Impacts of climate change on hydropower generation and developing adaptation measures through hydrologic modeling and multi-objective optimization

VINOD CHILKOTI

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Impacts of climate change on hydropower generation and developing adaptation measures through hydrologic modeling and multi-objective optimization

By

Vinod Chilkoti

A Dissertation
Submitted to the Faculty of Graduate Studies through the Department of Civil and Environmental Engineering in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy at the University of Windsor

Windsor, Ontario, Canada

2019

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Impacts of climate change on hydropower generation and developing adaptation measures through hydrologic modeling and multi-objective optimization

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DECLARATION OF CO-AUTHORSHIP / PREVIOUS PUBLICATION

I. Co-Authorship

I hereby declare that this thesis incorporates material that is result of joint research, as follows:

Chapters 2 through 6 of this thesis were completed under the supervision of my advisor, Dr. Tirupati Bolisetti, and co-advisor, Dr. Ram Balachandar. In all cases the key ideas, primary contributions, data analysis and writing were carried out by the author. The contribution of the co-authors (advisor and co-advisor) was primarily through the provision of the broad research idea, review of results, participation in scientific discussion, literature review and subsequently in editing the presentation material.

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II. Previous Publication

This thesis includes five original papers that have been previously published/submitted for publication in peer reviewed journals, as follows:

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</table>
5 Investigating the role of hydrological model parameter uncertainty in streamflow projection
6 Assessment of climate change impacts and operational adaptation for a hydroelectric facility in Northern Ontario

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ABSTRACT

The climate change resulting from anthropogenic factors is driving governments and policymakers to provide additional thrust on renewable energy. Hydropower, which is the dominant renewable component of the energy-mix, is also under threat due to the changing climate conditions. The present study aims to quantify the impact of climate change on hydropower generation, the associated revenues and subsequently suggest the adaptation measures through adaptive reservoir management. A modeling chain consisting of hydrologic and hydropower simulation models is adopted to evaluate the impacts of projected climate change on hydropower generation.

Calibrated hydrologic models forced with the climate data from various climate models have been widely employed for future streamflow projection. A reliable modelling framework should ensure the simulation of reality with limited uncertainty, thus enhancing its predictive ability. In the literature, the hydrologic model assessment is reported to be inadequate when carried out based on only statistical objectives or limited number of evaluation metrics. In the present research, the thrust is given on improving the hydrologic model simulation through model diagnostic assessment, incorporating hydrologic signatures and multi-objective model calibration. Multi-objective evolutionary algorithm (MOEA) is coupled with the hydrologic model, Soil and Water Assessment Tool (SWAT), to perform model calibration. The methodology was first tested for Saugeen River watershed in Southern Ontario and then applied to the Magpie River watershed model located in Northern Ontario.

The uncertainties contributed by the hydrologic models have generally been given a lesser focus in climate change impact analysis. In the present research, the uncertainty emanating from model
parameters was investigated and found to dominate during some periods. The accounting of hydrologic model uncertainty is found to be vital for providing an improved assessment.

Steephill Falls hydroelectric project located on Magpie River in Northern Ontario is considered as a case study for assessing climate change impacts on hydropower. The results show that the annual generation is not considerably affected but there is a significant seasonal redistribution on energy production. The changes in the hydropower revenues compared to the present level for the four seasons viz., winter, spring, summer and autumn are estimated to be 21.1%, 18.4%, -13.4% and -15.9%, respectively, for mid-century and 23.1%, 19.5%, -20.1% and -22.9% for end-century scenarios.

In order to reduce the vulnerability of hydropower system to climate change and consequently mitigate the impacts, it will be profitable for the project owners to provide suitable adaptation measures. Adaptive reservoir management through multi-objective optimization of reservoir level was found to be an effective approach to develop adaptation measures provided additional live storage is made available. It also reduced the vulnerability of the system to climate change by 24%. The seasonal alteration in the energy production will require the project owners to arrange modification in power purchase/sharing agreement with the buyers.
DEDICATION

उद्धरेदात्मनात्मां नात्मानमवसादयेत्
आत्मैव ह्यात्मनो बन्धुरात्मैव रिपुरात्मन: ।

Let a man elevate himself by his own Self alone, and let him not lower himself; for, this Self alone is the friend of oneself, and this Self is the enemy of oneself.
- Bhagwad Gita, Ch.6, v5

Dedicated to my spiritual guru

Swami Chinmayananda
(1916- 1993)

for guiding me on the path of true knowledge.
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CHAPTER 1 INTRODUCTION

Climate change has been a phenomenon of growing concern for humanity. Climate change can be defined as “a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer” (Field et al., 2014). The Intergovernmental Panel on Climate Change (IPCC), the leading international body for the assessment of climate change, attributes the causes of changing climate to both natural as well as anthropogenic factors (Pachauri and Meyer, 2014a). All these changes are making an irreversible impact on the environment and are adversely affecting both the natural systems as well as the man-made systems.

The impacts of climate change arise out of the interactions of the climate change and the vulnerability of an exposed system (Field et al., 2014). The evidences of climate change impacts are strong and comprehensive for the natural systems (Pachauri and Meyer, 2014b), while the impacts on the man-made systems, such as crop productivity and infrastructure, are also very concerning. These impacts are projected to become worse in the years to come for vulnerable systems.

Governments across the globe are taking various measures in order to tackle the threats expected due to climate change. The United Nations Framework Convention on Climate Change (UNFCCC) acts as the entity tasked with supporting the global response to the threat of climate change (“UNFCCC,” 2019). It sets out a legal framework for stabilizing atmospheric concentrations of greenhouse gases (GHGs) in order to limit the global temperature rise to an acceptable level. GHGs are significant drivers for climate change (Cubasch et al., 2013), therefore reduction of their emissions is the prime focus. The latest legislation of UNFCCC, referred to as Paris Agreement, aims to strengthen the global response to the threat of climate change by keeping a global temperature rise in this century well below 2 degrees Celsius above the pre-industrial levels. The agreement compelling the ambitious efforts to combat climate change was ratified and approved at the 24th meeting of the Conference of the Parties (COP) at Katowice, Poland in December 2018.

1.1 Climate Change and Infrastructure

The impacts of climate change on man-made systems are inevitable. The effects of changing climate will have (mostly) unfavorable impacts on the existing infrastructure. Infrastructure
related to water plays a vital role in human development. There are reliable evidences of significant increase of freshwater-related risks due to climate change (Field et al., 2014). Changes in water quality and quantity are expected to play a key role in driving the impacts of climate change on human settlements and infrastructure (Bates et al., 2008). The extreme weather events (such as storms and hurricanes) are likely to intensify in the changed scenario (Min et al., 2011; Mukherjee et al., 2018) which may lead to flooding. This flooding, accompanied by the sea-level rise, poses threats to transportation networks in some areas and also causes damage to buildings. Infrastructure in low-lying coastal areas is vulnerable to damage from sea-level rise, flooding, hurricanes and other storms (Bates et al., 2008). Energy infrastructure is also likely to be impacted by the global changes and may need suitable adaptation (Edenhofer et al., 2012). Hydrological changes will directly affect the potential output of hydroelectric facilities (Boehlert et al., 2016; Minville, 2010), but there will be regional and seasonal variations. In addition, cooling water availability is projected to decline (van Vliet et al., 2016) that could disrupt energy supplies by adversely affecting energy production in thermal and nuclear power plants.

All these projected changes are a cause of concern among the engineers, planners and the decision-makers. A good infrastructure is among the various elements needed to uphold the standard living. Generally, infrastructure projects are capital-intensive ventures that need a high level of effort in terms of material, planning, financial and human resources. Therefore, it is imperative to assess the impacts and suitably adapt to the changing climate conditions.

1.1.1 Climate change and the electricity sector

The supply of electricity acts as a catalyst for development, as it is vital for rudimentary standard of living and to uphold an overall social and economic growth. Globally, the total electricity generation by the end of 2017 was about 25,000 TWhr or 25,000 billion units of electricity annually (“Enerdata,” 2018). The sources of electricity generation can be broadly classified into: renewable and non-renewable. Non-renewable sector relies on burning of fossil fuels, thus adding GHGs to the atmosphere, whereas the renewable sources are considered to be environment-friendly. Currently 26.5% of the total generation is achieved through renewable sources (Hydropower Status Report - Sector Trends and Highlights, 2018) while remaining is dependent on fossil fuels. The growth of electricity generation in the last 25 years is about 107% (“Enerdata,” 2018) while the share of renewables has not changed significantly (Fig. 1-1a). This implies that
more fossil fuel is being burnt to generate the required electricity, thus contributing to the emission of GHGs, leading to global warming.

![Energy Generated](image)

**Fig. 1-1** (a) Growth in electricity generation over the last 25 years (Enerdata, 2018); (b) median life-cycle carbon equivalent intensity (gCO$_2$-eq/kWh) for different electricity generation sources (*WNA Report*, 2011)

The life-cycle carbon equivalent intensity (gCO$_2$-eq/kWh) provides a measure of the carbon footprint of a given energy source (Amponsah et al., 2014). The median gCO$_2$-eq/kWh for different electricity generation sources, such as coal, gas, solar, hydropower and wind are presented in **Fig. 1-1b** (*WNA Report*, 2011). Evidently, the renewable energy sources have very low gCO$_2$-eq/kWh as compared to the conventional sources. Moreover, electricity generation contributes over 25% (Pachauri et al., 2015) of the total GHG emissions. With governments firm on taking action against climate change, the phasing-out of emission causing sources of power generation and replacing them with cleaner options is inevitable as part of the climate change action strategy.

1.1.2 Impacts on hydropower generation

Hydropower generating facilities constitute a significant part of energy infrastructure. This environment friendly source has a total installed capacity of 1267 GW globally, which fulfils 16.4% of total electricity needs (*Hydropower Status Report - Sector Trends and Highlights*, 2018). IPCC postulates the likelihood of anthropogenic influences on the global water cycle (Pachauri and Meyer, 2014b). Research studies have also revealed varying levels of climate change impacts on the water availability (Eisner et al., 2017; Karlsson et al., 2016; Li et al., 2016), which is the only input for hydropower. The alteration in flow regime due to modification of regional hydrology resulting from climate change in turn affects the function and operation of existing water
infrastructure – including hydropower (Bates et al., 2008). This makes hydropower facilities vulnerable (de Queiroz et al., 2019) to the future climate scenarios and threaten the energy generation and the associated revenues. As the hydropower installations incur huge capital investments and are designed for service life that run into decades, it is very important to assess the impacts of changing climate scenarios on hydropower generation. This is also relevant for achieving a goal of sustainable electricity generation.

1.2 Hydropower in Canadian Context
Canada has a huge hydropower infrastructure. The total hydropower installed capacity in Canada, by 2017, was 81 GW (Hydropower Status Report - Sector Trends and Highlights, 2018) and it contributes 59% to the country’s total electricity generation (Natural Resources Canada, 2017). The country has one of the cleanest electricity grids in the world and it ranks globally fourth in terms of total hydropower installed capacity. Apart from fulfilling the energy needs, hydropower industry contributes $37 billion annually to the gross domestic product (GDP) and supports 135,000 jobs (PRISM, 2015). All these statistics depict the importance of hydropower to the Canadian economy.

As part of the country’s climate change action plan, Canada has targeted a reduction of 30% GHG emission by the year 2030 from 2005 levels (Environment and Climate Change Canada, 2017). Even though the electricity sector contributes only about 11% in the total greenhouse gas emissions, less than the global average of 25%, the phasing out of fossil fuel based sources of electricity generation is underway.

Considering the importance of hydropower to the Canadian electricity sector and its role in mitigating the climate change (Berga, 2016), it is first important to assess the impacts of changing climate on hydropower generation. This research work applies the current state-of-the-art scientific principles to focus on this issue by undertaking a case study based research of one of the existing hydropower facility.

1.3 Hydrologic Simulation for Hydropower Assessment
The energy of a flowing stream is harnessed as hydroelectric power. The extent of energy generated is dependent on the available head and quantum of water that can be used either directly or by providing an artificial storage along the river channel. The naturally flowing water in the streams is the only fuel for hydropower, thus the capacity of the hydroelectric facility is a function of economically exploitable water. The quantum of water available at a potential site of
a hydropower diversion structure is governed by the local climate and the catchment properties. The precipitation falling over the catchment realises as flow in the stream, subsequent to various abstractions. The other climatic parameters viz., temperature, relative humidity, solar radiation among others, also play a vital role in determining the streamflow. The changing climatic parameters are linked to the modification in the large scale hydrological cycle (Bates et al., 2008) and thus altering the streamflow availability. Various studies have been conducted that enlighten the community on this concerning issue (Eisner et al., 2017; Li et al., 2016; Mendoza et al., 2015; Arnell, 2011; Chen et al., 2011a; Prudhomme and Davies, 2009).

Hydrologic simulation models act as a transfer function between the inputs of climate-and-topography and the streamflow output. Hydrologic models are routinely adopted for assessing the impacts of climate change on hydropower (Chilkoti et al., 2017; Kopytkovskiy et al., 2015; Schaeffli et al., 2007; Haguma et al., 2014; Huaringa Alvarez et al., 2014; Christensen and Lettenmaier, 2007; Payne et al., 2004; Mimikou and Baltas, 1997). This makes a good hydrologic simulation vital for accurate hydropower assessment and rendering confidence to decision makers (Schäfl, 2005).

The increasing model complexity calls for intensive evaluation techniques. Better model evaluation approaches rooted in process insights rather than satisfying mere statistical-adequacy, would assist in overcoming the short-comings commonly reported in the conventional model assessments. This will result in reducing the uncertainty and enhancing the credibility of hydrological predictions. Thus, the need for stronger hydrologic model simulation with least uncertainties is mandatory.

### 1.4 Uncertainty Quantification

Uncertainty in the modeling process sprouts from various reasons, such as randomness, lack of knowledge (of model structure, parameters, forcing data, response data), simplification of process and different belief system (Beven, 2016; Athira and Sudheer, 2015). Uncertainty is inherent in the hydrologic modeling due to the presence of these factors and their quantification is one of the key issues in hydrologic simulation (Beven and Freer, 2001). With uncertain climate inputs for the scenario, there is high uncertainty associated with the assessment of future availability of water resources in a changed climate (Koutsoyiannis et al., 2009).

Parameter uncertainty is one of the important types of uncertainty that has been studied extensively in the hydrological literature. There are several parameters in a model that are
required to appropriately simulate various hydrologic processes. In order to accurately mimic the watershed hydrology, the knowledge of these parameters play an important role. Many hydrological models have parameters that cannot be estimated from some observed system characteristics and these parameters need to be calibrated (Schäfli, 2005). But the lack of knowledge on these parameters introduces uncertainty in the model outcomes.

Various climate change impact assessment studies have identified different sources of uncertainties in the modeling chain and quantified them suitably (Karlsson et al., 2016; Arnell, 2011; Chen et al., 2011b; Prudhomme and Davies, 2009; Wilby and Harris, 2006). Despite the increasing awareness of the implications of hydrological simulation on the portrayal of climate change impacts, the effect of parameter uncertainty is not very clear. Furthermore, this source of uncertainty has not been dealt with extensively. Some researchers have demonstrated the significance of parameter non-uniqueness in the climate change impacts (Mendoza et al., 2016; Jung et al., 2012; Brigode et al., 2013; Bastola et al., 2011; Wilby, 2005), but this is a promising research area with lot of implications. This is one of the key focus areas of the present research.

1.5 Adaptation Measures for Climate Change

Hydropower operators will need to adapt to changing climate scenarios to preserve optimum productivity (Arsenault et al. 2012). The increased knowledge about future hydrological conditions, improved hydrological simulations and good assessment of modeling uncertainty can assist in focusing on the management of water resources in an altered climate scenario. This will enhance confidence in formulating the adaptation measures. Adaptation measures are imperative to reduce the vulnerability of hydropower system to climate change and consequently mitigate the impacts.

Haguma et al. (2017) categorizes the hydropower adaptation into two groups, structural and non-structural. The former involves modification in the physical system configuration, while the later focusses on operational alteration or adaptive reservoir management without altering of the existing physical system in order to minimize the adverse impacts.

Most of the previous studies focused on the operational adaptations. Minville (2010) and Payne et al., (2004) concluded in their research that reservoir operating rules need to be revisited to account for the modifications in hydrology anticipated due to climate change. Arsenault et al., (2013) also found that optimizing the operating rules may be an adequate adaptation measure
for a hydropower system. The present study focuses on the operational adaptation through multi-objective optimization. The operational adaptation is different from other studies in terms of the objective functions and the algorithm. The objective of optimization is to maximize the hydropower revenue which is more relevant than considering the optimization of only the energy generation.

The effect of the changing trends in climate cannot be generalized for hydropower (Gaudard et al., 2014; Schaefli, 2015) and will vary based on the individual project location, size and configuration. Two projects of different configuration, for example one being a run-of-the-river and other being a storage type, but located in same area, will have different impacts of the changing scenarios. Considering the profound regional disparities in the nature of climate change impacts, it is deemed important to evaluate the impact on an individual project.

1.6 Objectives of the Present Research

The major objectives of present research are to:

1. Assess the impact of climate change on streamflow and hydropower generation
2. Develop methodology to improve hydrologic simulation
3. Quantify the uncertainties in the climate change impact modeling chain
4. Formulate an adaptation measures for hydropower against climate change

1.7 Research Methodology and Organization of Thesis

An independent simulation-based research is conducted to achieve the above-listed objectives. The climate change impact assessment process adopted in the present work involves a modeling chain (Fig. 1-2). First the streamflow is simulated at the project location for a historical period through a hydrological model. The model is suitably calibrated to generate a range of parameter sets. A computational scheme is formulated to compute the hydropower generation. The climate data for future scenario periods is extracted from an ensemble of regional climate models (RCMs). The climate forcing on the pre-calibrated hydrological model then provides the scenario streamflow projections. The future period energy generation is computed subsequently. Based on the assessment of monthly and seasonal impacts on hydropower energy and revenue, optimal reservoir levels are suggested as a suitable adaptation measure. The objective of optimization is to enhance the revenue and it does not include socio-economic parameters.
Chapter 1
Introduction

The thesis is organized as a collection of peer-reviewed manuscripts. Three of the research studies are already published in the peer-reviewed journals, while two have been submitted and are under the review process. The dissertation begins with this Introduction chapter and closes with a Conclusions chapter. The references in the individual chapters are listed at the end of the respective chapters.

Chapter 2 presents a case-study of climate change impacts on a small hydropower project located in Florida, USA, partly following the methodology presented in Fig. 1-2. The analysis adopts a conceptual hydrological model and a routinely followed model assessment strategy. The work has been published in Renewable Energy.

The literature review revealed that strong hydrological simulation is essential for portrayal of reliable climate change impacts (Clark et al., 2016; Bloschl and Montanari, 2009). This renders motivation to undertake a concrete effort towards improved hydrologic simulation in terms of (a) model assessment, (b) use of semi-distributed hydrological model, (c) multi-objective model calibration strategy, and (d) uncertainty quantification. To this end, Chapter 3 focuses on the significance of hydrologic model evaluation. The objective function(s) in any model assessment primarily computes the statistical fit between the simulation and the observation. The mathematical optimum obtained through a calibration scheme may be different from the hydrological optimum (Andréassian et al., 2012). The models, therefore need to be evaluated not
only based on statistical measures but also diagnosed from hydrological perspectives (Gupta et al., 2008). The idea of diagnostic model evaluation was extended further by applying conceptual model in 17 watersheds in southern United States. The work has two components, first the model evaluation and later a methodology for parameter selection. The first part of work was carried forward in the thesis. The research has been published in ASCE Journal of Hydrologic Engineering.

Chapter 4 presents the methodology for model calibration by applying a multi-objective evolutionary algorithm (MOEA). The Borg MOEA is coupled with Soil and Water Assessment Tool (SWAT), a semi-distributed hydrological model. Role of signature measures, that provide an insight into the hydrologic function of a catchment (Sawicz et al., 2011), was also demonstrated. The research led to the enhancement of model performance, primarily for the low flow simulation. Low-flows play an important role especially in the context of the present work, as hydropower generation is directly affected by it. The research is already published in Hydrological Science Journal.

Chapter 5 presents the hydrologic simulation for Magpie river watershed located in Northern Ontario. The methodology developed in previous chapters was extended here. Subsequently, the model was used for streamflow projection for two future scenario periods. Here, the uncertainty assessment in the estimated flows focused on hydrological model parameter uncertainty, which lacks clarity in the available hydrological literature. The research was presented in two international conferences and is currently under the process of peer-review in the Journal of Hydrologic Engineering.

Chapter 6 uses the future scenario streamflow derived in the previous chapter to make an assessment of scenario hydropower generation. One of the aspects that most studies in the literature lack is the impact on hydropower revenue and the development of adaptation measures based on revenue generation. The present work proposes operational adaptation of the hydropower facility to mitigate the projected climate change impacts. The proposed adaptive reservoir management includes optimizing the existing reservoir rule curve through multi-objective optimization, in order to maximize the revenue. The research is currently under the process of peer-review in Renewable Energy.

Some of the key project data for this research was shared by the project owners and they have been apprised of research results as the study is directly relevant to them.
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Introduction

1.8 References


Chapter 1

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CHAPTER 2 CLIMATE CHANGE IMPACT ASSESSMENT ON HYDROPOWER GENERATION USING MULTI-MODEL CLIMATE ENSEMBLE

2.1 Chapter Synopsis

Hydropower is the primary renewable source of energy that harnesses the power of the naturally flowing water streams and its potential is strongly impacted by the hydrological regime. The objective of the present research is to carry out a hydrological model based study to assess the impacts of climate change on hydropower generation by using the regional climate model (RCM) data available through coordinated regional downscaling experiment (CORDEX), and subsequently to analyse the effect of using model ensemble in projecting the future hydrology and energy generation scenario. C.H.Corn hydroelectric project located on River Ochlockonee near Tallahassee in Florida, USA, has been considered as a case study. A hydrologic model of the basin, draining into the dam, is developed using a conceptual model HYMOD with the historical climate and flow data extracted from the model parameter estimation experiment (MOPEX) dataset. The future projected climate scenario (2091-2100) is generated following the Representative Concentrated Pathways (RCP) 4.5 with the ensembles of six climate models. The impact of the future climate on water availability indicates a significant seasonal variability among the model ensemble results with an overall annual increase of statistics for the climate variables, corresponding inflows and a marginal increase in the energy generation.

