publishing Ltd, UK.
- Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Binger, R.L., Harmel, R.D., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Am. Soc. Agric. Biol. Eng.* 50, 885–900. <https://doi.org/10.13031/2013.23153>
- Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., Van Vuuren, D.P., Carter, T.R., Emori, S., Kainuma, M., Kram, T., Meehl, G.A., Mitchell, J.F.B., Nakicenovic, N., Riahi, K., Smith, S.J., Stouffer, R.J., Thomson, A.M., Weyant, J.P., Wilbanks, T.J., 2010. The next generation of scenarios for climate change research and assessment. *Nature* 463, 747–756. <https://doi.org/10.1038/nature08823>
- Moulin, L., Gaume, E., Obled, C., 2008. Uncertainties on mean areal precipitation: assessment and impact on streamflow simulations. *Hydrol. Earth Syst. Sci.* 5, 2067–2110. <https://doi.org/10.5194/hessd-5-2067-2008>
- Nash, J.E., Sutcliffe, J. V., 1970. River Flow Forecasting Through Conceptual Models Part I-A Discussion of Principles. *J. Hydrol.* 10, 282–290. [https://doi.org/10.1016/0022-1694\(70\)90255-6](https://doi.org/10.1016/0022-1694(70)90255-6)
- Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Williams, J.R., 2011. *Soil & Water Assessment Tool Theoretical Documentation Version 2009*, Texas Water Resources Institute, TR-406. Texas. <https://doi.org/10.1016/j.scitotenv.2015.11.063>
- Ngo, L.A., Masih, I., Jiang, Y., Douven, W., 2018. Impact of reservoir operation and climate change on the hydrological regime of the Sesan and Srepok Rivers in the Lower Mekong Basin. *Clim. Change* 149, 107–119. <https://doi.org/10.1007/s10584-016-1875-y>
- Nicholls, R.J., Wong, P.P., V.R. Burkett, J.O. Codignotto, J.E. Hay, R.F. McLean, S.R. and C.D.W., 2007. Coastal systems and low-lying areas, in: M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der L. and C.E.H. (Ed.), *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK, pp. 315–356.
- Nilawar, A.P., Waikar, M.L., 2019. Impacts of climate change on stream flow and sediment concentration under RCP 4 . 5 and 8 . 5 : A case study in Purna river basin , India. *Sci. Total Environ.* 650, 2685–2696. <https://doi.org/10.1016/j.scitotenv.2018.09.334>
- Njoku, E.G., Jackson, T.J., Lakshmi, V., Chan, T.K., Nghiem, S. V., 2003. Soil moisture retrieval from AMSR-E. *IEEE Trans. Geosci. Remote Sens.* 41, 215–228. <https://doi.org/10.1109/TGRS.2002.808243>
- Pechlivanidis, I.G., Jackson, B.M., McIntyre, N.R., Wheeler, H.S., 2011. Catchment scale hydrological modelling: a review of model types, calibration approaches and uncertainty analysis methods in the context of recent developments in technology and applications. *Glob. NEST* 13, 193–214.
- Pelletier, J.D., 2012. A spatially distributed model for the long-term suspended sediment

- discharge and delivery ratio of drainage basins. *J. Geophys. Res. Earth Surf.* 117, 1–15. <https://doi.org/10.1029/2011JF002129>
- Perlman, K., 2016. Streamflow and water cycle [WWW Document]. *Water Sci. Sch.* URL <https://water.usgs.gov/edu/watercycle.html> (accessed 5.4.19).
- Pervez, M.S., Henebry, G.M., 2015. Assessing the impacts of climate and land use and land cover change on the freshwater availability in the Brahmaputra River basin. *J. Hydrol. Reg. Stud.* 3. <https://doi.org/10.1016/j.ejrh.2014.09.003>
- Piman, T., Cochrane, T.A., Arias, M.E., Dat, N.D., Vonnarart, O., 2015. Managing hydropower under climate change in the Mekong tributaries, in: Shrestha S., Anal A., Salam P., van der V.M. (Ed.), *Managing Water Resources Under Climate Uncertainty: Examples from Asia, Europe, Latin America, and Australia*. Springer Water. Springer, pp. 223–248. https://doi.org/10.1007/978-3-319-10467-6_11
- Pokhrel, B., 2018. Impact of Land Use Change on Flow and Sediment Yields in the Khokana Outlet of the Bagmati River, Kathmandu, Nepal. *Hydrology* 5, 22. <https://doi.org/10.3390/hydrology5020022>
- Price, K., Purucker, S.T., Kraemer, S.R., Babendreier, J.E., Knightes, C.D., 2014. Comparison of radar and gauge precipitation data in watershed models across varying spatial and temporal scales. *Hydrol. Process.* 28, 3505–3520. <https://doi.org/10.1002/hyp.9890>
- Pushpalatha, R., Perrin, C., Moine, N. Le, Andréassian, V., 2012. A review of efficiency criteria suitable for evaluating low-flow simulations. *J. Hydrol.* 420–421, 171–182. <https://doi.org/10.1016/j.jhydrol.2011.11.055>
- Quenouille, A.M.H., 1956. Notes on Bias in Estimation. *Biometrika* 43, 353–360. <https://doi.org/10.2307/2332914>
- Rajib, M.A., Merwade, V., Yu, Z., 2016. Multi-objective calibration of a hydrologic model using spatially distributed remotely sensed/in-situ soil moisture. *J. Hydrol.* 536, 192–207. <https://doi.org/10.1016/j.jhydrol.2016.02.037>
- Ranasinghe, R., 2020. On the need for a new generation of coastal change models for the 21st century. *Sci. Rep.* 10, 1–6. <https://doi.org/10.1038/s41598-020-58376-x>
- Ranasinghe, R., Wu, C.S., Conallin, J., Duong, T.M., 2019. Disentangling the relative impacts of climate change and human activities on fluvial sediment supply to the coast by the world ' s large rivers : Pearl River Basin , China. *Sci. Rep.* 9, 1–10. <https://doi.org/10.1038/s41598-019-45442-2>
- Rientjes, T.H.M., Muthuwatta, L.P., Bos, M.G., Booij, M.J., Bhatti, H.A., 2013. Multi-variable calibration of a semi-distributed hydrological model using streamflow data and satellite-based evapotranspiration. *J. Hydrol.* 505, 276–290. <https://doi.org/10.1016/j.jhydrol.2013.10.006>
- Robinson, R.A.J., Bird, M.I., Oo, N.W., Hoey, T.B., Aye, M.M., Higgitt, D.L., Lu, X.X., Swe, A., Tun, T., Win, S.L., 2007. The Irrawaddy River Sediment Flux to the Indian Ocean : The Original Nineteenth-Century Data Revisited. *J. Geol.* 115, 629–640. <https://doi.org/10.1086/521607>
- Rode, M., Suhr, U., Wriedt, G., 2007. Multi-objective calibration of a river water quality model-Information content of calibration data. *Ecol. Modell.* 204, 129–142. <https://doi.org/10.1016/j.ecolmodel.2006.12.037>

