Modelling climate change impacts on the Brahmaputra streamflow resulting from change in snowpack attributes

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Publication Date: 2020

DOI: https://doi.org/10.26190/unswworks/2158

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Modelling climate change impacts on the Brahmaputra streamflow resulting from change in snowpack attributes

Ahmad Hasan Nury

A thesis in fulfilment of the requirements for the degree of

Doctor of Philosophy

School of Civil and Environmental Engineering
Faculty of Engineering
The University of New South Wales
August 2020
Abstract

The Tibetan Plateau (TP) plays a critical role in modulating the hydrology for a number of prominent river basins. Despite its importance, changes in hydrological processes of the region are not closely monitored. It is now well known that rising temperatures are impacting the water cycle in the Plateau. The Upper Brahmaputra Basin, originating from the TP, provides fresh water for a large population downstream and its likely change in reference to future water availability is the focus of this thesis.

One possible way to ascertain and project such changes is to formulate hydrological models and use simulations from General Circulation Models (GCMs) and Regional Climate Models (RCMs) as inputs. This thesis seeks to investigate climate change impacts on snowpack and streamflow as its two key aims. The first part of the thesis explores snowpack changes in terms of within-year accumulation and depletion across the Northern Hemisphere using measured spatially distributed snow water equivalent (SWE) information. Following this, a catchment-scale investigation of uncertainties in precipitation downscaling across the TP is then presented. Such uncertainties affect future projections of precipitation, which in turn influence streamflow simulations. Next, an evaluation of GCM and RCM-derived SWE is reported, which reveals that both GCM and RCM products suffer from significant uncertainties and biases. Such uncertainties and biases in SWE and other climatic variables are reduced significantly using a multivariate bias correction approach.

In the second part of the thesis, a conceptual hydrological model is proposed to assess the impact of temperature-driven changes in snowpack attributes on the streamflow, considering the lack of data available for the upper Brahmaputra basin. The model simulates snow cover fraction, SWE and streamflow using temperature and precipitation information. The results show that SWE is likely to decrease in the near future (2041 to 2064) as well as in the far future (2071 to 2094), which will impact streamflow, and hence water availability for a significant portion of the global population that depends on the water supplied by the Brahmaputra as well as the other major rivers originating from the Tibetan Plateau.
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<tr>
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<tr>
<td>Journal or book name: Earth Future</td>
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<td>Volume/page numbers:</td>
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<tr>
<td>Journal or book name: Advances in Water Resources</td>
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<tr>
<td>Volume/page numbers: 129/189-197</td>
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<td>Date accepted/published: July 2019</td>
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Details of publication #3:
Full title: Future change in snowpack due to climate change in the Tibetan Plateau
Authors: Ahmad Hasan Nury, Ashish Sharma, Raj Mehrotra, Lucy Marshall and Ian Cordery
Journal or book name: Journal of Climate
Volume/page numbers:
Date accepted/published:

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Full title: A conceptual model for simulating streamflow in a changing snow-cover catchment: Application to the data sparse Brahmaputra River basin
Authors: Ahmad Hasan Nury, Ashish Sharma, Lucy Marshall and Ian Cordery
Journal or book name: Journal of Hydrology
Volume/page numbers:
Date accepted/published:

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**Details of publication #5:**

**Full title:** Modelling climate change impacts on the Brahmaputra streamflow resulting from change in snowpack attributes

**Authors:** Ahmad Hasan Nury, Ashish Sharma, Lucy Marshall and Ian Cordeny

**Journal or book name:** Journal of Climate

**Volume/page numbers:**

**Date accepted/published:**

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Acknowledgements

I would like to acknowledge and give most sincere thanks to my supervisor Professor Ashish Sharma for supporting me throughout my time here and believing in my abilities. This thesis would not have been possible without his encouragement, guidance, and enthusiasm. I would also like to express my gratitude towards my co-supervisors, A/Prof Ian Cordery and A/Prof Lucy Marshall for their guidance, constructive feedback, encouragement, and support. I would also like to thank Dr. Raj Mehrotra for his insightful collaborations which helped this work so much.

I am grateful to the following individuals for their advice and kind assistance during this research: A/Prof Fiona Johnson, Dr. Md. Mamunur Rashid, Dr. Seokhyeon Kim and Dr. Hung Pham. My special thanks to the several other members in the WRC and School of Civil and Environmental Engineering, especially Patricia McLaughlin, Robert Steel, Ozair Turabi, Warassamon Kate Brown, and Patrick Vuong for tolerating my several requests.

I gratefully acknowledge the Endeavour Postgraduate Leadership Award for the generous funding for my study in UNSW, Australia.

I am highly thankful to all of my colleagues and friends for their motivations and generosity during this PhD. Special thanks to Clare Michelle Stephens, Dr. Mst Shakera Karim Khan, and Rounak Afroz for your kind support. I would also like to thank Dr. Nazly Yasmin, Dr. Jannatun Nahar, Dr. Mahedi Hasan, Dr. Syed Abu Soweb, Dr. Mohammad Zaved Kaiser Khan, Xia Wu, Clare Bales, Xudong Han, Ze Jiang, Dr. Ademir Prata Junior, Dr. Ruth Fisher, Philippa Higgins, Johan Visser, Dr. Tomas Beuzen, Jhilam Sinha, Dr. James Hayes, Dr. Anna Yeung, Calvin He, Danial Khojasteh, Nur Fadhilah Idris, Rebecca Li, Shuang Liu, Cilcia Kusumastuti and Song Thao.

My heartiest thank to my mum, dad, brothers and sisters for respecting my choice to undertake the PhD thesis and supporting me. I am also thankful for the support of my mother-in-law, brothers-in-law and sisters-in-law. I am grateful to my wife Taspia Nahar Tania for her patience, love as well as unconditional encouragement, and support over all these years of study.

Above all, I am extremely grateful to the Almighty, who enabled me to complete the journey of this research work.
Abstract

The Tibetan Plateau (TP) plays a critical role in modulating the hydrology for a number of prominent river basins. Despite its importance, changes in hydrological processes for the region are not closely monitored. It is now well known that rising temperatures are impacting the water cycle in the Plateau. The Upper Brahmaputra Basin, originating from the TP, provides fresh water for a large population downstream and its likely change in reference to future water availability is the focus of this thesis.

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List of Publications

Journal Articles


Nury, A. H., Sharma, A., Marshall, L., and Cordery, I. (submitted), Changing patterns of snowpack accumulation and depletion due to rising global temperatures, *Earth’s Future*


Nury, A. H., Sharma, A., Marshall, L., and Cordery, I. (submitted), Modelling climate change impacts on the Brahmaputra streamflow resulting from change in snowpack attributes, *Journal of Climate*

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<tr>
<td>P</td>
<td>Precipitation</td>
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<tr>
<td>T</td>
<td>Temperature</td>
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<tr>
<td>PET</td>
<td>Potential evapotranspiration</td>
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<tr>
<td>Q</td>
<td>Streamflow</td>
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<tr>
<td>SWE</td>
<td>Snow water equivalent</td>
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<tr>
<td>SCF</td>
<td>Snow cover fraction</td>
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<tr>
<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
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<tr>
<td>GCM</td>
<td>General Circulation Model</td>
</tr>
<tr>
<td>RCM</td>
<td>Regional climate model</td>
</tr>
<tr>
<td>RCP</td>
<td>Representative Concentration Pathway</td>
</tr>
<tr>
<td>APHRODITE</td>
<td>Asian Precipitation highly Resolved Observational Data Integration Towards Evaluation of Water Resources</td>
</tr>
<tr>
<td>NCEP2</td>
<td>National Centre for Atmospheric Research Reanalysis 2</td>
</tr>
<tr>
<td>ERAI</td>
<td>ERA-Interim</td>
</tr>
<tr>
<td>$W_i$</td>
<td>Wet-day occurrence probability on day $i$</td>
</tr>
<tr>
<td>VIF</td>
<td>Variance inflation factor</td>
</tr>
<tr>
<td>$S_e$</td>
<td>Standard error of model</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>residuals (observed data minus modelled data)</td>
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<tr>
<td>MCMC</td>
<td>Markov Chain Monte Carlo</td>
</tr>
<tr>
<td>BIC</td>
<td>Bayesian Information Criteria</td>
</tr>
<tr>
<td>DIC</td>
<td>Deviance Information Criteria</td>
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<tr>
<td>STD</td>
<td>Standard deviation</td>
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<tr>
<td>ACCESS 1.3</td>
<td>The Australian Community Climate and Earth System Simulator 1.3</td>
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<tr>
<td>MRNBC</td>
<td>Multivariate recursive nesting bias correction</td>
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<tr>
<td>CanSISE</td>
<td>Canadian sea ice and snow evolution network</td>
</tr>
<tr>
<td>Symbol</td>
<td>Definition</td>
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<tr>
<td>MSE</td>
<td>Mean squared error</td>
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<td>NSE</td>
<td>Nash Sutcliffe efficiency</td>
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<td>RMSE</td>
<td>Root mean squared error</td>
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<td>RSR</td>
<td>RMSE-observations standard deviation ratio</td>
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<tr>
<td>CC</td>
<td>Correlation coefficient</td>
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<tr>
<td>$M_t$</td>
<td>Snowmelt at time $t$</td>
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<tr>
<td>$\delta$</td>
<td>Melt parameter</td>
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<tr>
<td>$\gamma$</td>
<td>Loss parameter</td>
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<tr>
<td>$K$</td>
<td>Storage delay parameter</td>
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<tr>
<td>$m$</td>
<td>Non-linearity parameter</td>
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<tr>
<td>$R$</td>
<td>Reliability of a reservoir system</td>
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<tr>
<td>$\phi$</td>
<td>Resilience of a reservoir system</td>
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1 Introduction

This chapter introduces the motivation for the research reported in the thesis. Key issues pertaining to the data scarce Tibetan Plateau and Brahmaputra basin are discussed, along with a summary of recent literature aiming to address the research gaps and articulating the need for a flexible hydrologic model that accounts for dynamically changing snow cover. At the end of the chapter, the research objectives and thesis structure are outlined.
1.1 Research motivation

The highest plateau of the world, Tibet (TP), includes a number of complex mountains, and substantial volumes of fresh water in snow form outside of the two poles (Liu et al., 2020, Dai et al., 2018, Orsolini et al., 2019). Runoff from these snow covered mountains feed significant volumes of water to some of the largest Asian river systems including the Brahmaputra, Yellow, Yangtze, Mekong, Salween and Indus Rivers (Zhao et al., 2019a, Tian et al., 2020, Wang et al., 2020). The water supply from the TP is used in energy generation and agriculture and exerts a large influence on the water and food security of almost 1.35 billion people downstream (Zhang et al., 2013, Cuo et al., 2014, Li et al., 2019b). In addition, the TP has great impact on the monsoon rainfall in downstream regions and even on the global climate through thermal and mechanical forcing processes (Gertler et al., 2016, Dai et al., 2018, Liu et al., 2020, Bai et al., 2013, Chen et al., 2017, Zhu et al., 2019). Moreover, the upper Brahmaputra basin supplies water to a large and growing population for hydro-economic and consumption needs (Shi et al., 2011, Ray et al., 2015). In these circumstances, any change in the snowpack, both within the year and over time, is of significant concern for the water availability across this region.

According to the Intergovernmental Panel on Climate Change (IPCC, 2013), the increase in mean atmospheric carbon dioxide concentrations during the last century are unparalleled in the previous twenty-two thousand years. Even if carbon dioxide emissions are reduced in future, warming will continue beyond 2100 or even the millennia owing to long-term feedbacks in regards to the carbon cycle and ice loss (Clark et al., 2016b, Eby et al., 2009b). Increased population growth, changes in land use as well as fossil fuel has increased carbon dioxide emissions by 67% since the pre-industrial era and the average rate of warming increase has almost doubled in the last hundred years (IPCC, 2014). Projected global surface air temperature changes over the end of this century with respect to pre-industrial times (AD 1850-1900) is \(\approx 1.6^\circ C\) (Representative Concentration Pathway (RCP), 2.6 ) to \(\approx 4.3^\circ C\) (RCP 8.5) (Morice et al., 2012, IPCC, 2013). This change is higher in the Arctic (\(-3^\circ C\) at RCP 2.6 to \(-12^\circ C\) at RCP 8.5) and more warming is projected across the land than ocean (Kraaijenbrink et al., 2017). Over the recent decades, while climate changes affect natural and human systems around the world, stronger and more comprehensive signs of climate change influences are visible for natural systems (Arnell et al., 2019, Hawkins et al., 2017, Snyder, 2016, Jeong et al., 2017, Byun et al., 2019). Ongoing increase in global warming is substantially affecting the hydrological processes (e.g. altered precipitation pattern, changes in soil moisture and runoff, reduced snow cover and wide spread ice melting) (Fischer et al., 2018b, Li et al., 2019b, Barnett et al., 2005, Harpold and Brooks, 2018a, Hlavčová et al., 2015, Kapnick and Hall, 2012, Littell et al., 2018).

Similarly, the Brahmaputra basin is highly sensitive to changes in temperature and precipitation,
which will subsequently affect snowmelt and ecosystem services on which humanity depends (Shi et al., 2011, Wijngaard et al., 2017, Ding et al., 2018a, Kuang and Jiao, 2016, You et al., 2007). Hydrological systems are being altered in this basin and surrounding areas, increasing the risk of extreme flow events and scarcity of water (Li et al., 2020).

Considering the importance of the Brahmaputra basin and the climate change impacts on it, the focus of this thesis is modelling the impact of climate change on streamflow due to temperature driven changes in snowpack attributes in the upper Brahmaputra basin. Hence, two important questions are addressed in this thesis. The first question focuses on the changing pattern of snow attributes with respect to within-year accumulation and depletion rate in a warming climate. After characterising the uncertainty in downscaling climate variables, the second question focuses on how the impact of climate change on the Brahmaputra streamflow can be modelled considering the lack of data availability for this region and the consequent implications on the type of model that can be developed. The downscaling uncertainty has significant impact in the catchment scale hydrologic simulation and climate change impact studies.

The aforementioned questions are discussed in the literature review in three parts. In the first part, the gap in the comprehensive investigation of the changing pattern of snow attributes in terms of within-year accumulation and depletion rate across the Northern Hemisphere is discussed. Then in the second part, a catchment-scale exploration of uncertainties in downscaling precipitation in the TP is discussed. Here, the need of characterising such uncertainties in hydrologic investigations is demonstrated. After that, the impact of uncertainty and bias in climate models and derived snow attribute SWE (snow water equivalent) is presented. Finally in the third part of literature review, the need for change in existing hydrologic models for meaningful and reliable application to the data sparse upper Brahmaputra basin in the assessment of climate change impact on the streamflow is illustrated.

1.2 Literature Review

1.2.1 Changing patterns of snowpack accumulation and depletion in a warming climate:

The change of snowpack due to rising global temperatures has not been documented or interpreted in detail to date owing to limited access and uncertainty of ground observations (Nury et al., 2019, Musa et al., 2015) across the Northern Hemisphere. Because of the orographic complexity, high elevation and harsh climate conditions of most of this snow-covered region, meteorological stations are few in number (Zhang et al., 2020, Terzago et al., 2017). This region
feeds some of the most populated river basins of the world and forms the basis for energy generation infrastructure (including the Three Gorges dam, the largest dam globally). Roughly 1/6th of the world’s population relies directly or indirectly on snowmelt water for their agriculture, energy and consumption needs (Sturm, 2015, Simpkins, 2018). Any change of snow dynamics in this area could severely impact water availability and the sustainability of large agricultural operations around the world.

Takala et al. (2011) used an assimilation methodology to derive Globsnow datasets from satellite and ground-based measurement for validation. A decline in SWE in the Northern Hemisphere was reported by Luojus et al. (2011) using hemispheric scale SWE trends, Jeong et al. (2017) considered the anthropogenic effect on spring SWE changes and Wu et al. (2018) reported on reduced streamflow due to the changes of spring snowmelt. However, this thesis provides a coherent picture of large scale change in snowpack over a few important regions. These observations demonstrate the hypothesis of visible changes in snowpack accumulation and depletion changing the seasonal pattern of snow as well as its over-year change due to temperature rise. Rate of SWE change is a function of the duration of each accumulation and depletion period, plus the minimum SWE which is different at the start and the end of the year across most of the world. This study is the first-ever attempt to inspect more detailed SWE change at the scale reported and was overlooked in the previous studies (presented in Chapter 2).

1.2.2 Identification and improvement of uncertainties and bias

To project the impact of climate change in the future, temperature, precipitation and SWE outputs derived from global circulation models (GCMs) and regional climate models (RCMs) are frequently used (Immerzeel et al., 2010, Sánchez et al., 2015, Devineni and Sankarasubramanian, 2010, Huang et al., 2013, Guo et al., 2018). At present, meteorological processes cannot be captured by GCMs at sufficient resolution to be suitable in the generation of climate variables (Yao et al., 2020, Aryal et al., 2019, Hawkins and Sutton, 2011). So, GCMs do not well represent the local climate and hence are insufficient for impact studies of climate change at the catchment scale (Johnson and Sharma, 2009, Eghdamirad et al., 2017a, Eghdamirad et al., 2016, Sachindra et al., 2014, Jeong et al., 2012). In this context, downscaling techniques are necessary to simulate finer scale precipitation from existing coarse scale information from the GCM simulations.

Downscaling is a very useful method to transform the coarse-scale GCM grid covering the study area to a local scale (Zhang et al., 2019b, Wilby et al., 2014, Forsythe et al., 2019, Rashid and Beecham, 2019, Mehrotra, 2005). In statistical downscaling,
connections based on statistics are developed between GCM output or reanalysis predictors of coarse resolution and point station climate variables (predictands) to simulate the station scale climate from large scale outputs of the GCM (Hamlet et al., 2019, Jia et al., 2019, Rashid et al., 2016). In a dynamical downscaling method, the information from the large scale outputs of GCM is transferred to fine scale resolution grid based on modelling of the atmospheric physics (Moalafhi et al., 2017b, Rocheta et al., 2017b). Models for dynamic downscaling are often known as Regional Climate Models (RCMs). But, dynamical downscaling models are not largely used in all areas and include remarkable methodical and computational difficulties (Maraun, 2019, Wilby and Dawson, 2013, Beecham et al., 2014). So, statistical downscaling approach is often helpful to extract the change of climate scenarios over finer temporal and spatial scales (Wilby and Dawson, 2013, Fowler et al., 2007, Sachindra et al., 2013).

Statistical downscaling methods are typically calibrated using reanalysis datasets (Charles et al., 2004, Wilby et al., 2002, Frost et al., 2011, Rashid et al., 2015), which are very useful for the adequate representation of atmospheric processes. However, Moalafhi et al. (2016) found that multiple reanalysis products show differences particularly at regional scales. Such differences will make the downscaling model parameters uncertain, including downscaled precipitation (Nury et al., 2019, Nury et al., 2017). The impact of this uncertainty is not well characterised in other downscaling case studies and this thesis quantifies the extent of uncertainty in precipitation downscaling using a Bayesian framework (presented in Chapter 3).

Again, snow water equivalent (SWE) is one of the important inputs for streamflow simulation in the snow dominated catchments and projection of SWE has turned into the major focus for the modelling of streamflow in the future (Dressler et al., 2006, Jörg-Hess et al., 2015, Dziubanski and Franz, 2016). As of now, a number of studies have used GCMs and RCMs derived SWE around the world for the discussion about inter-dataset spread and snowpack change (Terzago et al., 2017, Jeong et al., 2017, Gobiet et al., 2014, Rupp et al., 2013). However, GCMs suffer from biases because of errors in the model structure, initial conditions and scenarios (Woldemeskel et al., 2012, Woldemeskel et al., 2016, Woldemeskel et al., 2014, Eghdamirad et al., 2016). In addition, while RCMs are used for downscaling GCMs output in the catchment scale, these models also suffer from bias due to errors in the input data, discrepancies in the boundary condition and model parameterisations (Teutschbein and Seibert, 2012, Rocheta et al., 2017b, Sánchez et al., 2015). Existing studies did not address bias correction of SWE although
identification and correction of bias in climate modelled SWE is necessary to overcome the mismatch between simulations and observations.

There are a number of bias correction approaches available in the literature and these approaches include local intensity scaling, linear scaling and quantile mapping (Theimßl et al., 2011, Piani et al., 2010, Li et al., 2010, Teutschbein and Seibert, 2012, Schmidli et al., 2006, Vrac et al., 2016). To improve inter-annual variability in climate models through correcting distributional and persistence bias, Johnson and Sharma (2012) proposed a nesting bias correction (NBC) approach for precipitation. The NBC was then further refined by Mehrotra and Sharma (2015) which is a multivariate bias correction approach to correct biases of multiple variables at a time and applied three times in the recursive nature to accomplish better performance. To this end, this thesis employed a multivariate bias correction approach for correcting biases jointly across multiple climate variables (SWE, temperature and precipitation) to preserve dynamic relationships amongst variables and over multiple timescales to investigate the change of SWE in the near future (2041 to 2064) and far future (2071 to 2094) with respect to the historical period (1981 to 2004). Details on the multivariate bias correction of SWE, temperature and precipitation as well as its impact on the improvement of both bias and uncertainty are presented in the Chapter 4.

1.2.3 Modelling climate change impacts on streamflow resulting from changes in snowpack attributes in a warming climate

Increased global warming with its augmented climate variability will increase the risk of extreme events such as droughts, floods and large snowmelts (Immerzeel et al., 2020, Siderius et al., 2013, Alfieri et al., 2015, Barnett et al., 2005). Wang et al. (2016b) also reported that increased warming led to decrease in snowfall/rainfall ratio during 1961-2013 in the Tibetan Plateau. Therefore, adequate understanding of likely changes in snowpack attributes and resulting streamflow under changing climate in the upper Brahmaputra basin is an important research issue for water planning and management (Li et al., 2018, Ray et al., 2015). Previously, many physically based hydrological models were used for the simulation of snowmelt (Jin et al., 1999, Krogh et al., 2017, Lafaysse et al., 2011) as well as streamflow (Brunner and Simmons, 2012, Li et al., 2013, Chen et al., 2007, Zhang et al., 2008) to monitor the dominant hydrological process. These models require large datasets to capture the physical catchment processes, but the increased number of parameters creates uncertainties in the model outputs (Rashid and Beecham, 2019, Bai et al., 2016, Nayak et al., 2013). These models are not feasible for use in the TP due to limited ground observation data resulting from the complex terrain and harsh climate (Cai et al., 2017, Jia et al., 2019, Basang et al., 2017). Although empirical
hydrological models have mitigated this shortcoming using mathematical transfer functions to transfer climate variables into streamflow, the applicability of these models in the investigation of climate change impact in water resources is limited (Modarres and Ouarda, 2013, Kisi et al., 2013). These models lack the realism of the hydrologic processes necessary to make them useful and reliable under changing system given the sparse data available and the complexity of the processes being studied.

To overcome data availability challenges, the degree-day method (or temperature index model) is widely adopted in hydrology for snowmelt estimation at regional scales especially for remote basins (Singh and Kumar, 1997, Rango, 1992, Singh and Bengtsson, 2004, Arora et al., 2008, Singh et al., 2006, Kumar et al., 2007, Tong et al., 2016, Ding et al., 2018b). Formulation of the degree-day method is quite general and it follows the assumption of a linear relation between accumulated temperature and snowmelt (Hock, 2003, Singh et al., 2009, Smith and Marshall, 2010). However, it cannot be useful when a basin has dynamically changing snow covered area (such as Brahmaputra, Yellow, Yangtze Rivers in the TP), as the precipitation-runoff processes is different in frozen ground and snow free condition under warming temperatures. Additionally, in the literature, most studies on the topic of hydrologic model in the catchments of TP have focussed on simulation of snow attributes (Stigter et al., 2017, Fan et al., 2019, Liu et al., 2019, Gao et al., 2018b, Zhong et al., 2018) or hydrological attributes such streamflow and groundwater (Su et al., 2020, Liu et al., 2017, Ma et al., 2018, Bai and Liu, 2018, Ruan et al., 2017). However, few studies discuss and test ideas for improving model performance under climate change (Liu et al., 2018b, Pan et al., 2017, Liu et al., 2018a). These studies examine change of streamflow ignoring dynamically varying snow cover fraction which is important to differentiate the hydrologic processes of frozen ground versus non-frozen ground under changing climate conditions, and that could result in misunderstanding the actual process and likely change of future water resources. Owing to the lack of data and uncertainty in future projections, a comprehensive representation of the response of a varying snow covered basin in a changing environment is commonly overlooked by water modellers and managers. Considering this, it is important to develop a new flexible hydrologic model for the Brahmaputra basin to address the aforementioned issues, which is described in Chapter 4 (hydrologic model development) and Chapter 5 (implications of the proposed hydrologic model under changing climate).

1.3 Aims and Objectives of the thesis

This thesis addresses the main gaps existing in the literature (as discussed above) by proposing an improved methodological framework to investigate the climate change impact on streamflow
considering temperature driven changes of snow storage and non-snow storage in the upper Brahmaputra basin. To fill this gap, the changes in snowpack across Northern Hemisphere in a warming climate are explored. After that, the downscaling uncertainties and biases of climate variables are quantified as well as improved for future projection. Then, a flexible hydrological model is proposed considering the lack of data available and applied to assess the effects of climate change in the upper Brahmaputra basin. The overall aim of this thesis is achieved by addressing the following four specific questions:

i) How to develop a metric to investigate snowpack accumulation and depletion due to global warming?

ii) How to characterise uncertainty resulting from the use of alternate reanalysis datasets in statistical downscaling?

iii) What is the pattern of change of SWE in future after correcting uncertainties and biases of different GCMs and RCMs?

iv) How to develop a framework of a hydrological model for a data scarce basin containing changing snow cover and increasing temperature profile to address climate change impacts on streamflow originating from change in snowpack attributes?

A comprehensive assessment of large-scale snowpack change in both its accumulation and depletion periods as well as its over year change because of temperature rise is provided in this thesis focusing on the first question. Then, underlying uncertainties of precipitation downscaling are discussed and investigated by means of the question two which will affect catchment-scale snowpack change assessment, and thus streamflow simulation. After that, uncertainties and biases of large-scale climate modelled snowpack attributes are corrected for the further investigations of snowpack change in the future answering the question three. Finally, a flexible modelling framework is proposed to assess water resources impact into the future considering the question four. Moreover, Figure 1.1 outlines the relationship between the chapters in terms of previously mentioned questions.