1 This chapter was published as a journal article: Chilkoti, V., Bolisetti, T., and Balachandar, R. (2017). “Climate change impact assessment on hydropower generation using multi-model climate ensemble.” Renewable Energy, 109, 510–517
2.2 Introduction

The energy supply acts as a catalyst for an overall development of a society (Intergovernmental Panel on Climate Change and Metz 2007) and the supply of electricity, which is one of the major sources of energy and also the highest-value energy carrier (Intergovernmental Panel on Climate Change and Metz 2007), is imperative for basic humane comfort of living and to uphold an overall social and economic growth. Electricity generation for mass usage primarily comes from two broad sources: renewable and non-renewable. Non-renewable sector relies on burning fossil fuels whereas the renewable sector of electricity consists of hydro, solar, wind, biomass and geothermal. Though most of the nations fulfill the major segment of their energy demands through non-renewable sources (Edenhofer et al. 2012), about twenty-one countries worldwide are able to manage 80% of the electricity consumption through renewable means (“World Bank Data” 2016). Hydropower is a renewable energy source where power is derived from the energy of water moving from higher to lower elevations. The installed capacity of hydro across the globe is 926 GW by the year 2009 (Edenhofer et al. 2012) which constitutes about 19% of the total installed capacity. In the renewable sector alone its contribution is about 85% in terms of annual energy generation (Statham and World Energy Council 2007). Among all the energy sources the hydropower has the best conversion efficiencies of the order of 90% (from water to wire) (Edenhofer et al. 2012) and is termed as one of the cleanest energy resources.

The hydropower potential is strongly impacted by the hydrological regime which in turn is influenced by the local as well as regional climate pattern. Climate change is a complex phenomenon which is under an intense study by scientific community for the risk it poses to the sustainable human development. Any infrastructure project that has a life span of few decades is prone to the potential dangers of climate change unless the system is designed for the prevailing environmental conditions. The hydropower installations which are huge investment schemes with a proposed life of several decades (Schaeffli 2015), are equally prone to the environmental changes as their functioning is commensurate to the regions’ hydrology, which is under pressure due to the climate change phenomena (Bates et al. 2008). Impacts of changing climate on hydropower would be an additional stress which the system already faces due to other factors, such as demographic variations, land use changes, and changing economic activity (Schaeffli 2015; Bates et al. 2008). Different researchers have carried out studies on impact of climate change on water resources (Majone et al. 2012; Rahman et al. 2012; Raneesh and Thampi 2011; Shrestha et al.)
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2012). Bates et al. (2008) presents in detail the impacts of climate change on fresh water system and is a much cited technical paper by Intergovernmental Panel on Climate Change (IPCC), which is a leading international body on assessment of climate change. There have been several studies on the streamflow projection under climate change (Chen et al. 2011; Graham et al. 2007a; Graham et al. 2007b; Lenderink et al. 2007; Wi et al. 2015; Wilby and Harris 2006). As the energy production in hydropower is directly dependent on the quantum of water available in a given stream, the changing climate conditions are posing threat to the hydropower resource potential (Edenhofer et al. 2012). The studies related to hydropower are limited in comparison to the climate change effect in other sectors. Schaeffli (2015) presents a review of various model-based studies pertaining to climate change and hydropower. In particular the impacts on hydropower have been reported in some of the studies in recent decades (Christensen et al. 2004; Christensen and Lettenmaier 2007; Harrison et al. 1998; Kopytkovskiy et al. 2015; Mimikou and Baltas 1997; Minville 2010; Schaeffli 2015). The study on Colorado River basin by Christensen and Lettenmaier (2007) is a much cited work in this field and is an extension to their earlier work (Christensen et al. 2004); the same basin has also been studied later (Kopytkovskiy et al. 2015 and Kopytkovskiy 2010). The operational aspect of hydropower in the climate change scenario was included by some of the researchers (Christensen and Lettenmaier 2007; Larijani 2009; McDonald 2013; Minville 2010; Oni et al. 2012; Schäffli 2005a). A coupled model of hydrology and power market has been reported in Pereira-Cardenal et al. (2014), whereas there are studies including an energy based model without incorporating the streamflow and reservoir-volume generation computations (Larijani 2009). An extensive literature review on the impact of climate change on the electricity sector has been carried out by Chandramowli and Felder (2014).

Changing climate implies a variability of precipitation and temperature pattern which in turn may affect the streamflow regime and thus altering the resource potential of a given basin (Schaeffli 2015). As the hydrological inputs are foremost in assessing the exploitable potential for a hydropower system, the climate change impact assessment (CCIA) study should also integrate a hydrologic model, decently representing the catchment that feeds to the system. Any climate change study that incorporates hydrological modeling is bound to possess uncertainty in the results (Bloschl and Montanari 2009; Chen et al. 2011; Ludwig et al. 2009; Poulin et al. 2011; Wilby 2005). Poulin et al. (2011) mentions various sources of uncertainties in the climate change modeling, among which the uncertainty due to the climate model and the emission scenario is
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found to be the major source in quantifying the climate change impacts (Chen et al. 2011; Bloschl and Montanari 2009; Prudhomme et al. 2003). In order to better assess the future impacts and enumerate the uncertainty many researchers suggest conducting an ensemble based study (Schaefli 2015; Minville 2010; Bloschl and Montanari 2009). Some of the hydrologic-model-based studies for assessing the climate change effects on hydropower have also included climate model ensembles (Christensen and Lettenmaier 2007; Minville 2010; Kopytkovskiy et al. 2015).

Climate change studies rely on various climate models that simulate the future climate scenario for different greenhouse gas emission scenarios (GHGES) (Intergovernmental Panel on Climate Change and Metz 2007). The projected data for an array of climate variables can be extracted from the results of the various simulation runs of different category of climate models, most common among them being general circulation model (GCM). A GCM typically represents climate simulation based on coarse grid of approximately 2.5° (~250 km) on map. For CCIA study, the climate information at a better scale is imperative in order to generate more reliable estimates. Therefore, for a regional climate variable to be represented in detail, the climate simulations at finer resolutions shall be used. Regional climate models (RCM) offers a solution in this respect. RCMs are high resolution climate models that provide climate information at spatial scales much finer than the GCMs’ grid and are driven using the information provided by GCMs as lateral boundary condition (Buontempo et al. 2015; Dosio et al. 2015). The RCM resolution also assists in reducing the uncertainty (Chen et al. 2011) but the uncertainty inherent in the driving GCM persists in RCM (Dosio et al. 2015). There have been various international projects to accomplish the downscaling of climate data at a regional scale, Coordinated Regional Downscaling Experiment (CORDEX) (Giorgi et al. 2009) is one among others and is described in further sections.

Most of the CCIA studies for hydropower have used data from GCM’s only and limited studies are available that implement RCM data. Pereira-Cardenal et al. (2014) implemented results from three RCM’s under one emission scenario to study the coupled hydrological and power market model. Data from various RCMs were incorporated in a study of hydropower system in Swiss Alps (Schäfl 2005b) and RCM ensemble were used in the study of northern European basins (Graham et al. 2007a). de Queiroz et al. (2016) in their study on several hydropower projects in Brazilian river basins using one climate model, presents the effects of different climate scenarios in the water inflows and shown that climate change may drastically impact the system assured energy. It is evident from the diverse scientific literature that in order to assess the impact of the changing
climate at a local scale, it is vital to utilize the results of climate simulation conducted at an advanced resolution like that in RCM. Hence it is realised that for a meaningful CCIA study for hydropower, the ensembles of such climate model data shall be utilized. CORDEX offers an opportunity to directly exploit the downscaled data for impact assessment studies; and as per the knowledge of the authors none of the studies have implemented the RCM simulation outputs from CORDEX for quantifying the impacts on hydropower system. The objectives of the present research is to carry out a hydrological model based study to assess the impact of climate change on hydropower generation using the RCM data available through CORDEX, and to analyse the effect of using model ensemble in projecting the future hydrology and energy generation scenario.

2.3 Description of Study Area
The present study considers C.H. Corn Hydroelectric project (C. H. Corn Hydroelectric Generating Station, 2016) located on Ochlockonee River in United States as a case study (Fig. 2-1). The project which is located 20 miles southwest of Tallahassee is one of the only two hydroelectric facilities in the state of Florida and is a dam toe type of scheme. With an installed capacity of 12 MW, water for power generation is stored in the lake Talqin formed behind the Bluff dam.

![Fig. 2-1 Drainage area of Ochlockonee River upstream of C.H. Corn Hydroelectric project](image)

The facility comprises a total of three turbines with one unit of Kaplan and other two as Propeller turbines. When working at full capacity it fulfills about 3% of Tallahassee’s typical power needs.
The project was built in 1929 by West Florida Power Company but was abandoned as a power plant in 1970. Refurbished in 1981 by City of Tallahassee as a hydroelectric demonstration project it became fully operational in 1985 under City of Tallahassee Electric Utility Services. Lake Talquin stretches upstream towards Tallahassee and apart from electricity generation is used as recreational lake and also for flood control purpose.

2.4 Methodology

The climate change impact assessment for the C.H.Corn hydroelectric project has been carried out by first developing a conceptual hydrological model which is calibrated and validated based on the observed streamflow. The monthly energy generation computations are then carried out and are validated with the actual generation of the hydropower facility. The hydrological model is subsequently forced with the projected future climate data extracted from the RCMs available under CORDEX regional downscaling project. Energy generation model is again used to compute the future generation and compared with the present energy production. Schaeffli (2015) also discusses the relevance of undertaking a hydrological-model based CCIA study for the hydropower system.

2.4.1 Hydrological model

There are various types of hydrologic model either a conceptual/lumped, partially distributed or a distributed model. In a Conceptual rainfall-runoff (CRR) model, the overall hydrologic response of the watershed system is generated at sub-watershed scale on the basis of governing hydrologic phenomena. In the present research a CRR namely HYMOD (Boyle 2001) having an ability of continuous-process simulation has been used for basin hydrologic simulation. The model is considered as a relatively simple but producing robust runoff simulation. The model consists of five parameters viz., storage capacity of watershed C [L], percentage of impervious portions of watershed $\alpha$[, ], recession coefficient for quick flow/surface runoff $k_q$ [T ], recession coefficient for slow/base flow $k_s$[T ], degree of spatial variability of soil moisture capacity within watershed $b_{exp}$[ ]. For further details of the model configuration Boyle (2001) can be referred.

2.4.2 MOPEX dataset

Model parameter estimation experiment (MOPEX) is an international project that consists of a comprehensive database of historical climate and land surface characteristics for numerous hydrologic basins across the world (Duan et al. 2006). The concept of MOPEX was recommended
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by Global Energy and Water Cycle Experiment (GEWEX) Hydrometeorology Panel (GHP) in 1996 which was then adopted as projects of the International Association of Hydrological Sciences (IAHS)/World Meteorological Organization (WMO) Committee on GEWEX and of the WMO Commission on Hydrology. As part of MOPEX, data from 438 catchments in United States and several others from across the world are already included. The data set for US includes daily time series of mean aerial values for various climate variables namely precipitation, potential evaporation, maximum temperature and minimum temperature among others. For each of the basins daily streamflow record is also available. For the present work, the dataset from one of the MOPEX basins has been utilized to develop and calibrate the hydrological model.

2.4.3 Power generation computation

The energy generation has been computed based on the available streamflow and driving water head behind the dam holding the lake water. The computations are carried out for the daily flow data and then presented on monthly basis. Due to lack reservoir bathymetric information the operational aspects have not been considered in the current study. As our present goal is only to make an assessment of the energy generation at a broad scale, lack of such information would not hamper the analysis.

2.4.4 Climate change projections

For a reliable climate change projection a multi-model ensemble approach (Schaefli 2015) has been adopted in the current study. Data from six RCM’s as part of CORDEX (Giorgi et al. 2009) experiment has been extracted. CORDEX is a regional climate downscaling project that aims to generate an ensemble of high-resolution historical and future climate projections at a regional scale, by downscaling different GCMs participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5)(Asrar 2011). CMIP5 data holds a large potential for assessment of renewable energy viz. solar, wind and hydro in future especially under changing climate scenario. van Vliet et al. (2016) have carried out an extensive study of rivers worldwide, using a CMIP5 multi-model ensemble, to show the potential impacts of climate change on global hydropower and cooling water discharge availability. Data from 21 models of CMIP5 was utilized by Carvalho et al. to assess future changes in the wind energy resource in Europe (Carvalho et al. 2017).

The data available under CORDEX project are divided into 14 domains (Giorgi et al. 2009) that covers majority of land area across the globe. The present study area falls under domain-3 termed
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as North America (NAM), and therefore the data pertaining to corresponding domain has been retrieved. The selected models for the present study are listed in Table-1.

Using the climate models, data for two different time horizons were extracted, one for historical duration termed as control period and other for the future period following the Representative Concentrated Pathways (RCP) 4.5 that represents one of the intermediate GHGES as per the latest IPCC guidelines (Pachauri et al. 2014). The control period data from year 1971-2000 is used to bias correct the model data with the available observation data. The future time horizon for assessing the climate change impacts in the present study is considered from the year 2091 to 2100. Henceforth the climate models shall be described by their respective numbers (as in Table 2-1) rather than the name, for simplicity sake.

<table>
<thead>
<tr>
<th>Model No</th>
<th>Regional Climate Model (RCM)</th>
<th>Modeling Agency*</th>
<th>Driving Global Climate Model (GCM)</th>
<th>Modeling Agency*</th>
</tr>
</thead>
<tbody>
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<td>1</td>
<td>CanRCM4</td>
<td>CCCma</td>
<td>CanESM2</td>
<td>CCCma</td>
</tr>
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<td>2</td>
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<td>HIRHAM5</td>
<td>DMI</td>
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</tr>
<tr>
<td>5</td>
<td>CRCM5</td>
<td>UQAM</td>
<td>CanESM2</td>
<td>CCCma</td>
</tr>
<tr>
<td>6</td>
<td>CRCM5</td>
<td>UQAM</td>
<td>MPI-ESM-LR</td>
<td>MPI-M</td>
</tr>
</tbody>
</table>

* CCCma - Canadian Center for Climate Modeling and Analysis
SMHI – Swedish Meteorological and Hydrological Institute
DMI – Danish Meteorological Institute
ICHEC – Irish Center for High End Computing
UQAM-Université du Québec à Montréal
MPI – Max Planck Institute of Meteorology

The climate projection data consists of an array of climate variables. The hydrological model currently being used only requires precipitation and potential-evapotranspiration (PET) data to generate streamflow simulation. PET is a derived climate variable and has been computed using Hargreaves method (Hargreaves et al. 1985) in the present study. Therefore, only three climate variables viz. precipitation, near surface minimum and maximum air temperature corresponding to daily time step frequency have been extracted from the climate projection data.
2.4.5 Bias correction

The meteorological parameters derived from the climate models may not possess the statistical characteristics of the observed data of the study area (Schaefli 2015). In such case the climate model data, from however refined simulation grid is obtained, need to be corrected before RCM outputs are transferred into hydrological models (Graham et al. 2007a) and thus to be more representative for a given location. The problem is resolved using the technique called Bias correction (Schaefli 2015); various methods for carrying out bias correction are summarized in Chen et al. (Chen et al. 2011). In the present study we adopt the commonly used Delta change method (Minville 2010; Poulin et al. 2011; Graham et al. 2007a), where the monthly averaged climate model data during the control period is compared with the observed data over the same period. The monthly bias factors thus computed are applied over the daily model data, for the respective months, as per Eq. 2-1 through Eq. 2-4.

\[
\delta_{P,m} = \frac{\sum_{i=1}^{n} P_{i,Obs}}{\sum_{i=1}^{n} P_{i,RCM}} \text{ControlPeriod}
\]

Eq. 2-1

\[
P_{modelCorr,m} = \delta_{P,m} P_{model,m}
\]

Eq. 2-2

\[
\delta_{T,m} = \left( \frac{1}{n} \sum_{i=1}^{n} T_{Obs,i} - \frac{1}{n} \sum_{i=1}^{n} T_{RCM,i} \right) \text{ControlPeriod}
\]

Eq. 2-3

\[
T_{modelCorr,m} = \delta_{T,m} + T_{model,m}
\]

Eq. 2-4

Notations:

\(\delta_{P,m}\) - bias in precipitation (P) for month m

\(P_{i,Obs}\) - observed precipitation for \(i^{th}\) day of given month

\(P_{i,RCM}\) - RCM precipitation for \(i^{th}\) day of given month

\(P_{modelCorr,m}\) - corrected model precipitation of month m

\(P_{model,m}\) - model precipitation of month m

\(T\) - temperature; other notations for temperature are similar to precipitation
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2.5 Results and Discussion

The results pertaining to hydrological modeling, climate scenario projection, simulation of future hydrological projections and energy generation in future period are detailed in the present section.

2.5.1 Hydrologic model calibration

The hydrologic model HYMOD for the present study area has been calibrated based on the data available from MOPEX database for gauge ID 02329000. The climate data for the period 1980-1994 has been used for the model development. Generalized Likelihood Uncertainty Estimation, GLUE (Beven and Binley 1992) method is adopted to generate a range of model parameters which in turn allows to generate a streamflow ensemble that also assist in analysing the modeling uncertainty. All model simulations having a Nash-Sutcliffe efficiency greater than 0.75 are retained. The model is validated with respect to energy generation data which is available from 1996 to 2014, giving an efficiency of 0.84. The detailed results of calibration and validation are not presented here for brevity. Daily precipitation and PET data is used for hydrologic modeling while the daily streamflow data is used for model calibration. A set of model parameters is generated and all the model simulations having an efficiency of more than 0.75 with respect to observed data are retained. Fig. 2-2 presents the summary of simulation of the daily streamflow patterns during the calibration period. The model parameters generated during the calibration are then employed for model run in future climate scenario.

Fig. 2-2 Observed streamflow (dashed lines) and model median simulated streamflow (solid lines)
2.5.2 Projected climate model results

Subsequent to extraction of precipitation and near surface air temperature data from six different climate models, the data were bias corrected based on the method described earlier. The analysis here has been carried out on annual as well as seasonal basis; the whole year is divided into four seasons viz., winter (DJF), spring (MAM), summer (JJA) and autumn (SON). Similar treatment of the results has been reported in the previous studies also (Christensen and Lettenmaier 2007; Minville 2010).

Based on the analysis of control period data, various climate models uniformly depict a bias factor greater than unity for precipitation, which implies that the model projects lesser precipitation than actual during the same period. The average bias among all the models is about 13% but on the seasonal scale the winter period has the highest bias of 20%. The variance of bias among all the models is maximum during autumn and least during summer period. The maximum air temperature presents a positive bias in the range of 0.97°C to 4.32°C among different models and seasons whereas the minimum air temperature variable has a larger bias range of -0.21°C to -4.73°C. The variance of bias among models is larger during the summer and autumn period for precipitation whereas for temperature, winter and spring period presents higher variance in bias than other seasons.

For future scenario, the precipitation projection for the basin clearly indicates an overall increase in annual depth with an average increment among all the models to be about 14%. All the models unequivocally indicate towards an increase in winter and spring precipitation ranging between 8-43% whereas three out of the six models project a marginal decline during the summer months in the range of 1-6% with reference to the control period statistics. The overall range of change in the precipitation depth in the model ensemble on seasonal basis is -14% to 43%. Fig. 2-3 presents the comparison of monthly precipitation distribution of all the models and the control period.
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The range of projections for the monthly as well as seasonal precipitation is presented by means of box plot in Fig. 2-4; the larger band during the autumn and winter months represents the uncertainty in projection by different models especially during these periods. An average warming, as expected, is indicated by all the models in maximum and minimum air temperature projections except for model-2 which point towards a decrease in temperature with reference to the control period temperatures. The annual average warming is of the order of 2°C for maximum temperature and 1.35°C in minimum temperature. But the concerning picture is during the spring period where an average increase in maximum daily temperature is of the order of 3°C with two of the models projecting an increase of over 4°C. During the same period the minimum temperature also increases by 2.7°C and three models projecting a raise of over 4°C. Projections among various models have least variance during the summer period wherein the results can be accepted with more confidence.

Fig. 2-3 Average monthly precipitation; comparison between individual climate model projections and control period observed data

Fig. 2-4 Comparison of projected and historical (circles) seasonal precipitation
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An average increase of all the models is $1.8^\circ C$ and $0.9^\circ C$ in minimum and maximum air temperature respectively, during this season. The monthly temperature projections in comparison to the historical average temperatures are presented in Fig. 2-5; the trend of average increase in precipitation and air temperature have also been reported in earlier studies (Minville 2010; Chen et al. 2011).

Fig. 2-5 Average monthly near surface (a) maximum air temperature and (b) minimum air temperature of each climate change projection compared to control period observed data

2.5.3 Hydrologic scenario projection

Subsequent to interpreting the projections in climate variables the projection in hydrologic scenario is assessed. Streamflow of the basin is generated by forcing the projected climate data into the earlier calibrated hydrological model. The runoff generation for the future scenario shall be the combined effect of precipitation and temperature projections. Future streamflow pattern by each of the model scenarios is presented in Fig. 2-6 and compared with the historical average monthly flows.

Fig. 2-6 Monthly streamflow comparison between climate model ensemble (shaded) and observed (firm line) control period streamflow
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The model ensemble results portray more uncertain projections during the winter and spring than during other seasons, as evident from box plot in Fig. 2-7. The striking feature of the 6-model ensembles is that there is a large divergence in the results among different models especially during the winter and autumn periods. The range of projected change is -33% to 176% in model ensemble results and the same for autumn period is 2% to 98%. Such a large increase in the predicted flow estimates especially during the autumn period had also earlier been reported (Chen et al. 2011). The most predictable results are during the summer period where the streamflows decline in the range of -2% to -39% having an average reduction of 24% and the simulation has least variance. Spring period results also point towards a decreasing trend of flow with an ensemble average of -8% but with a variance larger than summer predictions. Increase in winter flows and decline in the summer flows in the future scenario has also been reported in most of the earlier studies (Minville 2010; Chen et al. 2011; Graham et al. 2007a).