- Rodriguez-Lloveras, X., Buytaert, W., Benito, G., 2016. Land use can offset climate change induced increases in erosion in Mediterranean watersheds. *Catena* 143, 244–255. <https://doi.org/10.1016/j.catena.2016.04.012>
- Rompaey, A.J.J. Van, Verstraeten, G., Oost, K. Van, Govers, G., Poesen, J., 2001. Modelling mean annual sediment yield using a distributed approach. *Earth Surf. Process. landforms* 26, 1227–1236.
- Rostamian, R., Jaleh, A., Afyuni, M., Mousavi, S.F., Heidarpour, M., Jalalian, A., Abbaspour, K.C., 2008. Application of a SWAT model for estimating runoff and sediment in two mountainous basins in central Iran. *Hydrol. Sci. J.* 53, 977–988. <https://doi.org/10.1623/hysj.53.5.977>
- Ruan, Y., Liu, Z., Wang, R., Yao, Z., 2019. Assessing the Performance of CMIP5 GCMs for Projection of Future Temperature Change over the Lower Mekong Basin. *Atmosphere (Basel)*. 10, 93. <https://doi.org/10.3390/atmos10020093>
- Running, S.W., Mu, Q., Zhao, M., Alvaro Moreno, 2017. User's Guide MODIS Global Terrestrial Evapotranspiration (ET) Product (NASA MOD16A2/A3).
- Saito, Y., Chaimanee, N., Thanawat, J., Syvitski, J.P.M., 2007. Shrinking Megadeltas in Asia : Sea-level Rise and Sediment Reduction Impacts from Case Study of the Chao Phraya Delta. *LOICZ Inprint* 3–9.
- Sanderson, E.W., Jaiteh, M., Levy, M.A., Redford, K.H., Wannebo, A. V., Woolmer, G., 2002. The Human Footprint and the Last of the Wild. *Bioscience* 52, 891–904. [https://doi.org/10.1641/0006-3568\(2002\)052\[0891:thfatl\]2.0.co;2](https://doi.org/10.1641/0006-3568(2002)052[0891:thfatl]2.0.co;2)
- Sayasane, R., Kawasaki, A., Shrestha, S., Takamatsu, M., 2016. Assessment of potential impacts of climate and land use changes on stream flow : a case study of the Nam Xong watershed in Lao PDR. *J. water* 07, 184–197. <https://doi.org/10.2166/wcc.2015.050>
- Schaeffli, B., Gupta, H. V., 2007. Do Nash values have value? *Hydrol. Process.* 21, 2075–2080. <https://doi.org/10.1002/hyp.6825>
- Schmidli, J., Frei, C., Vidale, P.L., 2006. Downscaling from GCM precipitation: A benchmark for dynamical and statistical downscaling methods. *Int. J. Climatol.* 26, 679–689. <https://doi.org/10.1002/joc.1287>
- Schoof, J.T., Pryor, S.C., 2001. Downscaling temperature and precipitation: A comparison of regression-based methods and artificial neural networks. *Int. J. Climatol.* 21, 773–790. <https://doi.org/10.1002/joc.655>
- Segond, M., Wheeler, H.S., Onof, C., 2007. The significance of spatial rainfall representation for flood runoff estimation : A numerical evaluation based on the Lee catchment , UK. *J. Hydrol.* 347, 116–131. <https://doi.org/10.1016/j.jhydrol.2007.09.040>
- Seibert, J., McDonnell, J.J., 2002. On the dialog between experimentalist and modeler in catchment hydrology: Use of soft data for multicriteria model calibration. *Water Resour. Res.* 38, 23, 1–14. <https://doi.org/10.1029/2001WR000978>
- Seibert, J., Vis, M.J.P., 2012. Teaching hydrological modeling with a user-friendly catchment-runoff-model software package. *Hydrol. Earth Syst. Sci.* 16, 3315–3325. <https://doi.org/10.5194/hess-16-3315-2012>