1.4 Organisation of the thesis

The data, methods, results and analyses for each investigation are presented in the associated chapters, each of which is a published or submitted journal publication. The rest of this thesis is organized as follows. Chapter 2 proposes a comprehensive method to evaluate snowpack change in both its accumulation and depletion periods, demonstrating the hypothesis that as
time has advanced the dynamics of snowpack variation have changed (with change being different in snow accumulation and depletion periods). This change is assessed over most of the Northern Hemisphere with respect to time and temperature respectively. Snowpack change is also discussed at a regional scale and the effect of potential climate characteristics of major snow-covered regions in this change is highlighted as well. Chapter 3 quantifies the extent of uncertainty arising from the use of alternate reanalysis variables in the context of statistical downscaling in the Tibetan Plateau. It shows the influence of downscaling model structure, rigidity and parameter uncertainty on the downscaled precipitation. Chapter 4 attempts to provide a reliable assessment of the future changes in snowpack changes using GCMs and RCMs simulation in the Tibetan Plateau. The proposed methodology assists in improving both biases and uncertainties of climate models. Chapter 5 develops a simplified conceptual hydrologic model for the upper Brahmaputra basin to simulate snow cover fraction, SWE and streamflow considering temperature and precipitation as inputs. Chapter 6 expands the approach presented in Chapter 5 to include climate change scenarios in the future. Finally, Chapter 7 summarises the outcome of the thesis, highlights the limitation of this study, and offers recommendations for further research.

Figure 1.1 Thesis chapters and their associated key objectives
2 Changing patterns of snowpack accumulation and depletion due to rising global temperatures

This chapter provides a coherent picture of large scale snowpack change demonstrating the hypothesis that clear changes are visible in snowpack accumulation and depletion over most of the Northern Hemisphere. Such change will impact on availability of snowmelt driven streamflow including some of the largest populated basins in the world. The content in this chapter has been reproduced (with reformatting) from the journal manuscript referenced below.

Changes in global snowpack distributions have received increased attention in recent decades due to growing concerns about water planning and hydrologic modelling in regions where snowmelt is a dominant source of water. This study assesses trends in snowpack during accumulation and depletion periods against time as well as temperature using global snow water equivalent datasets (SWE). Our results show that a majority of regions exhibit decreased yearly maximum SWE in recent decades (1998-2016) compared to the past (1980-1997), which may be attributed to warmer temperature. In addition, large areas reveal decreasing snow accumulation rates while deeper snowpack regions show increasing snow depletion rates over the years from 1980 to 2016. The same pattern of change is observed when assessed with respect to temperature.

Nury, A. H., Sharma, A., Marshall, L., and Cordery, I. (submitted), Changing patterns of snowpack accumulation and depletion due to rising global temperatures
2.1 Introduction

Snow has an important role in the coupled atmosphere-land-ocean system and terrestrial water storage in many parts of the world (Mudryk et al., 2015, Jennings et al., 2018, Pritchard, 2018). It is one of the essential elements of water resource systems in many water-stressed regions where rivers are often fed by snowmelt from distant mountains (Sturm, 2015). Water is supplied from accumulated snow recharge reservoirs (Snapir et al., 2019, Anghileri et al., 2016), although rapid snowmelt can also cause threatening floods (Parajka et al., 2019). Snow attributes such as snowfall, snow covered area, snow depth, are important inputs to hydrological simulations and water management (Dong, 2018). However, snow resources are closely linked to temperature, and changes in snowpack reveal the strongest hydrologic signs of climate change (Byun et al., 2019, Blöschl et al., 2017).

Global average surface temperature has increased by 0.85°C since the late twentieth century (IPCC, 2014), and by 2100 this warming is expected to range from 1.6°C (Representative Concentration Pathway 2.6) to 4.3°C (Representative Concentration Pathway 8.5) as per IPCC (2013). Climate records suggest higher temperatures in the Northern Hemisphere (Papalexiou et al., 2018, Fischer et al., 2018a), with warming being greater on land than oceans (Fischer et al., 2018a). Furthermore, it is now widely expected that warming will continue beyond 2100 due to long term feedbacks even if greenhouse gas emissions are reduced (Clark et al., 2016a, Eby et al., 2009a, Raftery et al., 2017). In response to this warming, snowfall to precipitation ratios show decreasing trends (Wang et al., 2016b, Berghuijs et al., 2014) accompanied by significant decline in snow covered areas (Kunkel et al., 2016, Déry and Brown, 2007), with snow depths having decreased considerably in the northern hemisphere to date (Xu et al., 2017). A significant decline in snow cover extent (SCE) around coastal margins in the northern hemisphere, Scandinavia, northern Russia, and Himalayas in spring is additionally expected as per Brown and Mote (2009) using eight GCMs from the 3rd phase of the Coupled Model Intercomparison Project (CMIP3).

While historical changes in overall snow cover on a global scale can be well identified, the impact of declining snow cover for water resources management are difficult to explain. Snow water equivalent (SWE) incorporates both snow depth and density, and may be more useful than snow cover extent to understand the water resources implications of change in snow-dominated catchments (Egli et al., 2009, Takala et al., 2011). For instance, Barnhart et al. (2016) used snow water equivalent to show how snowmelt rate dictates subsequent streamflow. Few ground precipitation or snow datasets exist, creating challenges in assessing change into the future (Nury et al., 2019). Remote sensing measurements of precipitation and snow also pose challenges (Libertino et al., 2016, Sivasubramaniam et al., 2018), especially for high altitudes.
Satellite based SWE datasets (Takala et al., 2011) are useful in snowpack change studies to overcome the lack of ground based observed data in developing countries and remote areas. A decline in SWE in the Northern hemisphere was reported by Luojus et al. (2011) using hemispheric scale SWE trends, Jeong et al. (2017) considering anthropogenic effect on spring SWE changes, and by Wu et al. (2018) due to changes of spring snowmelt. However, annual variations in SWE will be a function of the temporal trends in snow accumulation and depletion rates, and warming climates can affect these rates considerably in spite of the noise in the observations resulting from variations in rainfall and humidity. Varying rates in snow accumulation can modulate peak snowpack depth and volume, affecting the availability of water for spring runoff. Similarly, changes in snow melt rates will affect the timing of runoff events with implications for ecosystems, agriculture, and human consumption.

In this study we evaluate snowpack change in both its accumulation and depletion periods testing the hypothesis that as time has advanced, the dynamics of snowpack variation have changed (with the change being different in snow accumulation and depletion periods). We assessed this change over most of the Northern Hemisphere and at a regional scale. We emphasise the focus here is the change in accumulation and depletion rate, instead of the change in the maximum SWE during a year. A change in rate is indicative of a change in the timing of the peak SWE, as well as factoring in the changes in SWE from one year to the next. The framework of this study is threefold. Initially, we discuss the overall change in maximum SWE for the Northern Hemisphere since 1980. Then, the rates of snow accumulation and depletion are evaluated and changes ascertained. Finally, we assess the sensitivity of snow accumulation and depletion rates with temperature. A positive or negative sensitivity of a variable is suggestive of its corresponding positive or negative trend, given temperature trends have remained positive since the mid-20th century (Sharma et al., 2018).

2.2 Data and Methods

Maximum monthly SWE were obtained from the European Space Agency (ESA, 2014) for the period 1980 to 2016 (referred to as the GlobSnow dataset). This dataset uses two different satellite passive radiometers [i.e., Scanning Multichannel Microwave Radiometer (SMMR) and Special Sensor Microwave/Imager (SSM/I)] combined with ground-based meteorological station data. This provides a monthly SWE time series of the Northern Hemisphere land surface resulting from weekly SWE estimates at a spatial resolution of 25 km excluding glaciers and Greenland. The GlobSnow dataset is selected for assessment of SWE change in this study as it is known to better reproduce the maximum accumulation and seasonal cycle of SWE than other earth observation products such as AMSR-E (The Advanced Microwave Scanning Radiometer
for Earth Observing Satellite) /Aqua Global Snow Water Equivalent and Global EASE-Grid 8-day Blended SSM/I (Special Sensor Microwave/Imager) and MODIS (The Moderate Resolution Imaging Spectroradiometer) Snow Cover of NASA (Hancock et al., 2013, Luojus et al., 2011, Cho et al., 2017). Luojus et al. (2011) validated the GlobSnow SWE product using ground observations from 1264 stations in Russia and found good agreement with a bias of +3.0 mm for SWE values from 0 to 150 mm. Li et al. (2014) evaluated the monthly SWE of GlobSnow and NSIDC (National Snow and Ice Data Centre) using ground observations from global historical climatology network daily (GHCN) weather stations and identified more realistic SWE values (for SWE ranging 30 to 200 mm) in the GlobSnow dataset than NSIDC. Global monthly mean surface air temperature data between the years 1900 and 2016 at a grid resolution of 0.5° x 0.5° were similarly available from University of Delaware temperature dataset at https://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html. For convenience, SWE datasets were re-gridded following the resolution of the available temperature data (0.5° x 0.5°) using a conservative interpolation approach (Jones, 1999).

To evaluate SWE changes at each grid cell in snow accumulation and depletion periods, a water year (or hydrological year) was defined as starting from October of the previous year (t-1) to September of the following year (t). The snowpack accumulation period was defined as spanning from the month of minimum SWE to the month of maximum SWE in a water year. The snowpack depletion period was defined to span from the month of maximum SWE to the month of minimum SWE in the rest of the water year. Then, accumulation rate and depletion rate were calculated from magnitude of snow accumulation and depletion divided by the number of months in the respective accumulation/depletion periods. Therefore, the rate considered here is a function of the duration of each accumulation and depletion period considering the minimum SWE is different at the start and the end of the year.

The average temperature in the corresponding SWE accumulation and depletion periods was also calculated from the available monthly data. A trend line of the within year accumulation/depletion rates respective to temperature across years was fitted using flexible local regression following the procedure of Bowman and Azzalini (1997). For estimating changes in SWE accumulation and depletion rates with time and temperature, a least squares regression approach was applied to ascertain the regression coefficients of interest.
2.3 Results and Discussions

2.3.1 Change in Maximum SWE

To assess the overall change in maximum SWE for the Northern Hemisphere, the maximum SWE for each year was ascertained and its change (mean of 1980-1997 minus mean of 1998-2016 as the SWE data is available for the period 1980 to 2016) is illustrated in Figure 2.1. The proportion of pixels that have a lower yearly maximum SWE in the second period (1998-2016) than in the first period (1980-1997) is 60% in Figure 2.1(f). The maximum SWE in each water year is shown to be decreasing as temperature increases during the accumulation period as per Figure 2.1(a) for Canada, (b) for USA, (c) for Finland, (d) Sweden and (e) for Tibet. A detailed description of SWE change in terms of time and temperature is discussed respectively in the next sections.

Figure 2.1 Differences between the averages of maximum SWE for the periods 1980-1997 and 1998-2016. In Figure (f) the number of pixels with positive difference equals 60%. Here positive difference indicates less SWE in the latter period (1998-2016) than the former period (1980-1997). Yearly maximum SWE versus air temperature in accumulation periods for each year are shown for (a) Canada, (b) USA, (c) Finland, (d) Sweden, and (e) Northern Tibet. The red line in inset figures are local regression fits.

A summary of Figure 2.1 results is presented in Table 2.1. For each major snow-covered region in the Northern Hemisphere, the proportion of area where there was a positive increase in average SWE was calculated based on a relative count of the number of pixels where this was
observed. From these results, it is evident that the yearly maximum SWE is lower in the second period compared to the first for higher proportion of pixels except for Tibet, which has been argued to possibly be a result of local atmospheric and topographic conditions (Xu et al., 2017, Li et al., 2018) as discussed later. Another possible reason for less decrease of SWE in Tibet than USA and other regions could more snowfall since temperature remains negative in the snow season (Dahe et al., 2006; Tahir et al., 2011). Wang et al., (2017) also found that there is no widespread decline of snowpack in Tibet during because of complex topography and no change in snow formation temperature threshold of 0 °C for global warming. Furthermore, the relationship between proportions of pixel with decreased SWE and temperature trend is not noticeable. Remotely sensed snow products have uncertainties due to gaps in revisit times of the satellite, limitation of sensor observations, and the effect of atmospheric conditions (Li et al., 2018, Mudryk et al., 2015, Slater et al., 2013), which will affect the association between trend of SWE and temperature. Gridded temperature datasets include uncertainties arising from data interpolation approaches and the algorithms that produce the interpolated temperature series from the observations although these datasets are widely used in data sparse region (Terzago et al., 2017; Moalafhi et al., 2016; Terzago et al, 2014).

Table 2.1 Proportion of pixels with a decrease in the average maximum SWE between the periods 1980-1997 and 1998-2016 along with the rate of change of averaged temperature for each region over time

<table>
<thead>
<tr>
<th>Region</th>
<th>Proportion of pixels with a decreased SWE (%)</th>
<th>Temperature trend (°C per month)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canada</td>
<td>70</td>
<td>0.0027</td>
</tr>
<tr>
<td>USA (northern)</td>
<td>53</td>
<td>0.0014</td>
</tr>
<tr>
<td>Finland</td>
<td>67</td>
<td>0.0046</td>
</tr>
<tr>
<td>Sweden</td>
<td>86</td>
<td>0.0034</td>
</tr>
<tr>
<td>Tibet (northern)</td>
<td>21</td>
<td>0.0025</td>
</tr>
</tbody>
</table>

2.3.2 Change of accumulation and depletion rates for SWE from 1980-2016

To demonstrate change over time, the rate of change of the maximum SWE in accumulation and depletion periods from 1980-2016 is presented in Figure 2.2. The number of pixels with a decreasing snow accumulation rate (75%) is greater than the number of pixels with a decreasing snow depletion rate (39%). Overall, snow depletion rate is higher than snow accumulation rate from 1980-2016. Therefore, snowpack change in the Northern Hemisphere
follows a different pattern of accumulation (decreasing accumulation rates) and depletion (increasing depletion rates) in warmer temperatures. In addition, to investigate the change in timing of maximum snow accumulation (the start of snowmelt after maximum accumulation), average timing over the first period (1980 to 1997) is compared with that over the second period (1998 to 2016) for SWE datasets in Table 2.2. In the second period, the majority of pixels show an earlier (February) start of snowmelt which could be a result of the warming climate.

Table 2.2 Timing of maximum snow accumulation. Months of maximum snow accumulation are being averaged from 1980 to 1997 and 1998 to 2016 respectively.

<table>
<thead>
<tr>
<th>Average timing</th>
<th>No. of pixels in first half of study period (1980-1997)</th>
<th>No. of pixels in second half of study period (1998-2014)</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>15</td>
<td>697</td>
</tr>
<tr>
<td>February</td>
<td>11343</td>
<td>20288</td>
</tr>
<tr>
<td>March</td>
<td>32644</td>
<td>12736</td>
</tr>
<tr>
<td>April</td>
<td>12712</td>
<td>2756</td>
</tr>
<tr>
<td>May</td>
<td>794</td>
<td>7</td>
</tr>
</tbody>
</table>

Figure 2.2 (a) Trend of accumulation rate (mm/month) of the monthly maximum SWE, and (b) depletion rate (mm/month) of the monthly maximum SWE, from 1980-2016, with units mm/month/year. Here region 1, 2, 3, 4 and 5 are Canada, USA, Sweden, Finland and northern Tibet respectively. Note maximum SWE occurs at the end of the accumulation and the start of the depletion periods and, by definition, each year’s accumulation rate will be positive and depletion rate negative.
To highlight the regional pattern of change, the trend of accumulation and depletion rates of max SWE from 1980-2016 are presented in Table 2.3. The number of pixels for decreasing snow accumulation rates is greater than number of pixels of decreasing snow depletion rates in Canada, northern USA, Finland, Sweden and Tibet respectively. It is noteworthy that more pixels are experiencing an increasing snow depletion rate than increasing snow accumulation rate which supports the hypothesis. Warming climate in Northern Hemisphere (Delworth et al., 2016, Reid et al., 2016) resulting from continuous increase of greenhouse gas in the last several decades could be a major factor for the wide spread decline of snowpack. Higher air temperature in all study regions, namely Canada (Zhou et al., 2018a), northern USA (Overland et al., 2018, Wuebbles et al., 2014), Finland (Irannezhad et al., 2015, Mustonen et al., 2018), Sweden (Isles et al., 2018) and northern Tibet (Ding et al., 2018a) have been observed. Increasing air temperature is generating more rainfall than snowfall (Zhou et al., 2018b) and the time of snowmelt is changing such as winter snow is melting in early spring (Blöschl et al., 2017). Moreover, while warmer temperature triggers snow depletion, increasing rainfall contributes to accelerating snowmelt as well.

<table>
<thead>
<tr>
<th>Region</th>
<th>Accumulation period (% pixels)</th>
<th>Depletion period (% pixels)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Increasing</td>
<td>Decreasing</td>
</tr>
<tr>
<td>Canada</td>
<td>22</td>
<td>77</td>
</tr>
<tr>
<td>USA (northern)</td>
<td>33</td>
<td>64</td>
</tr>
<tr>
<td>Finland</td>
<td>33</td>
<td>67</td>
</tr>
<tr>
<td>Sweden</td>
<td>26</td>
<td>73</td>
</tr>
<tr>
<td>Tibet (northern)</td>
<td>11</td>
<td>83</td>
</tr>
</tbody>
</table>

Natural climate variability will contribute to the variations in SWE changes across the selected regions shown in Table 2.3. For instance, temperature and precipitation which are varying due to atmospheric circulation patterns (Papalexiou et al., 2018, Mohtadi et al., 2016), could be potential drivers for regional snowmelt variations. Furthermore, there is evidence that humidity has an important role in snowmelt, which strongly influence local climate characteristics, and causes some locations to be more sensitive to changes in climate than others (Harpold and Brooks, 2018a, Harpold et al., 2017a). Humid days with higher temperature prevent the snow
releasing energy and cooling the snowpack, consequently resulting in larger snow melt events (Harpold and Brooks, 2018a).

To illustrate SWE changes considering temperature, sensitivity of maximum SWE variation rate with temperature in accumulation period and depletion period for all years are shown in Figure 2.3. From the map, the number of pixels for decreasing accumulation rate (38%) is greater than the number of pixels with decreasing depletion rate (12%). Again, a larger proportion of pixels are experiencing increasing snow depletion rate (85%) than those experiencing increasing snow accumulation rate (59%). Overall, snow depletion with increasing temperature is higher than snow accumulation, since warmer temperature contributes to melting or sublimation, and affects the ratio of rainfall to snowfall. Therefore, snowpack change in the Northern Hemisphere is following different roles in the accumulation period (decreasing accumulation rates) from the depletion period (increasing depletion rates). Canada, Finland and Sweden show decreasing accumulation rate and increasing depletion rate whereas Tibet presents increasing accumulation.

Figure 2.3 (a) Temperature sensitivity of SWE accumulation rate each year over 1980-2016 (number of pixels with positive sensitivity = 59%, number of pixels of negative sensitivity = 38% and number of neutral pixels=3%). (b) Temperature sensitivity of SWE depletion rate each year over 1980-2016 (number of pixels of positive sensitivity = 85%, number of pixels of negative...
rate and depletion rate respectively in insets. Here, accumulation rate shows both increasing and decreasing pattern as well as depletion rate which is the same pattern as in USA during the study period.

Sensitivity of accumulation rates and depletion rates of max SWE with temperature in selected regions are presented in Table 2.4. Interestingly, more pixels are experiencing decreasing snow accumulation rates with rising temperature than decreasing snow depletion rate. Furthermore, more pixels are experiencing an increasing snow depletion rate with temperature than an increasing snow accumulation rate. Therefore, snowpack change is following a different pattern in accumulation period and depletion period across Northern Hemisphere in the warmer climate.

<table>
<thead>
<tr>
<th>Region</th>
<th>Accumulation period (% pixels)</th>
<th>Depletion period (% pixels)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Increasing</td>
<td>Decreasing</td>
</tr>
<tr>
<td>Canada</td>
<td>56</td>
<td>42</td>
</tr>
<tr>
<td>USA (northern)</td>
<td>88</td>
<td>8</td>
</tr>
<tr>
<td>Finland</td>
<td>28</td>
<td>72</td>
</tr>
<tr>
<td>Sweden</td>
<td>15</td>
<td>82</td>
</tr>
<tr>
<td>Tibet (northern)</td>
<td>71</td>
<td>19</td>
</tr>
</tbody>
</table>

To further explain melt rate in the depletion period, based on average annual maximum SWE and spatial extent, snowpack is categorised as shallow snowpack (<50mm) which is 20% of total pixels, moderate snowpack (50-100mm) which is 33% of total pixels and deep snowpack (>100mm) which is 47% of total pixels. Total meltwater volume produced at different melt rates namely low (<60 mm/month), moderate (60-70 mm/month), and high (>70 mm/month) melt rate from 1980 to 2016 were presented in Table 2.5. Low melt rates produce more water among all rates from shallow and moderate snowpack, whereas high melt rates produce more water from deep snowpack. However, Musselman et al. (2017) show that high melt rates in deep snowpack will be reduced in the future. So, low melt rates might be linked to the widespread decline of snow during depletion periods in the future.

The statistical significance of the change in accumulation rates and depletion rates against time and temperature at a 5% significance level are presented in Table 2.6. These results further support our hypothesis that there is a clear difference between the change in snow accumulation and depletion against both time and temperature.
Table 2.5 Melt water volume due to different melt rates for the study area.

<table>
<thead>
<tr>
<th>Rate (mm/month)</th>
<th>Water volume from shallow snowpack (%)</th>
<th>Water volume from moderate snowpack (%)</th>
<th>Water volume from deep snowpack (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low melt rate (&lt;60 mm/month)</td>
<td>99</td>
<td>56</td>
<td>1</td>
</tr>
<tr>
<td>Moderate melt rate (60-70 mm/month)</td>
<td>1</td>
<td>25</td>
<td>8</td>
</tr>
<tr>
<td>High melt rate (&gt;70 mm/month)</td>
<td>0</td>
<td>19</td>
<td>91</td>
</tr>
</tbody>
</table>

Table 2.6 Percentage (%) of pixels of accumulation and depletion rates over time and temperature. All results are statistically significant at the 5% level. Significance is established against a null hypothesis that a trend line slope equals zero from 1980 to 2014.

<table>
<thead>
<tr>
<th>Accumulation rates over time (Increasing, % pixels)</th>
<th>Depletion rates over time (Increasing, % pixels)</th>
<th>Accumulation rates over time (Decreasing, % pixels)</th>
<th>Depletion rates over time (Decreasing, % pixels)</th>
</tr>
</thead>
<tbody>
<tr>
<td>9.1</td>
<td>25.6</td>
<td>64.6</td>
<td>10.1</td>
</tr>
<tr>
<td>Accumulation rates against temperature (Increasing, %)</td>
<td>Depletion rates against temperature (Increasing, %)</td>
<td>Accumulation rates against temperature (Decreasing, %)</td>
<td>Depletion rates against temperature (Decreasing, %)</td>
</tr>
<tr>
<td>28.3</td>
<td>79.3</td>
<td>3.8</td>
<td>1</td>
</tr>
</tbody>
</table>

Most of the snow regions in the Northern Hemisphere have complex terrain as well as harsh climate conditions. Therefore, existing precipitation datasets consist of solid (snow) and liquid forms (rain), and do not have particular information about rain which has a comparatively strong influence in creating snowmelt. Available global precipitation datasets cannot describe the aforementioned change of SWE in detail, as any such inference will be misleading without rainfall data. In addition, global precipitation data are often less accurate than temperature and include uncertainties (Moalafhi et al., 2016, Eghdamirad et al., 2016, Slater et al., 2013). Given the lack of rainfall data available and the uncertainties of precipitation data, the question is that in a warming climate, how could one understand the change in snow accumulation and depletion processes? One of the possible ways is described in this research, and uses the rate of accumulation or depletion instead of the change in SWE alone, as the rate allows quantification of the change in amount as well as the duration of snow accumulation and depletion in each year. As of now, a decline in SWE has been reported considering a specific region (Terzago et al., 2017, Terzago et al., 2014, Luojus et al., 2011) or season (Wu et al., 2018) and anthropogenic effect (Jeong et al., 2017). However, this study discusses the within year change of snow accumulation and depletion process comprehensively over time. It also assesses the sensitivity of snow accumulation and depletion rates with respect to temperature. Such change was assessed over most of the Northern Hemisphere and at a regional scale, allowing discussion...
of similarities in rates between some of the regions analysed. This tabulated change would decrease snowpack widely which will affect runoff and water supply in this region.