![Fig. 2-7 Range of average (a) monthly and (b) seasonal streamflow projections (2091-2100)](image)

On further investigating the results of the climate variables and subsequently the streamflows, it is evident that among all the climate models the results of model-1 and model-2 are producing maximum variability in the ensemble results. The change in maximum temperature and percentage variation in the seasonal precipitation depth is found out to have maximum scatter for model-1 and model-2 followed by model-5, as evident from the plots in Fig. 2-8. Similar but more pronounced patterns are found for the simulated hydrologic streamflow scenario. The common variable among these models is CanESM2 which is the driving GCM and provides the boundary conditions for simulating the RCM.
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Fig. 2-8 Seasonal change in (a) minimum air temperature (b) maximum air temperature (c) precipitation and (d) streamflow with reference to the historical period observed data

Hence as discussed in the previous studies (Chen et al. 2011; Prudhomme et al. 2003), the uncertainty introduced due to the climate models is one of the major sources of uncertainty in future projection and moreover the driving GCM is an important source of uncertainty (Majone et al. 2012) and plays a central role in assessing the hydrological change (Graham et al. 2007a). The concern of boundary conditions imposed by the driving GCM and the associated uncertainties in projections has also been raised in other studies (Lenderink et al. 2007; Chen et al. 2011; Wilby and Harris 2006).

2.5.4 Energy generation

Prior to the simulation of hydropower generation for the future scenario, the hydropower model is validated for the present scenario. The monthly power generation data are available from year 2001 to 2014 (U.S.Energy Information Administration, 2016) and also available are the annual generation statistics from 1996 to 2000 (Global Energy Observatory). The energy computations are carried out for the available hydrological data during this period and validated using the available data, the results of which are presented in Fig. 2-9.
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Fig. 2-9  Validation of hydropower generation for (a) annual energy and (b) monthly energy (2001-2014)

For the future scenario the projected hydrologic data from the climate models is forced into the hydropower model and the average monthly generation corresponding to each of the model is simulated. The energy generation follows the similar trend as streamflow projection (Table 2-2).

The uncertainty in the projections during the winter and spring period is evident from the box plot depicted in Fig. 2-10. Similar to the projections for precipitation and streamflow, the uncertainty is markedly persisting in the energy generation also, which implies that uncertainty in the climate projections is propagating (Majone et al. 2012) through the subsequent hydrological and hydropower modeling process. On the seasonal time scale the changes anticipated in the energy generation in comparison to the present generation illustrates a large range in the multi-model ensemble (Table-2). Results of the climate projections indicate an increase in winter production which averages at a considerably high value of 56%, while that of spring is 4%. Later period also has lease variance in projection.

Table 2-2: Seasonal changes in energy generation (in %) with reference to the present generation

<table>
<thead>
<tr>
<th>Season</th>
<th>Model-1</th>
<th>Model-2</th>
<th>Model-3</th>
<th>Model-4</th>
<th>Model-5</th>
<th>Model-6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter</td>
<td>121.6</td>
<td>151.2</td>
<td>25.2</td>
<td>-37.6</td>
<td>69.5</td>
<td>7.3</td>
</tr>
<tr>
<td>Spring</td>
<td>-13.4</td>
<td>39.5</td>
<td>2.9</td>
<td>6.3</td>
<td>-6.2</td>
<td>-4.8</td>
</tr>
<tr>
<td>Summer</td>
<td>-32.0</td>
<td>11.1</td>
<td>-26.2</td>
<td>9.2</td>
<td>-23.2</td>
<td>-23.0</td>
</tr>
<tr>
<td>Autumn</td>
<td>41.7</td>
<td>61.6</td>
<td>-39.6</td>
<td>-30.4</td>
<td>30.7</td>
<td>26.2</td>
</tr>
</tbody>
</table>

*Negative value indicates a reduction in power generation*
Reduction in energy generation is quite pronounced during the summer period with most of the models projecting a decrease in production which averages at -14%. Similar to winter period, there is an average increment in energy generation projected during the autumn and the result exhibits a significant variance among all models in the future scenario during this period. On the basis of seasonal analysis the spring and summer periods have lesser uncertainty in the projection than other two seasons. The annual average hydropower generation is projected to increase by 15%. But it is essential to view the projections from seasonal perspective of each of the ensemble components rather than the overall average annual figures. On investigating the seasonal changes as presented in Table-2, the extreme variability in the winter generation is evident. Model-1 and model-2 results are outliers in the ensemble story especially for the winter period and for other seasons also where both these models have generally higher values. As discussed in the previous section, both these models have a common driving GCM, hence the climate model uncertainty is evidently propagated here (Majone et al. 2012). **Fig. 2-11** portrays the uncertainty in the seasonal changes in generation as anticipated by different climate models.

**Fig. 2-10** Uncertainty of hydropower projection for scenario period (2091-2100) for (a) monthly and (b) seasonal generation
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Fig. 2-11 Ensemble of seasonal variation in hydropower generation between historical (2001-2014) and future scenario projection (2091-2100)

2.6 Conclusions

The present research was carried out to assess the changes in hydropower generation resulting from projected climate change conditions. The changing climate is posing a great threat to the future civilizations, due to the variations in precipitation and temperature patterns which indirectly is bound to alter hydrological cycle and consequently the streamflow pattern at a given place (Bates et al. 2008). Any society is dependent on the rivers as it directly utilizes the stream for various activities like irrigation, drinking, industrial use, power generation, etc. which are imperative for its sustenance and development.

With the varying streamflow regime due to changing climate, the entire dependent infrastructure is likely to get affected consequently. Hydropower potential relies on the quantum of available water in the given stream and the extent of energy generation is hence allied with the streamflow pattern. It is vital to carry out an impact assessment for the existing hydropower facilities as they are huge capital investment schemes and a realistic study shall incorporate a hydrologic model (Schaefli 2015).

In the present study the C.H. Corn Hydroelectric project located in Ochlockonee River in Florida United States was considered as a case study for CCIA. The streamflow data of the nearby USGS gage was used to calibrate the hydrological model of the project basin and also to validate the power generation model. The hydrology of the basin was simulated using the conceptual hydrological model HYMOD which was forced with the climate data from MOPEX dataset. Future horizon of study was period from year 2091 to 2100 whereas year 1970 to 2000 was taken as
control period for climate data. An ensemble approach was used to conduct the climate change impact assessment study wherein a 6-model ensemble belonging to the CORDEX regional downscaling project was used. Before using the climate data for future period, the data was bias corrected with the factors derived by analysing the observed and climate model data corresponding to the control period. The bias corrected future precipitation is found to have an increased annual depth of about 14% whereas the seasonal variation among all the models ranges from -14% to 43%. The average daily near surface air temperature projections has a significant increase over the present values. The minimum temperature increases by 1.35°C whereas maximum temperature increment stands at 2°C based on the model ensemble results. The range of amplification for the maximum temperature during the summer season is 0.4°C to 2.2°C whereas during the spring it is as high as 1.7°C to 5.5°C. Some of the models even project a decrease in temperature during autumn period. The cumulative effect of alterations in climate variables is studied for the consequences in streamflow simulation. Similar to the precipitation the overall effect on the streamflow is an increase in the annual flow averaging at 21%, but the seasonal variations are more pronounced than that in the precipitation and have larger variance among results of different models. The maximum variation is during winter period with an increase of 72% whereas the summer projections are for a decrease in inflow flow by about -24%.

Consequent to the projections of hydrology the impacts of climate change on power generation were studied. The pattern of seasonal changes in the energy generation was same as that in the streamflow. The winter period indicates an increase in production by about 56% for a 72% average increase in the inflows; the higher inflow than the design flow for hydropower might not be exploited and will lead to additional spill of the inflow. The autumn period projections are for 15% average increase whereas a decline of energy generation by -14% during the summer period would be a matter of concern for the energy managers. The uncertainty in projections which is least during the summer and maximum during the winter period, is evident from the seasonal model ensemble results.

The climate model uncertainty which has been widely discussed in the literature (Bloschl and Montanari 2009; Chen et al. 2011; Poulin et al. 2011; Prudhomme et al. 2003) is apparent in the results of present research. It is found that the models producing the maximum scatter in the ensemble projection are driven by the same boundary conditions imposed by the parent GCM (Majone et al. 2012). The climate change studies shall be undertaken with great care and using
multi-model ensembles in order to ascertain the range of projections anticipated. With the above results it is evident that the future projections are not likely to render a narrow enough water scenario range suited for specific infrastructure projects but would prepare us for the direction of change anticipated over various seasons. Also, for the hydropower schemes the operational policies shall be adapted to counteract the ill effects of climate change.

2.7 Acknowledgements

The present research is funded by the Natural Sciences and Engineering Research Council (NSERC) of Canada through the Discovery grant programme to the senior author. We acknowledge the World Climate Research Programme’s Working Group on Regional Climate, and the Working Group on Coupled Modelling, former coordinating body of CORDEX and responsible panel for CMIP5. We also thank the climate modelling groups (listed in Table 2-1 of this chapter) for producing and making available their model output for the present research on impact assessment.
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2.8 References


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CHAPTER 3 DIAGNOSTIC EVALUATION OF HYDROLOGIC MODELS EMPLOYING FLOW DURATION CURVE

3.1 Chapter Synopsis

The assessment of water availability using hydrological models is subjected to modeling uncertainties. Model performance evaluation based on the conventional likelihood measures on an overall time-series simulation has shortcomings. To overcome this, a model diagnostic evaluation is carried out. The main objectives of the study are to: (a) demonstrate the strength of the model diagnostic assessment, (b) formulate an improved likelihood measure through a flow duration curve (FDC)-based flow portioning to enhance the model performance, and (c) correlate the model simulation to the basin hydro-climatic features. The objectives are achieved through the use of a conceptual rainfall-runoff model within Generalized Likelihood Uncertainty Estimation (GLUE) framework applied on seventeen basins of south-eastern United States. The results indicate that the diagnostic assessment is crucial in model evaluation. The two-phase model assessment assisted in improving the model performance by 6% in terms of Nash-Sutcliffe efficiency for overall flow time-series, 32% in terms of average volume efficiency and 24% in terms of ratio of root-mean-squared-error to the standard deviation of observation for the low flows.

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2 This chapter has been published as a journal article: Chilkoti, V., Bolisetti, T., and Balachandar, R. (2019). “Diagnostic evaluation of hydrologic models employing flow duration curve.” Journal of Hydrologic Engineering, 24(6), 5019009
Chapter 3
Diagnostic evaluation of hydrologic models employing flow duration curve

3.2 Introduction
Development of reliable hydrological models is a vital component in the decision-making process. A good quality model setup includes a realistic model structure and appropriate parameterization (Gharari et al. 2013). For a given model structure, identifying the best model parameters governs the model performance. To this end, the calibration process is generally adopted which involves identifying the sensitive model parameters and their optimal values. This is followed by the comparison of the observed and the model simulated variables, and quantification of model performance through an objective function or likelihood that measures the statistical fit between the variables. The performance of the identified model parameters is further confirmed during an independent evaluation period (validation). The calibration-validation approach has become a standard protocol in hydrological modeling especially those involving conceptual hydrological models (Andréassian et al. 2009).

The calibration involves three key aspects: (a) identifying parameters to be calibrated, (b) objective function for calibration and (c) state variable used for calibration. Here, the state variables refer to the simulated variables or model output. The models involving several parameters require parameter sensitivity analysis before initiating the calibration (Saltelli et al. 2000). In the present case, since the applied model has only five parameters and all are being calibrated, this aspect of parameter identifiability is not further explored.

The next aspect of calibration is the objective function that evaluates the statistical fit of the simulated and the observed variable. In a calibration process various types of objectives are generally implemented (Krause et al. 2005). The conventional likelihood measures that are based on squared error for the overall time-series, and quite commonly adopted, have been reported to render a biased judgement (Fowler et al. 2018; Legates and McCabe 1999; Schaefli and Gupta 2007). There has been significant activity within the hydrological community to refine the calibration process in order to enhance the predictive ability of the models (Hrachowitz et al. 2014). To make a reliable model assessment, various other approaches such as log transformed likelihood functions (Krause et al. 2005), multi-objective framework (Efstratiadis and Koutsoyiannis 2010; Reed et al. 2013) and inclusion of hydrological signatures (Sawicz et al. 2011) are being increasingly adopted.

The third aspect of calibration is the state variable or the simulated variable. In most of the hydrologic modeling studies, streamflow is the output variable that is screened for calibration.
Depending upon the model output, other derived variables such as sediment load, or water quality variables (e.g. Phosphorous load) can also be calibrated. The observed streamflow at the catchment outlet, commonly used in calibration, is consequent to the various sub-processes such as infiltration, lateral flow, evaporation, shallow ground water flow and deep percolation occurring in the catchment (Arnold et al. 2012). The objective function(s) that primarily compute the statistical fit between the simulation and the observation may not be able to account for these runoff generation processes. The mathematical optimum obtained through a calibration scheme may be different from the hydrological optimum (Andréassian et al. 2012). The models, therefore need to be evaluated not only based on statistical measures but also from hydrological perspectives (Gupta et al. 2008). In this regard, mere use of hard data in the form of observed variables may not be adequate, and the same data need to be used to extract additional information in terms of signature indices that disclose some specific properties of watershed dynamics (Vrugt and Sadegh 2013). Several studies have adopted hydrological signature based likelihood measures to enhance model performance (Haas et al. 2016; Pfannerstill et al. 2014a; Pokhrel et al. 2012). In doing this, the diagnosis of the model performance is carried out. The ‘diagnostic evaluation’ is a promising approach wherein the ability of the model to simulate various processes can be further analyzed (Gupta et al. 2008).

Another aspect that impacts the model evaluation is the temporal domain over which the likelihood measures are evaluated. In most of the model assessment studies, the likelihood measures are computed over the entire evaluation period, i.e., the aggregated flow statistics are judged. This may lead to erroneous decisions (Wagener 2003) as poor performance in some phases of the model may be masked (Pfannerstill et al. 2014a). To this end, the model performance for different flow regimes need to be assessed. The role of flow duration curve (FDC) has been highlighted by various researchers as a tool to comprehend the process dynamics and subsequently aid the model calibration procedure (Haas et al. 2016; Boscarello et al. 2015; Shafii and Tolson 2015; Coxon et al. 2014; Hrachowitz et al. 2014; Pfannerstill et al. 2014a; Pokhrel et al. 2012; Westerberg et al. 2011; Yilmaz et al. 2008). Vogel and Fennessey (1994) described FDC as a complement of the cumulative distribution function of the daily streamflow. FDC also provides valuable qualitative insight into the catchment behavior (Kavetski et al. 2011) as the initial steep portion of curve represents the quick flow and the lower portion characterizes the base flow. Therefore, FDC can be employed as a tool to separate the different flow regimes to
assist the model evaluation. Assessment of objective functions computed over different flow regimes aid in identifying the poor performing parts of the model (Pfannerstill et al. 2014a; van Werkhoven et al. 2009), thus supporting the diagnostic model evaluation procedure.

Several studies have been carried out employing FDC as a diagnostic tool. In the research carried out by Yilmaz et al. (2008), a diagnostic approach for model evaluation was presented, wherein three out of five flow signatures were extracted from FDC viz., percentage bias (%Bias) in FDC high flow volume, %Bias in FDC low flow volume, %Bias in FDC mid-segment slope, %Bias in overall runoff ratio and %Bias in watershed lag time. Calibration of hydrologic model based on FDC was demonstrated by Westerberg et al. (2011). Pfannerstill et al. (2014a), Pokhrel et al. (2012) and Pfannerstill et al. (2014b) have presented the combination of performance measures such as Nash-Sutcliffe Efficiency (NSE) and percentage bias (PBIAS) together with evaluation of different segments of FDC. While elaborating the need for a model structure choice based on the catchment behavior, Coxon et al. (2014) have adopted three different sets of signature measures viz., catchment mean flow, inter-annular variability and intra-annular variability, in their experiment on 24 catchments in England and Wales; one out of the three signature measures used was evaluated based on FDC. Hrachowitz et al. (2014) have utilized the performance of FDC simulation as one of the calibration objectives in their investigation of different models. Various signature measures for model evaluation were also studied, with three out of thirteen signatures derived from FDC. Shafii and Tolson (2015) have utilized thirteen flow signatures based on water balance, FDC, discharge statistics and monthly flow, through a scoring method to incorporate into the multi-objective model calibration formulation along with conventional goodness-of-fit criteria. Various flow signatures derived from FDC were combined into a new performance measure, termed as standardized signature index sum (SIS) by Ley et al. (2015). They attempted to investigate various performance measures for model structure assessment as a tool for catchment classification.

The current study is in a similar direction as the above-mentioned studies in terms of employing FDC as a diagnostic evaluation tool, but extended further in developing new likelihood measure based on FDC. The study proposes a two-phase model calibration strategy for seventeen basins of varying climate. In a two-phase assessment procedure, FDC is demonstrated as a valuable tool for diagnosing the deficiency of model evaluation during the first phase. Subsequently, the FDC partitioning is employed for evaluating a new likelihood function for improved model
performance. The study is aimed towards an approach beyond the simple traditional statistical assessment, utilizing the soft information content in the available data to bring about a robust model assessment (Seibert and McDonnell 2002).

Another aspect of model calibration that is being researched is the link between model evaluation and catchment climatic characteristics. A given model structure and a given evaluation methodology may be appropriate for some catchments depending upon their physical and climatic pattern (Coxon et al. 2014); while the same may not be suitable for other catchments across the climate gradient. Coxon et al. (2014) have demonstrated that the model performance varied with the catchment characteristics that included wide-ranging physical as well as climatic features. There are limited studies that relate the model diagnostic evaluation and catchment climate characteristics. Therefore, there is a need for providing further insights into the model evaluation and its association with the corresponding climatic features and how diagnostic evaluation can assist in robust model assessment.

The main objectives of the study are to (a) demonstrate the strength of model diagnostic assessment, (b) formulate an improved likelihood measure through a FDC-based flow portioning to enhance the model performance, and (c) correlate the model simulation to the catchment hydro-climatic features. The objectives are achieved through the model evaluation for the seventeen basins having diverse hydrological features that are part of the Model Parameter Estimation (MOPEX) project (Duan et al. 2006).

### 3.3 Model Description, Dataset and Study Area

#### 3.3.1 Model description

A hydrologic model can be either a conceptual/lumped, partially distributed or a distributed model. In a conceptual rainfall-runoff (CRR) model, the runoff is computed at sub-watershed scale on the basis of governing hydrologic phenomena without considering the minor processes, but providing reasonable overall hydrologic response of the watershed system. In the present research the conceptual model HYMOD (Boyle 2001) has been used for catchment hydrologic simulation. The model is widely accepted, applied across a range of hydrologic regimes and for various applications (Chilkoti et al. 2017; Sikorska et al. 2014; Formetta et al. 2011; Gharari et al. 2013; Montanari 2005; Wagener et al. 2001). HYMOD is a relatively simple but strong runoff generation model and has the ability to provide continuous-process simulation. The model was
chosen primarily due to its wide acceptability, low number of parameters, adequate process representation that includes slow and fast responses. The model incorporates a non-linear soil moisture component which is computed through Moore loss model (Moore 1985). The five model parameters include the storage capacity of watershed $C$, percentage of impervious portions of watershed $\alpha$, recession coefficient for fast flow $k_q$, recession coefficient for slow flow, i.e., base flow $k_s$, and degree of spatial variability of soil moisture capacity within a watershed $b_{\text{exp}}$. For further details of the model configuration, Boyle (2001) can be referred. The prior range of parameters adopted in the analysis is reported in Table 3-1. Initially it is not easy to assess the parameter values for a given study area in spite of knowing the catchment physical characteristics. It may be safe to begin with a wide parameter range, as the GLUE procedure will refine the range of acceptable parameter sets. The suitability of the selected range may be later estimated by comparing the predicted model response (Beven and Binley 1992).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$C$</th>
<th>$\alpha$</th>
<th>$k_q$</th>
<th>$k_s$</th>
<th>$b_{\text{exp}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Units</td>
<td>mm</td>
<td>-</td>
<td>days</td>
<td>days</td>
<td>-</td>
</tr>
<tr>
<td>Minimum</td>
<td>0</td>
<td>0</td>
<td>0.1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Maximum</td>
<td>500</td>
<td>1</td>
<td>0.99</td>
<td>0.1</td>
<td>2</td>
</tr>
</tbody>
</table>

3.3.2 MOPEX dataset and study area

Model Parameter Estimation (MOPEX) is an international project that consists of a comprehensive database of historical climate and land surface characteristics for numerous hydrologic basins across the world (Duan et al. 2006). In the present study the data for seventeen basins in the southern United States (Fig. 3-1) have been extracted from the MOPEX database. Table 3-2 briefly summarizes the physical and hydro-climatic features of each of the study watersheds. The drainage areas of the basins lie in the range of 919 km$^2$ to 9885 km$^2$ having diverse aridity levels and soil types. The basins are categorized as per the classification scheme proposed by Coopersmith et al. (2012). The basin wetness is computed based on the annual average potential evapotranspiration (PET) and precipitation (P). The table presents PET/P ratio as the wetness index. The soil types range from low permeability rocky strata to highly permeable sandy soils. It assists in assessing the infiltration potential of the basin. The strata in all the arid basin comprises of soil having very low saturated hydraulic conductivity. The climate variables in the MOPEX
dataset include a long term daily mean areal precipitation, maximum and minimum air temperature and potential evapotranspiration. Daily streamflow data is also an integral part of the dataset. In the present study, the data from 1980 to 1994 are considered for model calibration and 1995-1999 for model validation. Henceforth, the basins will be referred by their respective basin numbers (as in Table 3-2) instead of basin ID, for the sake of simplicity.

3.4 Methodology

The methodology used for model calibration and uncertainty assessment as carried out in the present research is described in this section. A flow chart summarizing the methodology is
presented in Fig. 3-2. The procedure outlined in figure is further explained in the subsequent subsections.

**Table 3-2**: Overview of the basins studied (Source: MOPEX dataset (Duan et al. 2006)); PET/P is the annual average ratio of potential evapotranspiration to precipitation over the basin, basin classification is as per Coopersmith et al., (2012), soil type is the dominant soil type in the top 1.5 m layer, $K_{\text{sat}}$ refers to saturated hydraulic conductivity of the dominant soil type.