- Sharma, D., Gupta, A. Das, Babel, M.S., 2007. Spatial disaggregation of bias-corrected GCM precipitation for improved hydrologic simulation: Ping River Basin, Thailand. *Hydrol. Earth Syst. Sci.* 11, 1373–1390. <https://doi.org/10.5194/hess-11-1373-2007>
- Shrestha, B., Babel, M.S., Maskey, S., Van Griensven, A., Uhlenbrook, S., Green, A., Akkharath, I., 2013. Impact of climate change on sediment yield in the Mekong River basin: A case study of the Nam Ou basin, Lao PDR. *Hydrol. Earth Syst. Sci.* 17, 1–20. <https://doi.org/10.5194/hess-17-1-2013>
- Shrestha, B., Maskey, S., Babel, M.S., van Griensven, A., Uhlenbrook, S., 2016. Sediment related impacts of climate change and reservoir development in the Lower Mekong River Basin: a case study of the Nam Ou Basin, Lao PDR. *Clim. Chang.* 9, 3339–3384. <https://doi.org/10.5194/hessd-9-3339-2012>
- Shrestha, N.K., Qamer, F.M., Pedreros, D., Murthy, M.S.R., Wahid, S.M., Shrestha, M., 2017. Evaluating the accuracy of Climate Hazard Group (CHG) satellite rainfall estimates for precipitation based drought monitoring in Koshi basin, Nepal. *J. Hydrol. Reg. Stud.* 13, 138–151. <https://doi.org/10.1016/j.ejrh.2017.08.004>
- Shrestha, S., Htut, A.Y., 2016a. Modelling the potential impacts of climate change on hydrology of the Bago River Basin , Myanmar Basin , Myanmar. *Int. J. River Basin Manag.* 0–13. <https://doi.org/10.1080/15715124.2016.1164177>
- Shrestha, S., Htut, A.Y., 2016b. Land Use and Climate Change Impacts on the Hydrology of the Bago River Basin, Myanmar. *Environ. Model. Assess.* 21, 819–833. <https://doi.org/10.1007/s10666-016-9511-9>
- Shrestha, S., Lohpaisankrit, W., 2017. Flood hazard assessment under climate change scenarios in the Yang River Basin, Thailand. *Int. J. Sustain. Built Environ.* 6, 285–298. <https://doi.org/10.1016/j.ijbe.2016.09.006>
- Shrestha, S., Thin, N.M.M., Deb, P., 2014. Assessment of climate change impacts on irrigation water requirement and rice yield for Ngamoeyeik Irrigation Project in Myanmar. *J. Water Clim. Chang.* 05, 427–442. <https://doi.org/10.2166/wcc.2014.114>
- Singh, V.P., 2018. Hydrologic modeling : progress and future directions. *Geosci. Lett.* 5, 1–18. <https://doi.org/10.1186/s40562-018-0113-z>
- Sirisena, T.A.J.G., Maskey, S., Ranasinghe, R., Babel, M.S., 2018. Effects of different precipitation inputs on streamflow simulations in Irrawaddy River Basin, Myanmar. *J. Hydrol. Reg. Stud.* 19, (Submitted). <https://doi.org/10.1016/j.ejrh.2018.10.005>
- Sitterson, J., Knightes, C., Parmar, R., Wolfe, K., Muche, M., Avant, B., 2017. An Overview of Rainfall-Runoff Model Types An Overview of Rainfall-Runoff Model Types, U.S. Environmental Protection Agency. Athens, Georgia.
- Sivapalan, M., Takeuchi, K., Franks, S.W., Gupta, V.K., Karambiri, H., Lakshmi, V., Liang, X., McDonnell, J.J., MENDIONDO, E.M., O’Connell, P.E., Oki, T., Pomeroy, J.W., Schertzer, D., Uhlenbrook, S., Zehe, E., 2003. IAHS Decade on Predictions in Ungauged Basins (PUB), 2003–2012: Shaping an exciting future for the hydrological sciences. *Hydrol. Sci. J.* 48, 857–880. <https://doi.org/10.1623/hysj.48.6.857.51421>
- Smitha, P.S., Narasimhan, B., Sudheer, K.P., Annamalai, H., 2018. An improved bias correction method of daily rainfall data using a sliding window technique for climate change impact assessment. *J. Hydrol.* 556, 100–118. <https://doi.org/10.1016/j.jhydrol.2017.11.010>

- Stamp, L.D., 2015. The Irrawaddy River. *Geogr. J.* 95, 329–352.
- Syvitski, J.P., Milliman, J.D., 2007. Geology , Geography , and Humans Battle for Dominance over the Delivery of Fluvial Sediment to the Coastal Ocean Delivery of Fluvial Sediment to the Coastal Ocean. *J. Geol.* 115, 1–19. <https://doi.org/10.1086/509246>
- Syvitski, J.P.M., 2003. Supply and flux of sediment along hydrological pathways : research for the 21st century. *Glob. Planet. Change* 39, 1–11. [https://doi.org/10.1016/S0921-8181\(03\)00008-0](https://doi.org/10.1016/S0921-8181(03)00008-0)
- Syvitski, J.P.M., Kettner, A.J., Overeem, I., Hutton, E.W.H., Hannon, M.T., Brakenridge, G.R., Day, J., Vörösmarty, C., Saito, Y., Giosan, L., Nicholls, R.J., 2009. Sinking deltas due to human activities. *Nat. Geosci.* 1–6. <https://doi.org/10.1038/ngeo629>
- Syvitski, J.P.M., Saito, Y., 2007. Morphodynamics of deltas under the influence of humans. *Glob. Planet. Change* 57, 261–282. <https://doi.org/10.1016/j.gloplacha.2006.12.001>
- Syvitski, J.P.M., Vörösmarty, C.J., Kettner, Ka.J., Green, P., 2005. Impact of Humans on the Flux of Terrestrial Sediment to the Global Coastal Ocean. *Science* (80-.). 308, 376–380. <https://doi.org/10.1126/science.1109454>
- Taft, L., Evers, M., 2016. A review of current and possible future human-water interactions in Myanmar ’ s river basins, *Hydrol. Earth Syst. Sci. Discuss.* <https://doi.org/10.5194/hess-2015-516>
- Tan, M.L., Gassman, P.W., Cracknell, A.P., 2017. Assessment of three long-term gridded climate products for hydro-climatic simulations in tropical river basins. *Water* 9, 1–24. <https://doi.org/10.3390/w9030229>
- Tan, M.L., Ibrahim, A.L., Duan, Z., Cracknell, A.P., Chaplot, V., 2015. Evaluation of Six High-Resolution Satellite and Ground-Based Precipitation Products over Malaysia. *Remote Sens.* 7, 1504–1528. <https://doi.org/10.3390/rs70201504>
- Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. *Bull. Am. Meteorol. Soc.* 93, 485–498. <https://doi.org/10.1175/BAMS-D-11-00094.1>
- Teutschbein, C., Seibert, J., 2012. Bias correction of regional climate model simulations for hydrological CC-impact studies_Review and evaluation of differnt methods. *J. Hydrol.* 456–457, 12–29. <https://doi.org/10.1016/j.jhydrol.2012.05.052>
- Thiemeßl, M.J., Gobiet, A., Leuprecht, A., 2011. Empirical-statistical downscaling and error correction of daily precipitation from regional climate models. *Int. J. Climatol.* 31, 1530–1544. <https://doi.org/10.1002/joc.2168>
- Thiemig, V., Rojas, R., Zambrano-Bigiarini, M., De Roo, A., 2013. Hydrological evaluation of satellite-based rainfall estimates over the Volta and Baro-Akobo Basin. *J. Hydrol.* 499, 324–338. <https://doi.org/10.1016/j.jhydrol.2013.07.012>
- Thomas, H.A., Fiering, M.B., 1963. Operations research in water quality management. Harvard Water Resources Group, Cambridge, Mass.
- Thompson, J.R., Green, A.J., Kingston, D.G., Gosling, S.N., 2013. Assessment of uncertainty in river flow projections for the Mekong River using multiple GCMs and hydrological models. *J. Hydrol.* 486, 1–30. <https://doi.org/10.1016/j.jhydrol.2013.01.029>