2.3.3 A possible explanation of the similarity between the USA and Tibet results

The Earth’s atmospheric circulation generates three large circulation cells namely Hadley Cell, Ferrel cell and the Polar cell, respectively. The Hadley cell lies between 0° to 30° latitude in north and south respectively where warm air rises from the equator and flows toward the pole until air sinks around 30° latitude, and flows back towards the equator converging with its counterpart from the Northern or Southern hemisphere. It is related to the trade winds in the tropics, subtropical deserts, the subtropical jet streams (a belt of strong upper level winds above regions of subtropical high pressure) and strongly influences low latitude weather patterns. Hadley cells have been noted to expand poleward in both the Northern and Southern Hemispheres which should affect the global weather patterns and the hydrological cycle (Lu et al., 2007). Climate model simulations over the last two decades disclose poleward expansion and a consistent weakening of the Hadley circulations (Seidel et al., 2008). In the Northern Hemisphere the subtropical jet stream, which marks the boundary between the Hadley and Ferrel cells, moved north, poleward, around 3.7° ± 0.3° degrees latitude between 1979 to 2010 (Hudson, 2012). Hu and Fu (2007) also found the expansion of the Hadley cell by 2° to 4.5° latitude using atmospheric reanalysis data in the period of 1979-2005. In this study the selected regions of USA and Tibet are located in 35°-50° and 35°-40° latitude respectively and within the influence of the Hadley cell (Hadley cell position over earth’s surface moves with the location of the sun, with a lag of one to two months and at times may extend to close to 40°N) (Tarbuck and Lutgens, 1979) which are lower latitudes than of the other locations and are likely to be directly influenced by the effects of the Hadley cell change. Both the USA and Tibet shows less variation in mean maximum SWE change with temperature in the insets of Figure 2.1 while Canada, Sweden and Finland reveal noticeable decreasing trend. The sensitivity of maximum SWE variation rate with temperature in accumulation and depletion periods (insets of Figure 2.3) reveal an almost similar pattern for USA and Tibet. In addition, the difference between the mean maximum SWE for the period 1980-1997 and the mean maximum SWE for the period 1998-2016 in Table 2.1 for USA and Tibet is close than other regions (below 60%). In the same way, the sensitivity of increasing and decreasing accumulation rates as well as increasing and decreasing depletion rates of maximum SWE with temperature (Table 2.4) show similar patterns for USA and Tibet, different from the other regions. These results might be linked to the ongoing observed poleward expansion of the Hadley Cell in the Northern Hemisphere discussed above.
2.4 Conclusions

Understanding the change in snow attributes is important for modelling long-term hydrological processes and extremes in snow-dominated regions. In this study, we explore changes of maximum SWE through the hypothesis that snowpack change is different during the accumulation and depletion periods of a snowpack as a result of warming. The change in SWE is presented here on the basis of the mean change of maximum SWE (mean of 1980-1997 minus mean of 1998-2016), the pattern of change of maximum SWE accumulation and depletion rates, and the change in the sensitivity of maximum SWE to temperature. These conclusions are formed using GlobSnow datasets which are based on satellite observation and ground data. This research provides an insight to snowpack changing pattern over seasons and over water years across the Northern Hemisphere with the aim of covering data-sparse regions that include remote areas susceptible to climate change.

A detailed coherent picture of large-scale snowpack change with respect to a few important regions is provided in this study considering the rate of snow accumulation and depletion changes is the function of the duration of snow accumulation and depletion period as well as amount (where minimum SWE varies in start and end of the water year). The outcomes reveal that more locations exhibit decreasing snow accumulation rates in the accumulation period and an increasing snow depletion rate in the depletion period. Such different patterns of change in snow accumulation rates (decreasing) and depletion rates (increasing) result in a trend of the respective rate with time since warmer temperatures are associated with the more recent past. Possible drivers for this change could be changing atmospheric humidity, varying temperature and precipitation. Furthermore, expansion of Hadley cells resulting from the ongoing climate change may also control the change of snowpack in low latitude e.g. USA and Tibet. Given this change of snowpack, snowmelt induced runoff increases in intensity, possibly contributing to floods in snow-dominated catchments. The usual gradual snowmelt in snow-dominated areas extends the life of the snowpack well into summer and provides a natural storage mechanism, reducing the capacity requirements for built reservoirs (Skaugen and Weltzien, 2016). However, accelerating snowmelt may cause a build-up of water storage earlier than usual, resulting in a lack of water supply in the warmer summer season. This has significant implications for water supply in water-stressed regions (Matti et al., 2016).

Because of the recent acceleration in global warming, snow resources are changing to a large extent in accumulation and depletion periods across the Northern Hemisphere. Wide-spread decline of snowpack in response to climate variability and anthropogenic climate change will affect the hydrology and stream flow of snow-dominated regions. Understanding the potential
patterns of change in snow accumulation and depletion and their subsequent impact on snow volume and melt timing is thus critical for management of water supply systems in impacted regions globally.
3 Characterising Uncertainty in Precipitation Downscaling using a Bayesian Approach

This chapter quantifies the extent of uncertainties resulting from the use of alternate reanalysis datasets in precipitation downscaling at a catchment scale. These uncertainties will affect evaluation of precipitation and snow pack changes in the future, which consequently will influence the hydrologic simulations. The content in this chapter has been reproduced (with reformatting) from the journal paper referenced below.

Statistical downscaling of GCM simulations is widely used for examining future changes in precipitation at different spatial and temporal scales. However, the downscaling process is affected by uncertainty associated with the downscaling model, its parameters, and also the use of different reanalysis products for model calibration. This study develops a Bayesian approach to calibrating a statistical downscaling model. The study investigates the impact of using two different reanalysis products, the National Centre for Environmental Prediction/National Centre for Atmospheric Research Reanalysis 2 (NCEP2) and the European Centre for Medium-Range Forecasts Interim Reanalysis (ERAI), in precipitation downscaling over the Tibetan Plateau, a region with sparse ground precipitation coverage. The selected reanalysis products are used for modelling precipitation at selected locations with long, high quality records and diverse geographic characteristics. An assessment of the downscaled precipitation results using atmospheric variables from the ACCESS 1.3 GCM to drive the downscaling model calibrated using a reanalysis dataset is also performed and the impact of calibration uncertainty quantified. The outcomes of this study reveal that the choice of the data length used and the type of reanalysis product adopted have a significant effect on downscaled precipitation characteristics and their uncertainties, such as the wetness fraction and average annual precipitations over the study locations. These findings point to a common problem in statistical downscaling applications and one that has not been recognised until now. The results show that downscaling model considering ERAI reproduce observed precipitation attributes to a better extent than NCEP2.

3.1 Introduction

Precipitation is a key variable for hydrologic impact studies and for understanding future catchment responses to climate scenarios. GCMs are widely used for precipitation projections, but suffer from a high degree of uncertainty (Charles et al., 2004, Hope et al., 2006, Fowler et al., 2007, Johnson et al., 2011) especially at the catchment scale. This uncertainty is considered a significant constraint in the derivation of hydrologic variables at the local scale (Tebaldi et al., 2011, Chen et al., 2011). Numerous studies have demonstrated that GCM uncertainty mainly arises from model structural error, ensemble error and scenario error (Hawkins and Sutton, 2011, Hawkins, 2011, Woldemeskel et al., 2012). Woldemeskel et al. (2016) established a basis for quantifying such uncertainties in space and time and named it as SREV (Square Root of Error Variance). Eghdamirad et al. (2016) quantified the sources of uncertainties in global upper air atmospheric variables which were applied for the downscaling of precipitation in the Tibetan Plateau. These uncertainties are amplified when considering predictions at finer spatial and temporal scale that are frequently needed for understanding climate change impacts in hydrology. For example, Kannan et al. (2014) found significant uncertainty from multiple reanalysis data usage in precipitation downscaling, and downscaled monsoon precipitation changes was spatially heterogeneous although changes in the GCM outputs were spatially uniform. To address uncertainty from multiple spatial resolutions, Shashikanth et al. (2014) compared downscaled precipitation at different spatial resolutions and computed signal to noise ratio (SNR) which denotes the signal of climate change in regard to the noise from multi-model uncertainty. They found that there is no significant change in SNR for a change in data resolution and increased resolution did not improve the SNR of climate projections.

Several downscaling approaches have been developed to translate climate model outputs from a coarse resolution to a catchment scale (Wilby et al., 2014, Chandler and Wheater, 2002, Jeong et al., 2014, Mehrotra and Sharma, 2006, Fu et al., 2013, Rashid et al., 2016). These include dynamical and statistical downscaling methods (Thatcher and McGregor, 2009, Wilby et al., 2003, Rocheta et al., 2017b) and use bias corrected atmospheric variable simulations as the basis for assessing changes in the future. Dynamical downscaling uses GCM regional simulations to drive a fine scale physical model to transfer the effects of large-scale climate processes to regional or local scales of interest. In statistical downscaling, observed relationships between local climate variable(s) and large-scale atmospheric variables are used. These models are simpler to use and better suited to capture climate change scenarios at finer temporal and spatial scales, as a result of which many statistical downscaling methods exist. These vary from simple linear regression based models to data driven Artificial Neural Network (ANN) and weather-state based models.
Although a wide variety of statistical precipitation downscaling models have been applied in different regions of the world (Mehrotra et al., 2015, Wilby et al., 2002, Chandler and Wheater, 2002, Jeong et al., 2012) few of these studies have dealt with downscaling over the Tibetan Plateau. Zhu et al. (2013) projected precipitation area averages using a statistical regional model for daily precipitation across Tibet. Three downscaling alternatives, the Statistical downscaling model (SDSM), the Generalised Linear Model for Daily Climate (GLIMCLIM), and Non-homogeneous Hidden Markov Model (NHMM) were applied by Hu et al. (2013) for daily precipitation over the Yellow River source region. They found that SDSM and GLIMCLIM showed better performance in reproducing temporal dependence although NHMM showed better performance in reproducing spatial correlation. Xu et al. (2009) studied the response of streamflow to climate change at a headwater catchment in the Yellow river basin considering SDSM and delta methods for daily temperature and precipitation downscaling. Both SDSM and Delta techniques agree with the observed data reasonably well in their study.

The SDSM statistical downscaling model (Statistical DownScaling Model) is a widely used technique proposed by Wilby et al. (2002). It includes deterministic transformations as well as stochastic components and is a combination of a stochastic weather generator and multiple linear regression models between large-scale atmospheric variables and local-scale variables (Wilby et al., 2002, 1999). Extensive literature is available on the application of SDSM for climate-related studies and downscaling. Huang et al. (2011) used SDSM for precipitation downscaling in the Yangtze River in China and their study revealed that SDSM has acceptable applicability. Hashmi et al. (2011) compared SDSM and LARS-WG to downscale precipitation in a watershed of Clutha River in New Zealand and reported good results for the area averaged extreme precipitation statistics. Chen et al. (2012) measured the difference in water balances resulting from two downscaling methods (smooth support vector machine (SSVM) and SDSM), GCMs and hydrological models. They concluded that SDSM had better applicability than SSVM in downscaling precipitation but results for runoff simulations using SDSM downscaled precipitation were poorer than that using SSVM downscaled precipitation. However, SDSM is known to have low explained variance in reproducing daily precipitation statistics (Wilby et al., 1998; Wilby and Dawson, 2008; Nguyen et al., 2004).

Downscaling approaches such as SDSM are typically calibrated via reanalysis datasets, which are of great use in studies where direct observations of the entire system being modelled are not possible to procure and when information on the state of the climate on a defined grid is necessary (Mooney et al., 2011). A variety of reanalysis products are available. While reanalyses have the advantage that they offer a more comprehensive representation of the dynamics of the earth’s atmosphere, different reanalysis products show discrepancies especially
at regional scales (Moalafhi et al., 2016). Moalafhi et al. (2017a) used reanalysis datasets to explore its influence on dynamical downscaling using the Weather Research and Forecasting (WRF) regional climate model over southern Africa. They found that precipitation tends to be overestimated over the domain considered although temperature was downscaled accurately, depending on the reanalysis dataset being adopted.

Overall, it is clear that downscaled products are likely impacted by uncertainties in the downscaling approach used. This may arise due to uncertainty in the observed data used to estimate the downscaled model parameters (i.e. the reanalysis data set), uncertainties in the selected downscaling model structure, or in the model parameters. To date, the impact of these uncertainties in different downscaling case studies is not well characterised or identified. To that end, this study attempts to assess and quantify the extent of downscaling model parameter uncertainty, the uncertainty resulting from the use of different reanalysis datasets in the context of statistical downscaling and the propagation of this uncertainty in the downscaled precipitation obtained by using GCM atmospheric variables. SDSM is used as the statistical downscaling tool, and the Bayesian Markov chain Monte Carlo (MCMC) approach is adopted to assess downscaling model parameters and the associated uncertainty at selected locations in the Tibetan Plateau.

To our knowledge, this is the first attempt at quantifying and characterising reanalysis data uncertainty in statistical downscaling models of precipitation. The framework of the study is multi-fold. In the first part we characterise the uncertainty in downscaling model parameters using different reanalysis datasets and observed precipitation at selected point locations by means of Bayesian inference. As a second part of the study, we identify the uncertainty in the downscaled daily precipitation introduced as a result of alternate reanalysis datasets used to drive the downscaling model in MCMC platform. Finally, in the third part, we look into the uncertainty in the downscaled daily precipitation obtained by using a GCM simulation that is bias-corrected using alternate reanalysis datasets.

### 3.2 Datasets

#### 3.2.1 Observed precipitation data:

Daily precipitation data between 1979 and 2005 from APHRODITE (Asian Precipitation highly Resolved Observational Data Integration Towards Evaluation of Water Resources) (Yatagai et al., 2012) were used as the observed data at 15 selected stations in this study. The dataset has a resolution of 0.25° x 0.25°. The selected stations were at different elevations to study any spatial variation in the downscaling model results. The location of the 15 stations and their average
climate characteristics from 1979 to 2005 are presented in Table 3.1. All locations considered represent markedly different climatic regimes and forcings, allowing a broad assessment of the downscaling uncertainty presented in later sections of this study.

### 3.2.2 Reanalysis and GCM products

The reanalysis products used in the selected 15 stations are the National Centre for Environmental Prediction/National Centre for Atmospheric Research Reanalysis 2 (NCEP2) and the Interim Reanalysis (ERAI) of the European Centre for Medium-Range Forecasts respectively (Kanamitsu et al., 2002, Dee et al., 2011). NCEP2 data was available from the Earth System Research Laboratory (ESRL) at [http://www.esrl.noaa.gov/psd/data/](http://www.esrl.noaa.gov/psd/data/), while ERAI data was sourced from the European Centre for Medium-Range Weather Forecasts (ECMWF) at [http://apps.ecmwf.int/datasets/](http://apps.ecmwf.int/datasets/). NCEP2 was available at $2.5^\circ \times 2.5^\circ$ whereas ERAI was available at $0.75^\circ \times 0.75^\circ$. ACCESS 1.3 was used as the GCM product in the selected stations, and obtained at $1.9^\circ \times 1.2^\circ$ resolution. For convenience, all datasets were selected for the common period of 1979 to 2005, and re-gridded following the resolution of APHRODITE ($0.25^\circ \times 0.25^\circ$) considering bilinear interpolation approach using climate data operator (CDO).

<table>
<thead>
<tr>
<th>Station Number</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Elevation (m)</th>
<th>Wetness fraction</th>
<th>Daily STD (mm)</th>
<th>Annual Precipitation (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>27.875</td>
<td>98.625</td>
<td>1583</td>
<td>0.49</td>
<td>4.6</td>
<td>921</td>
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<td>2981</td>
<td>0.46</td>
<td>9.3</td>
<td>1552</td>
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<tr>
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<tr>
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<tr>
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<td>5.4</td>
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<tr>
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<td>89.125</td>
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<td>0.49</td>
<td>5.0</td>
<td>978</td>
</tr>
<tr>
<td>15</td>
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<td>96.625</td>
<td>3643</td>
<td>0.48</td>
<td>9.0</td>
<td>1493</td>
</tr>
</tbody>
</table>
3.3 Methodology

3.3.1 Precipitation downscaling model

The Statistical Downscaling model (SDSM) is based on the concept of a multiple linear regression (MLR) that uses atmospheric variables as predictors and provides precipitation (occurrence or amount) at daily or monthly timescales as a response variable (Wilby et al., 2002, Wilby et al., 2014). SDSM generates multiple precipitation ensembles from which the uncertainty across attributes of interest can be quantified. Wilby et al., (2002) describe the general formulation of SDSM described in equations 3.1 and 3.2 where output represents precipitation occurrence as well as precipitation amount, respectively, and inputs are large scale atmospheric predictors (Table 3.2) for the 15 stations. SDSM characterises precipitation as consisting of a precipitation occurrence and a precipitation amount process. Each of these processes is simulated probabilistically using an assumed functional form based on the selection of relevant predictor variables. The precipitation occurrence model operates as:

\[ W_i = b_0 + \sum_{j=1}^{n} b_j Y_{ij} \quad 0 \leq W_i \leq 1 \]  

(3.1)

where, \( W_i \) = wet-day occurrence probability on day \( i \), from which an occurrence state is sampled, and \( Y_{ij} \) = \( j \)'th predictor variable (reanalysis and GCM variables) on day \( i \).

Each wet day is then used to calculate the precipitation amount via

\[ P_i = c_0 + \sum_{j=1}^{n} c_j Y_{ij} + \epsilon_i \]  

(3.2)

where, \( P_i \) = precipitation amount on day \( i \), \( Y_{ij} \) = \( j \)'th predictor variable (reanalysis and GCM variables) on day \( i \), and \( \epsilon_i \) = model error (assumed Gaussian with variance ascertained through the parameter estimation step). The residual term \( \epsilon_i \) is written as

\[ \epsilon_i = \sqrt{VIF} z_i S_e + d \]  

(3.3)

where, \( z_i \) = random variate from a standard Normal distribution, \( S_e \) = standard error of model, \( d \) = model bias and VIF = variance inflation factor. Terms \( d \) and VIF are calculated using (Hessami et al., 2008)

\[ d = \text{Mean}_{\text{obs}} - \text{Mean}_{\text{mod}} \]  

(3.4)

\[ \text{VIF} = \text{Var}_{\text{obs}} - \text{Var}_{\text{mod}} \]  

(3.5)

where, \( \text{Mean}_{\text{obs}} \) is the mean of the observed precipitation, \( \text{Mean}_{\text{mod}} \) is the mean of the modelled precipitation, \( \text{Var}_{\text{obs}} \) is the variance of the observed precipitation, \( \text{Var}_{\text{mod}} \) is the variance of the modelled precipitation, estimated at the time scale (daily or monthly) the model is specified at. Here modelled precipitation comes from the downscaling model outputs based
on reanalysis or GCM derived predictors. The term VIF changes the variance of the downscaled precipitation series by increasing the variability of the noise term $\epsilon_i$ in (3.2). For the calibration period where we use only reanalysis data, $d=0$ and $VIF=1$. The data from 1979 to 1996 is used to formulate the model and calibrate the model parameters, whereas data from 1997 to 2005 is used for model validation.

### 3.3.2 Predictor variable selection

In this study, 15 large-scale atmospheric variables are selected from NCEP2, and ERAI reanalysis datasets for screening potential predictor variables, as shown in Table 3.2. The choice of atmospheric variables used for downscaling (Table 3.2) arises from previous assessments and is based on both the stability these variables exhibit across GCMs in a future climatic setting (Johnson and Sharma, 2009, Eghdamirad et al., 2017a) and the relationship they exhibit with the response variable of interest (Sharma and Mehrotra, 2014). These predictor variable choices are consistent with previous studies (Hu et al., 2013, Xu et al., 2009) and are established choices for statistical downscaling in different climatic regimes (Mehrotra and Sharma, 2011, Tavakol-Davani et al., 2013). Correlation coefficients using the Pearson, Spearman's $\rho$ and partial correlation and the Partial Mutual Information (Sharma and Mehrotra, 2014) using the NPRED toolkit (Sharma et al., 2016) were ascertained to identify sets of significant predictors for precipitation downscaling. Table 3.2 represents the overall list of variables that were identified across each of the response precipitation locations this study considers.

<table>
<thead>
<tr>
<th>Predictor code</th>
<th>Description of the predictor</th>
<th>Predictor code</th>
<th>Description of the predictor</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIR_850</td>
<td>Air Temperature at 850hpa</td>
<td>RH_500</td>
<td>Relative Humidity at 500hpa</td>
</tr>
<tr>
<td>AIR_700</td>
<td>Air Temperature at 700hpa</td>
<td>UW_850</td>
<td>Zonal wind component at 850hpa</td>
</tr>
<tr>
<td>AIR_500</td>
<td>Air Temperature at 500hpa</td>
<td>UW_700</td>
<td>Zonal wind component at 700hpa</td>
</tr>
<tr>
<td>GPH_850</td>
<td>Geopotential Height at 850hpa</td>
<td>UW_500</td>
<td>Zonal wind component at 500hpa</td>
</tr>
<tr>
<td>GPH_700</td>
<td>Geopotential Height at 700hpa</td>
<td>VW_850</td>
<td>Meridional wind component at 850hpa</td>
</tr>
<tr>
<td>GPH_500</td>
<td>Geopotential Height at 500hpa</td>
<td>VW_700</td>
<td>Meridional wind component at 700hpa</td>
</tr>
<tr>
<td>RH_850</td>
<td>Relative Humidity at 850hpa</td>
<td>VW_500</td>
<td>Meridional wind component at 500hpa</td>
</tr>
<tr>
<td>RH_700</td>
<td>Relative Humidity at 700hpa</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### 3.3.3 Bayesian inference

Bayesian inference is commonly used for calibration of model parameters with uncertainty and has been applied extensively in hydrologic model specification studies (Jeremiah et al., 2011, Marshall et al., 2006, Smith et al., 2015). The approach combines existing knowledge about model parameters and the information in the data to develop probabilistic parameter estimates. If we let $\theta$ denote the model parameters (total number of identified atmospheric predictors plus...
one for constant term and one for variance term) of SDSM model, and let x denote the observed precipitation data, then Equation (3.6) describes uncertainty about $\theta$ probabilistically after observing data x.

$$\rho(\theta|x) = \frac{\rho(\theta,x)}{\rho(x)} = \frac{\rho(\theta)p(x|\theta)}{\rho(x)} \quad (3.6)$$

where $\rho(\theta|x)$ is the distribution of $\theta$ given x, referred to as the posterior distribution, which allows one to statistically quantify the uncertainty about $\theta$ after observing x; $\rho(\theta,x)$ is the joint probability distribution for $\theta$ and x; $\rho(\theta)$ is the distribution of $\theta$ before collecting data representing prior knowledge of $\theta$, also known as the prior distribution; $\rho(x|\theta)$ is the likelihood function stating the distribution of the data x given the unknown $\theta$ and expressing the relationship between model and data for inferring errors; and $\rho(x)$ is a normalising constant. A uniform prior distribution is used in this study.

To fit the precipitation downscaling model in a Bayesian framework, an integrated likelihood for precipitation occurrence and amount is proposed in equation (3.7) which was applied by Smith et al. (2015) to follow an error model for ephemeral streams, a modelling task analogous to the intermittent precipitation (occurrence and amount) process of interest here. The underlying assumptions of this likelihood are that model error is independent and homoscedastic while the distribution of the errors is assumed to be Gaussian.

$$L_i = n_1 \log(p) + n_2 \log(1 - p) - \frac{n_2}{2} \log(2\pi \sigma^2) + \sum_{t_i=1}^{n_2} -\frac{\epsilon_{t_i}^2}{2\sigma^2} - \frac{n_3}{2} \log(2\pi \sigma^2) + \sum_{t_3=1}^{n_3} \frac{-\epsilon_{t_3}^2}{2\sigma^2} \quad (3.7)$$

Here, $L_i$ is the integrated likelihood, $\epsilon$ represents the residuals (observed data minus modelled data), $n_1$ is the number of zero precipitation values with zero error, $n_2$ is the number of zero values with nonzero error, $n_3$ is the number of nonzero observations, $\sigma$ is the standard deviation of precipitation, and $p = \frac{n_1}{n_1+n_2+n_3}$. Readers are referred to Smith et al. (2015) for a derivation of the likelihood function in Equation (3.7).
To evaluate the fitness of the proposed likelihood function, a residual plot along with an estimate of the Filliben r statistic (Filliben, 1975) in a calibration period at station 1 is showed in Figure 3.1. The Filliben statistic is used to measure the linearity of quantile–quantile plots; the statistic approaches 1.0 when the quantile–quantile plots become more linear. Linearity of a quantile–quantile plot and a symmetrically shaped histogram plot generally disclose characteristics of a Gaussian distribution (Smith et al., 2015). Figure 3.1(a) suggests mostly homoscedastic residuals. The quantile-quantile plot of residuals indicate that a majority of the errors (in the range -4 mm to 2 mm) follow a Gaussian distribution (a good fit between standard normal residuals and quantiles of simulated rainfall residuals) in Figure 3.1(b). Correspondingly, the Filliben r statistic shows a higher value. Residuals are auto-correlated in few lags although we also found that there is no autocorrelation when zero rainfall days are excluded from the analysis. However, a heavier tail is evident for residuals in the higher range (2mm to 4mm). This suggests that the downscaling model might underestimate the frequency/magnitude of larger rainfall events (Figure 3.1(a)) as the residuals larger than 2 mm do not follow the Gaussian assumption (Figure 3.1(a, b)).
3.3.4 Approach

Markov chain Monte Carlo (MCMC) parameter sampling is a convenient way to implement Bayesian inference for models where the posterior distribution is analytically intractable (Marshall et al., 2006). MCMC generates samples of the parameter values from the posterior distribution by simulating a random process that has the posterior distribution as its stationary distribution (Marshall et al., 2004). The Adaptive Metropolis (AM) algorithm (Haario et al., 2001) has been used for MCMC simulation in this study. It is characterised by a multivariate normal proposal distribution including mean at the current parameter value and varying covariance. The proposal covariance matrix is updated at each iteration based on the covariance matrix of the sampled parameter values in the parameter chain to that point following the equation (3.8):

\[ B_t = \begin{cases} B_0 & t \leq t_0 \\ h_d \text{Cov}(\alpha_{t-1}) + h_d I_d & t > t_0 \end{cases} \]

where, \( B_t \) is the proposal covariance; \( B_0 \) is arbitrary initial covariance; \( \varepsilon \) is a small value selected to confirm \( B_t \) does not become singular; \( I_d \) is the identity matrix; and \( h_d \) is the scaling parameter for reasonable acceptance rates of the proposed states.

For drawing the posterior distribution, a full MCMC run is started by proposing initial parameters values from a prior distribution, with sequential values as the iteration proceeds, from a proposal distribution centred at the parameter value in the preceding iteration. The chain is run following the acceptance probability of \( \beta \). Parameters are accepted when \( \beta \) is greater than a generated uniform random number. Here, \( \beta \) is defined as,

\[ \beta = \min \left( 1.0, \frac{\text{proposed (likelihood)}}{\text{current (likelihood)}} \right) \]

The MCMC algorithm was run for 50000 iterations on each dataset in order to properly characterise the posterior distribution and achieve convergence. From a visual inspection of the sampled parameters and their means (Marshall et al., 2004), the sampled parameters convergence was diagnosed after approximately 10000 iterations for each dataset.