<table>
<thead>
<tr>
<th>No</th>
<th>BasinID</th>
<th>River</th>
<th>State</th>
<th>Catchment Area (km²)</th>
<th>PET/P</th>
<th>Classification</th>
<th>Soil Type</th>
<th>$K_{\text{sat}} \times 10^{-5}$ m/s</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2492000</td>
<td>Bogue</td>
<td>LA</td>
<td>3141</td>
<td>0.68</td>
<td>Humid</td>
<td>Loam</td>
<td>4.44</td>
</tr>
<tr>
<td>2</td>
<td>2479300</td>
<td>Red Creek</td>
<td>MS</td>
<td>1142</td>
<td>0.69</td>
<td>Humid</td>
<td>Sandy loam</td>
<td>6.36</td>
</tr>
<tr>
<td>3</td>
<td>7375500</td>
<td>Tangipahoa</td>
<td>LA</td>
<td>1673</td>
<td>0.68</td>
<td>Humid</td>
<td>Silt loam</td>
<td>4.01</td>
</tr>
<tr>
<td>4</td>
<td>2475000</td>
<td>Leaf</td>
<td>MS</td>
<td>9052</td>
<td>0.74</td>
<td>Humid</td>
<td>Sandy loam</td>
<td>5.84</td>
</tr>
<tr>
<td>5</td>
<td>2375500</td>
<td>Escambia</td>
<td>AL</td>
<td>9885</td>
<td>0.75</td>
<td>Humid</td>
<td>Sandy clay loam</td>
<td>7.56</td>
</tr>
<tr>
<td>6</td>
<td>2475500</td>
<td>Chunky</td>
<td>MS</td>
<td>956</td>
<td>0.80</td>
<td>Temperate</td>
<td>Loam</td>
<td>5.39</td>
</tr>
<tr>
<td>7</td>
<td>2472000</td>
<td>Leaf</td>
<td>MS</td>
<td>1924</td>
<td>0.76</td>
<td>Temperate</td>
<td>Clay</td>
<td>4.30</td>
</tr>
<tr>
<td>8</td>
<td>2478500</td>
<td>Chickasawhay</td>
<td>MS</td>
<td>6967</td>
<td>0.76</td>
<td>Temperate</td>
<td>Sandy loam</td>
<td>5.34</td>
</tr>
<tr>
<td>9</td>
<td>2365500</td>
<td>Choctawhatchee</td>
<td>FL</td>
<td>9062</td>
<td>0.80</td>
<td>Temperate</td>
<td>Sandy clay loam</td>
<td>11.50</td>
</tr>
<tr>
<td>10</td>
<td>2482000</td>
<td>Pearl</td>
<td>MS</td>
<td>2341</td>
<td>0.82</td>
<td>Temperate</td>
<td>Clay</td>
<td>5.32</td>
</tr>
<tr>
<td>11</td>
<td>2329000</td>
<td>Ochilocknee</td>
<td>FL</td>
<td>2952</td>
<td>0.87</td>
<td>Temperate</td>
<td>Sandy clay loam</td>
<td>17.6</td>
</tr>
<tr>
<td>12</td>
<td>2296750</td>
<td>Peace</td>
<td>FL</td>
<td>3540</td>
<td>1.08</td>
<td>Temperate</td>
<td>Sand</td>
<td>35.70</td>
</tr>
<tr>
<td>13</td>
<td>8172000</td>
<td>Marcos</td>
<td>TX</td>
<td>2170</td>
<td>1.88</td>
<td>Arid</td>
<td>Clay</td>
<td>0.747</td>
</tr>
<tr>
<td>14</td>
<td>8171000</td>
<td>Blanco</td>
<td>TX</td>
<td>919</td>
<td>1.95</td>
<td>Arid</td>
<td>Clay loam</td>
<td>0.359</td>
</tr>
<tr>
<td>15</td>
<td>8171300</td>
<td>Blanco</td>
<td>TX</td>
<td>1067</td>
<td>1.94</td>
<td>Arid</td>
<td>Bedrock</td>
<td>0.374</td>
</tr>
<tr>
<td>16</td>
<td>8095000</td>
<td>North Bosque</td>
<td>TX</td>
<td>2507</td>
<td>1.97</td>
<td>Arid</td>
<td>Bedrock</td>
<td>2.84</td>
</tr>
<tr>
<td>17</td>
<td>8167500</td>
<td>Guadalupe</td>
<td>TX</td>
<td>3406</td>
<td>2.01</td>
<td>Arid</td>
<td>Bedrock</td>
<td>0.47</td>
</tr>
</tbody>
</table>

### 3.4.1 Uncertainty estimation

In the present work, GLUE methodology (Beven and Binley 1992) has been adopted to carry out the uncertainty estimation of the hydrologic model simulation. It is a widely employed uncertainty method in environmental simulation models (Fraga et al. 2016; Athira and Sudheer 2015; Alazzy et al. 2015; Cibin et al. 2014; Westerberg et al. 2011; Jin et al. 2010; Xiong and O’Connor 2008; Montanari 2005).
3.4.2 Phase-wise model simulation

The model assessment is carried out in two phases. The key difference in the two phases is the likelihood function and its computation. Phase-2 is initiated only when phase-1 is found to be unsatisfactory. In the first step of phase-1, the hydrological model is run with the randomly generated 10000 parameter sets (within the range as specified in Table 3-1). Since the original parameter distribution is unknown, a uniform distribution is assumed a priori. The goodness-of-fit, also termed as likelihood function, is computed between the observed flows and the model simulated flows corresponding to each parameter set.

Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe 1970), which is a widely used measure to judge the performance of hydrological models is used as a likelihood function during the first step. NSE, as presented in Eq. 3-1, is computed by subtracting from unity the sum of squared difference

\[ \text{NSE} = 1 - \frac{\sum (Q_{\text{obs}} - Q_{\text{sim}})^2}{\sum (Q_{\text{obs}} - \bar{Q}_{\text{obs}})^2} \]
between the observed and simulated values normalized by the variance of observed values during the period under investigation.

\[
NSE = 1 - \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}
\]  
Eq. 3-1

Here, \(S_i\) is simulated value by model, \(O_i\) is observed value at time step \(i\), \(\bar{O}\) is the mean of observed values and \(n\) is number of observations.

As the second step in phase-1, the behavioral simulations are further analyzed for their ability to efficiently simulate different flow regimes. Volume efficiency (VE) (Criss and Winston 2008) for different flow zones is used as an evaluation measure as described in the following sub-section in further detail. If the model simulation is not found satisfactory, it is proposed to carry out phase-2 for optimizing the parameter set.

The phase-2 simulation is performed for the poorly performing basins. In the first step, similar to phase-1, the hydrological model is run with the randomly generated parameter but this time with 25000 sets. Subsequently the behavioral simulations are identified based on a modified likelihood function. First the flow is divided into four zones as shown in Fig. 3-3 (the figure is further explained in detail in the next sub-section). Ratio of root-mean-squared-error to the standard deviation of observation, also termed as RSR (Moriasi et al. 2007), is computed as per Eq. 3-2, for each flow-zone and for every simulation.

\[
RSR = \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}
\]  
Eq. 3-2

RSRs for each of the zones are then ranked separately in an ascending order, as lower RSR is indicative of a better model fit. Parameters from each of the zones are intersected and top 25% of the common parameters are considered as behavioral. In this manner the ensemble parameter set is expected to enclose the parameter range that is representative of the overall catchment dynamics. A similar approach of parameter filtering was adopted by Kundu et al. (2016) in their study of model consistency. Their calibration framework involved two stages of parameter filtering based on the metrics of PBIAS and Kling-Gupta efficiency (KGE) (Gupta et al. 2009). Our
approach is different in terms of the flow partitioning, likelihood function and the need for two phases. We propose to partition the flow into four zones with two segments for the larger value flows (exceedance <20%). Further details on flow partitioning are described later. The initial portion of the FDC that presents the distribution of higher flows, describes the dynamic response of the catchment (Westerberg et al. 2011) and are little influenced by the climate seasonality (Yokoo and Sivapalan 2011). Information on the model parameters sensitive to the high flows are contained in this flow zone (Westerberg et al. 2011), which also has a very steep slope. Therefore, by providing an additional partition for the peak flow it is proposed to extract maximum information for the corresponding flow regime. While evaluating the likelihood function, the statistics such as PBIAS, may underestimate the relevance of lower discharge in each of the zones, if no absolute values of deviations are calculated (Pfannerstill et al. 2014b). To prevent this underestimation, RSR is adopted as the likelihood function for parameter filtering.

As a second step of phase-2, the model performance for the behavioral simulations is computed for the various flow zones and also compared with that of phase-1.

### 3.4.3 Model performance evaluation

Once the model parameters are identified in each of the phases, as described above, the performance of the model is further analyzed for its robustness in terms of flow timing and flow volume for different flow zones. Diagnosing the model performance for different flow regimes has been adopted in some recent research studies (Kundu et al. 2016; Pfannerstill et al. 2014a; Yilmaz et al. 2008). Such diagnostic evaluation of the model (Gupta et al. 2008) assists in identifying the poor performing regions of the model. In the current research, FDC is utilized to partition the flow regime into four zones, as presented in **Fig. 3-3**. The peak flows (PF) in a catchment are primarily indicative of the catchment response to the major precipitation events; values upto 1% of flow exceedance are considered in peak flow zone. Apart from the peak events, the catchment is subjected to other high flow events that may have slightly different governing parameters and hence considered separately.
Fig. 3-3 Partitioning of flow based on flow duration curve (FDC) into four zones - peak flow (0 – 1%), high flow (1 – 20%), mid flow (20 – 70%) and low flow (70 – 100%)

High flow (HF) zone encapsulates flows between 1% and 20% exceedance. Lesser in magnitude to the high flow are moderate flows or mid flow (MF) that occur in response to the small rainfall events combined with the baseflow, if any. MF is represented in an FDC as the slope of the curve between 20% and 70% flow exceedance. Low flows (LF) represent the baseflow contribution of the catchment having exceedance greater than 70%. The flows in this range would primarily occur during the dry periods and are governed by relationship between base flow and riparian evapotranspiration (Yilmaz et al. 2008).

The GLUE behavioral simulations, in phase-1, are evaluated for two different metrics on disaggregated flow: (a) Volume efficiency (VE) and (b) FDC flow signature (Shafii and Tolson 2015; Yilmaz et al. 2008). VE represents the fraction of water delivered at the respective time and is computed by Eq. 3-3.

\[
VE = 1 - \frac{\sum_{i=1}^{n} |O_i - S_i|}{\sum_{i=1}^{n} O_i} \quad \text{Eq. 3-3}
\]

VE ranges from 0 to 1, with 1 representing the fraction of volume simulated being equal to the observed value over the same period of time. When VE for each of the zone if found to be greater than zero, the simulation is considered acceptable.

Apart from judging the flow volume at proper time, it is worthwhile to evaluate the distribution of the flow. This is computed as the flow volume under the FDC for peak, high and low flow zones.
Diagnostic evaluation of hydrologic models employing flow duration curve

and as slope of the curve for the mid segment and termed as FDC signatures. Bias between the observed and simulated median value is then computed to judge the model performance. FDC signature bias for flow volume is computed as per Eq. 3-4.

\[
V_{\text{Bias}(i,j)} = \frac{V_{\text{Sim}(i,j)} - V_{\text{obs}(i,j)}}{V_{\text{obs}(i,j)}} \times 100
\]

Eq. 3-4

Here, \( V_{\text{Sim}(i,j)} \) is the simulated volume and \( V_{\text{obs}(i,j)} \) is the observed volume between \( i^{th} \) and \( j^{th} \) flow exceedance and \( V_{\text{Bias}(i,j)} \) is the corresponding bias computed w.r.t observed volume. Slope of FDC is computed between 20% and 70% flow exceedance. It is a common signature adopted by many researchers (Shafii and Tolson 2015; Singh et al. 2014; Yokoo and Sivapalan 2011; Yilmaz et al. 2008). On the basis of aggregated and disaggregated flow statistics, the under-performing zones of the model and also the poorly simulated basins are identified.

The efficiency of ensemble simulation capturing maximum observed discharge is assessed by pFactor and rFactor (Abbaspour et al. 2015). The pFactor measures the observed data bracketed by 95% prediction uncertainty and varies between 0 and 1, whereas the rFactor indicates the thickness of the simulation band. The pFactor of 1 implies 100% enclosing of the observed data by the simulations while a rFactor of 0 indicates a crisp simulation. Abbaspour et al. (2015) recommends a value of p-factor greater than 0.7 and r-factor less than 1.5 for an acceptable streamflow simulation.

3.5 Results and Discussion

Results of the model simulation, uncertainty assessment, computation of signature measures and their association to basin climatic patterns are presented in this section.

3.5.1 Phase-1 simulation

The model was run with 10000 parameter sets; each run produced consequent hydrologic response of the basin subjected to daily precipitation for 15 years. Top 3% of all the simulations for the likelihood function are retained as behavioral during the phase-1 of the analysis. The behavioral sets are presumed to contain the parameters that are equally likely simulator of the system following the equifinality concept (Beven and Freer 2001). The suitability of HYMOD as a representative hydrological model in the present case is established using a quantile-quantile (QQ) plot (Fig. 3-4). The y-axis of the plot represents the quantile of residuals (using median of
behavioral simulation), while the x-axis is the quantile of a standard normal distribution (Jin et al. 2010). **Fig. 3-4** indicates a reasonable model fit for one of the study basins, results being similar for other basins. The QQ plot is used to verify the type of distribution of the residual errors (Datta and Bolisetti 2016).

![Model Residual Quantile vs. Standard Normal Quantile](image)

**Fig. 3-4** Quantiles of model residuals and standard normal quantiles

The model residuals falling on the straight line implies that the residual distribution is also Gaussian with zero mean and constant variance. The empirical Q-Q plot can provide information that cannot be extracted from a lumped metric alone (Kumarasamy and Belmont 2018).

At first the model performance is evaluated for the ensemble of behavioral model simulations. The simulation efficiency in terms of NSE and KGE values of the ensemble median are presented in **Fig. 3-5(a)**. For most of the basins NSE and KGE values are greater than 0.6 which is indicative of a satisfactory model performance. Even though these metrics render a lumped performance evaluation of the simulation, they provide a good estimate of the model performance. As stated earlier, NSE tends to be more biased towards the high flow. The KGE statistic, which decomposes NSE and mean squared error (MSE) into a three-dimensional criteria space and finds a Pareto front in terms of the shortest Euclidean distance (ED) (Gupta et al. 2009), provides a more realistic performance assessment.

**Fig. 3-5(b)** indicates the uncertainty range of the ensemble in terms of pFactor and rFactor. A higher value of pFactor while a smaller value for rFactor is desirable. A balance must be reached between the two as larger pFactor can be achieved at the expense of a larger rFactor (Abbaspour et al. 2015). Relatively high pFactor with low rFactor for most of the basins is representative of a very good simulation.
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**Fig. 3-5** HYMOD model performance during phase-1 simulation; (a) Efficiency factor in terms of NSE and KGE values for median ensemble simulation (b) Uncertainty factor in terms of pFactor and rFactor for ensemble simulation

Along with the statistic for median simulation, the analysis of behavioral ensemble simulation gives a picture of the uncertainty present in the modelling process. **Fig. 3-6** presents the spread of the median flow values for the behavioral ensemble members. Each box plot represents 300 values corresponding to each behavioral set. Even though flow median values are for behavioral parameter sets, several basins also have outliers. This implies that the parameter set found suitable based on a given criterion (NSE in this case), gives the simulated median flow, which does not lie in the inter-quantile range of median flow provided by other behavioral members. Also, it is evident from the plots that the simulation uncertainty is much larger for the wet or humid basins than for the drier basins.

**Fig. 3-6** Simulation uncertainty represented by (a) median and (b) variance of streamflow ensemble generated by GLUE behavioral parameter set over calibration period for the study basins; Triangles indicate the outlier values
A typical time series plot comparing observed data and the ensemble model simulation results corresponding to behavioral sets is presented in the Fig. 3-7. For the sake of clarity, only the last five years of the simulation are plotted. The grey band indicates the 95 percentile uncertainty range of model simulation. The visual inspection of the time-series can provide an initial assessment of the model performance. For most of the flow period, the observed data is enclosed within the 95% prediction uncertainty (PPU) limit of the simulated flow. This was also evident from the higher pFactor value, as discussed earlier.

Fig. 3-7 Comparison between daily observed and simulated streamflow; dashed line indicates the observed flow and shaded ribbon indicates the 95% prediction uncertainty (PPU)

3.5.2 Flow duration curves

For each of the studied basins, FDC of the observed data as well as the upper and lower bound values resulting from numerous behavioral simulations have been plotted (discharge in log base 10 scale). FDCs for some of the study basins are presented in Fig. 3-8. From the plots it is apparent that the observed range of flow is bounded by the estimated uncertainty for the entire range of flow for most of the basins, except in some cases where the extreme low flows are projecting away from the uncertainty band. Since FDC characterizes the distribution of streamflow probabilities (Sawicz et al. 2011), the presented plots also indicate how the modeling uncertainty is distributed along different flow regimes. Westerberg et al. (2011) have also presented the uncertainty bounds for FDC in GLUE framework.
In order to estimate this uncertainty, the relative interval lengths (RIL) at various flow exceedances for the simulated model values are computed and presented in Fig. 3-9. RIL primarily quantifies the parameter uncertainty in the modeling and computes the spread of the simulated streamflow w.r.t. its median value. It is similar to the average relative interval length (Jin et al. 2010), but here the relative interval corresponding to various flow exceedances is computed. A similar measure for the low flow simulation was adopted by Demirel et al. (2013) which was termed as the relative confidence interval. As seen from Fig. 3-9, the RIL value increases from high flow towards lower magnitude flows, implying the parameter uncertainty also follows that order. This plot assists in comprehending which flow zone has a large simulation uncertainty. Westerberg et al. (2011) also reports large uncertainties in low flows than in high flows in their study.
Diagnostic evaluation of hydrologic models employing flow duration curve

3.5.3 Model diagnostic assessment

It has been reported in the literature that the aggregate measure of model fit hampers the evaluation of a model in terms of consistency and process representation (Shafii and Tolson 2015; Wagener 2003). Considering the diagnostic model approach (Gupta et al. 2008), it is worthwhile to evaluate the model performance for different flow regimes. In the model assessment employing FDC signature as an evaluation metric, there is a potential caution for the modeller. Although FDC presents a key signature of runoff variability, the FDC does not contain information on the timing of the flow (Ley et al. 2015). Hence, when FDC is employed as an additional measure of assessment it would be a more powerful tool for model evaluation which is one of the objectives of the present research. To this end, the volume efficiency (VE) of various flow segments and the FDC signatures are computed, as described earlier in the methodology section. The volume efficiency is indicative of the fraction of water delivered at proper time (Criss and Winston 2008) whereas FDC signature computes the volume of water under the FDC segment. As depicted in Fig. 3-10 (a) and (b), the ability of the model to simulate the volume during the peak and high flow periods is found to be good and for majority of the basins, high flow is better represented than the peak flow. Mid flow performance progressively declines from humid basins towards arid basins. The model output in terms of low flow volumetric simulation is acceptable only for the humid basins, while for arid basins it is very poor.
Coxon et al. (2014) in their study also concluded that the catchment characteristics had an impact on a given model performance; based on their analysis of 24 catchments across the climate gradient it was also found that the wet catchments performed well, while the drier catchments had poor model performances.

The spread in the median FDC signature bias for all the basins under study are presented in Fig. 3-11. It is evident that there is a considerable variability in the various bias measures amongst the study basins. The range of bias for the four flow segments, indicate the varied response of the model to the precipitation input in the respective segment. Since an FDC summarizes a catchment's ability to produce flow values of different magnitudes, the plot assists in identifying
at which part of the hydrograph these biases occur. The biases in the high flows, $V_{PF}$, have the least variability while that in low flow zone has the highest. Ley et al. (2015) also reported similar behavior for the high flow zone. Basin-16 is found to be mostly in the extreme range for each of the signature bias values indicating a poor model simulation.

![Fig. 3-11 Spread of FDC signature bias computed between model median FDC and observation FDC during phase-1. VPF-peak flow signature, VHF-high flow signature, SMS-mid segment slope and VLF-low flow signature. Basins with extreme bias values are marked.](image)

3.5.4 Phase-2 simulation

In an attempt to improve the model simulation for arid basins, phase-2 of the simulation is undertaken. Phase-2 simulation involves the estimation of parameters independent of Phase-1 and it is initiated only when phase-1 simulation fails to provide the expected results. The HYMOD is simulated under the GLUE framework and the RSR value is computed between observed and simulated flows at respective time steps for each of the flow zones. Subsequent to the ranking, well performing common parameters are intersected and top 25% of the parameter sets are retained. Number of parameter sets retained for the five arid basins under study, range from 0.4% to 1.2% of the initial simulation of 25000 for the phase-2. In the present study, phase-2 was attempted only for the arid basins since the performance of the model for basins in other climatic regions was mostly satisfactory.

Behavioral simulation results of phase-2 are compared with those of phase-1 for some of the metrics and are presented in Fig. 3-12. Comparison of the aggregate time-series statistics in terms of NSE, pFactor and RSR is presented in Fig. 3-12(a), (b) and (c), respectively. The last sub-plot in the figure presents the percentage change in the volume efficiency for the various flow zones,
between the two assessment phases. Since phase-2 was carried out for arid basins only, the plot compares the result for these basins. While a marginal improvement of about 6% in the aggregated flow statistics in terms of NSE and the pFactor is observed, the model performance shows a varied level of enhancement for different zones of the flow. With respect to flow volume and flow timing error, each of the zones has performed better than the earlier phase.

![Comparison between phase-1 and phase-2 simulations for various model performance metrics for arid basins. (a) NSE (b) pFactor (c) Low flow RSR and (d) percentage improvement in volume efficiency (VE) from (phase-1 to phase-2) in different flow zones for the arid basins](image)

**Fig. 3-12** Comparison between phase-1 and phase-2 simulations for various model performance metrics for arid basins. (a) NSE (b) pFactor (c) Low flow RSR and (d) percentage improvement in volume efficiency (VE) from (phase-1 to phase2) in different flow zones for the arid basins

Average flow volume for all the basins, computed by VE, was improved by 32% among various flow zones, while the maximum improvement was measured for the low flows. In terms of flow timing measured in RSR, the low flows in phase-2 has done better by about 24% when compared to phase-1. The low flows percentage-change may present an exaggerated picture but in terms of absolute change also, two out of five arid basins have shown marked improvement. For Basin-15 VE has changed from -2.6 in phase-1 to -2.0 in phase-2, while for Basin-16 it has sharply improved from -14.8 to -0.8.
In phase-2 of simulations the biases in the FDC signature have also shown improvement as evident from Fig. 3-13. For all the flow signatures, the spread of the biases is reduced and is closer towards the zero bias line in phase-2 in comparison to phase-1. Lower bias in the FDC implies closer match between the observed and simulated FDC representing an improved distributional response of the flow regime, leading to better model consistency and reduced uncertainty in the predictions. Thus, it has been shown that the model performance improved from phase-1 to phase-2 in terms of various metrics. Even though phase-2 simulation enhances the calibration results, it is computationally more intensive than the conventional calibration. Therefore, as of now, it is applied only to the under-performing catchments.