- Tobin, K.J., Bennett, M.E., 2017. Constraining SWAT calibration with Remotely sensed Evapotranspiration data. *J. Am. Water Resour. Assoc.* 1–12. <https://doi.org/10.1111/1752-1688.12516>
- Toté, C., Patricio, D., Boogaard, H., van der Wijngaart, R., Tarnavsky, E., Funk, C., 2015. Evaluation of satellite rainfall estimates for drought and flood monitoring in Mozambique. *Remote Sens.* 7, 1758–1776. <https://doi.org/10.3390/rs70201758>
- Trambauer, P., Dutra, E., Maskey, S., Werner, M., Pappenberger, F., Beek, L.P.H. Van, Uhlenbrook, S., Park, S., Section, W.R., 2014. Comparison of different evaporation estimates over the African continent. *Hydrol. Earth Syst. Sci.* 18, 193–212. <https://doi.org/10.5194/hess-18-193-2014>
- Trambauer, P., Maskey, S., Winsemius, H., Werner, M., Uhlenbrook, S., 2013. A review of continental scale hydrological models and their suitability for drought forecasting in (sub-Saharan) Africa. *Phys. Chem. Earth* 66, 16–26. <https://doi.org/10.1016/j.pce.2013.07.003>
- Trang, N.T.T., Shrestha, S., Shrestha, M., Datta, A., Kawasaki, A., 2017. Evaluating the impacts of climate and land-use change on the hydrology and nutrient yield in a transboundary river basin: A case study in the 3S River Basin (Sekong, Sesan, and Srepok). *Sci. Total Environ.* 576, 586–598. <https://doi.org/10.1016/j.scitotenv.2016.10.138>
- Tuo, Y., Duan, Z., Disse, M., Chiogna, G., 2016. Evaluation of precipitation input for SWAT modeling in Alpine catchment: A case study in the Adige river basin (Italy). *Sci. Total Environ.* 573, 66–82. <https://doi.org/10.1016/j.scitotenv.2016.08.034>
- Vaighan, A.A., Talebbeydokhti, N., Bavani, A.M., 2017. Assessing the impacts of climate and land use change on streamflow, water quality and suspended sediment in the Kor River Basin, Southwest of Iran. *Environ. Earth Sci.* 76. <https://doi.org/10.1007/s12665-017-6880-6>
- Varis, O., Kummu, M., Salmivaara, A., 2012. Ten Major River Basins in Monsoon Asia-Pacific: An assessment of vulnerability. *Appl. Geogr.* 32, 441–454. <https://doi.org/10.1016/j.apgeog.2011.05.003>
- Verburg, P.H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V., Mastura, S.S.A., 2002. Modeling the spatial dynamics of regional land use: The CLUE-S model. *Environ. Manage.* 30, 391–405. <https://doi.org/10.1007/s00267-002-2630-x>
- Vigiak, O., Malagó, A., Bouraoui, F., Grizzetti, B., Weissteiner, C.J., Pastori, M., 2016. Sustainability of Water Quality and Ecology Impact of current riparian land on sediment retention in the Danube River Basin. *Sustain. Water Qual. Ecol.* 8, 30–49. <https://doi.org/http://dx.doi.org/10.1016/j.swaqe.2016.08.001>
- Vigiak, O., Malagó, A., Bouraoui, F., Vanmaercke, M., Poesen, J., 2015. Adapting SWAT hillslope erosion model to predict sediment concentrations and yields in large Basins. *Sci. Total Environ.* 538, 855–875. <https://doi.org/10.1016/j.scitotenv.2015.08.095>
- Vörösmarty, C.J., Meybeck, M., Fekete, B., Sharma, K., Green, P., Syvitski, J.P.M., 2003. Anthropogenic sediment retention: Major global impact from registered river impoundments. *Glob. Planet. Change* 39, 169–190. [https://doi.org/10.1016/S0921-8181\(03\)00023-7](https://doi.org/10.1016/S0921-8181(03)00023-7)
- Vörösmarty, C.J., Sahagian, D., 2000. Anthropogenic Disturbance of the Terrestrial Water