The Bayesian information criteria (BIC) of Schwarz (1978) which analytically approximates the marginal likelihood and the Deviance information criteria (DIC) of Spiegelhalter et al. (2002), balance model fit and complexity. To compare the downscaling model considering both ERAI and NCEP2 reanalysis data sets, we compare the BIC and DIC estimates. The BIC is defined as,

\[ BIC_k = 2L_k + \theta_k log(n) \]
\[ L_k \] is the negative log-likelihood, \( \theta_k \) is the number of parameters, and \( \text{BIC}_k \) is the Bayesian information criteria for model \( k \). The best model is the one that minimises the BIC value (Marshall et al., 2005).

The DIC is defined as,

\[
\text{DIC} = D(\bar{\theta}) + 2p_D \tag{3.11}
\]

where, \( D(\bar{\theta}) \) is the Bayesian deviance, \( p_D \) is the effective number of parameters. However, for a flat prior, the approximation \( D(\bar{\theta}) \approx -2\log L(\bar{\theta}) \) and \( p_D \approx p \) (Ward, 2008, Pooley and Marion, 2018, Van Der Linde, 2005, Ellison, 2004) may be assumed. Lower DIC values represent a better model (Spiegelhalter et al., 2002).

### 3.4 Results and discussions

#### 3.4.1 Analysis of model parameter uncertainty with data length

Bayesian inference characterises the uncertainty in model parameters via their posterior distribution, rather than a single best-fit parameter set. In this study, it is used to characterise uncertainty in the downscaling model parameters obtained using different reanalysis datasets.

Figure 3.2 shows the ratio of the posterior and prior variance of the model parameters as a function of sample length used in model calibration period at station 1. Significant variations in the posterior variance of the model parameters with the variation in the data length highlights...
the importance of using long samples in establishing SDSM parameters for applications. Both models show similar variability with increased data length for all atmospheric variables.

The posterior distribution of all parameters in calibration period ascertained using kernel density estimation (Bowman and Azzalini, 1997) for station 1 are presented in Figure 3.3. Significant differences are apparent among reanalysis datasets in the plots, although, the uncertainty between relative humidity at 500hPa (rh500) of ERAI and NCEP2 is comparatively less than other reanalysis variables which might be due to better association between atmospheric variables rh500 of ERAI and NCEP2 (correlation coefficient =0.92).

In order to explore if the differences in the parameters values across both datasets have any physical relevance, we plot these differences with respect to station elevations. Figure 3.4 showed differences of maximum log likelihood (higher maximum likelihood means better agreement with observed precipitation) across different elevations which were determined by subtracting maximum log likelihood of NCEP2 from ERAI in different stations. Notable maximum log likelihood differences are visible at all stations across different elevations. These fluctuations might be due to the variations of atmospheric variables of ERAI and NCEP2 across elevations in this region. This indicates that the downscaling model developed for these stations will have significant differences across the two reanalysis datasets along elevations, hence impacting the simulations obtained for future climates.

To investigate the contribution of downscaling parameters uncertainty in downscaled precipitation, we considered two cases using a single reanalysis dataset, NCEP2 at station 1. As
Figure 3.4 Maximum log likelihood differences across different elevations. Here number 1, 2, 3 etc. are stations number.

Figure 3.5 Wetness fraction and standard deviation of downscaled precipitation using NCEP2 in station 1.

the aim is to assess the importance of accounting for uncertainty, in the first case, a single maximum likelihood parameter set was ascertained, and 2000 downscaling replicates generated. This case (termed A) is analogous to how SDSM is used in most applications. To assess the impact of uncertainty, in case B, 2000 parameter sets from the posterior distribution of SDSM were taken, and a single downscaling replicate generated for each one. Any differences between case A and B are now solely a function of the parameter uncertainty that exists within SDSM.

Figures 3.5a and 3.5b present the wetness fraction of the downscaled precipitation for cases A and B at station 1, respectively. Results of case B exhibit more variations than case A. Similarly, Figures 3.5c and 3.5d show the standard deviation of the downscaled precipitation for case A and case B, respectively. Remarkable variability is seen more in Figure 3.5d than Figure 3.5c. These differing results highlight the influence of parameter uncertainty and/or downscaling
model structure rigidity on the downscaled precipitation. This added variability has significant implications in a range of hydrologic applications.

### 3.4.2 Implications of using different reanalysis datasets for downscaling

This section will discuss variations in the few important characteristics of the downscaled daily precipitations from posterior distributions across different datasets and locations in the validation period (1997-2005). This assessment is based on the 2000 downscaled simulations reported in case B in the results in Figure 3.5.

The reproduction of the mean wetness fraction, standard deviation and average annual precipitation are essential in simulating the water balance in any modelling exercise in which downscaled precipitation may be used. Important downscaled precipitation attributes expressed as anomalies (observed precipitation attribute-downscaled precipitation attribute) using different reanalysis datasets are presented in Figure 3.6. Wetness fraction results showed few variations across different stations except for station 11. Both ERAI and NCEP2 showed good agreement for the wetness fraction with observed rainfall at station 11. In this station relative humidity at 500hpa of both ERAI and NCEP2 exhibits better correlation with observed rainfall (correlation coefficient =0.51) than other predictors. This could explain the improved representation of precipitation that is offered, in comparison to other locations where this relationship is not as strong. Standard deviations at different stations showed some variations whereas average annual precipitation exhibited remarkable differences across alternate reanalysis. It is interesting that at station 10 differences in average annual precipitation is the highest across the two reanalyses, while in station 11 differences in average annual precipitation is the lowest. This might be due to the non-stationarity in the predictor-predicted relationships which can result in region or station specific biases in the derived precipitation fields. At almost all stations, NCEP2 generated higher standard deviation anomaly and average annual precipitation anomaly than ERAI which indicates higher variability of atmospheric variables and downscaling model parameters of NCEP2 although average annual precipitation anomaly of ERAI is higher at station 2 and station 15 respectively.
Figure 3.6 Downscaled precipitation attributes anomaly (observed precipitation attribute - downscaled precipitation attribute) using ERAI and NCEP2 reanalysis datasets. Figure 3.6(a) is wetness fraction anomaly, Figure 3.6(b) is daily standard deviation anomaly and Figure 3.6(c) is average annual precipitation anomaly of downscaled precipitation at all stations.

Figure 3.7 (a) Wetness fraction of downscaled precipitation of ACCESS 1.3 at station 1. (b) Daily standard deviation of downscaled precipitation of ACCESS 1.3 at station 1. (c) Average annual precipitation of downscaled precipitation of ACCESS 1.3 at station 1.
3.4.3 Assessment of downscaled precipitation of GCM variables over the observed period

Further, it is also of interest to look into the downscaled precipitation results when the climate variables of a GCM are bias-corrected using individual reanalysis datasets and are used to drive the downscaling model. This evaluation is again based on the 2000 downscaled ensembles in the validation period.

Daily precipitation was obtained using the identified atmospheric variables of ACCESS 1.3 GCM and downscaling coefficients of different reanalysis datasets in a Bayesian setting. Figure 3.7 presents boxplots of wetness fraction, daily standard deviation and average annual downscaled precipitation of GCM ACCESS 1.3 at station 1. The ranges of wetness fraction, standard deviation and average annual precipitation vary markedly within and across both datasets at the same location.

Important downscaled precipitation attributes anomaly of ACCESS 1.3 obtained using ERAI and NCEP2 reanalysis variables (for model calibration) for all stations were presented in Figure 3.8. Wetness fraction and average annual precipitation shows noteworthy discrepancies at different stations. In station 4 differences in average annual precipitation is the highest while in station 8 differences in average annual precipitation is the lowest. This might be the result of uncertainties in the downscaling model parameters which interfere to capture local climatic features well. Here ACCESS 1.3 is also following the same pattern of reanalysis downscaling i.e. NCEP2 shows higher standard deviation anomaly and average annual precipitation anomaly than ERAI whereas average annual precipitation anomaly of ERAI is higher at station 15.

3.4.4 Comparison of precipitation downscaling model considering BIC

Deviance Information Criteria (DIC) and Bayesian Information Criteria (BIC) values for the downscaling model using ERAI and NCEP2 reanalysis are presented in Table 3.3. In all the stations both the DIC and BIC of NCEP2 is higher than ERAI, although the BIC of ERAI is higher than NCEP2 in station 8 due to a lower likelihood (better agreement with observed precipitation). Hence, the downscaling model considering ERAI can be considered to be comparatively closer to observed precipitation than NCEP2 except for station 8.
Figure 3.8 Downscaled precipitation attributes anomaly (observed precipitation attribute-downscaled precipitation attribute) of GCM ACCESS 1.3 using ERAI and NCEP2 reanalysis datasets compared with the historical record. Figure 3.8(a) is wetness fraction anomaly, Figure 3.8(b) is daily standard deviation anomaly and Figure 3.8(c) is average annual precipitation anomaly of downscaled precipitation.

Table 3.3 Comparison of downscaling model using alternate reanalysis

<table>
<thead>
<tr>
<th>Stations</th>
<th>DIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ERAW</td>
<td>NCEP</td>
</tr>
<tr>
<td>1</td>
<td>75550.23</td>
<td>78795.07</td>
</tr>
<tr>
<td>2</td>
<td>85462.20</td>
<td>90531.23</td>
</tr>
<tr>
<td>3</td>
<td>48823.50</td>
<td>51130.75</td>
</tr>
<tr>
<td>4</td>
<td>91602.33</td>
<td>95722.86</td>
</tr>
<tr>
<td>5</td>
<td>37811.84</td>
<td>40043.93</td>
</tr>
<tr>
<td>6</td>
<td>73020.06</td>
<td>76406.25</td>
</tr>
<tr>
<td>7</td>
<td>22237.04</td>
<td>22955.14</td>
</tr>
<tr>
<td>8</td>
<td>21980.69</td>
<td>21665.01</td>
</tr>
<tr>
<td>9</td>
<td>63564.56</td>
<td>68680.30</td>
</tr>
<tr>
<td>10</td>
<td>62012.01</td>
<td>66529.34</td>
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<tr>
<td>11</td>
<td>34519.31</td>
<td>35147.77</td>
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<tr>
<td>12</td>
<td>91480.58</td>
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<td>13</td>
<td>86101.10</td>
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<td>14</td>
<td>35202.02</td>
<td>37235.17</td>
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<tr>
<td>15</td>
<td>97470.21</td>
<td>105267.41</td>
</tr>
</tbody>
</table>

40
3.5 Conclusions

Recent research has evaluated the sources of uncertainty in GCMs, and it is clear that these uncertainties are likely to propagate through to case studies making use of GCM products for understanding the impacts of future changes in climate. In developing downscaled models for such studies, the uncertainties associated with the input (reanalysis) calibration data, the model parameters, and the model itself are less well known. This study develops a Bayesian framework for the assessment of the relative performance of commonly used reanalysis products under uncertainty for precipitation downscaling across the Tibetan Plateau.

Overall, the approach presented here is general and flexible, allowing the investigation into the impact of uncertainty on key precipitation variables of interest for water resource studies. By characterising the posterior distribution of model parameters, it is evident that the length of data available to specify the parameters can have a significant impact on the total parameter uncertainty. Significant differences in precipitation attributes are observed when calibrating models with different reanalysis data sets. The uncertainties in the calibrated model propagate through to analyses for downscaled precipitation from GCM ACCESS 1.3, and when compounded with the uncertainty in the input (GCM) data, it is likely these uncertainties will persist when used for a variety of water resource management applications, highlighting the importance of such uncertainty estimation. We note that a part of the uncertainty may be a result of the structure of the downscaling model used here. The use of another downscaling model where the relationship between predictor and predictand is non-linear, might help reducing the uncertainties across the datasets, and this will be the subject of future investigation. Different resolution of reanalysis datasets might also have influenced the results.
4 Future change in snowpack due to climate change in the Tibetan Plateau

This chapter explicitly characterises and corrects biases of climate model derived snow water equivalent, temperature and precipitation. Along with the discussion of likely changes of future snow climatology, possible reasons for such changes are also investigated. The content in this chapter has been reproduced (with reformatting) from the journal manuscript referenced below.

Snowpack is a critical part of the global hydrologic cycle and understanding its potential change due to increased warming is important for proper planning and management of water. The Tibetan Plateau provides significant water to most Asian rivers, and consequently the downstream population is dependent on its availability. Despite its importance, potential change in snowpack in this region due to climate change is poorly understood to date, largely because of remoteness and the orographic complexity of the area. This study inspects the impact of climate change on the snowpack change over Tibet considering historical simulations (1981-2004), near future projections (2041-2064) and far future projections (2071-2094) from global climate models (GCMs) and regional climate models (RCMs) of derived temperature, precipitation and snow water equivalent (SWE). A multivariate nesting bias correction approach (MRNBC) was employed to correct possible biases in GCM and RCM derived temperature, precipitation and SWE jointly over multiple timescales, to preserve interdependencies amongst the variables. The MRNBC reduced bias in model simulations significantly and provided improved projections of snow climatology. The results indicate that the annual maximum spell of snow free days will increase whereas the snowy days fraction will decrease in the future compared to the historical period. In addition, annual SWE are noted to be decreasing in both the near future and far future with respect to historical averages. Changes in SWE will result from warming temperatures but also from changes in precipitation, which will consist of more rainfall than snowfall thus affecting snowmelt processes.

4.1 Introduction

Snowpack plays a significant role in regulating the earth’s climate system, the hydrological cycle, and ecosystems in many parts of the world. Changes in snowpack covering the ground and changes in snow melt will have crucial impacts on water supplies and water resources. Snow-albedo affects variations in monsoonal and summer rainfall across Asia (Wu and Qian, 2003, Zhao et al., 2007). Furthermore, water melt from seasonal snowpack provides permanent water flow to the major Asian rivers (Brahmaputra, Indus, Yangtze, Yellow, Salween, Mekong and Ganges) and highly populated river basins (Lutz et al., 2014). These river basins provide water for 1.65 billion people living downstream (Cuo et al., 2014, Cuo and Zhang, 2017). Over the last three decades, Tibet has been characterised as a possible amplifier for global climate change (Mao et al., 2018) and it is now established that the Tibetan snowpack has responded directly to climate change (Littell et al., 2018). Therefore, assessment and projection of snowpack change over the Asian water tower of Tibet is of considerable importance.

Snowpack observations generally include different attributes such as snow cover, snow depth and snow water equivalent (SWE). SWE (defined as the amount of water contained within the snowpack) is a function of both snow depth and density (Sturm et al., 2010). SWE is much more useful than other snow parameters to attribute snowpack change for planning and management of water supplies (Egli et al., 2009). For instance, Harpold and Brooks (2018b) estimated snow melt from SWE, and Barnhart et al. (2016) showed strong relations between streamflow and snowmelt using SWE. SWE observations are useful for improving streamflow simulation in snow dominated catchments (Berg and Mulroy, 2006, Smith and Marshall, 2010). Moreover, SWE has a great impact in streamflow drought events and flood forecasting (Jörg-Hess et al., 2015). Spatial variability of SWE also plays an important role in spring flood forecasting in the large basins (Hlavčová et al., 2015).

In recent decades Tibet has witnessed a significant increase in temperature which can be attributed to a continued increase in the concentration of carbon dioxide in the atmosphere (Song et al., 2014, Guo and Wang, 2012). The rise in surface air temperature over the past half century in Tibet was 1.8°C (Wang et al., 2008). There is convincing evidence that the warming rate per decade in Tibet is approximately 1.5 times the rate of global warming (Zhang et al., 2014, Kuang and Jiao, 2016, Zhu et al., 2013). This warming will lead to a decrease in the snowfall / rainfall ratio (Wang et al., 2016b). As a result, the assessment of future climate change and its impact on SWE is crucial for water availability and management strategies. To project SWE in the future considering climate change, global circulation models (GCMs) simulate SWE at coarse spatial scales, while regional climate models (RCMs) use GCM
simulations as initial and boundary conditions to downscale SWE at finer scales (Rocheta et al., 2017b), improving the regional and local climate characterisation. GCMs and RCMs provide a comprehensive picture of temporal and spatial patterns of snowpack via SWE at the large and regional scale, respectively, including remote areas and data sparse regions.

Despite their usefulness, GCMs have systematic biases due to the various assumptions of atmospheric physics, and numerical schemes are adopted to address these biases (Johnson et al., 2011, Mehrotra and Sharma, 2016, Mehrotra and Sharma, 2019, Nguyen et al., 2019). The uncertainties in GCM projections will arise from errors in the model structure, scenarios and initial conditions (Woldemeskel et al., 2012, Woldemeskel et al., 2016, Eghdamirad et al., 2016). Furthermore, different GCMs have different atmospheric modules as well as land surface schemes (Terzago et al., 2017) which also affect the uncertainties in the projected climate variables. In addition, RCMs also suffer from bias due to errors in the reference datasets, spatio-temporal gaps between RCMs and observations and differences in model parameterisations (Willkofer et al., 2018, Christensen et al., 2008, Kotlarski et al., 2014).

Climate model biases in complex terrain and high mountainous regions (as in Tibet) will be amplified as these models consider comparatively simplified physical processes and smooth topography. For example, Su et al. (2013) evaluated CMIP5 coupled GCMs over the Tibetan Plateau, and found that models tend to underestimate temperature (cold bias). Guo et al. (2018) evaluated the applicability of regional climate models in Tibet using temperature and precipitation datasets. They found significant cold and wet biases in the temperature and precipitation climatology compared to station observations. Nury et al. (2019) showed that downscaled precipitation from GCMs and reanalysis present uncertainty which might affect future projections in Tibet. Therefore, future snowpack changes should be projected carefully to account for bias and uncertainties in climate model simulations.

There have been several efforts to correct bias in climate model simulations. These approaches are mostly statistical, and mean-based or distribution-based procedures namely linear scaling (Lenderink et al., 2007, Teutschbein and Seibert, 2012), local intensity scaling (Schmidli et al., 2006), and quantile mapping (Jakob Themeßl et al., 2011, Dosio and Paruolo, 2011, Ashfaq et al., 2010, Piani et al., 2010). Chen et al. (2013) described the advantages and limitations of these methods. A nesting bias correction approach (NBC) for rainfall was proposed by Johnson and Sharma (2012) to overcome such limitations. The NBC approach assumes biases in the future projection of GCMs are the same as in current climate simulations. Statistics of observed climatic data and corresponding GCM data are used to correct biases in future projections (Sarhadi et al., 2016). The NBC method has been used to investigate change in floods and drought due to its good performance in correcting biases (Apurv et al., 2015, Asadi Zarch et al.,
On the other hand, joint bias correction is needed to maintain dynamic relationships (observed dependence) among the climatic variables. To address joint correction, Mehrotra and Sharma (2015) proposed a multivariate recursive nesting bias correction approach (MRNBC) using a multivariate autoregressive model in NBC framework.

In recent years, few studies have discussed biases in climate modelled SWE and its changes around the world. Terzago et al. (2017) found considerable bias in the few GCM and RCM derived SWE estimates in the Alps, and emphasised the need to develop more reliable snow simulations. In addition, Wrzesien et al. (2019) characterised biases in mountain SWE from commonly used global datasets such as GLDAS, MERRA, ERA-interim and VIC. Table 4.1 provides further details of the approach, region, outcomes and gaps in studies that deal with snow attributes. These studies did not correct the biases although quantification as well as correction of biases in climate model simulation is essential to provide fair information for water supply management strategies. In addition, there is no bias corrected projection of snowpack changes in a high-elevation area like Tibet, and snow in that region is a major component of total water resources in Asia. The present study attempts to investigate future snowpack changes using climate model projections, accounting for their uncertainties in the Tibetan Plateau. To achieve this aim, this study is twofold. In the first part, GCM and RCM estimates of daily SWE, temperature and precipitation data were improved by correcting systematic bias jointly using the MRNBC approach. Then, using this corrected data, the study is aimed at investigating how changing climate affects snowpack change in the future.

4.2 Study area and Datasets

4.2.1 Study area

This study focuses on the so called third pole of the world, the Tibetan Plateau, that includes complex topography with varying elevations and represents one of the highest regions in terms of altitude (Basang et al., 2017, Mao et al., 2018). The complex terrain and snowpack build-up play an important role in the local atmospheric circulation, water resources and ecosystems (Zhu et al., 2019). The average elevation of Tibet is 4000m above sea level and it has influence on the global climate via thermal forcing mechanisms (Ding et al., 2018a, Sato and Kimura, 2007). Tibet has a large area of snow, mountains, glaciers, mountain lakes and permafrost (Su et al., 2013). Figure 4.1 shows the elevation of the study area and the location of the 31 stations used in this study.
## Table 4.1 Previous studies investigating snow attributes

<table>
<thead>
<tr>
<th>Approach</th>
<th>Region</th>
<th>Input data</th>
<th>Outcomes</th>
<th>Gaps</th>
<th>Studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global circulation models and Regional climate models</td>
<td>Alps, Europe</td>
<td>SWE, Snow depth, RCMs from CORDEX GCMs from CMIP5</td>
<td>- Discussion on inter-dataset spread. - Found significant cold bias. - Snow cover and natural hazards will be affected by global warming.</td>
<td>- Limited discussion of snowpack change. - Climate model data were not bias corrected.</td>
<td>Terzago et al. (2017) Gobiet et al. (2014)</td>
</tr>
<tr>
<td>Global circulation models</td>
<td>Northern Hemisphere</td>
<td>SWE, Snow cover extent, GCMs from CMIP5</td>
<td>- The D–A approach is applied to demonstrate the anthropogenic effects on the spring SWE changes.</td>
<td>- Limited validation of GCMs against observed data. - Bias correction not used.</td>
<td>Jeong et al. (2017) Rupp et al. (2013)</td>
</tr>
<tr>
<td>Global circulation models</td>
<td>Northern Hemisphere</td>
<td>SWE, Precipitation, Temperature, GCMs from CMIP5</td>
<td>- Slower snowmelt rates in spring. - Changes in the fraction of precipitation falling as snow contribute to decreases in snowfall.</td>
<td>- Limited validation of GCMs against observed data.</td>
<td>Wu et al. (2018) Krasting et al. (2013)</td>
</tr>
<tr>
<td>Satellite products</td>
<td>Tibet</td>
<td>Temperature, Precipitation, Snow cover (MODIS)</td>
<td>- The distributions of snow cover over the TP exhibit a large spatiotemporal heterogeneity.</td>
<td>- No discussion of future change of snowpack. - Bias correction not used.</td>
<td>Li et al. (2018) Immerzeel et al. (2009), Tang et al. (2013)</td>
</tr>
</tbody>
</table>

**Figure 4.1** Study area with location of stations and elevations (m).
4.2.2 Observed data

Daily snow water equivalent datasets from 1981 to 2010 from the CanSISE (Canadian Sea Ice and Snow Evolution Network) observation-based ensembles (Mudryk et al., 2015) were used as the observed SWE for 30 selected stations in this study. These datasets use available ground based weather station data with passive microwave information. It verified with ground data as well as shows consistency and very good correlation with ERA-Interim reanalysis, MERRA reanalysis and Globsnow SWE products in the Northern hemisphere (Mudryk et al., 2018; Mudryk et al., 2015). The selected stations are located in diverse topographic regions and at varying altitudes to help in the broad assessment of the SWE changes and to study any spatial variations (Figure 4.1) the study region might have. Daily temperature and precipitation data between 1979 and 2005 from APHRODITE (Asian Precipitation Highly Resolved Observational Data Integration To- wards Evaluation of Water Resources) (Yatagai et al., 2012) were used as the observed precipitation and temperature for these stations.

4.2.3 Climate model data

Daily SWE, temperature and precipitation datasets of four global circulation models (GCMs) from CMIP5 and four regional climate models (RCMs) from CORDEX were collected as modelled climate data. Both GCMs and RCMs provide historical simulations as well as future projections considering different RCP (Representative Concentration Pathway) scenarios. This study considered RCP8.5 scenario for future climate, which represent that radiative forcing increase over the 21st century to 8.5 Wm$^{-2}$ towards the end of the century (van Vuuren et al., 2011). Spatial resolutions of the observed, GCM and RCM datasets used in this study are presented in Table 4.2. For convenience, all datasets were re-gridded to the common resolution of 0.4° x 0.4° and time frames of 1981 to 2004 (historical), 2041 to 2064 (near future) and 2071 to 2094 (far future), respectively, were selected.

4.3 Methodology

4.3.1 Multivariate bias correction approach

The Multivariate Recursive Nested Bias Correction (MRNBC) approach (Mehrotra and Sharma, 2015) is used in the study. MRNBC is based on a multivariate autoregressive order 1 model (Salas, 1980) applied at multiple timescales. At each timescale, the series was first corrected for mean and standard deviations and thereafter was corrected to match the lag one autocorrelations, lag one and lag zero cross correlations of the observed data in time and across variables (Mehrotra and Sharma, 2015).
Table 4.2 Spatial resolution of data used in this study. All RCMs were obtained from CCLM5-V2 model (Institution: Climate Limited-area Modelling Community).