Fig. 3-13 Comparison between phase-1 and phase-2 FDC signature bias for arid basins. VPF-peak flow signature, VHF-high flow signature, SMS-mid segment slope and VLF-low flow signature

3.5.5 Modeling correlation with hydro-climatic features

Considering a significant variability in the model simulation amongst the basins, there arises a need to correlate the simulation results with the basin hydro-climatic features (Yokoo and Sivapalan 2011). Based on the average monthly data during the calibration period, the study basins are classified into three categories in accordance with the scheme proposed by Coopersmith et al. (2012) as provided earlier in Table 3-2. The basin wetness is computed based on the ratio of annual average potential evapotranspiration (PET) and precipitation (P) computed over the calibration period. The same factor is referred to as dryness index by Yokoo and Sivapalan, (2011). In the present study the PET/P value for arid basins fall in a close range of 1.88 to 2.01, so we propose to call all of them as ‘Arid’ instead of ‘Somewhat Arid’ (as per Coopersmith et al. (2012)) for values less than 2.0. Average monthly precipitation and PET of all the basins are
presented in Fig. 3-14. Humid basins have almost evenly distributed precipitation pattern all through the year (subplot-a) with highest in winter and lowest in autumn. Temperate basins have uneven precipitation pattern (subplot-b). While the arid basins also have an uneven pattern across the year but its similar for the basins. The annual average for arid basins is lower as compared two other two groups (Fig. 3-14c).

Fig. 3-14 Variation of average monthly precipitation for (a) humid basins, (b) temperate basins, (c) arid basins; (d) PET in all the study basins – upper band indicates range of PET in arid basins and lower band indicates range of PET in humid and temperate basins - during the calibration period

PET for all the basins have a similar distribution pattern across the year, but arid basins have significantly larger PET during the second half of the year, as compared to humid and temperate basins. The dynamic response of the basin which is represented by the first segment of FDC (having flow exceedance < 1%), is primarily controlled by intensity of precipitation, infiltration characteristics and would be little influenced by climatic seasonality (Yokoo and Sivapalan 2011). This is also reflected from the results in Fig. 3-10, where PF is less variable among the study basins.
which have diverse aridity levels and variable precipitation patterns across seasons (Fig. 3-14). The steeper mid-segment slope of the FDC for the basins having lower PET/P value (Fig. 3-8), an evenly distributed rainfall pattern (Fig. 3-14) and precipitation-PET being out of phase (Yokoo and Sivapalan 2011) can be attributed to their humid basin categorization. Low flow simulation has a significant variance among the basins of different hydro-climatic regions. The discharge during the low flow periods is primarily governed by the baseflow. It is mostly found to be underperforming for all the arid basins and most of the temperate basins. For temperate basins, the higher simulation of low flow discharges can be associated with the in-phase of precipitation and PET.

There is an evident pattern of streamflow generation linked to the basin climate features. Thus association of model simulation with catchment’s hydro-climatic characteristics seems identifiable (Coxon et al. 2014; Yokoo and Sivapalan 2011).

3.6 Conclusions

Hydrologic models have become vital tools for carrying out various assessments pertaining to water resources and the reliability of these model predictions is of paramount importance. The present research identified the need for improved diagnostic assessment approaches for hydrological models. It was demonstrated that the model diagnostic analysis was crucial to avoid the misjudgments in model simulation. Evaluating the model performance only on the basis of conventional aggregated metrics approach may lead to erroneous conclusions about the model performance. The major contribution of the present study is a model calibration and diagnostic assessment framework where the conventional statistical model evaluation statistics are coupled with hydrological process signatures to achieve improved model performance.

The framework consists of a two-phase process of model evaluation. In the first phase, the model simulations were carried out within the GLUE framework. Behavioral simulations filtered based on widely adopted likelihood measure of NSE, were further diagnosed with the help of flow duration curves (FDC) as a model investigative tool. The flow regime was divided into four zones through the partitioning of the FDC. Volumetric efficiency for individual flow zones was the criteria adopted for diagnostic evaluation. Subsequent to model deficiency diagnosis, the underperforming catchments were forced with the second phase of simulation. RSR was adopted as the likelihood function and was computed for each of the four flow zones, based on the FDC
partitioning. The final set of behavioral parameters was collected by intersecting the well performing parameters from the four different flow zones.

The above methodology was employed to investigate the conceptual rainfall-runoff model HYMOD within the GLUE framework for 17 basins that are part of the MOPEX dataset, located in the southern United States. It has been demonstrated that the model which appears to perform at a reasonably acceptable level based on the aggregate simulation metrics, is found to underperform during further investigations. The first phase diagnostic assessment enabled better model performance as the improvements in simulation were reported in second phase for the under-performing catchments. The two-phase model assessment assisted in improving the model performance by 6% in terms of NSE for overall flow time-series, 32% in terms of average volume efficiency and 24% in terms of RSR for the low flows. Thus, the partitioning of flow employing an FDC, assisted in properly diagnosing the model simulation. Flow signatures computed on the basis of this flow partitioning facilitated the evaluation of hydrologic model performance through the flow distributional response; at the same time this partitioning assisted in evaluating the model consistency in terms of volume delivered taking into account the flow timing. Therefore, more realistic simulation of the conceptual hydrologic model for the study basins has been achieved on the basis of both the hard as well as soft data. Moreover, the current method of assessment can also be extended to other hydrologic simulation models for better prediction.

On the basis of analysis of various catchments lying in different climatic regions, it was evident that the same model structure generates varied response for different flow regimes. Humid and temperate basins demonstrated a satisfactory performance in phase-1 while arid basins were under-performing for mid flow and mostly for the low flows. Thus an association of model simulation and hydro-climatic condition was also established.

In the present work, the likelihood measure as in phase-2 is a new contribution that leads to an improved simulation. Also, the work brings forth the value of model diagnostic assessment. Therefore, the methodology presented in this research will lead to strengthening of the scientific basis for model development and evaluation. As part of future work, the strength of the studied flow signatures can be utilized in a multi-objective model calibration framework that would assist in developing a better calibrated model with enhanced predictive ability.
Chapter 3
Diagnostic evaluation of hydrologic models employing flow duration curve

3.7 Acknowledgements

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Diagnostic evaluation of hydrologic models employing flow duration curve

3.8 References


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Chapter 4
Multi-objective auto calibration of SWAT model for improved low flow performance for a small snowfed catchment

CHAPTER 4 MULTI-OBJECTIVE AUTO CALIBRATION OF SWAT MODEL FOR IMPROVED LOW FLOW PERFORMANCE FOR A SMALL SNOWFED CATCHMENT

4.1 Chapter Synopsis
A reliable modelling framework needs to ensure that the model is simulating the reality with limited uncertainty, thus enhancing its predictive ability. In literature, the hydrologic model assessment using one or more metrics is reported to be inadequate when the river flow regime is required to be reproduced comprehensively. The present research is carried out to: (a) calibrate the Soil and Water Assessment Tool (SWAT) based on the concept of multi-objective optimization by applying Borg multi-objective evolutionary algorithm (MOEA) (b) apply hydrological signatures as objective functions, and (c) adopt a multi-metric approach for model evaluation. SWAT model has been coupled with a relatively newer and powerful Borg MOEA. The inclusion of hydrological signatures as objective functions along with the conventional statistical functions assisted in improving the performance for low flows by 135% in terms of volume efficiency and 65% for flow time series simulation.

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3 This chapter was published as a journal article: Chilkoti, V., Bolisetti, T., and Balachandar, R. (2018). “Multi-objective auto calibration of SWAT model for improved low flow performance for a small snowfed catchment.” *Hydrological Sciences Journal*, 63(10), 1482–1501
4.2 Introduction

Hydrologic models are increasingly being used to assess the effects of anthropogenic alterations viz., land use and climate change on water quality and quantity (Thirel et al. 2015). With the growing scientific effort on the assessment of these changes for the future scenarios, it is imperative to generate well calibrated models in order to reduce the uncertainty of future prediction (Peel and Bloschl 2011). A good model calibration is always the backbone of a satisfactory scientific outcome. Conceptual hydrologic models with few parameters are generally not very complicated to calibrate. But with growing model complexity the process of calibration becomes more complicated.

Soil and Water Assessment Tool (SWAT) (Arnold et al. 1998), a widely adopted watershed simulation model attempts to simulate the runoff generation process in detail and also includes options for management practices. The model has dozens of parameters to be calibrated for achieving a satisfactory simulation (Cibin et al. 2010). Different approaches to SWAT model calibration are detailed in the literature (Abbaspour et al. 2007a; Arnold et al. 2012; Moriasi et al. 2007; Van Liew et al. 2005). Most of the studies relied on single objective function by optimization of error statistics, such as Nash-Sutcliffe efficiency (NSE). The major drawbacks of an approach involving a single objective function as goodness-of-fit are: (a) a single measure is applied to judge the simulation performance (Pfannerstill et al. 2014b; Wagener 2003) (b) squared errors are frequently used but they have been shown to be biased towards the high flow (Shafii and Smedt 2009), (c) one objective function may not be adequate to incorporate the effect of several parameters under calibration, especially for complex models (Madsen 2000). In order to overcome these deficiencies of single objective calibration, evolutionary based multi-objective optimization (Coello et al. 2007) of hydrologic models has been in practice for the past two decades (Reed et al. 2013). Multi-objective optimization is applied in various fields of engineering and sciences (Reed et al. 2013; Zhou et al. 2011) and has gained a wide popularity in the water resources applications especially for hydrologic simulations. Efstratiadis and Koutsoyiannis (2010) summarises various case studies pertaining to multi-objective applications in hydrology.

In an effort to improve model calibration hydrologic signatures as objective functions have gained attention in the past decade (Asadzadeh et al. 2015; Pfannerstill et al. 2014a; Pokhrel et al. 2012; van Werkhoven et al. 2009). Hydrologic signatures provide insights into the functional behaviour
of the catchment (Sawicz et al. 2011) and thus attempt to extract maximum information from the available data (Reusser and Zehe 2011; Wagener and Montanari 2011). Initially the signatures were employed to better estimate the catchment response (Farmer et al. 2003), then for model evaluation (Hrachowitz et al. 2014; Pfannerstill et al. 2014a; Pokhrel et al. 2012; Yilmaz et al. 2008) and lately as objectives in model calibration (Asadzadeh et al. 2015; Shafii and Tolson 2015; van Werkhoven et al. 2009). Inclusion of hydrologic signature as objectives assists in constraining the model basing on hydrological features (Haas et al. 2016). Therefore, in the present study two hydrologic signatures have been adopted to formulate additional objectives, together with statistical objectives, to assist model calibration.

With large number of parameters to adjust and more than one objective to satisfy, the automatic model calibration has gained preference over manual calibration. Van Liew et al. (2005) presents the pros and cons of the automatic calibration procedure. Among the various approaches for automatic calibration, evolutionary algorithms have been proved to be more efficient in reaching satisfactory solutions (Shafii and Smedt 2009). Yapo et al. (1998) carried out one of the first research studies applying genetic algorithm for calibration of a conceptual hydrologic model. Since then there have been several attempts by various researchers to continue the work on multi-objective evolutionary algorithms (MOEA) (Gupta et al. 1998; Kollat and Reed 2006; Madsen 2000; Seibert 2000; Vrugt et al. 2003). Most of these studies involve the conceptual hydrologic models. There have been a limited number of case studies of MOEA application to SWAT model for achieving calibration (Bekele and Nicklow 2007; Confesor and Whittaker 2007; Rouhani et al. 2007; Zhang et al. 2011; Haas et al. 2016). It can be primarily attributed to the model complexity (Tang et al. 2006) and the large number of parameters involved in the calibration process. Ercan and Goodall (2016) attempted to perform multi-objective calibration of SWAT using NSGA-II through an R programming interface. Moreover, there are still limited case studies that involve hydrologic signatures as objectives. Asadzadeh et al. (2015) carried out SWAT calibration for a southern Ontario catchment using Pareto Archived Dynamically Dimensioned Search (PA-DDS) algorithm with three objective functions, one of them being derived from hydrologic signature. Pfannerstill et al. (2014a) presented a multi-metric evaluation framework incorporating signature measures to evaluate SWAT model performance of different hydrograph segments.
In the above cited multi-objective studies carried out for the SWAT model calibration, the authors have used one or two sets of objective combinations. Some of them include, (i) Root mean square error (RMSE) and log-RMSE (Bekele and Nicklow 2007), (ii) RMSE (low flow) and RMSE (peak flow) (Confesor and Whittaker 2007; Rouhani et al. 2007), (iii) water balance, Nash-Sutcliffe Efficiency (NSE) and flow duration curve (FDC) statistics (Asadzadeh et al. 2015). Zhang et al. (2010) used two combinations of objectives, (i) NSE (surface flow) and NSE (baseflow) and (ii) NSE (surface flow) and NSE (all) for comparing various multi-objective algorithms. Since the model simulations are affected by the choice of objective functions (Abbaspour et al. 2007b; Rajib et al. 2016), the suitable combination of objectives plays an important role in model calibration. Understanding the effect of combination of different evaluation objectives is the goal of the present study.

Moreover, for better representation of various watershed processes the parameters affecting the runoff generation process need to be identified (Cibin et al. 2010) and incorporated in the calibration process. For snowfed catchments, the snowmelt parameters also need to be adjusted. Efstratiadis and Koutsoyiannis (2010) suggest at least one objective function for every 5 to 6 parameters in the calibration. With the increasing number of objectives, the number of Pareto non-dominated solutions generated by the evolutionary algorithms become very large, leading to “dominance resistance” (Purshouse and Fleming 2007). Dominance resistance, which hampers the performance of the MOEA, refers to the difficulties in producing new candidate solutions that will dominate poorly performing, yet locally non-dominated, current solutions. Shafii and Tolson (2015) in their study involving 15 objectives have also highlighted this issue and same was the reason for converting the continuous objectives to binary objectives in their study. In order to overcome the problem of dominance resistance Hadka and Reed (2013) have proposed to use the Borg algorithm that incorporates the epsilon dominance concept and thus optimally separate the non-dominated solutions. Borg is a powerful algorithm that includes various features of evolutionary algorithm with some new concepts. Eckart (2015) had adopted Borg algorithm for optimization of low impact development using SWMM package. Computational strength of the algorithm was demonstrated in urban water planning where it was efficiently used for parallel computing (Reed and Hadka 2014). As per the knowledge of authors there are no case studies in the literature that couple SWAT with the Borg algorithm for model calibration.
The objectives of the present research are to (a) calibrate the SWAT model based on the concept of multi-objective optimization by applying Borg multi-objective evolutionary algorithm (MOEA) (b) apply hydrological signatures as objective functions, and (c) adopt a multi-metric approach for model evaluation. A SWAT model for a snowfed southern Ontario catchment is developed and calibrated based on four different combinations of objective functions from NSE, LogNSE, percent bias (PBIAS), ratio of the root mean square error to the standard deviation of measured data (RSR) for low flow, runoff coefficient (RoC) and FDC based flow signature. It is shown that incorporation of signature based metrics in the objective function improves the overall simulation performance.

4.3 Study Area

The upper reaches of the Saugeen River located in south eastern Ontario has been modeled using SWAT in the present research. Fig. 4-1 presents the map of the catchment. In the upstream portion of the catchment the river is flowing from north-eastern direction towards south western and in the downstream parts of the catchment the flow is mainly towards the western direction.

4.3.1 Physical characteristics

The total basin area at the considered outlet is 312 km$^2$ and the length of the main stream is about 71 km. The catchment elevation varies from 356 m to 540 m at the outlet. Catchment morphology is captured by using the 10 m digital elevation models (DEM) acquired from Environment Canada.

![Map of the Saugeen River catchment](image)
Chapter 4

Multi-objective auto calibration of SWAT model for improved low flow performance for a small snowfed catchment

The landuse data for the study area has been extracted from Southern Ontario Land Resource Information System (SOLRIS) which is a landscape-level inventory of natural, rural and urban areas for southern Ontario; version 2.0 of the dataset has been used in the current work (Fig. 4-5). The primary landuse is agriculture which constitutes 60% of the total catchment area followed by wetland which covers 30% of the area. The soil database has been prepared utilising the available dataset (SLC Working Group 2010) which is part of National Soil Database (NSDB) of Canadian Soil Information System (CanSIS). The dataset contains detailed information about the agricultural soils of Canada at a scale of 1 in 1 million. The dataset has been adopted in some of the earlier studies also (Asadzadeh et al. 2015; Shrestha et al. 2012). Latest version of the data, v3.2, has been used to develop the database compatible to SWAT model. Within the present study area 19 soil types were identified with loam and silt loam being the major soil types.

4.3.2 Climatic characteristics

Meteorological data are obtained from three monitoring stations located within the catchment (Fig. 4-1) and maintained by Environment Canada. Details of the stations used in the study are given in Table 4-1.

<table>
<thead>
<tr>
<th>Station</th>
<th>Long (°W)</th>
<th>Lat (°N)</th>
<th>Elev (m)</th>
<th>Data Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Porton Station</td>
<td>80.52</td>
<td>44.17</td>
<td>480</td>
<td>1970-2002</td>
</tr>
<tr>
<td>Priceville</td>
<td>80.64</td>
<td>44.20</td>
<td>472</td>
<td>1980-2014</td>
</tr>
<tr>
<td>Durham</td>
<td>80.82</td>
<td>44.18</td>
<td>384</td>
<td>1970-2003</td>
</tr>
</tbody>
</table>

The annual average precipitation and flow per unit area over the catchment are 1050 mm and 450 mm, respectively. During the winter period precipitation is primarily in the form of snow. The annual variation of precipitation and flow depth is depicted in Fig. 4-2(a). The maximum temperature in the Saugeen watershed ranges from -4.2°C in winters to 23.5°C in summer whereas the minimum temperature ranges from -13.3°C to 12.1°C (Fig. 4-2b). July is the warmest month, February the coldest and minimum temperature remains sub-zero for almost half of the year.
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4.3.3 Hydrological regime

The daily observed flow data at Environment Canada flow station No 02FC016 located upstream of Durham is available from 1976 to 1998 and from 2005 to 2015. The flow in the river varies from an extreme low flow of 0.2 m$^3$/s to 115 m$^3$/s with a mean of 4.5 m$^3$/s. The analysis of the observed flow data during the study period indicated that high flows occur during the spring season primarily due to the snowmelt. Every year the peak flow is found to exceed 30 m$^3$/s which corresponds to 1% exceedence probability of the observed flows. Summer season is typically the low flow period for the river. Daily time series of observed flow and flow duration curve of daily flows are presented in Fig. 4-3.

Fig. 4-2 Climatic and flow variation (a) Total annual precipitation (bars) and flow depth at watershed outlet (line); (b) monthly average minimum and maximum temperature

Fig. 4-3 (a) Daily observed flow and (b) the flow duration curve (FDC) of the observed flow
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The average monthly time-series of precipitation, flow and evapotranspiration (ET) in the watershed are analysed to assess hydrologic trend in the watershed, as depicted in Fig. 4-4. The precipitation has lower seasonal variability as compared to other two variables. ET follows a normal distribution peaking up during the summer while the flow has a bi-modal distribution. The snow accumulated during the winter season starts melting in spring period causing high discharges in the river. As also evident from Fig. 4-3(a), the river attains the peak discharge annually during the spring period. Snowmelt makes the depth of streamflow during this period (March and April) in excess of precipitation, as seen in Fig. 4-4, allowing the runoff coefficient to exceed one. Summer period has relatively lower precipitation and high evapotranspiration (ET); in fact the ET is higher than the precipitation for May-August months. As the watershed has predominantly agriculture land use, the available precipitation is utilized to fulfil the crop evapotranspiration demands. Therefore, the river discharge during summer period is principally due to the baseflow contribution. The annual average baseflow contribution is close to half of the total streamflow as computed using the baseflow separation programme (Arnold and Allen 1999). ET starts to decrease with the falling temperatures during the autumn period and thus the river flow during this period is primarily precipitation driven. Accordingly, the increase in average discharge during November is in sync with the incremental precipitation during the corresponding period.

![Fig. 4-4 Average monthly precipitation, evapotranspiration and flow for Saugeen River during the study period](image-url)
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Multi-objective auto calibration of SWAT model for improved low flow performance for a small snowfed catchment

4.4 Methodology

4.4.1 Soil and Water Assessment Tool

The Soil and Water Assessment Tool (SWAT version 2012 – revision 627) (Arnold et al. 1998) was employed in the present study to simulate the hydrology of the watershed. SWAT is one of the most widely adopted semi-distributed models to estimate runoff, sediment yield and nutrient load at sub-watershed level as a continuous watershed scale simulation model that operates on daily and sub-daily time steps. SWAT model has been extensively used for water quantity as well as quality assessment for numerous watersheds across the globe. The extensive popularity of the model is primarily attributed to its comprehensive nature, strong web based model support, and open access status of the source code (Gassman et al. 2014).

SWAT model for Saugeen River was created based on standard model setup protocol with watershed delineation being the primary step. In the study reach, the catchment was divided into 21 sub-watersheds ranging from 92 ha to 4684 ha with a median of 1179 ha; the number and size of sub-watersheds being a function of stream network distribution. The provided inputs of soil, landuse and slopes, as described in previous section, were reclassified to match the SWAT database requirement. Nineteen soil types, ten landuse classifications and two slope classes within the watershed were identified and intersected by the SWAT model to further delineate the sub-watersheds into hydrological response units (HRUs). Representing a unique soil, landuse and slope characteristics of the watershed, HRUs are the fundamental modelling units within SWAT model that have uniform hydrologic response. There are 337 such HRUs identified within the Saugeen River watershed model. HRU overlay was performed with a 10% threshold for land covers and soil types in the SWAT HRU distribution. Watershed topography, soil and landuse as part of model setup are presented in Fig. 4-5.