- Cycle. *Bioscience* 50, 753. [https://doi.org/10.1641/0006-3568\(2000\)050\[0753:adottw\]2.0.co;2](https://doi.org/10.1641/0006-3568(2000)050[0753:adottw]2.0.co;2)
- Vörösmarty, C.J., Syvitski, J.P., Day, J., SherBinin, A.D., Giosan, L., PaOla, C., 2009. Battling to save the world's river deltas. *Bull. At. Sci.* 65, 31–44. <https://doi.org/10.2968/065002005>
- Vu, M.T., Raghavan, S. V., Liong, S.Y., 2012. SWAT use of gridded observations for simulating runoff - A Vietnam river basin study. *Hydrol. Earth Syst. Sci.* 16, 2801–2811. <https://doi.org/10.5194/hess-16-2801-2012>
- Walling, D.E., 2009. The Impact of Global Change on Erosion and Sediment Transport by Rivers: Current Progress and Future Challenges, The United Nations World Water Assessment Programme.
- Walling, D.E., 2006. Human impact on land-ocean sediment transfer by the world's rivers. *Geomorphology* 79, 192–216. <https://doi.org/10.1016/j.geomorph.2006.06.019>
- Walling, D.E., Webb, B.W., 1996. Erosion and sediment yield: a global overview, in: *Proceedings of the Exeter Symposium*. pp. 3–20.
- Wang, L., 2015. Climate Change Impacts on River Floods: Uncertainty and Adaptation. TU Delft. <https://doi.org/10.4233/uuid:91e2668d-83e1-4ace-b110-3dc2109238e5>
- Wang, L., Ranasinghe, R., Maskey, S., van Gelder, P.H.A.J.M., Vrijling, J.K., 2016. Comparison of empirical statistical methods for downscaling daily climate projections from CMIP5 GCMs: A case study of the Huai River Basin, China. *Int. J. Climatol.* 36, 145–164. <https://doi.org/10.1002/joc.4334>
- Wang, W., Lu, H., Yang, D., Sothea, K., Jiao, Y., Gao, B., 2016. Modelling Hydrologic Processes in the Mekong River Basin Using a Distributed Model Driven by Satellite Precipitation and Rain Gauge Observations. *PLoS One* 11, 1–19. <https://doi.org/10.1371/journal.pone.0152229>
- Whitehead, P.G., Barbour, E., Futter, M.N., Sarkar, S., Rodda, H., Caesar, J., Butterfield, D., Jin, L., Sinha, R., Nicholls, R., Salehin, M., 2015. Impacts of climate change and socio-economic scenarios on flow and water quality of the Ganges, Brahmaputra and Meghna (GBM) river systems: Low flow and flood statistics. *Environ. Sci. Process. Impacts* 17, 1057–1069. <https://doi.org/10.1039/c4em00619d>
- Wi, S., Yang, Y.C.E., Steinschneider, S., Khalil, A., Brown, C.M., 2015. Calibration approaches for distributed hydrologic models in poorly gaged basins : implication for streamflow. *Hydrol. Earth Syst. Sci.* 19, 857–876. <https://doi.org/10.5194/hess-19-857-2015>
- Wilby, R.L., Dawson, C.W., Barrow, E.M., 2002. SDSM - A decision support tool for the assessment of regional climate change impacts. *Environ. Model. Softw.* 17, 145–157. [https://doi.org/10.1016/s1364-8152\(01\)00060-3](https://doi.org/10.1016/s1364-8152(01)00060-3)
- Wildlife Conservation Society-WCS and Center for International Earth Science Information Network - CIESIN - Columbia University, 2005. Last of the Wild Project, Version 2, 2005 (LWP-2): Global Human Footprint Dataset (Geographic). <https://doi.org/10.7927/H4M61H5F>
- Wildlife Conservation Society-WCS, Center for International Earth Science Information Network-CIESIN-Columbia University, 2005. Last of the Wild Project, Version 2, 2005 (LWP-2): Global Human Footprint Dataset (Geographic) [WWW Document].

- Palisades, NY NASA Socioecon. Data Appl. Cent.
<https://doi.org/10.7927/H4M61H5F>
- Williams, J.R., Berndt, H., 1977. Sediment Yield Prediction Based on Watershed Hydrology. *Trans. Am. Soc. Agric. Eng* 20, 1100–1104.
- Winsemius, H.C., Schaefli, B., Montanari, A., Savenije, H.H.G., 2009. On the calibration of hydrological models in ungauged basins: A framework for integrating hard and soft hydrological information. *Water Resour. Res.* 45.
<https://doi.org/10.1029/2009WR007706>
- WMO, 2008. Guide to Hydrological Practices. Volume I: Hydrology - From Measurements to Hydrological Information, 6th ed. World Meteorological Organization, Geneva.
- Woodroffe, C.D., Nicholls, R.J., Saito, Y., Chen, Z., Goodbred, S.L., 2006. Landscape variability and the response of Asian megadeltas to environmental change. N. Harvey (Eds.), *Glob. Chang. Integr. Coast. Manag.* 5, 277–314. <https://doi.org/10.1007/1-4020-3628-0>
- Wu, J., Miao, C., Zhang, X., Yang, T., Duan, Q., 2017. Detecting the quantitative hydrological response to changes in climate and human activities. *Sci. Total Environ.* 586, 328–337. <https://doi.org/10.1016/j.scitotenv.2017.02.010>
- Xu, R., Hu, H., Tian, F., Li, C., Khan, M.Y.A., 2019. Projected climate change impacts on future streamflow of the Yarlung Tsangpo-Brahmaputra River. *Glob. Planet. Change* 175, 144–159. <https://doi.org/10.1016/j.gloplacha.2019.01.012>
- Yang, J., Reichert, P., Abbaspour, K.C., Xia, J., Yang, H., 2008. Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China. *J. Hydrol.* 358, 1–23. <https://doi.org/10.1016/j.jhydrol.2008.05.012>
- Yang, S.L., Milliman, J.D., Xu, K.H., Deng, B., Zhang, X.Y., Luo, X.X., 2014. Downstream sedimentary and geomorphic impacts of the Three Gorges Dam on the Yangtze River. *Earth-Science Rev.* 138, 469–486. <https://doi.org/10.1016/j.earscirev.2014.07.006>
- Yang, S.L., Xu, K.H., Milliman, J.D., Yang, H.F., Wu, C.S., 2015. Decline of Yangtze River water and sediment discharge : Impact from natural and anthropogenic changes. *Nat. Sci. reports* 5. <https://doi.org/10.1038/srep12581>
- Yatagai, A., Kamiguchi, K., Arakawa, O., Hamada, A., Yasutomi, N., Kitoh, A., 2012. Aphrodite constructing a long-term daily gridded precipitation dataset for Asia based on a dense network of rain gauges. *Bull. Am. Meteorol. Soc.* 93, 1401–1415. <https://doi.org/10.1175/BAMS-D-11-00122.1>
- Young, R.A., Onstad, C.A., Bosch, D.D., Anderson, W., 1989. AGNPS: A nonpoint-source pollution model for evaluating agricultural watersheds. *J. Soil Water Conserv.* 44, 168–173.
- Yu, Z., 2015. Hydrology, Floods and Droughts: Modeling and Prediction. *Encycl. Atmos. Sci.* Second Ed. 3, 217–223. <https://doi.org/10.1016/B978-0-12-382225-3.00172-9>
- Yuan, F., Zhang, L., Win, K.W.W., Ren, L., Zhao, C., Zhu, Y., Jiang, S., Liu, Y., 2017. Assessment of GPM and TRMM multi-satellite precipitation products in streamflow simulations in a data sparse mountainous watershed in Myanmar. *Remote Sens.* 9. <https://doi.org/10.3390/rs9030302>
- Zarfl, C., Lumsdon, A.E., Berlekamp, J., Tydecks, L., Tockner, K., 2014. A global boom in