<table>
<thead>
<tr>
<th>Variables</th>
<th>Sources</th>
<th>Resolution (lon x lat degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily snow water equivalent</td>
<td>CanSISE (Canadian sea ice and snow evolution network)</td>
<td>1° x 1°</td>
</tr>
<tr>
<td></td>
<td>observation based ensemble of SWE (Mudryk et al., 2017)</td>
<td></td>
</tr>
<tr>
<td>Daily Temperature and Precipitation</td>
<td>APHRODITE’s Water resources</td>
<td>0.25° x 0.25°</td>
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GCMs

<table>
<thead>
<tr>
<th>Model identification</th>
<th>Modelling group</th>
<th>Resolution (lon x lat degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HadGEM2</td>
<td>Met office Hadley Centre, UK</td>
<td>1.25° x 1.875°</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td>Max Planck institute for Meteorology, Germany</td>
<td>1.8653° x 1.875°</td>
</tr>
<tr>
<td>CanEsm2</td>
<td>Canadian centre for climate model and analysis, Canada</td>
<td>2.812° x 2.812°</td>
</tr>
<tr>
<td>GFDL-CM3</td>
<td>NOAA Geophysical Fluid Dynamics Laboratory, USA</td>
<td>2.5° x 2.5°</td>
</tr>
</tbody>
</table>

RCMs

<table>
<thead>
<tr>
<th>Driving GCMs</th>
<th>Modelling group</th>
<th>Resolution (lon x lat degrees)</th>
</tr>
</thead>
<tbody>
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<td>EC-Earth</td>
<td>EC-Earth consortium, Europe</td>
<td>0.4° x 0.4°</td>
</tr>
<tr>
<td>HadGEM2</td>
<td>Met office Hadley Centre, UK</td>
<td>0.4° x 0.4°</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td>Max Planck institute for Meteorology, Germany</td>
<td>0.4° x 0.4°</td>
</tr>
</tbody>
</table>

Let $Y^h$ and $Y^g$ be the vectors of selected climate variables representing the observations and climate models (GCMs and RCMs) variables. Time series of observed and modelled data, $\tilde{Y}^h_t$ and $\tilde{Y}^g_t$ are formed by standardising these variables to have zero mean and unit standard deviation. The standard Multivariate Autoregressive order 1 model (MAR1) for both observed and climate models (GCMs and RCMs) data can then be written as follows (Salas et al., 1985)

\[
\tilde{Y}^h_t = CY^h_{t-1} + D\epsilon_t \quad(4.1)
\]

\[
\tilde{Y}^g_t = E\tilde{Y}^g_{t-1} + F\epsilon_t \quad(4.2)
\]

Where C and D are the lag zero and lag one cross correlations coefficient matrices of the observation $\tilde{Y}^h_t$ while E and F are the lag zero and lag one cross correlations coefficient matrices of the standardised climate model simulations $\tilde{Y}^g_t$, and $\epsilon_t$ is a vector of mutually independent random variates having zero mean and the identity covariance matrix. The auto and cross correlations of the standardised $\tilde{Y}^g_t$ time series are modified to match the observed
lag-0 and lag-1 auto and cross correlations (E and F) by rearranging equation (4.2) and
simplifying for $\varepsilon_t$ as follows:

$$
\varepsilon_t = F^{-1} \left| \tilde{Y}_t - E\tilde{Y}_{t-1} \right|
$$

(4.3)

Here $\varepsilon_t$ denotes a vector of standardised variates found from the $\tilde{Y}_t$ series where the lag-1 and lag-0 dependence structure were excluded. This standardised variate vector along with observed lag-1 and lag-0 attributes was used to modify $\tilde{Y}_t$ to $\tilde{Y}_t$ to keep the desired observed dependence structure. Superscript (-1) is considered to represent inverse of the matrix.

$$
\tilde{Y}_t = CY_{t-1} + DF^{-1}\tilde{Y}_t - DF^{-1}EY_{t-1}
$$

(4.4)

To correct periodic parameters (monthly and seasonal), let vectors $Y_{t,m}$ and $Y_{t,m}$ denote the observed and climate model time series for the month m and year t. The periodic time series with zero mean and unit variance is formulated as $Y_{t,m}$. Following equation (4.3), the modelled time series $\tilde{Y}_{t,m}$, preserving the observed lag-1 serial and cross dependence, can be defined as

$$
\tilde{Y}_{t,m} = C_{t,m}Y_{t,m-1} + D_{t,m}F_{t,m}^{-1}Y_{t,m} - D_{t,m}F_{t,m}^{-1}E_{t,m}Y_{t,m-1}
$$

(4.5)

Where, $Y_{t,m-1}$ is the value in the corrected time series from the previous month m-1 in year t. As a final step, the series $\tilde{Y}$ is rescaled using observed mean and standard deviation to provide final corrected time series $\tilde{Y}$. Readers are referred to Mehrotra and Sharma (2015) and Mehrotra et al. (2018) for detailed formulation on matrices C,D,E and F and the temporal nesting applied.

### 4.3.2 Stepwise procedure followed in MRNBC

The initial step for the multivariate bias correction is to calculate the daily mean and standard deviation of the observed and climate modelled (GCM and RCM) variables. This also includes calculation of daily lag-0 and lag-1 auto as well as cross correlations across variables and formulation of matrices of lag-0 and lag-1 correlation at multiple selected time steps. The bias correction is applied at daily, monthly, seasonal and annual time scales. As the time nesting at higher time scale(s) may distort the bias correction at the basic daily time scale, the whole nested bias correction is repeated using a recursive option (Mehrotra and Sharma, 2012). Figure 4.2 describes the MRNBC procedure followed. This procedure corrects biases in raw climate variables for the current climate. A similar procedure is used with observed and current climate statistical parameters to correct biases for the future climate. The underlying assumption of the MRNBC procedure is that model biases in the future will follow similar orders of magnitude as
those in the current climate (which is the underlying assumption of all bias correction approaches).

![Flowchart of MRNBC procedure.](image)

Figure 4.2 Flowchart of MRNBC procedure.
4.4 Results and discussions

4.4.1 Correction of systematic bias in climate model simulations

In this study the MRNBC approach is employed to correct potential systematic biases from raw GCM and RCM SWE, temperature and precipitation with time nesting at daily, monthly, seasonal and annual timescales. To explain the performance of bias correction model, a Taylor plot of SWE before and after bias correction is presented for all stations in Figure 4.3. Here, the correlation coefficient is related to the azimuthal angle (black dotted lines), the centred root mean square error (RMSE) is identified by green contours, and the standard deviation is proportional to the radial distance from the origin (blue contours). Mean and standard deviation of daily SWE of all models are scattered with low correlation, high RMSE in respect of observed SWE before bias correction in Figure 4.3 a) and 4.3 b). Maximum SWE and standard deviation of maximum SWE for all models are spread out with low correlation and high RMSE before bias correction in Figure 4.3 c) and 4.3 d). Mean and standard deviation for daily SWE for all models agree with the observed values after bias correction with high correlation and low RMSE as shown in Figure 4.3 a) and 4.3 b). Standard deviation of the bias corrected and observed values are almost the same across all time scales. Maximum SWE and standard deviation of maximum SWE of all models are closer to observed values containing high correlation and low RMSE in Figure 4.3 c) and 4.3 d). In this case, the standard deviations of the bias corrected SWE are closer to the observed values. Uncertainty among all models is reduced significantly after bias correction.

Owing to space limitations, bias correction results are provided for a single representative station (Station 1) in Table 4.3, noting that the performance of the bias correction is similar for all stations. Raw mean temperature (°C), annual minimum temperature (°C) per year and annual maximum temperature (°C) per year show noticeable bias in the current climate simulation in Table 4.3. Again, raw mean SWE (mm), annual maximum SWE (mm) per year, and maximum spell of snow free days per year show bias and remarkable uncertainty in historical periods. Furthermore, the sensitivity of daily SWE (mm/°C/day) to temperature before bias correction also shows considerable bias in current climate period simulations, and the corrected future period deviates significantly from the uncorrected values. Temperature shows lower bias and uncertainty than SWE. This could be due to the fact that all climate models have large uncertainties in representing the physical process of snowpack dynamics in orographically complex areas. However, the MRNBC leads to noticeable reduction in the differences between observed and modelled variables. There is a significant bias between observed and simulated temperature and SWE for raw GCMs as well as RCMs across the different exceedance
probabilities before bias corrections in the Figure 4.4 (probability distribution plots of raw and bias corrected variables for other stations are presented in the supplementary information). On the other hand, temperature attributes changed markedly after correction. Similarly, uncertainty in SWE attributes reduced significantly after correction. Following this, we expect the MRNBC model to improve the simulation of snowpack change for simulations representing the future climate.
4.4.2 Change of SWE in the future

To investigate changes in SWE in the future, changes in a few important attributes are considered including maximum spell of snow free days per year, snowy days fraction per year and annual mean SWE. For convenience, these attributes are discussed using the average of GCM and RCM bias corrected results. The maximum spell of snow free days per year for the historical and future periods in all stations are presented in Figure 4.5. The maximum spell of snow free days is increasing more in far future than the near future and historical period, respectively. Possible reasons could be a change in precipitation, increase in winter temperature, and relative increase in rainfall which will be discussed later. The change in the maximum spell of snow free days also might affect the change in daily SWE in the future.

Table 4.3 Bias correction results for Station 1 (see Figure 4.1). Attribute=avg. of all modelled values ± uncertainty

<table>
<thead>
<tr>
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<tbody>
<tr>
<td></td>
<td>Before bias correction</td>
<td>After bias correction</td>
<td>Before bias correction</td>
<td>After bias correction</td>
</tr>
<tr>
<td>Mean of daily temperature (°C)</td>
<td>3.59</td>
<td>0.66(±1)</td>
<td>3.59(±0)</td>
<td>4.23(±2)</td>
</tr>
<tr>
<td>Annual Minimum temperature per year (°C)</td>
<td>-9.7</td>
<td>-17.3(±2)</td>
<td>-9.8(±0)</td>
<td>-12.4(±3)</td>
</tr>
<tr>
<td></td>
<td>13.8</td>
<td>12.1±3</td>
<td>13.6±0</td>
<td>15.1±3</td>
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<td>--------------------------</td>
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<tr>
<td>Annual Maximum temperature per year (°C)</td>
<td>26.72</td>
<td>24.76±26.4</td>
<td>27.16±0</td>
<td>12.36±16</td>
</tr>
<tr>
<td>Mean of daily SWE (mm)</td>
<td>94.6</td>
<td>97.4±57</td>
<td>105.9±11</td>
<td>66.4±53</td>
</tr>
<tr>
<td>Annual Maximum SWE per year (mm)</td>
<td>30</td>
<td>88±97</td>
<td>45±64</td>
<td>119±115</td>
</tr>
<tr>
<td>Maximum spell of snow free days per year</td>
<td>-2.2</td>
<td>-1.2±1</td>
<td>-2.2±0</td>
<td>-1.5±1</td>
</tr>
</tbody>
</table>

Figure 4.4 Probability distribution plots of daily SWE (mm) and temperature (°C) of GCMs and RCMs at station 1. Figure s1 a) is for raw SWE, b) is for bias corrected SWE, c) is for raw temperature, and d) is for bias corrected temperature.

Figure 4.5 Maximum spell of snow free days per year of historical vs future climate. Here diagonal dashed line indicates historical=future.
The snowy day fraction $\left( \frac{\text{Total snowy days in a year}}{\text{Total number of days in the year}} \right)$ for historical and future climate is shown in Figure 4.6. The snowy day fraction is decreasing in the future with respect to the historical period. Again, the snowy day fraction of the far future is lower than for the near future. Possible reasons could be a decrease in snowfall due to warmer temperature and increase in rainfall. The change in the snowy day fraction will impact the change in SWE in the future.

Figure 4.6 Snowy days fraction per year of historical vs future climate. Here the diagonal dashed line indicates where historical=future.

Average daily SWE for the historical and future period is presented in Figure 4.7. Daily SWE is decreasing in the future with respect to historical periods, and lower SWE is more noticeable in the far future than the near future. The decreasing annual SWE might be a result of an increase in the maximum spell of snow free days and a decrease of the snowy day fractions. This region is sensitive to global climate change (Zhang et al., 2019a), and has experienced strong warming in the past 50 years (You et al., 2018). Change in SWE will suggest the magnitude of change in melt water volume. This declining SWE will affect streamflow and availability of water supply of this region in the future.

4.4.3 Why will SWE change in the future?

To understand the cause of the projected changes of SWE in the future, examination of the influencing factors is important. Correlations between the observed temperature, precipitation and observed SWE for the period 1981-2004 are presented in Figure 4.8 (a). At all stations, temperature has higher negative correlation with SWE. Precipitation (snow+rain) has negative correlations with SWE at all stations (except station 26 and 28). This might be due to the increase in rainfall with warmer temperatures (Wang et al., 2016b). However, positive correlations of precipitation with SWE in station 26 and 28 are due to dominant snowfall (rather
than rainfall) in these two stations. Again, these results are not consistent with the Table 2.1 in the Chapter 2 which presents the proportion of pixels with a decreased SWE (%) and Temperature trend (°C per month) for few regions (Canada, USA, Finland, Sweden, Tibet) of

Figure 4.8 a) Correlation of temperature and precipitation with SWE; b) Average daily temperature (°C) for historical vs future climate. Here diagonal dashed line indicates historical=future.
Northern hemisphere. The relationship between decreased SWE in percentage, and temperature trend is not consistent in the Table 2.1 because of large-scale evaluation which might contain uncertainties due to interpolation approaches and the numerical scheme that estimate the observed SWE from snow information. Precipitation below 0°C has positive correlations with SWE in all stations except station 22 and 30 where correlations are negative. This might be due to the effect of rain on snow events (Berghuijs et al., 2014, Kapnick and Hall, 2012) in station 22 and 30 respectively. Again, an increase in temperature is noticeable in Figure 4.8 (b) which will accelerate snow melt and contribute to a decrease in SWE in the future. Change of precipitation (snow + rain) in the future with respect to the historical period is presented in Figure 4.9 a). Precipitation is higher in the future with respect to the historical period, and increasing more in the far future than near future (Figure 4.9 a). However, Wang et al. (2016b) found a significant decrease in snowfall/rainfall ratio in the Tibetan Plateau from 1961 to 2013. Their study found that rainfall was increasing at a greater rate than snowfall from 1961 to 2013.

Figure 4.9 a) Average daily precipitation (mm) for historical vs future climate; b) Average daily rainfall (mm) for historical vs future climate. Here diagonal dashed line indicates historical=future.
To further investigate this aspect, rainfall (liquid) and precipitation below 0°C (solid) were separated on the basis of temperature, assuming that rain occurs if temperature is above 0°C (Harpold et al., 2017b). Then, the change in rainfall in the future with respect to the historical period is revealed (Figure 4.9 b). Rainfall is increasing in both the near and far future with respect to the historical period. Both increasing temperature and rainfall in the near and far future will strongly contribute to snowmelt which results in a decrease in annual SWE in the future for this region.

4.5 Conclusions

This study attempted to provide a reliable assessment of the likely changes in future snowpack using climate model simulations. For this purpose, historical and future projections of temperature, precipitation and SWE as well as observations of these climatic variables for the historical period were studied to determine potential snowpack changes in the future. Snow processes typically occur in regions with complex topography and steep precipitation as well as air temperature gradients. Therefore, GCMs and RCMs contain biases, and projecting the impact of climate change in snowpack is highly complicated. Again, good estimation of snowpack change is of great importance for spring runoff forecasting to support water management, flood/drought forecasting, and reservoir operations.

To address biases in climate projections, a multivariate bias correction approach, the MRNBC, was used. This approach is more effective than traditional univariate bias correction methods for correcting biases and variability in multiple climate model (GCM and RCM) derived variables over multiple time scales simultaneously. The MRNBC significantly improve the statistics of employed GCM and RCM simulations for temperature, precipitation and SWE.

The results of this study for the historical, near future and far future showed that the maximum spell of snow free days per year is increasing more in the far future than in the near future and the historical period, whereas the snowy day fraction is decreasing. Again, the trend in monthly SWE suggests SWE is decreasing in the future with respect to the historical period which might be the result of increasing snow free days and change of local climate characteristics. Furthermore, annual SWE is decreasing in the far future and near future with respect to the historical period for almost all stations, which is a concern for hydrological applications and ecosystems in the future. Increasing temperature will accelerate snowmelt and cause more rainfall which also triggers snowmelt. Therefore, the change in temperature and rainfall will strongly affect the projected SWE changes, impacting the timing and seasonality of flooding in downstream areas.
The outcome of this study will contribute to a better understanding of the variability and trends in historical and future SWE change in Tibet. A better knowledge of the snow climatology would help to project the future availability of meltwater resources in this region. Moreover, future projection of SWE will provide important information for water managers and policy makers to assist in the sustainable management of water resources for the downstream populations.
4.6 Supplementary information

4.6.1 Bias correction results for temperature

Figure 4.51: Probability distribution plots of temperature (°C) of GCMs and RCMs at station 2, 3, 4 and 5. Here the left panel figures are for raw temperature (a, c, e and g) and b) the right panel figures are for bias corrected temperature (b, d, f and h).
Figure 4.S2: Probability distribution plots of temperature (°C) of GCMs and RCMs at station 6, 7, 8 and 9. Here the left panel figures are for raw temperature (a, c, e and g) and b) the right panel figures are for bias corrected temperature (b, d, f and h).
Figure 4.S3: Probability distribution plots of temperature (°C) of GCMs and RCMs at station 10, 11, 12 and 13. Here the left panel figures are for raw temperature (a, c, e and g) and b) the right panel figures are for bias corrected temperature (b, d, f and h).
Figure 4.S4: Probability distribution plots of temperature (°C) of GCMs and RCMs at station 14, 15, 16 and 17. Here the left panel figures are for raw temperature (a, c, e and g) and b) the right panel figures are for bias corrected temperature (b, d, f and h).
Figure 4.55: Probability distribution plots of temperature (°C) of GCMs and RCMs at station 18, 19, 20 and 21. Here the left panel figures are for raw temperature (a, c, e and g) and b) the right panel figures are for bias corrected temperature (b, d, f and h).
Figure 4.S6: Probability distribution plots of temperature (°C) of GCMs and RCMs at station 22, 23, 24 and 25. Here the left panel figures are for raw temperature (a, c, e and g) and b) the right panel figures are for bias corrected temperature (b, d, f and h).
Figure 4.57: Probability distribution plots of temperature (°C) of GCMs and RCMs at station 26, 27, 28 and 29. Here the left panel figures are for raw temperature (a, c, e and g) and b) the right panel figures are for bias corrected temperature (b, d, f and h).
Figure 4.S8: Probability distribution plots of temperature (°C) of GCMs and RCMs at station 30 and 31. Here the left panel figures are for raw temperature (a, c, e and g) and b) the right panel figures are for bias corrected temperature (b, d, f and h).
4.6.2 Bias correction results for SWE

Figure 4.S9: Probability distribution plots of SWE (mm) of GCMs and RCMs at station 2, 3, 4 and 5. Here the left panel figures are for raw SWE (a, c, e and g) and b) the right panel figures are for bias corrected SWE (b, d, f and h).
Figure 4.S10: Probability distribution plots of SWE (mm) of GCMs and RCMs at station 6, 7, 8 and 9. Here the left panel figures are for raw SWE (a, c, e and g) and b) the right panel figures are for bias corrected SWE (b, d, f and h).
Figure 4.S11: Probability distribution plots of SWE (mm) of GCMs and RCMs at station 10, 11, 12 and 13. Here the left panel figures are for raw SWE (a, c, e and g) and b) the right panel figures are for bias corrected SWE (b, d, f and h).
Figure 4.S12: Probability distribution plots of SWE (mm) of GCMs and RCMs at station 14, 15, 16 and 17. Here the left panel figures are for raw SWE (a, c, e and g) and b) the right panel figures are for bias corrected SWE (b, d, f and h).
Figure 4.S13: Probability distribution plots of SWE (mm) of GCMs and RCMs at station 18, 19, 20 and 21. Here the left panel figures are for raw SWE (a, c, e and g) and b) the right panel figures are for bias corrected SWE (b, d, f and h).
Figure 4.S14: Probability distribution plots of SWE (mm) of GCMs and RCMs at station 22, 23, 24 and 25. Here the left panel figures are for raw SWE (a, c, e and g) and b) the right panel figures are for bias corrected SWE (b, d, f and h).
Figure 4.S15: Probability distribution plots of SWE (mm) of GCMs and RCMs at station 26, 27, 28 and 29. Here the left panel figures are for raw SWE (a, c, e and g) and b) the right panel figures are for bias corrected SWE (b, d, f and h).
Figure 4.S16: Probability distribution plots of SWE (mm) of GCMs and RCMs at station 30 and 31. Here the left panel figures are for raw SWE (a, c, e and g) and b) the right panel figures are for bias corrected SWE (b, d, f and h).
5 A conceptual model for simulating streamflow in a changing snow-covered catchment: Application to the data sparse Brahmaputra River basin

This chapter develops a conceptual hydrologic model considering minimal data availability as well as the dynamically changing snow cover for the Brahmaputra and surrounding basins. The content in this chapter has been reproduced (with reformatting) from the journal paper referenced below.

Hydrological processes in the Tibetan Plateau (TP) are not well understood largely as a result of orographic complexity and fairly limited accessibility of ground based observation datasets. Understanding the hydrological cycle in this remote area is an increasingly important as the snow resources in the TP strongly interact with the climate system, regulate the surface temperature and the water cycle, and feed the demand for freshwater for a vast downstream population. Given the limited information available, the task of formulating a hydrological model that characterises streamflow at downstream locations is challenging. Current studies consider either entire snow cover or unchanged snow cover with time although precipitation-runoff process in frozen ground and snow-free conditions in warming climate are different. A flexible conceptual hydrological model is proposed with the aim of characterising flow in the region into the future where temperature profiles will be considerably warmer than the present. The model’s novelty lies in its ability to simulate dynamically varying snow cover fraction, snow water equivalent and streamflow across this complex terrain using limited available data. The open access gridded APHRODITE datasets and satellite based snow products are used to specify the proposed model for the upper Brahmaputra and its surrounding basins (Yellow and Yangtze). Results show that modelled hydrologic variables agree with observed data and that the observed hydrologic variables are properly captured by the proposed hydrologic model.

5.1 Introduction

A substantial amount of the annual precipitation in the Tibetan Plateau (TP) is in the form of snow in both winter and summer at high altitudes (Yuan et al., 2020, Orsolini et al., 2019). The TP contains vast cryospheric elements including snow, glaciers and permafrost, amongst the largest globally outside of the Arctic and the Antarctic region (Xiao and Duan, 2016, Wang et al., 2016a). Snow regulates thermal infrared emissivity and the global atmospheric circulation through positive snow albedo feedback (Lüthi et al., 2019). Seasonal snow cover governs the regional climatological and hydrological processes significantly (Derksen and Brown, 2012).

Attributes such as snow cover fraction, snow depth and snow water equivalent (SWE) usually provide information on snowpack dynamics and are used in various hydrologic studies concerning snowmelt induced runoff simulation (Xuan et al., 2018, Weiler et al., 2018, Miao et al., 2019, Wu et al., 2020). Snow cover fraction (the fraction of a unit land area with snow cover) impacts radiation balance and determines the amount of liquid precipitation that falls on snow covered versus non-snow covered area (Niu and Yang, 2007, Cortés et al., 2014). Again, SWE is also an important parameter to generate information on stored water in the snowpack among other snow attributes as it includes both snow density and snow depth (Li et al., 2019a, Gichamo and Tarboton, 2019, Ryken et al., 2020). So, consideration of snow attributes such as SWE in streamflow modelling is needed for proper understanding of the potential future change in water and the efficient management of water resources in snow dominated catchments.

The Tibetan Plateau is the largest plateau on the earth with $2.5 \times 10^6 \text{km}^2$ area and an elevation difference of over 8 km (Wang et al., 2019b). Due to its remoteness and orographic complexity, observed ground streamflow data are limited in the Tibetan Plateau which feeds significant water to a number of Asian rivers (e.g., Brahmaputra, Yellow, Yangtze and Indus rivers). These rivers supply water to the hundreds of millions of people living in downstream, agriculture and ecosystems (Cuo et al., 2014, Zhang et al., 2013). Again, the integrated processes of cryosphere, atmosphere, hydrosphere and pedosphere yield streamflow in a basin which is highly complex, non-linear and non-stationary (Bai et al., 2016, Tong et al., 2014). So, streamflow in this region is very prone to be directly affected by climate change and human activities. Therefore, streamflow modelling is an important tool for proper planning and management of the water resources, environment, and ecosystems, however is difficult to undertake due to a lack of streamflow observations.

One of the most populated basins in the world- the Brahmaputra (Yarlung Zangbo), originates in the Tibetan Plateau, and is highly sensitive to changes in temperature and precipitation (Shi et al., 2011). However, ground temperature, precipitation, snow cover fraction and snow water
equivalent datasets in Tibet are not easily available. In addition, temperature and precipitation are important inputs in most hydrologic models to simulate streamflow and these variables also control hydrological processes and energy cycles (Wang et al., 2015). So, gridded datasets and satellite-based estimates are an important source for climatic variables in Tibet where the gauge distribution is sparse. APHRODITE (Asian Precipitation Highly Resolved Observational Data Integration To- wards Evaluation of Water Resources) (Yatagai et al., 2012) datasets for temperature and precipitation have been used for this region in multiple past studies (Yang et al., 2014, Zhang et al., 2013, Rahimi et al., 2019, Tan et al., 2020, Kong and Chiang, 2020, Nury et al., 2019). Satellite based snow cover fraction and snow water equivalent available from MODIS (Moderate Resolution Imaging Spectroradiometer) and GlobSnow (http://www.globsnow.info/) are also used by numerous hydrologic studies in remote areas (Li et al., 2018, Han et al., 2019, You et al., 2020, Jeong et al., 2017, Luojus et al., 2011, Takala et al., 2011). This also forms the approach the current study uses, as outlined in later sections of the paper.

Over the last century, numerous studies have been dedicated to streamflow modelling, resulting in many approaches and model structures (Evaristo and McDonnell, 2019, Mehdizadeh et al., 2019, Wu et al., 2019, Kebede et al., 2020). Physically based hydrological models require large datasets, and pose difficulty in implementation in regions such as the TP due to imperfect parameterisation of the complex natural process and surface and subsurface parameters for the mountainous region in TP (Rashid and Beecham, 2019, Nayak et al., 2013). These models are also generally time consuming, costly, hard to use in data sparse regions, which increases uncertainty in model outputs during future simulations (Modarres and Ouarda, 2013). In addition, existing hydrologic models applied in the Tibetan Plateau (Ruan et al., 2017, Liu et al., 2017, Tian et al., 2020, Wang et al., 2015, Zhang et al., 2013), may be difficult to reliably extrapolate due to data scarcity and restrictive data sharing policies (Ray et al., 2015). Although empirical models may require fewer datasets than physically based hydrological models, application of these models to understand the effect of change on water resources are limited (Kisi et al., 2013, Nourani et al., 2012). In this circumstance, a simple conceptual hydrological model is required, because it can be implemented with sparse data while still providing understanding of the change in catchment-scale hydrology owing to climate and snow cover change with more flexibility.