As part of the climate data requirement, daily precipitation and temperature data for the model simulations were provided for the stations listed in Table 4-1, whereas the other climate data for wind velocity, solar radiation and relative humidity were estimated using the weather generator routine within SWAT model. Based on the overlapping period of precipitation data and flow data record, it was decided to consider 1985 to 1997 as the analysis period for the model. For model simulation 1987 to 1993 is taken as calibration and 1994 to 1997 as model validation period with initial 2 years as warm up period.
In the SWAT model, snowmelt is included with rainfall in the calculation of infiltration and runoff. The model uses a temperature-index approach to estimate snow accumulation and melt. Snowmelt is calculated as a linear function of the difference between average snowpack maximum temperature and threshold temperature for snowmelt. SWAT does not include an explicit module to handle snowmelt processes in the frozen soil, but includes a provision for adjusting infiltration and estimating runoff when the soil is frozen (Neitsch et al. 2011).

Fig. 4-5 Saugeen River watershed (a) at Environment Canada flow station 02FC016; (b) SWAT model soil layer and (c) land use
4.4.2 Multi-Objective Evolutionary Algorithm (MOEA)

A multi-objective problem is generally formulated as:

\[
\text{Minimize } F(x) = (f_1(x), f_2(x), \ldots, f_p(x)) \quad x \in S \quad \text{Eq. 4-1a}
\]

subject to \( c_i(x) = 0, \ \forall \ i \in \varnothing \) \quad \text{Eq. 4-1b}

\( c_j(x) \leq 0, \ \forall \ j \in \varphi \) \quad \text{Eq. 4-1c}

where, \( f(x) \) is the objective function to be minimized, \( x \) is the set of decision variables, \( S \) is the decision space, \( c_i \) and \( c_j \) are the constraints within set \( \varnothing \) and \( \varphi \) (Deb 2001).

Many MOEAs have been applied for calibrating hydrologic models, including NSGA-II (Bekele and Nicklow 2007; van Werkhoven et al. 2009; Zhang et al. 2010; Ercan and Goodall 2016), AMALGAM (Shafii and Tolson 2015; Zhang et al. 2010, 2011), SCEM-UA (Datta and Bolisetti 2013; Vrugt et al. 2003), PA-DDS (Asadzadeh et al. 2015), etc. In the present research Borg multi-objective algorithm (Hadka and Reed 2013) is adopted to constrain the objectives and arrive at a suitable calibration of SWAT hydrologic model. Borg belongs to the class of evolutionary algorithms that evolve solution on the basis of genetic operators leading to an optimal Pareto solution set. Borg incorporates design principles from other MOEAs with several new characteristics (Hadka and Reed 2013) that include: (a) \( \epsilon \)-box dominance archive (b) \( \epsilon \)-progress (c) an adaptive population sizing operator (d) multiple recombination operators, and (e) elitist model of \( \epsilon \)-MOEA. Hadka and Reed (2013, 2012) may be referred for further details.

In the evolutionary process new solutions are generated from two parent solutions. One of the parent solutions is taken from the elite archive and the other parent is chosen from the population via tournament selection, which provides selection pressure by holding a competition among individuals from the population. The winner of the tournament is the one with the highest fitness which is measured by the objective function (Sivanandam and Deepa 2008). In Borg MOEA, it would be determined by dominance. If a solution in the competition dominates the other it moves on, if they are both non-dominated then one will be selected at random. Borg uses adaptive tournament sizing to maintain selection pressure. By changing the tournament size as the population grows, the chance that a non-dominated solution from the population will be selected to participate in the tournament will not drop as it otherwise would (Hadka and Reed, 2013). Once the parent solutions are determined their genes are combined to form a new solution. There are
six operators which can be used to recombine the parent genes to create a new solution. Over the course of the run the probability of any recombination operator being selected is updated based on how many solutions created using each operator have been added to the elite archive (Hadka and Reed, 2013). Tested against six state-of-the-art MOEAs on several test problems, Borg met or exceeded the performance of the other MOEAs on most of the tests (Hadka and Reed 2012).

4.4.3 Coupling of Borg with SWAT

In the present research Borg is coupled with SWAT hydrologic model through an R computation interface (*R*: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria, 2011; http://www.R-project.org/ R Development Core Team) as depicted in Fig. 4-6. The parameters generated by Borg are passed on to the SWAT_Edit executable programme (Abbaspour et al. 2007a) which then edits the required SWAT input files. Subsequently the SWAT is executed to simulate the model representing the new parameter set.

![Fig. 4-6 Borg-SWAT coupling framework](image)
The objective function evaluation is done between the observed streamflow and recently simulated flow at a given model node point that coincides with the stream gauge location. The objective function evaluation is sent back to the Borg program which then generates the new parameter set by suitable recombination between the initial population and the archive set. The resulting offsprings are evaluated and considered for inclusion in population and archive. \( \varepsilon \)-dominance criteria is adopted for suitability of including the offspring in the archive set. The Borg-SWAT MOEA is outlined in Fig. 4-7. The programming of the coupling as carried out in ‘R’ language is presented in Annexure-1.

Fig. 4-7 Borg-SWAT MOEA optimization framework; * P/A is population to archive ratio
4.4.4 Multi-metric evaluation

The model assessment is generally carried out on the basis of one or more statistical metrics computed on the aggregated streamflow statistics. Moriasi et al. (2007) presents the commonly used likelihood measures between observed and simulated streamflow and provide the quantification for varied levels of model calibration. While evaluating the model performance consisting of wide range of flow, any specific process inaptly simulated by the model, for example the low flow resulting from groundwater discharge, may be concealed in the cumulative value of the evaluation criteria. Therefore for a diagnostic model analysis (Gupta et al. 2008) it is imperative to take into account the evaluation criteria computed on aggregated as well as disaggregated flows (Shafii and Tolson 2015).

This would additionally ensure the model consistency and enhance the assessment through the multi-objective approach. The statistical metrics enumerate the properties of model residuals that may or may not indicate the model efficiency based on a hydrological perspective (Pfannerstill et al. 2014a; van Werkhoven et al. 2009). In order to overcome this Yilmaz et al. (2008) suggested various signature metrics to account for the relevant diagnostic information present in the data. Therefore, in our present research various objective functions consisting of both statistical as well as hydrological signatures (as listed in Table 4-2) are combined for calibrating the model and subsequently the model evaluation is carried out on multiple metrics.

Table 4-2: Objective functions adopted in the multi-objective analysis; 'C' refers to combination; C0 is not multi-objective but considered as a base simulation run

<table>
<thead>
<tr>
<th>Combination No</th>
<th>Objective Functions</th>
</tr>
</thead>
<tbody>
<tr>
<td>C0</td>
<td>Sufi2 (SWAT-CUP)</td>
</tr>
<tr>
<td>C1</td>
<td>NSE, PBIAS</td>
</tr>
<tr>
<td>C2</td>
<td>NSE, NSE(Log)</td>
</tr>
<tr>
<td>C3</td>
<td>NSE, RSRIlow, FDCsign</td>
</tr>
<tr>
<td>C4</td>
<td>NSE, RSRIlow, RoC</td>
</tr>
</tbody>
</table>
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Multi-objective auto calibration of SWAT model for improved low flow performance for a small snowfed catchment

4.4.5 Measures used for calibration

Multi-objective calibration is adopted to optimize the model parameter set. Combinations of various objectives listed in Table 4-2 are tested to arrive at a suitable model parameter set whose response matches closely the observed streamflow response. At the outset the model is simulated using the Sufi2 in SWAT-CUP (Abbaspour et al. 2007a) which is most widely used for SWAT model calibration and uncertainty assessment. Although SWAT-CUP includes various objective functions, the simulation runs are not strictly multi-objective as the user needs to select one likelihood measure for evaluation (Ercan and Goodall 2016). Considering this run as a base simulation, the multi-objective evaluations are then compared. In the proposed combinations, first two objective sets involve only the statistical criteria and in other two hydrologic signatures are also included. Each of the objectives is defined in Table 4-3.

4.4.6 Measures used for evaluation

Subsequent to multi-objective calibration, the assessment of model performance is carried out based on various statistical criteria apart from the objective functions used. By this way the diagnostic assessment (Gupta et al. 2008) of the model is conducted to identify the poor performance of the model for any specific part of hydrograph (Pfannerstill et al. 2014a; Pokhrel et al. 2012). Multi-criteria evaluation is adopted to minimize the model inconsistency due to various levels of model response (Kundu et al. 2016; Singh et al. 2016; Pfannerstill et al. 2014a; Pokhrel et al. 2012). Also, the high dimensionality in the flow time-series is bound to mask the poor performing model phase when evaluated on the aggregated flow statistics.

A better approach may be to disaggregate the various components of a streamflow hydrograph like low flow, peak flow, etc., and analyse them separately (Chilkoti et al. 2019). Disaggregated model evaluation would assist in attaining model consistency across varied flow signals (Kundu et al. 2016). In the present research the disaggregation is achieved by partitioning the period of record flow duration curve (FDC) into five segments. Initial steep portion of the FDC represents the peak flows events occurring rarely hence having a low exceedence probability. Apart from the peak events the other high flows that need consideration are the events having greater chances of occurrence, are mostly in response to the major precipitation events and may have slightly different governing parameters than the peak flow.
**Table 4-3:** Objective functions for model calibration. $O$ indicates observed flow and $S$ denotes model simulated flow in m$^3$/s

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Equation</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nash-Sutcliffe efficiency</td>
<td>$\text{NSE} = 1 - \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}$</td>
<td>(Nash and Sutcliffe 1970)</td>
</tr>
<tr>
<td>Nash-Sutcliffe efficiency-Log</td>
<td>$\text{NSELog} = 1 - \frac{\sum_{i=1}^{n}(\log O_i - \log S_i)^2}{\sum_{i=1}^{n}(\log O_i - \log \bar{O})^2}$</td>
<td>(Bekele and Nicklow 2007)</td>
</tr>
<tr>
<td>RSR</td>
<td>$\text{RSR} = \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}$</td>
<td>(Moriasi et al. 2007)</td>
</tr>
<tr>
<td>PBIAS</td>
<td>$\text{PBIAS} = \frac{\sum_{i=1}^{n}(O_i - S_i)}{\sum_{i=1}^{n}O_i} \times 100$</td>
<td>(Gupta et al. 1999)</td>
</tr>
<tr>
<td>FDC Signature (FDC$_{\text{sign}}$)</td>
<td>$S_{FDC} = \frac{1}{4} {s_{\text{peak}} + s_{\text{high}} + s_{\text{mid}} + s_{\text{low}}}$</td>
<td>(van Werkhoven et al. 2009; Yilmaz et al. 2008)</td>
</tr>
<tr>
<td></td>
<td>$s = \frac{\sum_{j=1}^{J_m}</td>
<td>O_j - S_j</td>
</tr>
<tr>
<td></td>
<td>$s_{\text{ms}} = \frac{</td>
<td>(O_{E3} - S_{E3}) - (O_{E4} - S_{E4})</td>
</tr>
<tr>
<td></td>
<td>$S_{FDC}$ – FDC signature</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$S$ – signature for peak, high and low segment of FDC</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$j$ – flow exceedance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$j$ (for peak) – 0, 0.2, 0.4 ... 1.8, 2.0 %</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$j$ (for high) – 2, 3, 4, ..., 18, 20 %</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$j$ (for mid) – 20, 70 %</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$j$ (for low) – 70, 71, 72 ..., 99, 100 %</td>
<td></td>
</tr>
<tr>
<td></td>
<td>E3-exceedance at start of segment-3 i.e 20%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>E4-exceedance at start of segment-4 i.e 70%</td>
<td></td>
</tr>
<tr>
<td>Runoff coefficient (RoC)</td>
<td>$\text{RoC} = \frac{1}{N} \left( \frac{\bar{S}}{\bar{O}} - 1 \right)$</td>
<td>(van Werkhoven et al. 2009)</td>
</tr>
<tr>
<td></td>
<td>$\bar{S}$ - annual average simulated flow for each year, $\bar{O}$ - annual average observed flow for each year, $N$ – total number of years</td>
<td></td>
</tr>
</tbody>
</table>
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Multi-objective auto calibration of SWAT model for improved low flow performance for a small snowfed catchment

Moderate flows (also termed as Mid flow) in a catchment are in response to the small rainfall events combined with the baseflow, if any. Low flows are primarily the baseflow driven component of the streamflow. The high exceedence portion of FDC may be interpreted as an index of groundwater contribution to the streamflow (Smakhtin 2001) and thus represents the low flow. Apart from this, a relevant index for extreme low flow assessment is many times separately considered (Pfannerstill et al. 2014b; Smakhtin 2001) and is also used for further segmentation of the FDC in the present study. Therefore, on the basis of the percentage of flow exceedence the five segments considered are peak (0-2%), high (2-20%), mid (20-70%), low (70-100%) and V-low (95-100%).

Keeping this in view the model evaluation subsequent to calibration is carried out based on Kling-Gupta efficiency (KGE) (Gupta et al. 2009) and Volume efficiency (VE) (Criss and Winston 2008) on aggregate time-series and VE and RSR (Moriasi et al. 2007) on disaggregate time-series. The KGE statistic decomposes NSE and Mean Squared Error (MSE) into a three-dimensional criteria space and finds out a Pareto front in terms of the shortest Euclidean Distance (ED):

\[
\text{KGE} = 1 - \text{ED} \quad \text{Eq. 4-2a}
\]

\[
\text{ED} = \sqrt{(r - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \quad \text{Eq. 4-2b}
\]

\[
\beta = \frac{\mu_s}{\mu_o} \quad \text{Eq. 4-2c}
\]

\[
\gamma = \frac{\sigma_s}{\sigma_o} \quad \text{Eq. 4-2d}
\]

where \( r \) represents the correlation between observed and simulated river flow, \( \beta \) and \( \gamma \), respectively represent the bias and variability ratio between the simulated and observed variable; \( \mu \) and \( \sigma \) are the mean and standard deviation of the variable; the indices s and o denote simulation and observation, respectively. KGE ranges from \(-\infty\) to 1, with a value near to 1 implies a more accurate model.

VE represents the fraction of water delivered at the proper time and is computed by the Eq. 4-3. VE ranges from 0 to 1 with 1 being fraction of volume simulated being equal to the observed over same period of time.

\[
\text{VE} = 1 - \frac{\sum_{i=1}^{n} |O_i - S_i|}{\sum_{i=1}^{n} O_i} \quad \text{Eq. 4-3}
\]
where \( s_i \) and \( o_i \) denote simulated and observed flows, respectively at time step ‘i’. The efficiency of the ensemble simulation capturing maximum observed discharge is assessed by p-factor and r-factor (Abbaspour et al. 2015). The p-factor measures the observed data bracketed by 95% prediction uncertainty and varies between 0 and 1, with 1 implying 100% enclosing of the observed data by the simulations. The r-factor indicates the thickness of the simulation band. (Abbaspour et al. 2015) recommends a value of p-factor greater than 0.7 and r-factor less than 1.5 for an acceptable streamflow simulation.

### 4.4.7 Model parameter estimation

The primary goal of the optimization process is to derive the model parameters such that the resulting model simulation closely matches the actual watershed response. The SWAT model is capable of simulating various watershed processes, such as streamflow (resulting from surface runoff and groundwater discharge), sediment loading (erosion), nutrient loading, crop production etc., resulting in a complex model involving large number of parameters (Cibin et al. 2010). In the present exercise we intend to develop a model that aptly mimics the watershed hydrology. Therefore, only the parameters that affect the required model calibration have been placed under the optimization process. Watershed hydrology includes various sub-processes, such as surface flow, baseflow and snowmelt, and each of these processes is affected by several model parameters. The parameters to be optimized, as given in Table 4-4, are selected based on the previous studies in this region (Asadzadeh et al. 2015; Datta and Bolisetty 2013; Rahman et al. 2012) and other SWAT literature (Arnold et al. 2012; Rouhani et al. 2007).

### 4.5 Results and Discussion

The optimization runs were carried out for different combination of objective functions as outlined in the previous section. For Borg MOEA initial population of 100, population-to-archive-ratio (P/A) of 4 and selection ratio of 0.02 were considered and all the results presented are outcome of 1000 simulations. Although not presented here we did not find any improvement in the results by performing more than 1000 simulations. The initial population is generated randomly and all the subsequent populations result from the suitable recombination between population and \( \epsilon \)-dominance archive set. The optimization process constrain the objectives to arrive at a trade-off thus generating a Pareto optimal solutions as presented in Fig. 4-8. Since C1 and C2 (refer Table 4-2 for definition) are bi-objective optimization problems, the Pareto sets are
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2-dimensional; whereas for the other combinations of objective, the trade-off surface needs to be visualized on a multi-dimensional plane. The Pareto front is generated based on the tradeoff between the objectives under optimization.

Table 4-4: SWAT model calibration parameters; in the change type ‘R’ refers to relative change and ‘V’ as absolute change of parameter values during calibration process

<table>
<thead>
<tr>
<th>SNo</th>
<th>Parameter</th>
<th>Description</th>
<th>Unit</th>
<th>Range</th>
<th>Change Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CN2</td>
<td>Runoff curve number for moisture condition-II</td>
<td>-</td>
<td>-0.2 - 0.2</td>
<td>R</td>
</tr>
<tr>
<td>2</td>
<td>CH_N2</td>
<td>Manning’s n for main channel</td>
<td>mm/h</td>
<td>0.01 - 0.05</td>
<td>V</td>
</tr>
<tr>
<td>3</td>
<td>CH_K2</td>
<td>Hydraulic conductivity of main channel</td>
<td>mm/h</td>
<td>0 - 200</td>
<td>V</td>
</tr>
<tr>
<td>4</td>
<td>SOL_AWC(1)</td>
<td>Available water capacity of soil top layer</td>
<td>mm H2O/mm soil</td>
<td>-0.2 - 0.4</td>
<td>R</td>
</tr>
<tr>
<td>5</td>
<td>ESCO</td>
<td>Soil evaporation compensation factor</td>
<td>-</td>
<td>0.7 - 1.0</td>
<td>V</td>
</tr>
<tr>
<td>6</td>
<td>EPCO</td>
<td>Plant uptake compensation factor</td>
<td>-</td>
<td>0.5 - 1.0</td>
<td>V</td>
</tr>
<tr>
<td>7</td>
<td>OV_N</td>
<td>Manning’s n for overland flow</td>
<td>-</td>
<td>0 - 0.3</td>
<td>V</td>
</tr>
<tr>
<td>8</td>
<td>GWQMN</td>
<td>Threshold depth of water in shallow aquifer required for return flow to occur</td>
<td>mm</td>
<td>0 - 2000</td>
<td>V</td>
</tr>
<tr>
<td>9</td>
<td>GW_DELAY</td>
<td>Groundwater delay time</td>
<td>d</td>
<td>0 - 200</td>
<td>V</td>
</tr>
<tr>
<td>10</td>
<td>GW_REVAP</td>
<td>Groundwater ‘revap’ coefficient</td>
<td>-</td>
<td>0.02 - 0.2</td>
<td>V</td>
</tr>
<tr>
<td>11</td>
<td>REVAPMN</td>
<td>Threshold depth of water in shallow aquifer required for percolation to deep aquifer to occur</td>
<td>mm</td>
<td>0 - 1000</td>
<td>V</td>
</tr>
<tr>
<td>12</td>
<td>APLHA_BF</td>
<td>Baseflow alpha factor</td>
<td>1/d</td>
<td>0 - 1</td>
<td>V</td>
</tr>
<tr>
<td>13</td>
<td>SFTMP</td>
<td>Snowfall temperature</td>
<td>ºC</td>
<td>-3.0 - 5.0</td>
<td>V</td>
</tr>
<tr>
<td>14</td>
<td>SMTMP</td>
<td>Snowmelt base temperature</td>
<td>ºC</td>
<td>-2.0 - 5.0</td>
<td>V</td>
</tr>
<tr>
<td>15</td>
<td>SMFMX</td>
<td>Melt factor for snow on June 21</td>
<td>mm H2O/ºC-day</td>
<td>0 - 10</td>
<td>V</td>
</tr>
<tr>
<td>16</td>
<td>SMFMN</td>
<td>Melt factor for snow on Dec 21</td>
<td>mm H2O/ºC-day</td>
<td>0 - 10</td>
<td>V</td>
</tr>
<tr>
<td>17</td>
<td>TIMP</td>
<td>Snowpack temperature lag factor</td>
<td>-</td>
<td>0 - 1</td>
<td>V</td>
</tr>
<tr>
<td>18</td>
<td>SNOCOVMX</td>
<td>Minimum snow water content that corresponds to 100% snow cover</td>
<td>mm H2O</td>
<td>0 - 100</td>
<td>V</td>
</tr>
</tbody>
</table>

Among the Pareto solutions if one optimal solution is desired, generally a point along the Pareto front can be selected as a compromise solution giving an appropriate balance between the objectives (Madsen 2000; Pokhrel et al. 2012). Moving along the Pareto front, the relative importance of the objective function changes, thus affecting the process simulated by the model sensitive to the respective objective function. The Borg MOEA employs the concept of ε-progress for an efficient generation of the Pareto front (Hadka and Reed 2013), therefore each objective function is required to be specified with an ‘ε’ value as a minimum threshold for an improved solution. The smaller value would lead to fine tuning the solution but in order to have a reasonable trade-off between the objectives, meaningful precision shall be specified (Kollat et al.
2012). It was considered reasonable to adopt values of \( \varepsilon \) for each of the objective functions NSE, LogNSE, RSRlow, FDC_{\text{sign}} and RoC as 0.01, whereas for PBIAS it is 0.1, as these values would confine the error level of approximately 0.5 m\(^3\)/s for time-series of daily streamflow that in turn corresponds to 90% flow exceedence.