- hydropower dam construction. *Aquat. Sci.* 77, 161–170. <https://doi.org/10.1007/s00027-014-0377-0>
- Zhang, L., Karthikeyan, R., Zhang, H., Tang, Y., 2017. Estimation of sediment yield change in a loess Plateau basin, China. *Water (Switzerland)* 9. <https://doi.org/10.3390/w9090683>
- Zhang, Q., Liu, J., Singh, V.P., Gu, X., Chen, X., 2016. Evaluation of impacts of climate change and human activities on streamflow in the Poyang Lake basin, China. *Hydrol. Process.* 30, 2562–2576. <https://doi.org/10.1002/hyp.10814>
- Zhang, X., Xu, Y.P., Fu, G., 2014. Uncertainties in SWAT extreme flow simulation under climate change. *J. Hydrol.* 515, 205–222. <https://doi.org/10.1016/j.jhydrol.2014.04.064>
- Zhang, X.C., 2005. Spatial downscaling of global climate model output for site-specific assessment of crop production and soil erosion. *Agric. For. Meteorol.* 135, 215–229. <https://doi.org/10.1016/j.agrformet.2005.11.016>
- Zhao, G., Mu, X., Strehmel, A., Tian, P., 2014. Temporal variation of streamflow, sediment load and their relationship in the Yellow River Basin, China. *PLoS One* 9, 1–13. <https://doi.org/10.1371/journal.pone.0091048>
- Zheng, H., Chiew, F.H.S., Charles, S., Podger, G., 2018. Future climate and runoff projections across South Asia from CMIP5 global climate models and hydrological modelling. *J. Hydrol. Reg. Stud.* 18, 92–109. <https://doi.org/10.1016/j.ejrh.2018.06.004>
- Zhou, Y., Xu, Y.J., Xiao, W., Wang, J., Huang, Y., Yang, H., 2017. Climate Change Impacts on Flow and Suspended Sediment Yield in Headwaters of High-Latitude Regions—A Case Study in China's Far Northeast. *Water* 9, 966–982. <https://doi.org/10.3390/w9120966>
- Zhu, Q., Hsu, K., Xu, Y.-P., Yang, T., 2017. Evaluation of a new satellite-based precipitation data set for climate studies in the Xiang River basin, southern China. *Int. J. Climatol.* 37, 4561–4575. <https://doi.org/10.1002/joc.5105>
- Zhu, Y.-M., Lu, X.X., Zhou, Y., 2008. Sediment flux sensitivity to climate change: A case study in the Longchuanjiang catchment of the upper Yangtze River, China. *Glob. Planet. Change* 60, 429–442. <https://doi.org/10.1016/j.gloplacha.2007.05.001>
- Zuo, D., Xu, Z., Yao, W., Jin, S., Xiao, P., Ran, D., 2016. Assessing the effects of changes in land use and climate on runoff and sediment yields from a watershed in the Loess Plateau of China. *Sci. Total Environ.* 544, 238–250. <https://doi.org/10.1016/j.scitotenv.2015.11.060>

LIST OF FIGURES

Figure 2-1. Changes in (a) average surface temperature (b) average precipitation for 2081 to 2100	17
Figure 3-1. Digital elevation map of Irrawaddy River Basin, Myanmar	25
Figure 3-2. Land-use (a) and Soil (b) maps of Irrawaddy Basin	26
Figure 3-3. Digital elevation map of the Kalu River Basin, Sri Lanka.	27
Figure 3-4. Land-use (a) and Soil (b) maps of the Kalu River Basin, Sri Lanka	28
Figure 3-5. The overall methodological framework of the study	29
Figure 4-1. Sub-basins and climatic stations used in this study (a) Irrawaddy River Basin, Myanmar and (b) Kalu River Basin, Sri Lanka	38
Figure 4-2. Monthly precipitation of four precipitation datasets over the Irrawaddy River Basin	40
Figure 4-3. Spatial distribution of average annual precipitation values for the four precipitation datasets considered (2001-2010)	41
Figure 4-4. Spatial distribution of seasonal variations of the four precipitation datasets (GP, IGP, PERSIANN-CDR, and CHIRPS) for the period 2001 to 2010	42
Figure 4-5. Comparison of simulated and observed monthly streamflow of best simulation at Pyay during Calibration (1991-2000) and Validation (2002 - 2010) periods	44
Figure 4-6. Uncertainty analysis of five selected model parameters	48
Figure 4-7. Spatial distribution of average annual precipitation values for the four precipitation datasets	49
Figure 4-8. Spatial distribution of seasonal variations of the two selected precipitation datasets (GP and IGP) for the period 1990 to 2015	50
Figure 4-9. Comparison of simulated and observed monthly streamflow of the best simulations at three stations during the calibration period (1991-2000)	51
Figure 4-10. Uncertainty analysis of five selected model parameters for the Kalu River Basin	53
Figure 5-1. Chindwin River Basin, Myanmar (a) location and topography, and (b) land-use (top) and soil type (bottom), and (c) climate	59
Figure 5-2. Inter-annual variability of GLEAM ET data over the Chindwin Basin for the period of 2003 – 2010 (a) and average annual evapotranspiration of each sub-basin (b)	60