Most of the existing degree day or temperature index modelling approaches widely used for snow dominated catchments at regional scales are attempts to overcome data challenges that limit more detailed physical representations from being adopted (Singh and Kumar, 1997, Arora et al., 2008, Kumar et al., 2007, Singh and Bengtsson, 2004). Such approaches consider average
air temperature, net radiation and melt factors to estimate snowmelt (Smith and Marshall, 2010, Singh et al., 2009). However, it is not feasible to understand or simulate properly the change in the snow processes that influence catchment behaviour due to the lack of information about the snowpack (Winstral et al., 2013, Mark and Martyn, 2014). Moreover, snowmelt-runoff processes in frozen ground and rainfall-runoff processes in snow free conditions under warmer temperatures are significantly different (Harpold and Brooks, 2018a). Frozen ground with thick snow cover has less permeability which will result in greater surface runoff than that in snow-free conditions (Zhao et al., 2019b, Gao et al., 2018a). Therefore, a flexible hydrologic model considering different processes of snow and non-snow covered areas under changing temperature regimes is important for adequately representing the water cycle in remote regions. To this end, this study uses remotely sensed snow cover fraction and snow water equivalent datasets to describe the aforementioned issues in the streamflow modelling performed. The fact that the proposed framework can accommodate changing snow-cover and the impact this causes to the streamflow generation, makes the proposed approach more suitable for simulating the impacts of global warming on streamflow in snow-covered catchments.

The main objective of this research is to develop a novel hydrologic model considering the lack of ground based observations available for the partly snow covered upper Brahmaputra basin to be able to simulate change as temperatures rise into the future, which will enhance our understanding of the dominant hydrological process. The model uses temperature and precipitation information as input and simulates snow cover fraction, snow water equivalent and streamflow. To our knowledge, we present here the first conceptual model which uses both snow cover fraction and SWE for considering snow storage in streamflow simulations, in a remote setting where uncertainty is significant. Finally, the performance of the proposed hydrologic model is assessed against observed datasets using different statistical metrics.

5.2 Study area and Datasets

5.2.1 Study area

The Brahmaputra river is the fifth largest river originating in China on the basis of length (2000 km in China) with an upstream basin that occupies a 201202 km² drainage area (Zhang et al., 2013). The Brahmaputra originates from the Gyima Yangzoin glacier in TP and passes through the Himalayan slopes to enter into the downstream country India before depleting into the Bay of Bengal, Bangladesh (Ray et al., 2015). In addition, the Yangtze and Yellow river basin occupy a 137704 km² and 121972 km² drainage area, respectively, also originating from the TP, and serving as surrogate catchment areas to verify the model proposed. About 92% of the upper
Brahmaputra basin and Yangtze are situated between the elevations 4000m-6000m while 99.5% of the Upper Yellow River is located between 3000m-5000m (Li et al., 2018). The study area with basin boundaries and elevation information is presented in Figure 5.1.

5.2.2 Observed data

Daily observed temperature and precipitation data of 0.25° x 0.25° resolution were acquired from APHRODITE (Yatagai et al., 2012) during 1961-2005 for this study (available at http://www.chikyu.ac.jp/precip/english/). Monthly observed MODIS Snow cover fraction data (0.05° x 0.05°) were collected from NSIDC (https://nsidc.org/data/MOD10CM) for the period 2001 to 2010. Daily observed SWE datasets of 1° x 1° resolution from the CanSISE (Canadian Sea Ice and Snow Evolution Network) (Mudryk et al., 2015) were also obtained for the period 1981 to 2010. For convenience, all datasets were re-gridded to a common resolution of 0.05° x 0.05° considering a conservative remapping approach (Jones, 1999). Data availability of all meteorological and hydrological variables used in this study is shown in Figure 5.2.

The monthly streamflow data of the Nuxia hydrological station (Cai et al., 2017) in the upper Brahmaputra River (Figure 5.1 and 5.2) were obtained for the period of 1981-2000 to calibrate the proposed hydrological model. To check model performance, three additional streamflow stations were used: Yangcun, Zhimenda and Tangnaihai at monthly scale for the periods 1970-1982, 1981-1997 and 1981-2010, respectively. The Yangcun hydrological station is located in the upper Brahmaputra river while the Zhimenda and Tangnaihai are situated in the Yangtze and Yellow river respectively (Figure 5.1). Monthly average runoff of Nuxia, Yangcun, Zhimenda and Tangnaihai stations are 1.64 ML/s, 0.88 ML/s, 0.29 ML/s and 0.62 ML/s respectively.

5.3 Methodology

We were faced with the challenge of formulating a hydrological model that relied on minimal data, could simulate snow processes, and could also allow for simulation of snow and streamflow processes into a warmer climate. Such a model was formulated (presented below) after undertaking an elaborate literature review that resulted in existing modelling alternatives being discounted either because of complexity (necessitating long and low uncertainty data for calibration and testing) or limited extrapolability (especially for the high temperature conditions.
Figure 5.1 Study area with basin boundaries (1-Brahmaputra, 2-Yangtze and 3-Yellow) and elevations in meter (colour bar). Black dot denote Nuxia hydrological station and red dots are Yangcun (Brahmaputra), Zhimenda (Yangtze) and Tangnaihai (Yellow) respectively for model checking.

Figure 5.2 Data availability of meteorological and hydrological variables. Here SCF is snow cover fraction, SWE is snow water equivalent, Nuxia, Yangcun, Zhimenda and Tangnaihai represent the hydrological stations respectively for model checking.

expected towards the end of the century). In formulating the model, we first listed a set of constraints that any proposed model must satisfy. These constraints were:

(a) The model must be physically based and follow established principles of mass and energy balance;

(b) The model must allow the simulation of snowmelt and surface water runoff based on availability of snow and incident temperature conditions; and,
(c) The model must allow for a dynamic representation of snow-cover in the catchment, which is allowed to change as a function of temperature or snow water equivalent, and controls the proportional representation of snowmelt compared to non-snowmelt flow. A schematic representation of the proposed model is illustrated in Figure 5.3.

![Schematic of the proposed model](image)

**Figure 5.3 Schematic of the proposed model.**

### 5.3.1 Proposed hydrologic model

The proposed model relies on the assumption that a site-specific relationship can be formulated relating the fraction of snow-cover with the volume of snowpack available. An empirical relationship between snow cover fraction and snow water equivalent was formulated using the datasets described before. Given the limiting conditions such a relationship poses, the following empirical form was used:

\[
A_s(t) = e \times SWE_t^f \quad 0 \leq A_s(t) \leq 100
\]  

(5.1)

where, \(A_s\) is snow cover fraction (in percentage terms), and \(e\) and \(f\) are coefficients obtained empirically using the remotely sensed datasets described before. For the observational record available (2001-2010, average of 2300 pixels representing the region), the above equation exhibited a fitted accuracy (NSE) of 0.84 (Figure 5.4). The sample coefficients \(e\) and \(f\) assume values of 16.9 (%) and 0.25 (%) respectively.
Following this, mass-balance is performed over a partly snow-covered pixel by approximating melt using a degree-day relationship:

\[ M_t = \max \{0, \delta (T_t - T_{thr})\} \]  

\[ SWE_t \times A_t = SWE_{t-1} \times A_{t-1} + (I_t P_t - M_t) A_t \left( I_t = 1, I_f \right) \] \( \text{if} \ T < T_{thr} \) \( I_t = 0, I_f \) \( \text{if} \ T > T_{thr} \)  

where, \( SWE_{t-1} \) and \( SWE_t \) are snow water equivalent at preceding and current time steps respectively, \( A_{t-1} \) and \( A_t \) are snow cover fraction at preceding and current time steps respectively, \( P_t \) is precipitation at current time step, \( M_t \) is snow melt at current time step, \( \delta \) is a snow melt parameter (often referred to as the “degree-day” coefficient), \( T_t \) is temperature at current time step and \( T_{thr} \) is threshold temperature (\( 1^\circ \text{C} \)) (Pistocchi et al., 2017). The range for the melt parameter is selected to lie within 0 to 9 mm\( ^\circ \text{C}^{-1} \text{time}^{-1} \) (Singh et al., 2000). It should be noted that Equation (5.2) can be used to represent the mass balance for warm as well as cold conditions. Under warm conditions (\( T > T_{thr} \)) the snowpack volume does not augment in the event of precipitation \( P_t \). Under cold conditions (\( T < T_{thr} \)) any precipitation adds to the volume of the snowpack while allowing for snowmelt to occur concurrently. This state-dependent mass-balance is accommodated by using the indicator variable \( I_t \) which specifies whether the precipitation is to be augmented to the snowpack or to be routed as surface water runoff.

Finally, streamflow is modelled considering storage, precipitation, snow melt flow and PET (potential evapotranspiration) employing Equations (5.4) to (5.10)

\[ (1 - A_t) S_t = (1 - A_{t-1}) S_{t-1} + (1 - A_t) P_t + A_t [(1 - I_t P_t) + M_t] - L_t - (1 - A_t) Q_t^m \]  

where, \( S_{t-1} \) and \( S_t \) (m³) are storage at preceding and current time steps, \( Q_t \) is streamflow at current time step, and \( L_t \) is evapotranspiration and sublimation loss which is estimated from PET and can be approximated as,

\[ L_t = \gamma \times PET \]  

where, \( \gamma \) is loss parameter and \( PET \) is potential evapotranspiration discussed later in equation (5.9). The expected range of the loss parameter \( \gamma \) is from 0 to 1.

Considering the system to behave as a non-linear storage, one can write the runoff generation process using the storage representation \( S = KQ^m \) where \( K \) and \( m \) are coefficients that need to be estimated. Substituting this in equation (5.4), one gets:
\[(1 - A_s t)K Q_t^n = (1 - A_s t-1)K Q_{t-1}^n + (1 - A_s t)P_t + A_s t[(1 - I_t P_t) + M_t] - L_t \]

\[(5.6)\]

where, \(K\) is the storage delay parameter and \(m\) is the non-linearity exponent. The proposed range of \(K\) and \(m\) are set to 0.1 to 10 and 0.1 to 1 respectively (Jothityangkoon and Sivapalan, 2003). Finally, the flow is ascertained as the sum of flow from snow storage and non-snow storage. So, the streamflow rate can be written as:

\[Q_t = \left(\frac{(1 - A_s t-1)K Q_{t-1}^n + (1 - A_s t)P_t + A_s t[(1 - I_t P_t) + M_t] - L_t}{(1 - A_s t) (1 + K)}\right)^{\frac{1}{m}} \]

\[(5.7)\]

In the approach outlined above, Potential evapotranspiration was calculated using the Thornthwaite equation (Thornthwaite, 1948).

\[PET = 16 \left(\frac{X}{12}\right) \times \left(\frac{N}{30}\right) \times \left(\frac{10 T_d}{H}\right)^b \]

\[(5.8)\]

where, \(PET\) is the potential evapotranspiration in mm per month, \(X\) is the average day length in hours (of the month being estimated), \(N\) is the number of days in the month being estimated, \(T_d\) is the daily temperature in degrees Celsius (using negative as zero) of the month being estimated. \(H\) is a heat index (Thornthwaite and Mather, 1955) calculated from 12 monthly mean temperatures \(T_i^{mn}\) presented in equation 5.9:

\[H = \sum_{i=1}^{12} \left(\frac{T_i^{mn}}{5}\right)^{1.514} \]

\[(5.9)\]

\[b\] (Thornthwaite and Mather, 1957) is estimated from heat index \(H\) and presented by,

\[b = (6.75 \times 10^{-7}) H^3 - (7.71 \times 10^{-5}) H^2 + (1.792 \times 10^{-2}) H + 0.49239 \]

\[(5.10)\]

### 5.3.2 Calibration methods and statistical metrics

The calibration of the proposed hydrologic model was implemented using the shuffled complex evolution algorithm (Duan et al., 1993). Mean squared error (MSE) was used as the objective function for model calibration. Observed and simulated streamflow as used to compute MSE as follows:

\[MSE = \frac{1}{n} \sum_{i=1}^{n} (O^i_0 - O^i_S)^2 \]

\[(5.11)\]

where, \(n\) is the total number of time steps, \(O_o\) is the observed value and \(O_s\) is the simulated value. MSE is automatically optimised by the shuffled complex evolution algorithm.

In addition to MSE, the correlation coefficient (CC), RMSE-observations standard deviation ratio (RSR) (Legates and McCabe Jr, 1999) and Nash Sutcliffe efficiency (NSE) (Nash and
Sutcliffe, 1970) were used to measure the closeness between observations and simulations as defined in the following equation 5.12, 5.13 and 5.14

\[
CC = \frac{\sum_{i=1}^{n}(o_i^o - \bar{O}_o)(o_i^s - \bar{O}_s)^2}{\sum_{i=1}^{n}(o_i^o - \bar{O}_o)^2 \sum_{i=1}^{n}(o_i^s - \bar{O}_s)^2} \quad (5.12)
\]

\[
NSE = 1 - \frac{\sum_{i=1}^{n}(o_i^o - o_i^s)^2}{\sum_{i=1}^{n}(o_i^o - \bar{O}_o)^2} \quad (5.13)
\]

\[
RSR = \frac{\sqrt{MSE}}{STD_o} \quad (5.14)
\]

where, \(\bar{O}_o\) and \(\bar{O}_s\) denote average observed and simulated value respectively. General performance rating using RSR and NSE for hydrological simulations (Moriasi et al., 2007) are presented in Table 5.1.

<table>
<thead>
<tr>
<th>RSR statistic</th>
<th>NSE statistic</th>
<th>Performance Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0 ≤ RSR ≤ 0.50</td>
<td>0.75 &lt; NSE ≤ 1.00</td>
<td>Very good</td>
</tr>
<tr>
<td>0.50 &lt; RSR ≤ 0.60</td>
<td>0.65 &lt; NSE ≤ 0.75</td>
<td>Good</td>
</tr>
<tr>
<td>0.60 &lt; RSR ≤ 0.70</td>
<td>0.50 &lt; NSE ≤ 0.65</td>
<td>Satisfactory</td>
</tr>
<tr>
<td>RSR &gt; 0.70</td>
<td>NSE ≤ 0.50</td>
<td>Unsatisfactory</td>
</tr>
</tbody>
</table>

5.4 Results

5.4.1 Snow attributes simulation

This study simulates two snow attributes, namely snow cover fraction and snow water equivalent. Owing to the sparse observation network in the TP, snow cover fraction information is provided by satellite remote sensing. Again, modelling of snow covered area fraction is important to understand the hydrological cycle in the mountainous regions as most of the satellite derived snow cover fraction products are available after the year 2000, facilitating the characterisation of frozen ground versus non-frozen ground in the streamflow simulation. Figure 5.4 presents observed versus modelled monthly snow cover fraction from 2001 to 2010. The modelled snow cover fractions considerably agree with the observed data, with a correlation coefficient of 0.92 and mean squared error of 0.54. The NSE (0.84) and RSR (0.40) statistics of the modelled snow cover fraction is in the level of good according to the Table 1.
Chapter 5

The model also captures the snow season (November to February of the next year) well (monthly correlation coefficient of November to October of the next year are 0.84, 0.80, 0.67, 0.65, 0.28, 0.69, 0.84, 0.80, 0.65, 0.42, 0.49 and 0.73 respectively). This modelled snow cover fraction will be used to simulate streamflow later.

Modelled and observed SWE are disclosed in Figure 5.5 with good correlation coefficient 0.82 and mean squared error 0.95. A reasonable correspondence of observed and modelled SWE is found in a number of points although in some points peaks are not captured. Uncertainties in satellite products will have an impact on SWE modelling (Slater et al., 2013), since monthly correlation coefficient for SWE from November to October of the next year are 0.57, 0.61, 0.57, 0.37, 0.36, 0.22, 0.17, 0.31, 0.18, 0.29, 0.30 and 0.17 respectively. Looking at this study, SWE is estimated from the temperature, precipitation and snow cover fraction datasets. Interpolation to prepare the observed climatic variables and satellite datasets may yield uncertainties due to elevation differences in complex terrain. The NSE and RSR statistics of the modelled SWE are 0.62 and 0.60 which is in the rank of satisfactory and good respectively following Moriasi et al. (2007).

Figure 5.4 Observed vs modelled snow cover area fraction.

Figure 5.5 Observed monthly SWE (mm) multiplied by snow cover area fraction vs 90% modelled intervals of multiple ensembles from optimisation method (shuffled complex evolution algorithm). CC (correlation coefficients) and MSE are found using observed and mean ensemble series.
5.4.2 Streamflow simulation

Table 5.2 shows four calibrated parameters for the snow melt, loss, storage delay and non-linearity of the proposed model. Modelled streamflow is compared with the observed where correlation coefficient is 0.85 and mean squared error is 0.62 in the Figure 5.6.

Table 5.2 Calibrated parameters of the proposed hydrologic model

<table>
<thead>
<tr>
<th>Station</th>
<th>δ (Melt parameter, mm°C⁻¹time⁻¹)</th>
<th>γ (Loss parameter)</th>
<th>K (storage delay parameter, Time)</th>
<th>m (non-linearity parameter)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuxia</td>
<td>5.5</td>
<td>0.6</td>
<td>3.5</td>
<td>0.4</td>
</tr>
<tr>
<td>Yangcun</td>
<td>1.2</td>
<td>0.3</td>
<td>4.6</td>
<td>0.5</td>
</tr>
<tr>
<td>Tangnaihai</td>
<td>3.7</td>
<td>0.5</td>
<td>3.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Zhimenda</td>
<td>1.3</td>
<td>0.4</td>
<td>6.7</td>
<td>0.9</td>
</tr>
</tbody>
</table>

Modelled streamflow is in good agreement with the range of observed values, although with apparent dispersions. Like SWE, streamflow is simulated from the forcing variable gridded precipitation and satellite-derived snow products which are important sources for the data scarce region but include uncertainties. The underestimation of the peaks will be partly due to the use of interpolated precipitation data which represent averaged values over a low resolution grid. Remotely sensed snow products have uncertainties due to gaps in revisit times of satellite and atmospheric conditions that affect the signals, which will impact the modelled streamflow as well. However, the NSE (0.70) and RSR (0.55) statistics of the modelled streamflow is in the category of good according to the Table 5.1.

Moreover, we presented results of other hydrologic stations in Table 3 for model checking. For all hydrologic stations statistical indicators are very good: monthly NSE values are higher than 0.75, RSR are below 0.50 and MSE are relatively low. Therefore, the overall performance of the proposed hydrologic model is reasonably good in simulating the hydrological process in this remote area.
Figure 5.6 Observed monthly streamflow vs 90% modelled intervals of multiple ensembles from optimisation method (shuffled complex evolution algorithm). CC (correlation coefficients), MSE, NSE and RSR are obtained using observed and mean ensemble series.

<table>
<thead>
<tr>
<th>Station</th>
<th>River basin</th>
<th>Correlation</th>
<th>MSE</th>
<th>NSE</th>
<th>RSR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zhimenda</td>
<td>Yangtze</td>
<td>0.90</td>
<td>0.01</td>
<td>0.81</td>
<td>0.44</td>
</tr>
<tr>
<td>Tangnaihai</td>
<td>Yellow</td>
<td>0.88</td>
<td>0.04</td>
<td>0.77</td>
<td>0.48</td>
</tr>
<tr>
<td>Yangcun</td>
<td>Brahmaputra</td>
<td>0.89</td>
<td>0.10</td>
<td>0.76</td>
<td>0.48</td>
</tr>
</tbody>
</table>

5.4.3 Model simulation for warmer conditions

The hydrologic model described here was developed with the intention of assessing change in the hydrology of the TP under future warming scenarios. This section presents the results of a sensitivity assessment that was performed with this aim in mind. The sensitivity assessment assumes that the only variable that changes into the future is temperature. Or, there is no accompanying change in precipitation, and hence the main hydrologic change that is occurring is the re-distribution of the snowpack into a surface water store. We emphasise that there exist significant limitations in such an extrapolation, but the use of a monthly time-step permits us to proceed, as much of the noted changes in precipitation that are occurring as a result of increasing temperature are at daily or sub-daily time scales (Wasko and Sharma, 2017a).

Model simulation for increasing temperature scenarios with a focus on snow water equivalent and streamflow are presented in Figure 7. It should be noted the hypothetical temperature rise scenarios are formulated using observed climate data, to which a step increase in temperature is added irrespective of season. In Figure 7a, an increase of 4°C temperature results in significant loss of SWE in March and April, whereas an increase of 5°C results in complete loss of SWE in
December, March and April. SWE decreases with increasing temperature due to reduced solid precipitation (snow), which highlights the impact of temperature change on the snowpack change in this region. In addition in Figure 7b, significant decrease in streamflow is visible under the increasing temperature of 4°C as well as 5°C owing to increasing PET and reduced SWE, which highlights the potential influence of warmer temperature on the streamflow of the Brahmaputra basin. Overall, the results demonstrate the usefulness of the model for extrapolating current conditions to those under assumed future temperature and precipitation dynamics.

![Model simulation at different temperature scenarios for monthly a) available SWE and b) streamflow using the 1980-2000 period precipitation as input.](image)

**Figure 5.7** Model simulation at different temperature scenarios for monthly a) available SWE and b) streamflow using the 1980-2000 period precipitation as input.

### 5.5 Discussion

This study attempted to formulate a simple conceptual model to represent the hydrological processes for the Tibetan Plateau (TP). The proposed model was formulated under a number of significant constraints. First, fairly limited climate data were available for the region, as a result of which gridded, reconstructed precipitation and temperature were used. Second, and quite importantly in the context of the results presented, snow water equivalent data was ascertained at a fairly coarse resolution using satellite remote sensing, and related to snow cover fraction again with considerable uncertainty present. Third, the lack of soil, stream roughness, along
with the coarse modelling time step (monthly), necessitated the use of a simple conceptual model rather than an elaborate hydrodynamic model that would have been impossible to verify. The novelty of the model lies in its ability to simulate different subsurface storage for snow covered vs non-snow covered areas. While remotely sensed SCA (snow cover area) provides valuable information on snowpack extent to potentially constrain any model, it is not easily reconciled with modelled fluxes for models that represent snow as SWE only (i.e. the vast majority of conceptual snow models). The model developed here allows simulations to be constrained by both SWE and SCA observations, improving the dependability of the model under extrapolation.

Given these constraints, the model made a number of simplifying assumption, leading to results that require discussion to appreciate their limitations and identify the needs for further refinements. Our discussion of these results is grouped under different sub-headings below.

### 5.5.1 Use of an empirical relationship between snow water equivalent and snow covered fraction

We used the satellite remote sensing derived CANSISE dataset to quantify observed snow water equivalent and relate it to the MODIS derived snow water fraction data. CANSISE comes from a merger of remote sensing and ground data, but is formulated at a 50km x 50km resolution. To counter the coarse resolution of the data, aggregation was done to a monthly time step from its raw daily resolution. While this aggregation reduces any underlying uncertainty, systematic biases, if present, are not addressed. As a result, there remains uncertainty in the quantification of the snow water equivalent data which should be addressed in follow-up studies.

While the snow cover fraction is available at finer spatial resolutions, there is uncertainty in its quantification due to cloud blockage and aggregation to the CANSISE resolution. However, given the scale of the catchment and the coarse temporal resolution of the study, as well as the varying impact of snow-cover on the streamflow generation in the proposed model, this limitation is less serious than the former. We do, however, note that for a follow-up study that is focussed on smaller catchments and finer temporal resolutions, care must be taken in developing a more accurate relationship (possibly with more covariates than just snow water equivalent) between snow cover and SWE.

### 5.5.2 Use of a dynamic snow-cover fraction to represent snowmelt and surface water runoff

We feel the biggest novelty behind our study is the consideration of a dynamic snow-cover fraction as a means of representing the flow generation in the catchment. Past approaches
assume either full snow cover, or a snow cover that does not change over time. Our approach considers snow cover to change and snowmelt occurs or the snowpack expands due to new precipitation (snow). It should, however, be noted that we do assume evaporation and other losses are occurring over the entire catchment. In reality, the nature of loss will be different over the snow-covered part and the non-snow covered part, with the latter having greater infiltration while the former having sublimation in contrast. Issues such as the melting of permafrost also come into play. Such details are ignored in our formulation given the coarse spatial and temporal resolutions we operate at, as well as the severe data limitations this study is conducted under. Future work, especially that projecting the simulations to a warmer climate, will be impacted more by the limitation of the assumptions above. Further work should aim to address these limitations by possibly considering a loss function that is dependent on snow-cover as well as temperature.

5.5.3 Use of a nonlinear storage routing approach to approximate the streamflow process

A key simplification that was made was in the assumption that a storage routing model can characterise the streamflow generation process in this complex catchment with part snowmelt and part surface water flow contributions. This assumption was required again due to the lack of detailed data. A simpler assumption, of considering a linear storage routing model, was first assessed, and discarded given the clear nonlinearity there exists in the system due to the dynamic contribution of snowmelt and surface water runoff. The parameters of this model was calibrated using monthly data, which again is a limitation as such models are often used to simulate flood processes that occur at finer time steps. Future work must try to reduce the temporal resolution of this study while taking into account the added uncertainty this could entail given the data limitations already noted before. It is hoped that opening up of data sharing across the countries that span the region will provide accurate ground observations of precipitation and temperature (as well as snow-depth and density where available) to help refine the approach presented here.

5.5.4 Implications of uncertainty and the limitations of extrapolation into warmer climate regimes

This study was undertaken with the intent of simulating change in snowpack, water availability, and flooding at downstream locations expected to be impacted adversely due to global warming. While the coarse time steps of the study restrict us from using the proposed approach for flood assessments, the proposed model is applicable for use in water availability assessments at
downstream locations less impacted by anthropogenic factors. Two concerns, however, should be noted. Firstly, the model here, while conceptual and relying mostly on incident temperature and precipitation information, uses an empirical relationship between snow-cover and snow water equivalent. This relationship has been developed at a fairly coarse resolution and may change into the future. More detailed assessments of how this change will occur can be performed in smaller catchments subject to larger temperature variations. Lack of on-ground and high-resolution data limits us from undertaking this task. However, this is recommended for further refining the proposed approach and for using it in a future setting. Secondly, there exists considerable uncertainty in both the model specification as well as the model structure that is used. While much of this uncertainty is unavoidable, it is important to keep it in mind especially when extrapolating into the future. For instance, the sensitivity to increasing temperature reported in the previous section, assumes that only temperature is impacted, with no impact on precipitation. This is a poor assumption especially at fine (daily or sub-daily) time steps, but is made here because of the much larger timescales the model operates over. Other assumptions regarding losses, permafrost, and the possible role of vegetation under a warmer climate, again limit the extrapolatability of the model to significantly warmer conditions. The uncertainty associated with such extrapolation needs to be noted and discussed in such follow-up work.