![Fig. 4-8 Pareto sets from SWAT-Borg multi-objective simulation; for definition of objective function combination (C1 to C4, refer Table 4-2)](image)

4.5.1 Model parameters

The optimal parameter range is reflective of the hydrological processes simulated by the model, hence the range of parameters by Pareto optimal solutions shall be studied. But for the sake of better comprehension the median of the parameter range corresponding to the Pareto optimal parameter set is presented in Table 4-5. From the results it is evident that the governing parameters for the surface flow, CN2 and SOL_AWC, have a higher variability among various combinations. Lower SOL_AWC implies higher baseflow, which is also reflected in the time series simulation plot (Fig. 4-9) for C1 having lowest SOL_AWC.
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Table 4-5: Median of the Pareto optimal parameter range for different objective function combination (for definition of each objective function combination and parameter refer Table 4-2 and Table 4-4, respectively)

<table>
<thead>
<tr>
<th>S.No</th>
<th>Parameter</th>
<th>Initial Range</th>
<th>C0</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Min.</td>
<td>Max.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>*CN2</td>
<td>-0.2</td>
<td>0.2</td>
<td>0.00</td>
<td>0.07</td>
<td>-0.02</td>
<td>-0.07</td>
</tr>
<tr>
<td>2</td>
<td>CH_N2</td>
<td>0.01</td>
<td>0.05</td>
<td>0.04</td>
<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td>3</td>
<td>CH_K2</td>
<td>0</td>
<td>200</td>
<td>131</td>
<td>149</td>
<td>141</td>
<td>135</td>
</tr>
<tr>
<td>4</td>
<td>*SOL_AWC(1)</td>
<td>-0.2</td>
<td>0.4</td>
<td>0.06</td>
<td>-0.17</td>
<td>0.19</td>
<td>0.12</td>
</tr>
<tr>
<td>5</td>
<td>ESCO</td>
<td>0.7</td>
<td>1.0</td>
<td>0.88</td>
<td>1</td>
<td>0.92</td>
<td>0.77</td>
</tr>
<tr>
<td>6</td>
<td>EPCO</td>
<td>0.5</td>
<td>1.0</td>
<td>0.75</td>
<td>0.51</td>
<td>0.65</td>
<td>0.86</td>
</tr>
<tr>
<td>7</td>
<td>OV_N</td>
<td>0</td>
<td>0.3</td>
<td>0.16</td>
<td>0.16</td>
<td>0.19</td>
<td>0.26</td>
</tr>
</tbody>
</table>

Groundwater flow factors

| 8    | GWQMN     | 0             | 2000 | 552 | 334 | 456 | 1046 | 794 |
| 9    | GW_DELAY  | 0             | 200 | 75.3 | 68.3 | 30.6 | 36.1 | 19.2 |
| 10   | GW_REVAP  | 0.02          | 0.2 | 0.09 | 0.05 | 0.05 | 0.1 | 0.09 |
| 11   | REVAPMN   | 0             | 1000 | 520 | 291 | 905 | 579 | 313 |
| 12   | APLHA_BF  | 0             | 1 | 0.74 | 0.85 | 0.8 | 0.87 | 0.81 |

Snow melt factors

| 13   | SFTMP     | -3.0          | 5.0 | -0.8 | 1.8 | -0.8 | 0.5 | -1.4 |
| 14   | SMTMP     | -2.0          | 5.0 | 1.8 | 2.2 | 1.2 | 3.1 | 2.7 |
| 15   | SMFMX     | 0             | 10 | 5.5 | 4.9 | 7.6 | 6.7 | 5.1 |
| 16   | SMFMN     | 0             | 10 | 5.6 | 8.9 | 7.8 | 6.8 | 4.4 |
| 17   | TIMP      | 0             | 1 | 0.56 | 0.81 | 0.05 | 0.68 | 0.75 |
| 18   | SNOCOVMX  | 0             | 100 | 51 | 76 | 15 | 53 | 42 |

*Indicates the relative change factor

Among the parameters governing groundwater flow, except GW_DELAY and ALPHA_BF, other parameters have a wider range among various combinations. Higher values of GWQMN and GW_REVAP are indicative of lower baseflow which is for the case C3. This combination has the best VE and RSR for low as well as very low flows (refer Table 4-6 and Table 4-7) suggesting that the lower simulated baseflow is desirable; as discussed earlier, low flows occur during the summer period and are primarily baseflow driven. For C1 the parameters GWQMN and GW_REVAP have relatively lower values and GW_DELAY has a relatively higher value making the baseflow generally higher causing a misfit in the low flow region as indicated from the very poor statistics for VE in Table 4-6 and a poor time-series simulation (Fig. 4-9). Therefore, when the low flows are rendered additional focus in the calibration, as in C3 and C4, appropriate parameters of the governing
process, that is groundwater discharge, are generated viz., higher GWQMN and GW_REVAP and lower GW_DELAY, causing the desirable reduction in simulated baseflow and thus mimicking the observed flow suitably.

4.5.2 Time series simulation

All the Pareto solutions (Fig. 4-8) obtained are non-dominated solutions in the optimization process and hence considered as the best likely simulator of the hydrological model. Following the concept of equifinality (Beven 2006), it is advisable to consider that several parameter sets may lead to equally satisfactory simulations (Madsen 2000). Hence the ensemble of SWAT model runs resulting from the Pareto optimal set is assumed to bound all the possible optimal simulation scenarios. As stated earlier the model simulation is affected by the choice of evaluation objectives (Abbaspour et al. 2007b; Rajib et al. 2016), therefore different combinations of objective functions generated varied results.

Fig. 4-9 presents the time-series simulation of various objective-function combinations C1 through C4; C0 represents Sufi2 simulation using SWAT-CUP and is used as a reference case. The plots indicate good level of calibration and the model appears to have mimicked the observed streamflow reasonably well. The time-series plots appear to be similar for all the cases with some differences. For combination C1 all the simulations sets have over-predicted the discharge whereas for all other combinations the simulation ensemble appears to have enclosed the observed flow. C2 has generated very crisp simulation band primarily due to fewer ensembles. The efficiency of the model simulations is further judged based on aggregated as well as disaggregated flow statistics, as presented in Table 4-6 and Table 4-7. The maximum value of NSE falls in the narrow range between 0.64 and 0.68 whereas the median value range is a bit wider, from 0.44 to 0.65.

4.5.3 Aggregated flow statistics

On investigating the simulations based on the aggregated flow statistics for NSE, PBIAS, KGE and VE, the combinations other than C1 are found to perform equally well. C1 has comparable maximum NSE but performs poorly on other metrics; the time series plot and the FDC plot show that the river flow is overestimated. Several authors have highlighted the deficiencies of NSE for simulating low flows.
Jain and Sudheer (2008) have shown in their study that high NSE values do not necessarily correspond to a good simulation. Superior model performance in periods with high flow may produce high value of NSE, as NSE being sensitive to high flows, but may mask poor model performances during the periods of low flow (Pfannerstill et al. 2014a; Zhang et al. 2011). Similarly if we judge the model performance for any of the objective function combinations based on NSE alone, the results may be biased. Therefore, a multi-metric evaluation approach is necessary.

Maximum p-factor is obtained for C4 and minimum for C1. The p-factor of C4 is higher than C3 in spite of more samples available for later in terms of number of Pareto sets which indicates the efficiency of C4 ensemble. Uncertainty in the simulations is evaluated using r-factor which gives
thickness of the simulation band. Combination C2 has minimum r-factor and the lowest p-factor value which is undesirable. The results of multi-objective simulation can be compared with that of Sufi2. The simulations perform equally well for most of the combinations based on the aggregated flow statistics, while for PBIAS metric Sufi2 performs better.

Table 4-6: Simulation statistics on aggregated flow; PBIAS, KGE and VE presented are for median Pareto simulation; critical value of each column is presented in bold

<table>
<thead>
<tr>
<th>Combination</th>
<th>Optimal sets</th>
<th>NSE</th>
<th>PBIAS</th>
<th>KGE</th>
<th>VE</th>
<th>p-Factor</th>
<th>r-Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>C0</td>
<td>53</td>
<td>0.55</td>
<td>0.62</td>
<td>5.0</td>
<td>0.63</td>
<td>0.45</td>
<td>0.85</td>
</tr>
<tr>
<td>C1</td>
<td>15</td>
<td>0.44</td>
<td>0.64</td>
<td>38.6</td>
<td>0.45</td>
<td>0.2</td>
<td>0.38</td>
</tr>
<tr>
<td>C2</td>
<td>7</td>
<td>0.65</td>
<td>0.67</td>
<td>8.7</td>
<td>0.69</td>
<td>0.53</td>
<td>0.42</td>
</tr>
<tr>
<td>C3</td>
<td>43</td>
<td>0.55</td>
<td>0.65</td>
<td>-15.1</td>
<td>0.73</td>
<td>0.48</td>
<td>0.73</td>
</tr>
<tr>
<td>C4</td>
<td>24</td>
<td>0.56</td>
<td><strong>0.68</strong></td>
<td>-2.7</td>
<td>0.70</td>
<td>0.46</td>
<td><strong>0.90</strong></td>
</tr>
</tbody>
</table>

Table 4-7: Simulation statistics on disaggregated flow; VE and RSR are for median Pareto simulation; flow segmentation is based on flow exceedance- peak (0-2%), high (2-20%), mid (20-70%), low (70-100%) and V-low (95-100%); critical value of each column is presented in bold

<table>
<thead>
<tr>
<th>Combination</th>
<th>Volume Efficiency (VE)</th>
<th>RSR</th>
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<tbody>
<tr>
<td></td>
<td>Peak</td>
<td>High</td>
</tr>
<tr>
<td>C0</td>
<td>0.53</td>
<td>0.58</td>
</tr>
<tr>
<td>C1</td>
<td>0.58</td>
<td>0.63</td>
</tr>
<tr>
<td>C2</td>
<td><strong>0.6</strong></td>
<td><strong>0.64</strong></td>
</tr>
<tr>
<td>C3</td>
<td>0.54</td>
<td>0.50</td>
</tr>
<tr>
<td>C4</td>
<td>0.56</td>
<td>0.52</td>
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4.5.4 Disaggregated flow statistics

In order to distinguish the performance of various combinations of objectives, the metrics are evaluated on the disaggregated flow signals in addition to the aggregated flow. This allows us to peek into the model’s ability to simulate various segments of the hydrograph governed by different hydrological processes. Volumetric efficiency (VE) is evaluated for different segments to analyse how well the model is performing in the respective segment. As indicated by some authors about the ability of SWAT to poorly simulate the low flows (Guse et al. 2014; Pfannerstill et al. 2014a), RSR is compared for low flows in addition to VE.
For peak flows all combinations perform almost equally well while for high flow C1 and C2 perform better than others. Apart from peak and high flow the mid flow, low flow and very low flow performance is poor for C1; poor model simulation was also evident from the aggregated flow metrics for this set of evaluation objectives. In spite of good representation for flows with exceedence less than 70%, the objective functions in C2 fail to generate parameters range that can simulate low flows well. C3 and C4 have reduced performance for peak and high flows when compared to C1 and C2 and comparable for mid range flows. But the significant improvement in simulation is achieved for the low flows. VE and RSR for low flows indicate better performance of C3 and C4 over C1 and C2 with C3 being superior among all. Simulations generated in SWAT-CUP employing Sufi2 algorithm (C0) have under-performed especially for the low flows and the objective function combination employing the hydrological signatures have demonstrated marked improvement for this range of flows.

**Fig. 4-10** presents the superiority of MOEA with signature objectives over the Sufi2 simulation results, for improved low flow model performance. On an average the low flow performance of the SWAT model is enhanced by approximately 135% in terms of volumetric efficiency and by 65% in terms of time series simulation.

**Fig. 4-10** Comparison of simulation performance of SWAT-CUP (Sufi2) and MOEA with hydrological signature objective functions; (a) reduction in RSR value and (b) increase in VE from SWAT-CUP to MOEA (C3 & C4)

4.5.5 Flow duration curves

Flow duration curves are important tools for evaluating the model performance. Apart from the flow time-series, the visual assessment of a simulation can be done by employing an FDC. A poorly
reproduced FDC implies a poor model performance (Ley et al. 2015). FDCs assist in evaluating the reproduction of discharges of different magnitudes (Vogel and Fennessey 1994; Yokoo and Sivapalan 2011). The controlling processes vary between the different segments and each FDC segment captures different hydrological processes (Guse et al. 2016; Pfannerstill et al. 2014b; Yilmaz et al. 2008). Thus incorporating a measure that aims to mimic the observed FDC would be fruitful in the model assessment. Results of the model performance that includes signature measure (C3 and C4) as evaluation objective is indicative of this fact. **Fig. 4-11** presents FDC for various simulation combinations.

![Flow duration curve (FDC) for SWAT-Borg simulation](image)

**Fig. 4-11** Flow duration curve (FDC) for SWAT-Borg simulation; dashed line represents the observed FDC, firm line represents the median simulation and cyan ribbon indicates region of 95PPU simulations
The poor model simulation is reflected for C1 as indicated earlier by various performance metrics also; apart from low exceedence flows, all other flow ranges have been over estimated. C2 is able to mimic well the entire range of flows which is also reflected in good aggregated flow statistics values. Here two aspects need to be noted, first the simulation band is narrow giving a very small r-factor; this is most likely due to very few number of optimal simulation sets. Secondly the low value of p-factor makes this combination less suitable. Observed flow range is well bounded for C3 and C4 simulation band for most of the flow exceedence except for the very low flows. Since FDC does not include the information on flow timing (Ley et al. 2015; Yilmaz et al. 2008), the low flow performance is evaluated using RSR apart from volumetric efficiency. RSR for low flows is better for combination C3 and C4 than for other sets, reflecting an improved model performance for the respective flow range.

4.5.6 Low flow residuals

Superior model performance for objective function sets represented in C3 and C4 can also be judged from the low flow residuals. Fig. 4-12 presents the residual plots for simulated low flows with respect to the observed flow with exceedence greater than 70%, for all the schemes under study. Residual is computed between the median of simulated flow and the observed flow. Sufi2 over predicts the low flows along almost the entire range of flows. Combination C1 of NSE and PBIAS has the maximum range of residual values among all the combinations. For C2 also simulated flow is higher than the observed flow for most of the flow range. Residuals are lower for C3 and C4 and most importantly evenly spread about the zero residual line. By model evaluation on the basis of various aggregated as well as disaggregated flow metrics our aim is to increase the use of information contained in the data and in the model results (Guse et al. 2016) thus adopting the idea of model diagnostic analyses.

The introduction of signature measures is able to improve the low flow simulation as evident from the various diagnostic measures. As pointed out by Wagener and Montanari (2011) regarding the approach involving hydrologic signatures “a basic assumption here is that signatures contain (at least) some of the information about watershed function that is usually extracted during model calibration from historical streamflow data”; the improvement in model performance validates the fact that the adopted signatures did contain additional information for the study catchment and hence they were helpful in improving the model performance.
4.5.7 Model validation

Subsequent to calibration, a four years period from 1994 to 1997 was adopted for model validation. The Pareto optimal parameters generated during calibration period were used to simulate the model during the validation period. Table 4-8 presents the key statistics as a measure of model performance for aggregated as well as disaggregated flows. Similar to the calibration period, simulation indicates an improved model behaviour for the low flows or high exceedence flows during validation and higher metrics values for aggregated flows is achieved for combination C2.
Table 4-8: Validation statistics for median simulation ensemble; critical value of each column is presented in bold

<table>
<thead>
<tr>
<th>Combination</th>
<th>Aggregated</th>
<th>Disaggregated</th>
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<tbody>
<tr>
<td></td>
<td>NSE</td>
<td>KGE</td>
</tr>
<tr>
<td>C0</td>
<td>0.45</td>
<td>0.60</td>
</tr>
<tr>
<td>C1</td>
<td>0.37</td>
<td>0.55</td>
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<tr>
<td>C2</td>
<td>0.52</td>
<td>0.70</td>
</tr>
<tr>
<td>C3</td>
<td>0.27</td>
<td>0.59</td>
</tr>
<tr>
<td>C4</td>
<td>0.36</td>
<td>0.66</td>
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4.6 Conclusions

Hydrologic model performance is affected by various factors and single statistics may not be adequate for evaluating the models, especially physically based ones (Rajib et al. 2016). Apart from the overall statistical assessment of the models, it is imperative that the various flow processes are well simulated leading to a higher model consistency (Hrachowitz et al. 2014). In the present research the well-established physically based SWAT model was calibrated based on a multi-objective approach involving the standard statistical metrics and signature measures as evaluation objectives. Borg algorithm was coupled with SWAT model to arrive at a suitable calibration. The model simulations corresponding to the Pareto optimal solution set was assessed based on the metrics computed over aggregated as well as dis-aggregated flows.

- It was found that incorporating signature measures as calibration objectives improves the low flow performance of the model by an average 135% in terms of volume efficiency and 65% for time series imitation. The accurate simulation of the hydrology with a focus on low flows assumes significance for water management and carrying capacity of the stream.

- On the basis of the obtained results in the present analysis it is reinforced that a calibration scheme should focus on various segments of the hydrograph rather than just one objective of a satisfying a cumulative statistic. Introducing hydrologic signature provides an additional calibration measure. So any set of objective functions that is able to simulate the various hydrologic processes well can be adopted (C3 and C4 in this case). Also it is desirable to evaluate the model performance based on the multiple metrics.
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- The performance corresponding to specific process i.e., low flow generation, was getting masked in the model assessment based on aggregated flow; this was highlighted by disaggregated model assessment and improved by adopting the flow signatures as objective functions. Thus the model parameters, generated by varying the objective, also improves the understanding of processes in the model (Guse et al. 2016).

- Four different combinations of objective functions were tested and also compared with the simulation generated by Sufi2 algorithm in SWAT-CUP. Sufi2 gives an overall good model simulation but the low flow period gives deprived results.

- Objective function based on the standard evaluation statistics between observed and simulated flow of NSE, LogNSE and PBIAS also had similar limitation.

- Inclusion of signature measures that provide an insight into the hydrologic function of a catchment (Sawicz et al. 2011) assisted in improving the low flow performance and amplified the process representation of the model.

As a future work it would be desirable to test the impact of increasing the number of objective functions and also effect of parameters’ temporal dynamics via a multi-objective approach. In the research involving the behaviour of watershed under changing climate, the role of signatures as information agents of temporal evolution (Wagener and Montanari 2011) needs to be examined in detail.

4.7 Acknowledgements

The present research was funded by the Natural Sciences and Engineering Research Council (NSERC) of Canada through the Discovery grant programme to the senior author. Vinod Chilkoti’s research was also supported through Ontario Graduate Scholarship and University of Windsor scholarship. The authors would like to thank Dr. David Hadka and Dr. Patrick M. Reed for providing the executable code of Borg for this research. The authors are thankful to Dr. Alberto Montanari for his insightful comments and suggestions and also other three anonymous reviewers for their review which helped in enhancing the presentation quality of the paper.
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4.8 References


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Chapter 4

Multi-objective auto calibration of SWAT model for improved low flow performance for a small snowfed catchment


Chapter 4

Multi-objective auto calibration of SWAT model for improved low flow performance for a small snowfed catchment

5.1 Chapter Synopsis

The impacts of changing climate pose a crucial threat to the seasonal availability and distribution of water. Calibrated hydrological models forced with the climate data from various climate models have been widely employed for future streamflow projection. But a major cause of concern in such an analysis has been the suit of uncertainties inherent in the modeling chain that begin from the climate models and end with the hydrological models. The uncertainties contributed by the hydrological models have generally been given a lesser focus. In the present research, the contribution of hydrological model parameter uncertainty has been investigated. Multi-objective evolutionary algorithm (MOEA) is employed for the calibration of hydrological model Soil and Water Assessment Tool (SWAT), developed for the Magpie River located in Northern Ontario. The parameter sets from thus obtained Pareto-optimal solution have been utilized to assess the relative uncertainty. The calibrated model was then forced with the data from an ensemble of six regional climate models for projecting the scenario streamflow and evaluating associated uncertainties. Significant variation in seasonal water availability is projected for the two scenario periods studied. The contribution of hydrological model parameter uncertainty in streamflow projection is found significant, lying in the range of 16% - 83%, across various months.

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4 This chapter has been submitted to Journal of Journal of Hydrologic Engineering and is under review.
Chapter 5
Investigating the Role of Hydrological Model Parameter Uncertainty in Streamflow Projection

5.2 Introduction

Hydrologists have the sensitive job of providing inputs of water availability to an engineer for designing the water infrastructure that is sustainable and resilient to the vagaries of climate. Future design scenarios can be estimated by utilizing the outputs of various climate models, developed by the climate scientists. An ensemble of climate models can be used for carrying out such an analysis.

Several studies have been carried out to assess the impact of climate change on water availability (Shadkam et al., 2016; Johnson and Sharma, 2015; Crossman et al., 2013; Majone et al., 2012; Rahman et al., 2012; Wilby and Harris, 2006). A standard protocol in such studies is to force the calibrated hydrological model with the climate scenario data extracted from the ensemble of climate models and compare the streamflow between the control and the scenario periods. Thus obtained streamflow projections are reported to have various sources of uncertainties and in varying degrees (Clark et al., 2016; Bosshard et al., 2013; Addor and Seibert, 2014; Bae et al., 2011; Chen et al., 2011). The suit of uncertainties in the climate projection makes the impact assessment results highly uncertain, thus rendering the process not fruitful for decision making (Bae et al., 2011). Therefore, it is crucial to comprehend and quantify the various sources of uncertainties in such a study. In this modeling chain, the hydrological models (HM) also contribute to the total uncertainty and can arise from two modes viz., model structure and model parameters (Bastola et al., 2011; Mendoza et al., 2015).

The present study focuses on the uncertainty pertaining to the hydrological model parameters that arises from the concept of parameter non-uniqueness (Clark et al., 2016). The intricate processes involved in the streamflow generation and their non-linear nature make it difficult to define a single set of model parameters that can assist in mimicking all the processes occurring in the catchment (Poulin et al., 2011). Moreover, the temporal variation of flow in terms of wet and dry periods further complicates this assessment. Therefore, uncertainty, that can be defined as an attribute of data (Tung and Yen, 2005), is inherent for hydrological simulations. Accordingly, there can be several parameter sets that are equally likely simulators of the system, the phenomenon commonly known as equifinality (Beven, 2006). The idea of equifinality that is advocated for hydrological simulation during model development should also be carried forward while extrapolating the model. In this manner the uncertainty arising out of HM parameterization, which should not be ignored (Brigode et al., 2013; Wilby, 2005), can also be accounted for.
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The contribution of uncertainty owing to the HM parameters has been found to be significant with respect to the total uncertainty in some of the studies (Bastola et al., 2011; Mendoza et al., 2016), while some studies have found its impact very less (Dobler et al., 2012; Prudhomme and Davies, 2009) and many have neglected this aspect altogether (Bosshard et al., 2013; Karlsson et al., 2016). Most of the impact assessment studies tend to consider a single set of best performing or median of the ensemble model parameters, as obtained during the model calibration period, for projecting the scenario simulation (Muerth et al., 2013; Thorne, 2011; Chen et al., 2011). Wilby (2005) was one of the first to advocate for quantifying uncertainty due to such parameter non-uniqueness. Subsequently, this aspect of uncertainty in the climate change impact modeling chain has been explored by various researchers.