Figure 5-3. Model performance of each iteration in single variable calibration (a) NSE and (b) PBIAS, and (c) R^2	65
Figure 5-4. Comparison of simulated and observed (a) streamflow and (b) evapotranspiration	68
Figure 5-5. Model performance of each iteration in the multi-variable calibration (a) NSE (b) PBIAS (c) R^2	70
Figure 5-6. Parameter values or absolute changes versus objective function MNSE for each iteration with 2000 simulations	73
Figure 5-7. Normalized uncertainty scores of selected parameters out of 22 parameters used	74
Figure 6-1. Gridded average annual precipitation from 1991 to 2005.	81
Figure 6-2. Procedure adopted in this study for GCM selection for streamflow simulation in the Irrawaddy River Basin	82
Figure 6-3. Approximate locations of the planned reservoirs (Capacity > 500 MW) in the Irrawaddy River Basin considered in this study.	86
Figure 6-4. Distribution of daily precipitation of ten CMIP5 GCMs compared with observed data at selected sub-basins over the base period (1991-2005)	90
Figure 6-5. NSE (a) and PBIAS (b) of simulated streamflow forced with GCM data	92
Figure 6-6. Monthly precipitation of observed and GCMs (without and with bias correction) for the selected sub-basins during 1991-2005	94
Figure 6-7. Monthly mean minimum temperature (T_{min} in shaded three plots) and maximum temperature (T_{max} in the bottom three plots) of observed and GCM data for the selected stations during 1991-2005	95
Figure 6-8. Observed and simulated monthly sediment load at three stations: Kalewa (top), Sagaing (middle), and Pyay (bottom) for the calibration period (1991 – 2010).	96
Figure 6-9. The model simulated (a) average annual sediment yield and (b) coefficient of variation of sediment yield at sub-basin level for the period of 1991-2010 in Irrawaddy River Basin.	97
Figure 6-10. Simulated (a) streamflow, and (b) sediment load at Pyay with bias-corrected GCM data (CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES) for the base period (1991-2005) in the Irrawaddy River Basin	100
Figure 6-11. Percentage change of precipitation under two RCPs (RCP 2.6 on the left and RCP 8.5 on the right) of the three selected GCMs (from left to right CSIRO Mk3.6, HadGEM2-AO, and HadGEM2-ES), relative to the base period (1991 – 2005) over each sub-basin of the Irrawaddy River Basin	103

Figure 6-12. Percentage change in projected mean monthly streamflow at Pyay relative to the base period (1991-2005) for simulations forced with the three different GCM data	105
Figure 6-13. Percentage change of projected mean annual flow (left) and sediment load (right) at Pyay relative to the base period (1991-2005) under RCP 2.6 and RCP 8.5 computed using the three selected GCM data as forcing	106
Figure 6-14. Percentage changes in projected mean monthly sediment load at Pyay relative to the base period (1991-2005) for simulations forced with the three different GCM data	107
Figure 6-15. Projected mean annual sediment load in the reservoir reaches (just downstream of reservoirs) from simulations with CSIRO Mk3.6 under RCP 8.5 with 50% trapping efficiency (left) and 95% trapping efficiency (right)	112
Figure 7-1. Gridded average annual precipitation from 1991 to 2005. (a) RegCM4/MIROC5, (b) RegCM4/MPI-M-MPI-ESM-MR, and (c) RegCM4/NCC-NORES1-M	119
Figure 7-2. Distribution of daily precipitation of three RegCM4 RCMs compared with observed data at selected sub-basins over the base period (1991-2005)	119
Figure 7-3. Monthly precipitation of observed and RCMs (without and with bias correction) for the selected sub-basins during 1991-2005	121
Figure 7-4. Monthly mean minimum temperature (Tmin in shaded 3 three plots) and maximum temperature (Tmax in bottom three plots) of observed and RCMs for three stations during 1991-2005	122
Figure 7-5. Annual sediment load at the Kalu River Basin outlet	123
Figure 7-6. The model simulated (a) average annual sediment yield, and (b) coefficient of variation of sediment yield at sub-basin level for the base period (1991-2000) in Kalu River Basin	124
Figure 7-7. Simulated (a) monthly streamflow at Putupaula, and (b) monthly, and (c) annual sediment load at basin outlet with bias-corrected RegCM4 RCM data (MIROC 5, MPI-M-MPI-ESM-MR, and NCC-NORES1-M) for the base period (1991-2005) in the Kalu River Basin	126
Figure 7-8. Percentage change of precipitation under RCP 2.6 (left) and RCP 8.5 (right) of three RegCM4 RCMs (from left to right MIROC5, MPI-M-MPI-ESM-MR, and NCC-NORES1-M) with respect to the base period (1991 – 2005) over each sub-basin of the Kalu River Basin	128
Figure 7-9. Percentage change in projected mean monthly streamflow at the basin outlet relative to the base period (1991-2005) for simulations forced with the three RegCM4 RCM data	129

Figure 7-10. Percentage change in projected mean annual flow (left) and sediment load (right) at basin outlet relative to the base period (1991-2005) under RCP 2.6 and RCP 8.5, computed using the three RegCM4 RCM data as forcing	130
Figure 7-11. Average monthly sediment load projections for RCP 2.6	131
Figure 7-12. Average monthly sediment load projections for RCP 8.5	131
Figure 7-13. Percentage change in projected mean monthly sediment load at the basin outlet relative to the base period (1991-2005) simulations of individual RegCM4 RCM	132
Figure 8-1. Vörösmarty et al. (2003)'s representation of a basin for estimating basin-wide sediment trapping for large reservoirs	137
Figure 8-2. Comparison of the mean annual sediment projections (Millions Tons (MT)) at the Irrawaddy basin outlet obtained from SWAT and BQART models	142
Figure 8-3. Comparison of the relative changes in mean annual sediment projections for future periods (2046-2065 and 2081-2100) compared to the base period model estimates at the Irrawaddy basin outlet using SWAT and BQART models	143
Figure 8-4. Comparison of the mean annual sediment projections (Million tons (MT)) at the Kalu basin outlet obtained from SWAT and BQART models	145
Figure 8-5. Comparison of the relative changes of mean annual sediment projections for future periods (2046-2065 and 2081-2099) compared to the base period model estimates at the Kalu basin outlet using SWAT and BQART models	146