5.6 Conclusions

The prediction of dominant hydrological process for the purpose of water planning is difficult when limited and highly uncertain ground data is all that is available. This difficulty is further enhanced if the catchment is undergoing significant change, even if this change is a result of a well-studied factor (global warming). In such a scenario, use of a physically detailed hydrologic simulation model is difficult to pursue as there exists little information from which such a model can be validated. Considering this issue this study develops a novel hydrologic model to simulate dynamically varying snow cover fraction, snow water equivalent and streamflow using available temperature and precipitation information. Three parameters describing melt, loss and storage delay were specified to formulate the model using monthly aggregated remotely sensed snow-water equivalent and downstream streamflow data. The framework of the model is flexible and general, allowing snow storage as well as non-snow storage divisions to explain dominant processes well. The model can assist in improving our understanding of discrepancies between observations and simulations and to improve the process representation as more accurate data becomes available. The performance of the model was assessed using a range of statistical model performance attributes. We demonstrate how the proposed hydrologic model yields snow attributes and streamflow to a reasonable extent, critically depending on the
accuracy of input precipitation and temperature, highlighting the importance of reliable climatic variables for robust modelling. Overall, the results show that the model predicted the observed hydrologic variables well for the upper Brahmaputra basin. The model can be used in the water resource management although caution is required for deriving extreme flows given the coarse time steps adopted. Moreover, the expanding satellite global snow dataset as well as global precipitation data will enhance the precision of the hydrologic model, making it possible to specify for smaller catchments and finer time-steps. Even with the coarse spatio-temporal scales adopted, the model can be of considerable use in planning for changes in water availability for the Upper Brahmaputra Basin.
6 Modelling climate change impacts on the Brahmaputra streamflow resulting from change in snowpack attributes

This chapter demonstrates the implications of the conceptual hydrologic model in Chapter 5 under a changing climate using a flexible framework for the data sparse Brahmaputra basin. The content in this chapter has been reproduced (with reformatting) from the journal paper referenced below.

Modelling the impact of climate change on streamflow for remote or data sparse regions is a challenging problem for hydrologists, as most of the hydrologic models require large datasets for streamflow simulation. This problem becomes even more complex when a sizeable proportion of the catchment surface is covered by snow. The Tibetan Plateau, which forms the head-water of the Brahmaputra and many other major rivers in the Indo-China region, is not closely monitored due to its harsh environment. The lack of monitoring is especially significant when it comes to the quantification of its substantial snow resources, of considerable impact as these influence the supply of water for downstream communities. This research uses a conceptual hydrologic model developed to simulate the impact of the changing climate in such large, snow-covered, data sparse catchments, to adequately understand the likely changes in future water availability in the highly populated Brahmaputra basin and surrounding areas in the Tibetan Plateau. A multivariate nested recursive bias correction (MRNBC) approach is used for correcting systematic biases present in the climate model simulations of temperature and precipitation jointly across multiple timescales preserving the dynamic relationships amongst the variables. The use of this framework reduces both the uncertainty and bias in the raw climate model simulations and delivers improvements which give confidence to run the proposed hydrologic framework into the future. The results show that monthly snow cover fraction in near future (2041-2060) and far future (2071-2090) will decrease with respect to historical period (1981-2000) owing to warming temperature. In addition, annual streamflow in the future compared to historical period will increase which will result from changes in temperature and precipitation.

Nury, A. H., Sharma, A., Marshall, L., and Cordery, I. (submitted), Modelling climate change impacts on the Brahmaputra streamflow resulting from change in snowpack attributes
6.1 Introduction

Any change in the hydrological process will affect streamflow, as streamflow is a culmination of various hydrological processes in the catchment including evapotranspiration, precipitation, infiltration, overland flow and snow melt (Liu et al., 2017, Su et al., 2020). Rapid changes in climate along with anthropogenic change (i.e. change in land use, population growth) are impacting these hydrological processes which in turn affect streamflow (Immerzeel et al., 2020, Wang et al., 2015, Wang et al., 2019a). The snowpack of the Tibetan Plateau (TP) has an important role in the water cycle for prominent Asian basins such as the Brahmaputra, Yellow and Yangtze (Cai et al., 2017, Bai et al., 2016, Pritchard, 2017). These rivers provide source of fresh water supply and feed some of the most populated regions of the world, satisfying agricultural, energy and consumption needs (Cuo et al., 2014, Han et al., 2019, Ray et al., 2015). Modelling the impact of climate change in streamflow for such regions and understanding the likely changes of future streamflow remain critical to decision-making regarding water planning and management, energy planning, as well as the environment for this large region that is a host to numerous endangered species of flora and fauna.

Over the past decades, emission of greenhouse gases has accelerated climate change and resulted in the increase of temperature (Fischer et al., 2018a). Furthermore, the TP has been noted to be experiencing rapid warming (increase of average temperature at twice the global average temperature rate) (Bai et al., 2013, Duan and Xiao, 2015, Kuang and Jiao, 2016) and this has significant influence in snow resources (Immerzeel et al., 2020, Wang et al., 2016b). Despite the vulnerability of snow resources in the TP, ground snow datasets are not easily available for the complex terrain and severe weather conditions. In addition, in-situ data of important climatic variables (including temperature and precipitation) and catchment characteristics (e.g., soil porosity, infiltration capacity and slope) are rarely available due to sparse monitoring networks. The low density of ground based data cannot represent spatial and temporal distribution of climatic and hydrological features owing to uncertainty in this region (Nury et al., 2019, Musa et al., 2015). However, a number of studies have attempted to model streamflow and discussed its future change in such data sparse regions (Wu et al., 2020, Zhang et al., 2013, Li and Gao, 2015, Li et al., 2019a, Barnett et al., 2005, Cai et al., 2017, Cuo et al., 2013). These studies have used physically based hydrologic models which includes detailed parameterisation of the surface and subsurface and requires large climatic datasets. As a result, such physically based hydrologic models are hard to apply in data sparse regions, and being computationally expensive due to their complexity, include more uncertainty in the model output owing to requirement of parameters that are difficult to meet. While an alternative is to use empirical rainfall-runoff models for assessing future water availability under changing
climate, this again is not viable given both the limited process change and length of the available hydrologic records (Modarres and Ouarda, 2013). Over the past decades, degree day models or temperature index models were used to overcome data challenges in catchments that include snowpack (Hock, 2003, Singh et al., 2005, Smith and Marshall, 2010). However, such a model is again not completely appropriate for climate change impact studies because it does not allow for changes in snow cover, one of the first signs of warming such catchments exhibit (Mark and Martyn, 2014). Therefore, a hydrologic model that is designed to cater to the above limitations (or data availability, of complex terrain, and of snow-cover change) using a simple methodological framework is important to assess climate change impacts in the TP.

Global circulation models (GCMs) are widely used for climate projection into the future and serve as inputs for hydrologic simulations of the future (Mukundan et al., 2019, Jahandideh-Tehrani et al., 2019, Zhang et al., 2016). However, GCMs suffer from both bias and uncertainty owing to limitations in atmospheric process representation and numerical schemes (Nguyen et al., 2019, Eghdamirad et al., 2016, Terzago et al., 2017, Woldemeskel et al., 2016). Woldemeskel et al. (2012) reported that GCM uncertainty arises from errors in the model structure, scenarios and initial conditions. In addition, outputs from regional climate models (RCMs) are not readily transferable due to similar uncertainty and bias, although these are used to improve the performance of future hydrologic simulation (Terzago et al., 2017, Willkofer et al., 2018). RCM biases result from the differences in model parameterisations, errors in reference datasets and biases in boundary conditions that are specified from GCM simulations of the future (Kotlarski et al., 2014, Christensen et al., 2008, Rocheta et al., 2017a, Rocheta et al., 2014). To improve the projections of future simulation from climate models, a number of bias correction techniques have been proposed recently such as quantile mapping, local intensity scaling, quantile scaling and linear scaling (Teutschbein and Seibert, 2012, Themeßl et al., 2011, Dosio and Paruolo, 2011, Schmidli et al., 2006). One of the flexible bias correction methods designed to better represent features such as drought is the nested bias correction approach (NBC), developed by Johnson and Sharma (2012) and used in various applications including GCM uncertainty assessment (Eghdamirad et al., 2016, Eghdamirad et al., 2017b, Woldemeskel et al., 2016), drought and flood investigation (Asadi Zarch et al., 2017, Woldemeskel et al., 2014, Johnson and Sharma, 2015, Apurv et al., 2015). As the joint dependence between precipitation and evaporation inputs is necessary to simulate streamflow without bias, a multivariate nesting bias correction approach (MRNBC) was proposed by Mehrotra and Sharma (2015) to correct biases jointly, which preserves the interdependencies among climatic variables.
The present study attempts to develop a flexible framework for conceptual hydrologic modelling considering data scarcity in remote regions and the added uncertainty introduced by detailed model parameter representations. To overcome the weakness of simulations arising from both GCMs and RCMs, the MRNBC technique was employed for correcting distributional and persistence biases across multiple timescales amongst climatic variables. The conceptual hydrologic model consists of a set of relations for snow storage and non-snow storage, and uses temperature, precipitation and potential evapotranspiration (PET) information to simulate snow cover fraction, snow water equivalent and streamflow. To our knowledge, this is the first comprehensive study which focuses on both the snow cover fraction and snow water equivalent for describing surface runoff over frozen and non-frozen ground into the future, especially for a remote area that is severely constrained in the length and quality of data available. Effective perception of these issues is critical as model simulations can assist in water planning given streamflow changes will impact societies and ecosystems through drought, flooding and hydropower production (Ray et al., 2015). Finally, how the changing climate affects snow cover change in the future is investigated to understand the alteration of future streamflow in the Brahmaputra basin and surrounding areas in the Tibetan Plateau.

6.2 Study area and datasets:

6.2.1 Study area:

The upper Brahmaputra basin is one of the largest populated basins originating from the TP at an elevation of almost 3100m and surrounded by a large snowpack (Cai et al., 2017). It occupies a drainage area of 201202 km² with an approximate length of 1500km in China. The basin has complex topography and diverse climate with a higher trend of temperature increase than the mean trend for China. You et al. (2007) conducted a study over the upper Brahmaputra basin using data from 1961 to 2005 and observed that the linear trend of warming in this basin is 0.28°C/decade. In addition, the Yangtze and Yellow Rivers, with drainage areas of 137704 km² and 121972 km², respectively, also originate from the TP and are used in this study for investigating water availability as basins surrounding the Brahmaputra. The study area with elevations and basin boundaries are depicted in Figure 6.1.
6.2.2 Observed and climate modelled datasets

Daily observed temperature and precipitation datasets were extracted from APHRODITE (Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation of Water Resources) (Yatagai et al., 2012) for 1979 to 2005. A number of previous studies used APHRODITE datasets for hydrologic assessments (Apurv et al., 2015, Burke and Stott, 2017, Sidike et al., 2016). Observed satellite snow cover fraction (MODIS) datasets were obtained from NSIDC (https://nsidc.org/data/MOD10CM) for the period 2001 to 2010. Daily observed snow water equivalent datasets from 1981 to 2010 were collected from the CanSISE (Canadian Sea Ice and Snow Evolution Network) (Mudryk et al., 2015) for this study as well. Furthermore, the monthly streamflow data for the Nuxia hydrological station (upper Brahmaputra basin) for the period 1981-2000, Zhimenda (Yangtze basin) for the period 1981-1997 and Tangnaihai (Yellow basin) for the period 1981-2010 were used in this study. The 90m resolution SRTM (Shuttle Radar Topographic Mission) digital elevation model (DEM) data were collected from the website http://srtm.csi.cgiar.org/.

For future projections, daily temperature and precipitation datasets of four GCMs from CMIP5 (Coupled Model Intercomparison Project phase 5) and three regional climate models (RCMs) from CORDEX (Coordinated Regional Climate Downscaling Experiment) of current climate as well as the future were obtained. This study considered RCP8.5 (Representative Concentration Pathway 8.5) scenario for assessing the future climate, consistent with several other studies attempting to assess changes in future climate precipitation and flow (Peters et al., 2013, Sillmann et al., 2013, Hettiarachchi et al., 2018). Spatial resolutions of the observed, GCM and RCM datasets are showed in Table 1. For convenience, all datasets were re-gridded to a
common resolution of \(0.4^0 \times 0.4^0\) considering a conservative remapping approach (Jones, 1999) using climate data operator (CDO) and time frames from 1981 to 2000 (historical), 2041 to 2060 (near future) and 2071 to 2090 (far future) respectively.

Table 6.1 Observed and climate modelled data used in this study. All RCMs were obtained from CCLM5-V2 model (Institution: Climate Limited -area Modelling Community)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Sources</th>
<th>Resolution (lon x lat degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature and Precipitation</td>
<td>APHRODITE’s Water resources</td>
<td>(0.25^0 \times 0.25^0)</td>
</tr>
<tr>
<td>Snow cover fraction</td>
<td>NSIDC</td>
<td>(0.05^0 \times 0.05^0)</td>
</tr>
<tr>
<td>Snow water equivalent</td>
<td>CanSISE ( Canadian sea ice and snow evolution network) observation based ensemble of SWE (Mudryk et al.,2017)</td>
<td>(1^0 \times 1^0)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>GCMS</th>
<th>Model identification</th>
<th>Modelling group</th>
<th>Resolution (lon x lat degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HadGEM2</td>
<td></td>
<td>Met office Hadley Centre, UK</td>
<td>(1.25^0 \times 1.875^0)</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td></td>
<td>Max Planck institute for Meteorology, Germany</td>
<td>(1.8653^0 \times 1.875^0)</td>
</tr>
<tr>
<td>CanEs2</td>
<td></td>
<td>Canadian centre for climate model and analysis, Canada</td>
<td>(2.812^0 \times 2.812^0)</td>
</tr>
<tr>
<td>GFDL-CM3</td>
<td></td>
<td>NOAA Geophysical Fluid Dynamics Laboratory, USA</td>
<td>(2.5^0 \times 2.5^0)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>RCMs</th>
<th>Driving GCMs</th>
<th>Modelling group</th>
<th>Resolution (lon x lat degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>EC-Earth</td>
<td></td>
<td>EC-Earth consortium, Europe</td>
<td>(0.4^0 \times 0.4^0)</td>
</tr>
<tr>
<td>HadGEM2</td>
<td></td>
<td>Met office Hadley Centre, UK</td>
<td>(0.4^0 \times 0.4^0)</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td></td>
<td>Max Planck institute for Meteorology, Germany</td>
<td>(0.4^0 \times 0.4^0)</td>
</tr>
</tbody>
</table>

6.3 Methodology

Figure 6.2 presents the flowchart summarising the methodological framework adopted to simulate streamflow over a varying snow-cover basin at coarse (monthly) temporal resolutions. This conceptual hydrologic model was calibrated using model forcing data including observed temperature, precipitation and PET as well as the observed streamflow for specifying the calibration objective function. Then, MRNBMC was applied to correct systematic biases in climate modelled (GCMs and RCMs) temperature and precipitation for projection into the future. Finally, snow cover fraction, snow water equivalent and streamflow were simulated for current climate and the future period to investigate impacts of climate change on hydrologic processes.
6.3.1 Hydrologic Model

This study used the hydrologic model from Nury (2020), where a portion of the flow originates from precipitation and snow melt in the snow-covered part of the basin, whereas the other portion of flow results solely from precipitation over the non-snow area. Consequently, total flow is the sum of runoff from snow-covered and non-snow covered areas taking account of evaporative and infiltration losses. The model consists of a set of equations for snow storage and non-snow storage and uses temperature, precipitation and PET to estimate snow cover fraction, snow water equivalent and streamflow.

Snow cover fraction (SCF) is a function of snow water equivalent and derived using the following equations (6.1):

\[
A_s(t) = e \times SWE_t^f \quad 0 \leq A_s(t) \leq 100
\]  
(6.1)

where, \(A_s(t)\) = snow cover fraction (in percentage) at time \(t\); \(e\) and \(f\) = coefficients with estimated values 16.9 and 0.25 respectively. It should be noted that the relationship in (6.1) to estimate the snow-cover fraction is derived using MODIS snow cover estimates and is pre-calibrated. Hence, the associated parameters (e, f) are not part of the hydrologic model parameter set detailed below.
Snow water equivalent was derived from temperature and precipitation. Next, flow from snow melt and non-snow storage were estimated using equations 6.2 and 6.4.

\[ M_t = \max [0, \delta (T_t - T_{thr})] \]  
\[ (1 - A_s) S_t = (1 - A_{s_{t-1}}) S_{t-1} + (1 - A_s) P_t + A_s [(1 - L_t P_t) + M_t] - L_t \]

where, \( M_t \) = snow melt (mm) at present; \( \delta \) = snow melt parameter; \( T_t \) = temperature (degrees Celsius) at time \( t \) and \( T_{thr} \) = temperature threshold (adopted equal to 1°C, (Pistocchi et al., 2017)). As reported by Singh et al. (2000), the melt parameter \( \delta \) ranges from 0 to 9 mm°C\(^{-1}\)time\(^{-1}\); \( SWE_t \) = snow water equivalent (mm) at present time step with \( t \) and \( t-1 \) representing the current and preceding time steps used; \( P_t \) = precipitation at present time step; and, \( I_t \) is an indicator variable to specify whether the precipitation is to be augmented to the snowpack or to be routed as surface water runoff. \( S_{t-1} \) and \( S_t \) (m\(^3\)) = storage at previous time step and present time step; \( Q_t \) = streamflow at present time step; \( L_t \) = loss which is derived from potential evapotranspiration (PET). Again, \( L_t \) estimated from equation (6.5) as:

\[ L_t = \gamma \times PET \]  

where, \( \gamma \) = loss parameter and PET is estimated using equation (6.8). The predicted range of loss parameter is 0-1.

Assuming a non-linear storage, \( S = KQ^m \) to represent the flow generation process, equation (6.4) specifies the mass balance as,

\[ (1 - A_s) KQ_t^m = (1 - A_{s_{t-1}}) KQ_{t-1}^m + (1 - A_s) P_t + A_s [(1 - L_t P_t) + M_t] - L_t \]

where, \( K \) is a delay parameter of storage and \( m \) is a parameter representing non-linearity. Following Jothityangkoon and Sivapalan (2003), the predicted range of \( K \) and \( m \) are adopted to fall in between 0.1 - 10 and 0.1 - 1 respectively. Finally, the total flow from snow storage and non-snow storage equals,

\[ Q_t = \left\{ \frac{(1 - A_{s_{t-1}}) KQ_{t-1}^m + (1 - A_s) P_t + A_s [(1 - L_t P_t) + M_t] - L_t}{(1 - A_s) (1 + K)} \right\}^{\frac{1}{m}} \]

The Thornthwaite (1948) approach was employed to estimate potential evapotranspiration which is shown in equation (6.8).
\[
\text{PET} = 16 \left(\frac{X}{12}\right) \times \left(\frac{N}{30}\right) \times \left(\frac{10T_d}{H}\right)^b
\]  
(6.8)

where, \(\text{PET}\) = potential evapotranspiration in mm per month, \(X\) = average day length in hours (of the month being estimated), \(N\) = number of days in the month being estimated, \(T_d\) = daily temperature in degrees Celsius (using negative as zero) of the month being estimated.

Coefficient \(b\) (Thornthwaite and Mather, 1957) was calculated from heat index \(H\) and presented by,

\[b = (6.75 \times 10^{-7})H^3 - (7.71 \times 10^{-5})H^2 + (1.792 \times 10^{-2})H + 0.49239\]  
(6.9)

Again, the heat index (Thornthwaite and Mather, 1955) was obtained from 12 monthly mean temperatures \(T_{i\text{mn}}\) presented in equation 6.10,

\[H = \sum_{i=1}^{12} \left(\frac{T_{i\text{mn}}}{5}\right)^{1.514}\]  
(6.10)

The model was optimised using the shuffled complex evolution algorithm (Duan et al., 1993) considering Mean Squared Error (MSE) as the objective function.

\[\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (O_o - O_s)^2\]  
(6.11)

where, \(n\) = total number of time periods, \(O_o\) = observed value and \(O_s\) = simulated value.

Calibrated parameters of the hydrologic model are presented in Table 6.2.

<table>
<thead>
<tr>
<th>Station</th>
<th>River basin</th>
<th>(\delta) (Melt parameter, mm°C^{-1}time^{-1})</th>
<th>(\gamma) (Loss parameter)</th>
<th>(K) (storage delay parameter, Time)</th>
<th>(m) (non-linearity parameter)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuxia</td>
<td>Brahmaputra</td>
<td>5.5</td>
<td>0.6</td>
<td>3.5</td>
<td>0.4</td>
</tr>
<tr>
<td>Tangnaihai</td>
<td>Yellow</td>
<td>3.7</td>
<td>0.5</td>
<td>3.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Zhimehna</td>
<td>Yangtze</td>
<td>1.3</td>
<td>0.4</td>
<td>6.7</td>
<td>0.9</td>
</tr>
</tbody>
</table>

### 6.3.2 Bias correction model

In the part of climate change impact assessment of the proposed framework, the MRNBC approach is used to correct systematic bias in GCM and RCM derived temperature and
precipitation. It uses a multivariate autoregressive model extended from the NBC framework (Johnson and Sharma, 2012) and applied at multiple timescales to correct mean, standard deviation, lag one autocorrelations, lag one and lag zero cross correlations following the observed data across the variables of interest (Mehrotra and Sharma, 2015).

The MRNBC is formulated on the basis of multivariate autoregressive model 1 (MAR1) which can be described by equations 6.12-6.13,

\[ Y_t^h = C_{t-1}^h + D_t \]  \hspace{1cm} (6.12)

\[ Y_t^g = E_{t-1}^g + F_t \]  \hspace{1cm} (6.13)

where, \( Y \) represents the vector of modelled variables (precipitation, temperature and potential evapotranspiration), \( C = \) lag zero cross correlation coefficient matrix of the observation (\( Y_t^h \)); \( D \) = lag one cross correlation coefficient matrix for the observation (\( Y_t^h \)); \( E \) = lag zero cross correlation coefficient of the standardised climate model simulations (\( Y_t^g \)); \( D \) = lag one cross correlation coefficient of the standardised climate model simulations (\( Y_t^g \)); \( \varepsilon_t \) = independent random variates with the zero mean and identity covariance matrix.

Bias corrected data was obtained using following model,

\[ \tilde{Y}_{t,m}^g = C_{m} \tilde{Y}_{t,m-1}^g + D_{m} F_{m}^{-1} Y_{t,m-1}^g - D_{m} F_{m}^{-1} E_{m} Y_{t,m-1}^g \]  \hspace{1cm} (6.14)

where, \( \tilde{Y}_{t,m-1}^g \) = corrected time series value from the preceding month m-1 in year t, with other notations as described before. Finally, the corrected time series \( \tilde{Y}_{t}^g \) is found from the series \( \tilde{Y}_{t}^g \), which is rescaled considering observed mean and standard deviation. For detailed derivation of matrices C, D, E and F readers are referred to Mehrotra and Sharma (2015).

Following the monthly bias correction, the series is aggregated and averaged to formulate seasonal time series and the corrections explained above re-applied, now indexing over the four seasons to give a seasonal time series. Finally this time series is aggregated to an annual time scale and the corrections again re-applied. This procedure ensures systematic biases in persistence and dependence are eliminated not just at monthly but also at longer time scales that are of relevance for water supply applications. The final step involves incorporating the corrected series at all time scales to the daily simulations (\( U_{t,m,n,t}^g \), where i represents the day, m the month, s the season and t the corresponding year, and \( U_{t,m,n,t}^g \) the corresponding bias corrected value) (Srikanthan and Pegram, 2009).
\[ \bar{U}_{l,m,n,t}^g = \left( \frac{Y_{m,n,t}^g}{Y_{m,n,t}^g} \right) \times \left( \frac{S_{n,t}^g}{S_{n,t}^g} \right) \times \left( \frac{A_{t}^g}{A_{t}^g} \right) \times U_{l,m,n,t}^g \] (6.15)

Here, \( Y_{m,n,t}^g \), \( S_{n,t}^g \), \( A_{t}^g \) represent the monthly, seasonal and annual bias corrected value respectively and \( Y_{m,n,t}^g \), \( S_{n,t}^g \), \( A_{t}^g \) represent the aggregated monthly, seasonal and annual value.

The MRNBC model is run in three stages to correct biases, firstly in the mean, then the standard deviation and lastly the correlations. This helps to preserve future climate change signals and ensure optimum results (Mehrotra et al., 2018). For improved performance in bias correction simulations, MRNBC is applied three times to ensure the corrections are spread over all aggregated time scales of interest (Mehrotra and Sharma, 2012). It should be noted that while the bias correction is performed at a daily time scale, the corrected values are aggregated to a monthly time scale to serve as inputs into the conceptual hydrologic model used.

6.4 Results

6.4.1 Bias correction of climatic variables over the historical time period

To correct biases of raw GCMs and RCMs modelled variables, we used APHRODITE temperature and precipitation datasets as observed data. The MRNBC bias correction model was applied with time nesting at daily, monthly, seasonal as well as annual timescales and repeated three times using the recursive option. All bias correction results presented in this section are for the historical period from 1981 to 2000 and for the Nuxia station in the upper Brahmaputra basin. For convenience, all attributes are discussed using the average of GCM and RCM results. Figure 6.3 shows the efficacy of bias correction through seasonal cycles of observed, raw and bias corrected temperature and precipitation. Raw temperature and precipitation show significant cold and wet bias, respectively, with respect to observed. This is likely a result of different atmospheric physics and numerical schemes in climate models. Diverse climatic variations and orographic complexity of the study area also influence the outputs of the climate model. In addition, Guo et al. (2018) found significant cold and wet bias in the temperature and precipitation climatology compared to station observations in the Tibetan Plateau using climate model datasets. However, MRNBC leads to remarkable improvements in the raw temperature and precipitation across the different months after correction.
Figure 6.3 Seasonal cycles of observed, raw and bias corrected a) temperature and b) precipitation. Note observed series is superimposed on the bias corrected series.

The raw and observed snow cover fraction is presented in Figure 6.4. The hydrologic model derives biased snow cover fraction when run using raw climatic variables. On the other hand, performance of snow cover fraction simulation has been significantly improved when the model is run using bias corrected variables.

Figure 6.4 Seasonal cycles of observed, raw and 90% bias corrected intervals of snow cover fraction.
Seasonal cycles of observed, raw and bias corrected data derived streamflow are presented in Figure 6.5. Simulated streamflow from raw climate model data includes noticeable bias with respect to observed and forcing data derived streamflow. In contrast, streamflow derived from bias corrected climatic input agrees with observed flow across the different months to a markedly improved extent. Following this, one can expect that the MRNDBC model corrected climatic inputs will improve the simulation of streamflow in the future time period assuming the systematic biases corrected remain dominant into the future.

![Figure 6.5 Seasonal cycles of observed, raw, and 90% bias corrected intervals of streamflow.](image)

### 6.4.2 Change of temperature and precipitation into the Future

Temperature and precipitation are the most important input variables for the hydrologic simulation in a catchment that includes snow resources. Investigations of these climatic variables are important for adequate understanding of the change in streamflow into the future as well as changes to future water availability. How does temperature as well as precipitation change over the historical period and into the future in this basin is illustrated in Figure 6.6. A significant increase in temperature in both near and far future with respect to the historical period is noticeable in Figure 6.6 a), which will leads to higher evaporation rate and lower snowfall. In addition, the increasing temperature will trigger snowmelt earlier in the future in this region. Again, a decrease in the precipitation during the dry period (from November to March of the next year) in the future compared to the historical period is noticeable whereas an increase during the wet period (April to October) is visible in the future with respect to the historical period in Figure 6.6 b). This pattern of precipitation change was also found in a few previous studies focussing on Tibet and other regions of the world (Su et al., 2016, Chou et al., 2013). However, annual precipitation both in the near and far future is higher than the historical period which may be a result of higher local evaporation as well as the convergence of atmospheric flux from lower reaches of the catchment. A few studies in the Tibetan Plateau also
found increasing trends of annual precipitation (Wijngaard et al., 2017, Cuo and Zhang, 2017, Guo et al., 2018) consistent with the results presented here.

Figure 6.6 Monthly temperature and precipitation in historical period (1981-2000), Near future (2041-2060) and Far future (2071-2090) for Nuxia station.

6.4.3 Snow cover fraction and streamflow in the future

To investigate changes in snow cover fraction into the future, monthly snow cover fraction in the historical period, near future and far future is presented in Figure 6.7. This attribute is obtained from the climate models derived SWE using equation 6.1. SCF is decreasing in both near and far future with respect to the historical period. A possible reason for this could be the increase in temperature which leads to more rainfall than snowfall along with greater rates of melt (Wang et al., 2016b).
Figure 6.7 Monthly snow cover fraction in historical period (1981-2000), Near future (2041-2060) and Far future (2071-2090) for Nuxia station.

Streamflow in the historical period and the future is shown in Figure 6.8. A decrease in streamflow both in the near future as well as far future in the dry period (November to March in the next year) is detectable, which will be the result of increasing temperature and the precipitation change discussed in the previous section. However, a significant increase in the streamflow is noticeable in the wet period (April to September), which is the results of the precipitation change in this period as discussed in the Figure 6.8. The decrease of streamflow in the dry period will impact water supply, agriculture and hydropower for this region. Moreover, annual precipitation at the Nuxia station and surrounding basins are presented in Table 6.3. Annual precipitation at Nuxia and other stations in the future is projected to be higher than historical period, which consequently results in higher annual streamflow.

Figure 6.8 Monthly streamflow in historical period (1981-2000), Near future (2041-2060) and Far future (2071-2090) for Nuxia station. Here red bars indicate uncertainty range (95% confidence interval).
Table 6.3 Annual precipitation and streamflow of the Brahmaputra basin and surrounding areas in the future

<table>
<thead>
<tr>
<th>Station</th>
<th>Basin</th>
<th>Precipitation (mm)</th>
<th>Streamflow (m³/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Hist. (1981-2000)</td>
<td>NF (2041-2060)</td>
</tr>
<tr>
<td>Nuxia</td>
<td>Brahmaputra</td>
<td>519</td>
<td>576</td>
</tr>
<tr>
<td></td>
<td></td>
<td>19179</td>
<td>22102</td>
</tr>
<tr>
<td>Tangnaihai</td>
<td>Yellow</td>
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</tr>
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<td></td>
<td></td>
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<td>Zhimenda</td>
<td>Yangtze</td>
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<td>326</td>
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<tr>
<td></td>
<td></td>
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<td>696</td>
</tr>
</tbody>
</table>

6.5 Discussion

Considering the high importance of the Brahmaputra basin for fresh water supply to a vast downstream population, and the impact climate change has on the catchments as well as the downstream population, this study proposed a framework for climate change impact assessment taking account the limitations associated with conducting such a study. We used a simple conceptual hydrologic model allowing minimal data requirement because the Tibetan Plateau is a gauge sparse region. Gridded climatic datasets and satellite snow products were used as ground observed data are not available and restrictive data sharing policies exist which limit us from modelling at high resolutions. However, gridded climatic datasets include uncertainties arising from data interpolation approaches (Slater et al., 2013) which must be factored in before arriving at any conclusions. In addition, satellite snow products include uncertainties due to clouds, limitation of sensor observations, and the algorithms that produce the snow estimates from the observations (Basang et al., 2017, Li et al., 2018). While these data challenges motivated us to formulate a simple conceptual model in such data scarce region, a discussion is required to appreciate the limitations of the proposed framework. Some of these issues are discussed in the sub-sections below.

6.5.1 Use of climate model derived temperature and precipitation

Increasing population growth, rapid changes in climate, altered land use and other anthropogenic factors increase the risk of change in hydrologic process which creates additional pressure on the water supply systems. The only way of quantifying this change in the future is to use the outputs of climate models for different scenarios. The climate models underestimate the observed temperature significantly in the winter in the Tibetan Plateau (Terzago et al., 2014,
Su et al., 2013) while, precipitation is overestimated in the Tibetan Plateau (Guo et al., 2018, Terzago et al., 2014). Such biases might be a result of allowing comparatively smooth topography in the climate models rather than the real orographic complexity of Tibet. To overcome uncertainties and biases in the climate models, a bias correction procedure was used. However, any bias correction makes the assumption of stationary bias (Johnson and Sharma, 2012, Cannon et al., 2015, Willkofer et al., 2018, Li et al., 2010), which implies that model biases in the future will follow the similar patterns as those in the current climate (Mehrotra et al., 2018). This underlying assumption can affect the results in both the near future and far future, although the use of multiple climate model simulations limits the risk of making significant and unnoticed errors in projections.

6.5.2 Derivation of snow cover fraction

We used an empirical relationship for the estimation of snow cover fraction from snow water equivalent. Snow water equivalent data from climate models (GCMs and RCMs) includes uncertainties. While bias correction of SWE leads to improved snow cover fraction simulation, a further refinement of the model will yield better snow cover fraction simulations. Note GCM and RCM derived SWE was bias corrected separately since SWE represents accumulated values which are different from temperature and precipitation simulation.

6.5.3 Use of dynamic snow cover fraction in the hydrologic model

We used a dynamic snow cover fraction representation to describe the change of snow and surface water runoff in the future, which represents a key difference to the earlier studies on the topic (Immerzeel et al., 2010, Singh et al., 2009, Mark and Martyn, 2014, Hock, 2003, Şorman et al., 2019, Kult et al., 2014, Siderius et al., 2013). These studies assume either complete snow cover or no change in snow cover with time although snowmelt-runoff processes in frozen ground and precipitation-runoff process in snow-free conditions under warming climate are different (Harpold and Brooks, 2018a). In addition, snow covered areas with thicker snow have lesser permeability, which consequently yield greater runoff than for snow-free conditions (Zhao et al., 2019b). The proposed framework considers snow cover to change and snowmelt to occur, or the snowpack expands due to new precipitation (snow). Our proposed approach assists in the proper representation of snow cover alteration under a changing climate and its impact in simulation of future streamflow. However, given the coarse spatial and temporal resolution adopted as a result of the significant data limitations, the hydrologic model assumes evaporation and other losses are occurring across the entire catchment. It should be noted that the nature of loss is not the same for snow-covered ground as compared to non-snow covered ground in the catchment, with the latter having greater infiltration, and the former having sublimation. This
assumption will have an impact on future hydrologic projections, and needs to be addressed by further work including specifying possibly a loss function in the model that is dependent on snow as well as temperature.

### 6.5.4 Consideration of non-linear storage routing to approximate the runoff process

Owing to the lack of data, our hydrologic model simplified the streamflow generation process considering snow and non-snow storage for this complex catchment and the surrounding basins. Given a clear nonlinearity in the system because of the dynamic contribution of snowmelt and surface water runoff, the model adopts a non-linear storage routing formulation. This formulation is specified at a monthly time-step instead of its use in modelling flood extremes at a daily or sub-daily time step. The choice of nonlinear versus linear routing was made based both on the dynamic nature of the flow generation process (which one would expect to be less consistent with a linear storage formulation) as well as the assessment of model performance using linear and nonlinear formulations (results not included but illustrated a clear differentiation in the two approaches).

The specification and calibration of the model using monthly data is another key limitation in representing the underlying physics and is a result of the lack of finer resolutions datasets. It should be noted that while the modelled climate data here can be at finer temporal resolutions (the bias correction is implemented at a daily time step), the observed data which forms the basis for model specification is monthly. Future work with lower temporal resolution is needed for comprehensively understanding the runoff process and its change under a warming climate. This is especially of importance for assessing changes in extremes, as both storm extremes and flood extremes are expected to change into the future (Sharma et al., 2018, Wasko and Sharma, 2017b).

### 6.5.5 Implications for reservoir storage

Application of the proposed framework in the context of reservoir storage estimation accounting for climate change impact can aid in water planning for the region (Turner and Galelli, 2016). To perform such an assessment, use is made of a recently published framework (Nguyen et al., 2020) where catchment storage is estimated by placing a hypothetical reservoir downstream of a catchment, with a capacity (or size) that ensures 90% reliability in supply for a demand kept equal to 75% of the flow.

The Behaviour diagram representing the change in storage over the historical period, near future and far future, is shown in Figure 6.9. As noted before, the storage capacity of this hypothetical
reservoir is one that results in 10% failure (or 90% reliability) for the observed record. Failure are noted to occur in 24 months and water spilled 48 times during the historical period. Reliability for meeting target demand in the near future and far future is lower compared to the historical period at Nuxia, which will be a result of the reduced precipitation and streamflow in the dry periods. Such decrease will have an impact on agriculture during the dry periods. In addition, the number of times water is spilled as well as the volume of spilled water is higher in the future compared to the historical period which will be a result of increasing precipitation and subsequently streamflow in the wet season.

![Reservoir behaviour diagram](image)

<table>
<thead>
<tr>
<th>Attributes</th>
<th>CanESM2</th>
<th>Average of all models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NF</td>
<td>FF</td>
</tr>
<tr>
<td>Reliability (%)</td>
<td>-7.8</td>
<td>-11</td>
</tr>
<tr>
<td>Number of times water spilled (%)</td>
<td>23</td>
<td>27</td>
</tr>
<tr>
<td>Spilled water volume (%)</td>
<td>20</td>
<td>28</td>
</tr>
</tbody>
</table>

Figure 6.9 Reservoir behaviour diagram in a) historical period, b) near future and c) far future at Nuxia station for CanESM2 GCM. Note dashed red lines indicate the capacity of the reservoir system. Inset table indicates change in the properties of the behaviour diagram for the near future (NF) and far future (FF) for CanESM2 GCM and average of all climate models.
6.6 Conclusions

Adequately understanding of the likely changes in snow resources and its impact on water resources systems in the future can allow society to plan and manage water resources to minimise the impacts of shortfalls or surpluses. How snow resources may affect streamflow in the future due to climate change is a question of interest to many sectors, especially the communities in water-stressed regions. Answering this question is difficult without assessing and correcting biases in climate model projections, and projecting these corrected simulations of the future using a defensible modelling approach to ascertain change in water availability. Previous hydrologic change assessments in the snow covered regions have focused on the future change in snow resources without explicitly considering biases in the climate modelled snowpack attributes, and therefore in the streamflow simulations. In this research we have proposed a comprehensive framework to assess the change in streamflow owing to change in snow resources for the climate-sensitive region of the upper Brahmaputra basin and surrounding area, the approach specially formulated considering lack of data availability as well as the need for bias correction of snow climatology. Improved results for climate modelled temperature, precipitation and snow water equivalent have been accomplished after using the multivariate bias correction approach adopted. Then, the framework is used for future projections to explore the impact of climate change in the snow resources and subsequently streamflow. The results showed that monthly snow cover fraction is projected to decline in both near and far future with respect to the historical period. Moreover, the future annual streamflow will increase due to the increase in precipitation under warming climate. Overall, the proposed framework is flexible for use in a data sparse region, and depends mostly on the precipitation and temperature information. The outcome of this study will assist in proper understanding of the variability and changes in snow resources and streamflow in the upper Brahmaputra basin where use of existing more complex hydrologic models is difficult due to the thin gauge network as well as restrictive data sharing policies.
7 Conclusion

While a summary was provided at the end of each chapter, the main research findings of the thesis are presented here. Key limitations are then outlined and recommendations are made for future work to guide further progress on streamflow modelling in a warming climate with limited data, accounting for dynamically changing snow cover.
7.1 Summary and synthesis

Increasing population growth, changes in land use and other anthropogenic impacts are leading to rapid changes in climate. These changes increase the risk of water insecurity in the major river basin Brahmaputra originating from the Tibetan Plateau. Adequate understanding of streamflow processes in this partially snow-covered basin is increasingly important for a wide range of purposes in hydrology and water resources, especially maintaining confidence in future water resource analyses. First, this thesis discussed and investigated changing patterns of snowpack with respect to within-year accumulation and depletion rate across the Northern Hemisphere. This was achieved using satellite-based snow water equivalent datasets and included exploration in remote areas where altered snowpack due to climate change is currently uncertain. After that, the performance of a precipitation downscaling model using various reanalysis products and with different data lengths was explored. Uncertainties in the statistical downscaling method, a key drawback of precipitation downscaling impacting catchment-scale hydrologic simulation, were identified using a Bayesian framework. Then, bias in the climate model (Global Circulation Model and Regional Climate Model) derived snow water equivalent with other climatic variables was characterised and corrected. Finally, a simple conceptual model that considers dynamic snow cover and other hydrological processes in a warming climate was proposed and implemented for the upper Brahmaputra basin. Implications of future climate change in the basin were demonstrated using this proposed conceptual model. In addition, key features that could impact the model performance were identified, leading to recommendations for further model improvement. On the whole, this body of work reveals the need to move towards flexible conceptual modelling that allows for limited input while facilitating the characterisation of frozen versus non-frozen ground in hydrologic simulations under warming climate.

7.1.1 Snowpack accumulation and depletion changes in a warming climate

To address gaps in previous assessments, Chapter 2 discussed previous snowpack change studies that ignored explicit inspection owing to limited access in remote areas. It also provided a detailed, coherent picture of large scale snowpack change for the first time, with a few important regions demonstrating the hypothesis that clear changes are visible in snowpack accumulation and depletion due to temperature rise. This change was assessed over most of the Northern Hemisphere, evaluating change of maximum snow water equivalent (SWE) since 1980. Changes in snow accumulation and depletion processes were investigated using the rate (a function of the duration of snow accumulation and depletion) as well as amount (where minimum SWE varies at the start and end of the water year). Then, the changes in snow
accumulation and depletion rates were evaluated with time. Finally, the sensitivity of snow accumulation and depletion rates with respect to temperature were assessed. These results supported the aforementioned hypothesis, which has implications in relation to widespread decline of snowpack due to global warming. Varying rates of snow accumulation could regulate peak snowpack depth and volume, influencing spring runoff. In addition, changes in snow depletion rates will modulate the timing of runoff events, impacting agriculture and water security.

Snowpack changes were analysed at a regional scale and similarities between some of the regions were discussed. The effect of potential climate characteristics of major snow-covered regions was also highlighted. The changes reported here will impact availability of snowmelt-driven streamflow throughout most of the world, with changes in terms of altered seasonal regime of snowpack accumulation and depletion as well as an overall change with time (or temperature). This has significant implications for the most populated regions of the world (including the Yangtze and the Ganges-Brahmaputra basins that support large flood and energy generation infrastructure).

### 7.1.2 Characterization and refinement of uncertainties and biases

Coarse-scaled global circulation model datasets do not capture catchment-scale climate and hydrology well due to uncertainties and biases. Chapter 3 of this thesis quantified the extent of uncertainty resulting from the use of alternative reanalysis datasets (National Centre for Atmospheric Research Reanalysis 2, NCEP2 and the European Centre for Medium-Range Forecasts Interim Reanalysis, ERAI) in the context of statistical downscaling in the Tibetan Plateau. A Bayesian approach was developed for calibration of a statistical downscaling model (SDSM) using the integrated likelihood of precipitation occurrence and amount. Then, the significance of data length and type of reanalysis dataset in the precipitation downscaling parameters was demonstrated, which had been overlooked in previous work. In addition, the influence of parameter uncertainty and downscaling model structure rigidity in the downscaled precipitation characteristics such as wetness fraction and average annual precipitation were investigated over the study locations. The uncertainties in the calibrated model propagated to the GCM ACCESS 1.3, which is a widely-used model for future precipitation projection. If such uncertainties, compounded with the uncertainty of the GCM derived data in the hydrologic model simulation, it is likely to persist for a range of water resource management applications. Therefore, addressing such uncertainties in precipitation or other climatic variables is important for hydrologic model robustness.
Again, biases in the climate model arise from errors in the climate model structure, initial conditions and scenarios. These biases need to be corrected in order to provide acceptable information for water planning and management strategies. Chapter 4 used a multivariate nesting bias correction approach to correct possible biases in the climate model (global circulation model, GCM and regional climate model, RCM) derived temperature, precipitation and snow water equivalent jointly across multiple time scales, to preserve dynamic relationships amongst climatic variables. The climate model derived snow-climatology showed substantial bias in Tibet, which might be due to the orographic complexity of this region. However, the bias correction approach corrected distributional and persistence bias, delivering significantly improved snow climatology in the historical period (1981-2004) and giving greater confidence in the climate model simulation of snowpack change in near (2041-2064) as well as far future (2071-2094). The results of Chapter 4 showed that the annual SWE is decreasing in both the near and far future with respect to the historical periods. Possible reasons for this are warming temperatures and changing precipitation i.e. more rainfall than snowfall.

7.1.3 Modelling climate change impacts on streamflow considering dynamically varying snow cover using a flexible framework

Existing complex physically-based hydrologic models require large datasets for running simulations, while empirical models are black box approaches that lack the process change necessary for adequate understanding. Complex physically-based modelling is inappropriate for water management in the Brahmaputra basin due to restrictive data sharing policies and data scarcity associated with complex topography. In addition, uncertainties in input datasets (remotely sensed data) as well as downscaling uncertainties (discussed in the Chapter 3) cause inconsistencies in model outputs. Again, the temperature index model used for snowmelt estimation overlooks snow processes and hence does not provide understanding of a changing system (although it overcomes data challenges). As of now, most hydrologic models do not consider either snow cover fraction or dynamic snow cover fraction, which prevents adequate representation of snow-covered catchments. Precipitation-runoff processes in frozen ground versus snow-free ground under warmer temperatures are different. To this end, Chapter 5 developed a simple conceptual model accommodating changing snow-cover as well as some of the realism associated with physically-based model in streamflow simulation, making the proposed model more suitable for assessment of global warming impacts in snow-covered basins. The proposed conceptual model was implemented in the partially snow-covered Brahmaputra basin and surrounding areas, where temperatures are increasing. Furthermore, it used a nonlinear routing approach to derive streamflow processes. Note that a linear storage routing model was first assessed, but it was discarded since a clear nonlinearity exists in the
system owing to the dynamic influence of snowmelt and surface water runoff. Overall, the model reconstructed the snow cover fraction, snow water equivalent and streamflow well. It also demonstrated that increasing temperature will significantly impact snow resources and consequently streamflow in this basin. In addition, the model needs minimal data, and the option of using open-access satellite data in this model will be valuable for water managers in data sparse regions.

Since the Brahmaputra basin supplies water to a large downstream population, any changes in future streamflow presents a significant concern for the sustainability of large agricultural operations and human consumption. Chapter 6 implemented the conceptual model developed in Chapter 5 using a flexible framework and considering the impact of climate change in the basin. The GCM and RCM derived temperature and precipitation suffer from cold and wet biases in this highly mountainous region with complex terrain. Such biases might be due to simplified physical processes and smoothed topography in the climate model relative to reality. A multivariate bias correction approach was used to correct the climatic variables over multiple time scales to improve the fitness of the climate model simulation. Bias correction results showed remarkable improvement in the climatic variables over the historical period (1981-2000), near future (2041-2060) and far future (2071-2090). Consequently, bias corrected variables also significantly improved snow cover fraction and streamflow simulation. Therefore, the hydrologic model in the historical period with the input bias-corrected climate model data worked well. The results of Chapter 6 revealed that snow cover fraction both in the near and far future will decrease, which might be attributed to increasing temperature in the region. Moreover, annual streamflow will increase in the future relative to the historical period, which will be driven by increasing precipitation and snowmelt in the future.

Overall, this thesis highlighted the need for development and application of a conceptual hydrologic model blending the simplicity of black box empirical models with physical principles of mass and energy balance in the data-sparse Brahmaputra basin, where snow cover is changing over time. Application of a temperature index or degree day model without inclusion of robust snowmelt processes will lead to greater uncertainty in future predictions. Moreover, existing hydrologic models without consideration of dynamic snow cover will not properly represent changes in snow processes under a warming climate. To this end, a simple conceptual hydrological model can be implemented for water planning with limited observed data and bias corrected data while still providing understanding of the change in catchment-scale hydrology owing to changing climate as well as snow cover change with more flexibility.
7.2 Limitations and recommendations for further research

The development of suitable conceptual models with low data requirements that still provide adequate hydrologic process representation for studying snow cover and streamflow changes in remote regions is an emerging area of research. This thesis has conducted a systematic study on the application of a novel conceptual hydrologic model for the future climate through a comprehensive investigation of snowpack change, model uncertainty and bias correction. As discussed in the preceding chapters and above, the outcomes are encouraging, indicating the significant advancement this thesis offers in the application of flexible hydrologic models that are suitable for simulating the impact of global warming in remote, snow-covered catchments.

Despite these, the present thesis is not completely without limitations. Limitations of the research have been discussed in the previous chapters; the following points summarise major limitations identified and further research recommendations that may overcome them:

(1) For investigation of snowpack change across the Northern Hemisphere, we assessed change in snow accumulation and depletion rate with respect to time as well as temperature. Since available gridded precipitation datasets are less accurate than temperature and contain uncertainties, we did not use them for the investigation of snowpack change. However, temperature has a very strong correlation with snowpack and it is well known that temperature is increasing rapidly in the Northern Hemisphere. In addition, it is not possible to get accurate rainfall data for the Northern Hemisphere, since available precipitation datasets represent a mixture of solid form (snowfall) and liquid form (rainfall). Use of precipitation without clear differentiation of rainfall would be misleading for discussions about snowmelt. Therefore, observed ground solid precipitation (snowfall) and liquid precipitation (rainfall) need to be available to facilitate progress in this respect.

(2) Snowpack change was investigated over the Northern Hemisphere, including in remote areas where change of snowpack due to climate change is uncertain to date. Globsnow datasets (http://www.globsnow.info/) that combine satellite and ground snow observations were used for this investigation. Opening up of ground snow data sharing across communities would assist in further analysis, particularly uncertainty analysis in detail.

(3) Part of the limitation in characterising precipitation downscaling uncertainty resulted from the structure of the selected statistical downscaling model (SDSM), in which the relationship between predictor and predictand was linear. Use of a non-linear predictor
and predictand relationship might reduce this uncertainty, which could be the subject of a future investigation.

(4) The satellite and ground data derived CanSISE dataset (observation based ensemble of Northern Hemisphere terrestrial snow water equivalent) was used to quantify observed snow water equivalent data. It was also applied for comparison with the MODIS (Moderate resolution imaging spectro-radiometer) derived snow cover fraction data in the proposed hydrologic model. Although the performance of the relationship was good, CanSISE has a coarse resolution of 1° x 1°. To counter the coarse resolution, snow water equivalent data was aggregated from its raw daily resolution to the monthly time step. However, these satellite snow datasets might include uncertainty due to cloud cover or remote sensing which could be addressed in a future study.

(5) The present study made efforts to implement varying snow cover fraction in streamflow simulation through hydrologic modelling. The assumption of the model was evaporation and other losses are occurring over the entire catchment due to the existence of little information in the study area, although in reality the nature of this loss is not same in the snow-covered part (sublimation) and the non-snow covered part (greater infiltration than frozen ground). Future work focused on projecting under warmer climate could be affected by this assumption. Further investigation could address this limitation by considering a loss function dependent on snow cover and temperature.

(6) A non-linear routing approach was used to approximate precipitation-runoff processes in the proposed hydrologic model. Monthly data were used to calibrate the parameters of this model due to data scarcity and restricted data sharing policies, which is a limitation since such concepts are often applied to model flood processes that occur at daily time steps. Open data sharing amongst the countries would assist to refine the framework presented here.

(7) This thesis only used temperature, potential evapotranspiration, precipitation, snow cover fraction and snow water equivalent data to study the change in precipitation-runoff processes since there is limited data available. However, since the catchment properties of snow-covered regions are influenced by many other hydro-climatic components (e.g. permafrost, glaciers, sublimation) and catchment components (elevation, land use, drainage area), inclusion of such components would lead to a more complete and reliable representation of streamflow process.

Along with the encouraging outcomes of this thesis, proper consideration of the above limitations and suggestions would certainly lead to a more accurate, complete and reliable
representation of dominant hydrologic processes in the Brahmaputra basin and surrounding areas. This would also provide new avenues and opportunities to address a whole range of problems associated with streamflow, including water planning and water resources management strategies. Given the drawbacks of black box models and physically-based complex models that require large datasets, a flexible conceptual model can be more suitable for simulating the impact of global warming on streamflow change in data sparse regions.
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