LIST OF TABLES

Table 2-1. Characteristics of model types	10
Table 2-2. Overview of the impacts of different precipitation inputs on hydrological simulations over South and Southeast Asia	12
Table 2-3. Overview of bias-corrected future climate projections for selected studies in South and Southeast Asia	18
Table 3-1. Spatial data used in this study	31
Table 3-2. Observed hydro-meteorological data	31
Table 3-3. Global data	31
Table 3-4. GCM and RCM data	32
Table 4-1. Hydrological parameters used in model calibration	39
Table 4-2. SWAT model performance for calibration and validation periods. Bold values indicate the highest model performances.	45
Table 4-3. SWAT model performance for calibration period (1991-2000)	51
Table 5-1. Model performance for monthly streamflow and evapotranspiration of the Chindwin River Basin	71
Table 6-1. Parameters used for sediment load calibration	85
Table 6-2. Basic characteristics of the planned reservoirs considered in this study	88
Table 6-3. Changes in projected seasonal streamflow at Pyay during the end-century period (2081-2100) under RCP 2.6 and RCP 8.5 with/without reservoirs	109
Table 6-4. Changes in projected seasonal and annual sediment load at Pyay during the end-century period (2081-2100) under RCP 2.6 and RCP 8.5 with/without reservoirs	110
Table 6-5. Projected mean annual streamflow and sediment loads at Pyay from the three GCMs for the base period (1991-2005) and mid-century periods (2046-2065)	113
Table 6-6. Projected mean annual streamflow and sediment loads at Pyay from the three GCMs for the base period (1991-2005) and end-century periods (2081-2100)	114
Table 8-1. Summary of model input parameters	139
Table 8-2. BQART projected mean annual sediment load in Million tons per year at the Irrawaddy basin outlet	140
Table 8-3. BQART projected mean annual sediment load in million tons per year (MT/yr) at the Kalu basin outlet under zero trapping condition (i.e., no reservoirs)	144

Table 8-4. Projected average annual sediment loads in Million tons per year (MT/yr) for the Irrawaddy and Kalu basins under RCP 2.6 and RCP 8.5, without reservoirs	148
---	-----

*Netherlands Research School for the
Socio-Economic and Natural Sciences of the Environment*

D I P L O M A

for specialised PhD training

The Netherlands research school for the
Socio-Economic and Natural Sciences of the Environment
(SENSE) declares that

***Thotapitiya Arachchillage
Jeewanthi Gangani Sirisena***

born on 5 October 1984 in Rathnapura, Sri Lanka

has successfully fulfilled all requirements of the
educational PhD programme of SENSE.

Enschede, 10 December 2020

The Chairman of the SENSE board

Prof. dr. Martin Wassen

the SENSE Director of Education

Dr. Ad van Dommelen

The SENSE Research School has been accredited by the Royal Netherlands Academy of Arts and Sciences (KNAW)

K O N I N K L I J K E N E D E R L A N D S E
A K A D E M I E V A N W E T E N S C H A P P E N

The SENSE Research School declares that **Thotapitiya Arachchillage Jeewanthi Gangani Sirisena** has successfully fulfilled all requirements of the educational PhD programme of SENSE with a work load of 31.0 EC, including the following activities:

SENSE PhD Courses

- o Environmental research in context (2016)
- o Research in context activity: 'Co-organizing UNESCO-IHE PhD Symposium on: From water scarcity to water security (Delft, 3-4 October 2016)'

Other PhD and Advanced MSc Courses

- o Data Collection and Analysis and Design, IHE Delft (2018)
- o Climate extremes and risk management, Nanjing University of Information, Science and Technology (2019)

Management and Didactic Skills Training

- o Teaching in the MSc course 'Data acquisition, pre-processing and modelling using SWAT' (2016)
- o Teaching in the MSc course 'River Basin Modelling using SWAT' (2017-2018)

Oral Presentations

- o *Comparison of four precipitation products for hydrological simulation in Irrawaddy River Basin, Myanmar.* Boussinesq Lecture 2017, 26th October 2017, Delft, The Netherlands
- o *Use of evaporation and streamflow data in hydrological model calibration, SWAT* Conference, 19-21 September, 2018, Brussels, Belgium
- o *Use of general circulation models' precipitation data for streamflow simulations in Irrawaddy basin, Myanmar.* The 9th International Conference on Sustainable Built Environment, 13-15 December 2018 Kandy, Sri Lanka

SENSE coordinator PhD education

Dr. ir. Peter Vermeulen

Streamflow and fluvial sediment load are inter-connected and through river networks contribute to the dynamic stability of river/coast systems. Robust assessment of catchment responses under changing climate and human activities is essential for understanding future status of the system. This study was undertaken to explore how different modelling approaches and input data sources may influence projections of streamflow and fluvial sediment loads accounting for climate change and human activities, particularly in data-poor river basins. In order to achieve this overarching objective, two case study sites were selected: the Irrawaddy River Basin in Myanmar and the Kalu River Basin in Sri Lanka. Results show that while not all global precipitation

products are equally good, application of carefully selected precipitation products and remote sensing-based evapotranspiration data have viable potential for simulating hydrological response in data-poor basins. Model projections indicate that, at the two selected study sites, streamflow and fluvial sediment supply to coasts would increase by 2100. In the Irrawaddy River Basin, significant alterations in seasonal streamflow and sediment loads are projected under climate change scenario combined with the effects of planned reservoirs. Comparison of annual fluvial sediment loads projected using the process-based SWAT model and the empirical BQART model indicates that the BQART model might be better suited for large basins (such as the Irrawaddy).