Steele-Dunne et al. (2008) used 100 model parameter sets, that are selected based on Monte Carlo approach, to account for parameter uncertainty during calibration as well as the scenario period. Based on their study on nine Irish catchments, the range of plausible projections was studied. Since only one climate model was used, the relative magnitude of uncertainty due to climate model and hydrological parameters could not be studied. A set of 100 near optimal parameter sets were also considered for streamflow projection by Prudhomme and Davies (2009). An elaborate assessment of uncertainty contribution by hydrological model and climate model was then presented. Even though the contribution of HM uncertainty was found to be small, the authors suggested carrying out the combined effect of climate and hydrological uncertainty. Chang and Jung (2010) and Jung et al. (2011) carried out climate change impact assessment (CCIA) on streamflow for various river basins in Oregon USA, wherein several sets of optimal parameters of Precipitation-Runoff Modeling System (PRMS) hydrologic model were used. They concluded that the HM parameter uncertainty has a seasonal impact on the streamflow projection.

While highlighting the role of HM uncertainty, Bastola et al. (2011) quantified the hydrological impacts of climate change on four Irish catchments. The parameter uncertainty was evaluated using Generalised Likelihood Uncertainty Estimation (GLUE) and Bayesian Model Averaging (BMA). It was found that HM uncertainty has a significant role in the overall uncertainty envelope for streamflow projection. Recently Zhu et al. (2016) presented the concept of k-simulation set approach that filters the parameter from various calibration sub-periods. It was found that using multiple parameter sets decreases the risk of overestimation or underestimation that may arise by adopting best-fit parameter set from the traditional optimization approach.
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One way of ascertaining hydrological model (HM) parameter uncertainty is to study the ensemble parameter sets that can be generated by different methods. When the model parameters are derived by providing multiple objectives of satisfying different segments of the streamflow hydrograph, it also assists in enhancing the model accuracy (Rouhani et al., 2007). Moreover, for complex hydrological models, reduced uncertainty is expected when the models are conditioned on multiple responses (Efstratiadis and Koutsoyiannis, 2010). Such calibration strategy can be helpful in generating more robust sets of parameters. To this end, multi-objective evolutionary algorithm (MOEA) has been widely used in calibrating hydrological models (Reed and Hadka, 2014; Zhang et al., 2010; van Werkhoven et al., 2009; Rouhani et al., 2007; Kollat and Reed, 2006; Vrugt et al., 2003; Madsen, 2000; Gupta et al., 1998). Although several studies also support the use of multi-criteria calibration to reduce uncertainties in climate change impact assessment (Addor and Seibert, 2014; Clark et al., 2016), to our best knowledge there are no studies that have adopted this strategy for extrapolating the model performance for future scenario based on Pareto-optimal parameter set.

Based on the literature review, some shortcomings have been found in the various approaches: (a) use of conceptual hydrological model by most of the studies (Bastola et al., 2011; Prudhomme and Davies, 2009; Steele-Dunne et al., 2008; Wilby, 2005). Lumped models do not simulate minor processes associated with streamflow generation. In order to enhance the predictive ability of the models and acquire the process understanding on the impacts of climate change, the use of distributed or semi-distributed process based models will be valuable (Clark et al., 2016; Ludwig et al., 2009); (b) use of Monte Carlo approach for sampling the parameters (Chang and Jung, 2010; Jung et al., 2011; Prudhomme and Davies, 2009; Steele-Dunne et al., 2008; Wilby, 2005) which involves the subjectivity of the objective function threshold; and (c) use of single objective function for parameter selection; a few studies have adopted multiple objectives (Brigode et al., 2013; Wilby, 2005) but not in a strict sense to arrive at Pareto-optimal sets. Multi-criteria model evaluation can evade the errors due to misallocation of water among the various processes associated with streamflow generation (Addor and Seibert, 2014). Moreover, season-specific trend of HM uncertainty is not very well known; even though a few research studies indicate towards season-specific uncertainty contribution (Bastola et al., 2011; Bosshard et al., 2013; Jung et al., 2011), there is scope of new insights.

The objectives of the present research are to quantify the hydrological model parameter uncertainty by improvising on the above-listed shortcomings as well as to demonstrate the
strength of multi-objective model evaluation in ascertaining the parameter uncertainty in the future streamflow projection.

5.3 Data and Methods

5.3.1 Study area

The CCIA study has been carried out for Magpie River which is one of the important river basins in Northern Ontario in Canada. Fig. 5-1 presents the location map of the catchment which falls in the Boreal shield region in accordance with the Canada’s terrestrial ecozones (Ecological Stratification Working Group (Canada), 1996). The river is primarily south flowing with the main stream length of about 190 km and drains into Lake Superior near the Town of Wawa. The catchment area at Steephill Falls dam site is 1772 km$^2$ which is 35 km upstream of the outlet. The total drainage area at the outlet is 2040 km$^2$. The hydrological modeling results are verified upto the Steephill Falls dam site. The catchment has mountainous terrain with the relief varying from 180 m to 545 m. Catchment morphology for the hydrologic modeling is captured by using the 20 m digital elevation models (DEM). Originating from Upper Magpie Lake, the Magpie River flows through a series of lakes. In the upper reaches of the catchment, the river flows towards northern and north-eastern direction for about 25 km before turning towards the south-western direction. For the remaining length the river is primarily south flowing.

![Fig. 5-1 Magpie River watershed](image)
Michipicoten river joins Magpie from the left bank just upstream of its mouth at Michipicoten Bay on Lake Superior. The three hydroelectric facilities on the Magpie River (from downstream to upstream) Mission Station, Harris Station and Steephill Falls are operated by Brookfield Renewable Power Limited (BRPL). The river has previously been studied for adaptive management to establish correlation between the flow rate and the corresponding ecological benefits (Murchie 2004, Smokowiski 2011) and also for climate change impacts (Oni et al., 2012).

5.3.2 Physical characteristics
The study area is primarily a forested region. The land use details for the study area have been extracted from ‘Provincial Landcover 2000-27 Classes’ which is a 25 m resolution landscape-level inventory of natural, rural and urban areas of Ontario. The forest constitutes almost 70% of the total catchment area and comprises of Deciduous, Evergreen and mixed type of forests classified as ‘Boreal forest’. The other land uses include Rangeland (18%), Water (11%) and low-density residential areas (<1%).

The physical, chemical and hydrological properties of soil as required for the hydrologic model setup were obtained from the harmonized world soil database which is a global database for 1 in 5 million scale FAO-UNESCO soil map (FAO 1971-81). In the present study area two distinct soil types could be identified with sandy-loam being the predominant type. Attributes for each soil polygon were obtained from FAO soil database which was then included in the hydrologic model database. The detailed soil classifications as part of the National Soil Database (NSDB) of Canadian Soil Information System (SLC Working Group, 2010) are available only for the major agriculture regions of the country that does not include Magpie basin. Therefore, the same dataset could not be utilized in the present case and FAO dataset was resorted to.

5.3.3 Climatic characteristics
The meteorological data becomes scarce in the northern regions of Ontario. Even though there are a few stations located within and in the vicinity of the project catchment, only the Wawa station maintained by Environment Canada has the observations available for the recent period and corresponding to the flow data record period. In order to obtain a reasonably representative precipitation and temperature data across the medium sized study catchment, the gridded climate data from Natural Resources Canada (Hutchinson 2009, Hopkinson 2011) has been utilized. The 10 km gridded climate dataset is available for entire Canada and several studies have adopted the same (Dibike et al., 2018; Chen et al., 2017; Haguma et al., 2014; Shrestha et al.,
2012). This dataset is referred to as ‘NRCan dataset’ henceforth in this manuscript. Fig. 5-1 indicates the locations of gridded climate points as adopted in the present study.

The annual average precipitation and flow per unit area over the catchment are 845 mm and 329 mm, respectively, giving an average runoff ratio of 0.39. Since the catchment is snow dominated with the maximum runoff occurring during the spring period, the average runoff coefficient during the spring months of April and May has a significantly higher value of 0.91, while that for the remaining part of the year is 0.25. Since it has predominantly forested landcover in the catchment, the low runoff ratio is justified. The annual variation of precipitation and flow depth, average monthly flow and runoff coefficient are depicted in Fig. 5-2. The average monthly flow distribution suggests that the flow has a bi-modal hydrograph. The peak during the first part of the year is principally due to the snowmelt while the smaller peak during autumn is precipitation driven.

Fig. 5-2 Observed precipitation and streamflow characteristics (a) Annual precipitation and runoff depth; (b) average monthly flow; (c) runoff coefficient during spring period (broken line) and during remaining year (firm line)
Two flow stations located on Magpie River are maintained by Environment Canada. Station 02BD005 at the Esnagi Lake in the upper reaches of the river has only the water level data, while station 02BD007, located in the lower reach of the river, has both flow and water level data. Since the latter hydrometric station is located at the downstream of Steep hill Falls dam the recorded flow is regulated data and hence is not suitable for hydrologic model calibration. A long term flow record has been maintained by Brookfield Renewable Power Limited (BRPL) at two locations along the river, one at Esnagi dam and other at the Steep hill Falls dam. The flow data for the present study has been acquired from BRPL.

The daily Magpie River flow varies from an extreme low value of 0.64 m$^3$/s to 250 m$^3$/s with a mean daily value of 17.7 m$^3$/s and median of 9.9 m$^3$/s. The analysis of the observed flow data during the study period indicated that high flows occur during the spring season primarily due to the snow melt and summer season is the low flow period. The non-spring period flow has a significant base flow portion with the average baseflow contribution being two-thirds of the total water yield. Daily streamflow and the flow duration curve (FDC) are presented in Fig. 5-3.

![Daily observed flow graph](image)

**Fig. 5-3** Daily observed flow: (a) time series; and (b) flow duration curve (flow value on y-axis is indicated in log scale and the broken line represents the mean daily flow)

### 5.4 Methodology

#### 5.4.1 Hydrologic model

The hydrologic response of a catchment can be simulated using a mathematical model. The choice of model is generally between the lumped, distributed or physically based models. The scope of the present research is to simulate the present hydrological regime and to extrapolate the same under the anticipated climate change conditions. Many research studies have suggested that the process based models are more suitable for climate change application (Ludwig et al., 2009; Poulin
et al., 2011). Therefore, it was decided to use the continuous-simulation model SWAT (Arnold et al., 1998) for the present study to simulate the hydrology of the Magpie River watershed. SWAT is one of the most widely adopted semi-distributed models to simulate hydrology and water quality at the sub-watershed level. It is a continuous watershed scale simulation model that operates on daily and sub-daily time steps. SWAT model has been extensively used for water budget (Kannan et al., 2007) and water quality assessment (Abbaspour et al., 2007; Rostamian et al., 2008) as well as for climate change impacts (Culbertson et al., 2016; Rahman et al., 2012; Wu and Johnston, 2007; Ficklin et al., 2009) and land use change effects (Karlsson et al., 2016) for numerous watersheds across the globe. In the current work, version 2012 – revision 627 of the SWAT model has been used. Further details can be found in Neitsch et al., (2011).

The model setup commenced with the stream network delineation using the DEM. The watershed was sub-divided into 41 sub-watersheds ranging from 13 ha to 20606 ha. Fig. 5-4 presents few snapshots of the model setup. The input physical characteristics of the watershed viz., soil, land use and slopes were reclassified to match the SWAT database standards. Two soil types, nine land use and three slope classes were identified for subsequent delineation of 878 hydrological response units (HRUs). The indices for various landuse patterns are: WATR – Water, WETN- Wetlands Non forested, WETF-Wetlands forested, FRSD-Forest Deciduous, FRST- Forest evergreen, FRST-Forest mixed, RNGE-Range brush, SWRN-Arid range and URML-Residential (low density).

The most recent available climate data from 2000 to 2012 was considered for the model simulation. The model calibration is performed using the data from 2003 to 2008 while the model was validated for 2009 to 2012. The initial three-year period (2000-2002) is considered as warm up period for model stabilization.

5.4.2 Climate data

As indicated earlier, the availability of observed climate data was very limited for the study area and the gridded climate dataset from NRCan has been adopted. Further details on the data set and data extraction are provided in Annexure-2a.
Fig. 5-4 Model Setup - (a) Climate and flow stations maintained by Environment Canada; (b) Topography as extracted by 20 m resolution DEM; (d) Sub-basin delineation, and (c) Landuse pattern
5.4.3 Calibration scheme

The accuracy of the hydrological processes simulated by the SWAT model for Magpie River, is verified and improved through the process of calibration based on the observed streamflow record. In the present research, a multi-objective model calibration methodology is adopted. In comparison to the conventional single objective calibration, the multi-objective calibration generates more robust models by limiting the parameter uncertainty (Peel and Bloschl, 2011; Rajib et al., 2016) and reduces parameter non-uniqueness problem (Abbaspour et al., 2007). Multi-objective Pareto-based optimal scheme also reduces the subjectivity of choosing likelihood threshold. This will be helpful, as the subjectivity of HMs may have large effect in the portrayal of climate change impacts (Mendoza et al., 2015). On analysing the observed streamflow for Magpie River, a strong seasonality is depicted in the streamflow hydrograph with a spring peak, a baseflow predominant summer period and rainfall driven autumn. A calibration routine with single objective is unlikely to be effective in a snowmelt dominated watersheds having such a strong seasonality (Ahl et al., 2008). Moreover, as the application of the present model is proposed for climate change application, a strong methodology is vital to enhance the model’s predictive ability (Clark et al., 2016).

Borg multi-objective evolutionary algorithm (MOEA) (Hadka and Reed, 2013) is used here for the multi-objective model calibration. The Borg-SWAT coupled model was first introduced by Chilkoti et al., (2018). Borg belongs to the class of evolutionary algorithms that evolves solution on the basis of genetic operators leading to an optimal Pareto solution set. Borg incorporates design principles from other MOEA’s with several new characteristics (Hadka and Reed, 2013). Further details on Borg-SWAT model can be found in Chilkoti et al. (2018).

Three objective functions are proposed to be used in the multi-objective scheme. The first objective is the Nash-Sutcliffe efficiency (NSE) and is the most widely used efficiency measure but is sensitive to the peak flows (Shafii and Smedt, 2009). For counter-balancing the peak flow, an objective to account for low flows is also adopted. The ratio of the standard deviation of simulated to observed (RSR) (Moriasi et al., 2007) for low flows is therefore computed.

In an effort to provide a more robust calibration, many researchers have recommended to implement the diagnostics measures (Daggupati et al., 2015; Gupta et al., 2008) in model evaluation. Accordingly, a hydrologic signature has been supplied as an evaluation objective to
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the multi-objective formulation. Several studies have proved that the hydrologic signatures provide an insight into the functional behavior of the catchment (Sawicz et al., 2011) by extracting maximum information from the available data (Reusser and Zehe, 2011; Wagener and Montanari, 2011). The signatures have been found to be effective calibration measures. In the present study, bias in the observed and simulated flow duration curve (FDC) is computed as the third objective function. Formulation of the objective functions is provided in Annexure-2b.

5.4.4 Climate model and scenario

For a reliable climate change projection a multi-model ensemble approach (Schaefli, 2015) has been adopted in the current study. Data from six Regional Climate Models (RCM’s) that are part of Coordinated Regional Downscaling Experiment (CORDEX, Giorgi et al., 2009) experiment has been extracted. The models used for the present study are same as the ones listed in Table 1-1 (Mearns, 2017). Henceforth, the climate models shall be described by their respective numbers rather than the name.

The climate model data for three different time horizons were extracted, one for historical duration termed as control period and other two for the future periods following the Representative Concentrated Pathways (RCP) 4.5 that represents one of the intermediate greenhouse gas emission scenarios (GHGES) as per the latest IPCC guidelines (Pachauri et al., 2014). The control period data (1976-2005) is used as a base data for comparison as well as to bias correct the model data with the available observation data. Two scenario periods one for mid-century (1941-1970) and other for the end of the century (2071-2099) period are considered for assessing the climate change impacts. Three climate variables viz., precipitation, near surface minimum and maximum air temperature corresponding to daily time step frequency have been extracted from the climate models.

5.4.5 Bias correction

The data extracted from the climate models have some inherent biases due to various reasons. These include, the inadequate representation of the atmospheric processes (Maraun, 2012), simplified assumptions in model construction (Phillips and Gleckler, 2006) and climate variability (Deser et al., 2012) among others. This bias is evaluated by obtaining a transfer function between climate model outputs and observation data based on available historical data (Piani et al., 2010). The obtained transfer function is then applied to future model projections to infer the possible trajectory of future observations. Various methodologies for bias correction have been proposed.
in the literature with each having their pros and cons. Teutschbein and Seibert (2012) has compared the different bias correction methods with respect to their application for hydrological studies. The study has proved the superiority of quantile mapping (QM) methods over others. Therefore, QM is used as the bias correction method in the current work. In quantile mapping method, the adjustment for precipitation in the \( i^{th} \) month can be expressed as empirical Cumulative Distribution Function (eCDF) and inverse eCDF (Fang et al., 2015), as represented by Eq. (8).

\[
\tilde{x}_{\text{adj},d}^i = eCDF_{\text{obs}}^{-1} \left( eCDF_{\text{mod}}^{i} \left( x_{\text{mod},d}^i \right) \right) \quad \ldots(8)
\]

where \( \tilde{x}_{\text{adj},d}^i \) is corrected precipitation on the \( d^{th} \) day of \( i^{th} \) month, and \( x_{\text{mod},d}^i \) is the raw model precipitation on the \( d^{th} \) day of \( i^{th} \) month. \( eCDF^{i}(\cdot) \) and \( eCDF^{i-1}(\cdot) \) are computed for both the model (\textit{mod}) and the observation (\textit{obs}) periods.

\section{Results}

\subsection{Gridded climate data}

The NRCan gridded climate data (Hutchinson et al., 2009) is used in the present study. One of the grid points in the dataset is compared to the closest observation station of Wawa A maintained by Environment Canada. It was found that, on the average, the gridded precipitation data is underestimated by about 12%, ranging between 2% to 20% for different months except in December where it is overestimated by about 4%. The minimum air temperature in the gridded dataset is lower than the observed temperature for all the months while the maximum temperature for different months has a varying bias pattern. Further details of the same are provided in Annexure-2a.

\subsection{SWAT model calibration}

SWAT model was calibrated based on the described methodology in the earlier sections. In streamflow generation, various hydrological processes, such as surface flow, baseflow, evapotranspiration and snowmelt are involved, which in turn are affected by several model parameters. The process of sequentially recognizing the key model parameters is explained in Annexure-2b. Subsequent to the preliminary analysis and prior experience, 13 SWAT parameters were identified as sensitive and were then optimized using the MOEA for deriving the final optimal parameter set. Out of the 13 parameters, as presented in Table 5-1, six are snow parameters, four are surface water (SW) and remaining three are groundwater (GW) parameters.
Chapter 5
Investigating the Role of Hydrological Model Parameter Uncertainty in Streamflow Projection

Table 5-1 SWAT model calibration parameters

<table>
<thead>
<tr>
<th>S.No</th>
<th>Parameter</th>
<th>Description</th>
<th>Unit</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Min</td>
</tr>
<tr>
<td>1</td>
<td>CN2</td>
<td>Runoff curve number for moisture condition-II</td>
<td>-</td>
<td>-0.2</td>
</tr>
<tr>
<td>2</td>
<td>CH_K2</td>
<td>Hydraulic conductivity of main channel</td>
<td>mm/hr</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>SOL_AWC ()</td>
<td>Available water capacity of soil top layer</td>
<td>mm H$_2$O/mm soil</td>
<td>0.03</td>
</tr>
<tr>
<td>4</td>
<td>ESCO</td>
<td>Soil evaporation compensation factor</td>
<td>-</td>
<td>0.7</td>
</tr>
<tr>
<td>5</td>
<td>RCHRG_DP</td>
<td>Deep aquifer percolation fraction</td>
<td>-</td>
<td>0.05</td>
</tr>
<tr>
<td>6</td>
<td>GW_REVAP</td>
<td>Groundwater ‘revap’ coefficient</td>
<td>-</td>
<td>0.02</td>
</tr>
<tr>
<td>7</td>
<td>APLHA_BF</td>
<td>Baseflow alpha factor</td>
<td>1/days</td>
<td>0.04</td>
</tr>
<tr>
<td>8</td>
<td>SFTMP</td>
<td>Snowfall temperature</td>
<td>$^0$C</td>
<td>-3.0</td>
</tr>
<tr>
<td>9</td>
<td>SMTMP</td>
<td>Snowmelt base temperature</td>
<td>$^0$C</td>
<td>-3.0</td>
</tr>
<tr>
<td>10</td>
<td>SMFMX</td>
<td>Melt factor for snow on June 21</td>
<td>mm H$_2$O/$^0$C-day</td>
<td>0</td>
</tr>
<tr>
<td>11</td>
<td>SMFMN</td>
<td>Melt factor for snow on Dec 21</td>
<td>mm H$_2$O/$^0$C-day</td>
<td>0</td>
</tr>
<tr>
<td>12</td>
<td>TIMP</td>
<td>Snowpack temperature lag factor</td>
<td>-</td>
<td>0</td>
</tr>
<tr>
<td>13</td>
<td>SNOCOVMX</td>
<td>Minimum snow water content that corresponds to 100% snow cover</td>
<td>mm H$_2$O</td>
<td>0</td>
</tr>
</tbody>
</table>

The coupled SWAT-Borg simulation generates the optimal parameter set, based on the evaluation of objective function between the observed and simulated streamflow during the calibration period of 2003 to 2008. The generated Pareto-optimal front of the three objectives is presented in Fig. 5-5.

![Fig. 5-5 Pareto-optimal front of three objective functions](image-url)
The optimization process resulted in 22 sets of best performing parameters for daily time-step simulation. Out of total iteration of 1000, relatively fewer optimal parameter sets is indicative of fairly comprehensive objectives supplied to the optimization routine. Selecting the Pareto-optimal set assists in evading the subjectivity of an objective function threshold for identifying behavioral parameter set. Also, multiple evaluation measures form the basis of a good calibration (Arnold et al., 2012). Thus the multi-objective formulation assists in reducing the problem of parameter non-uniqueness (Abbaspour et al., 2007).

Since the flow regime of the current study area is snowmelt driven, the snow melt parameters TIMP and SMTMP were found to be more sensitive. This is consistent with previous studies in snow-dominated watersheds (Ahl et al., 2008; Shrestha et al., 2012). The SWAT model streamflow simulation for the Pareto-optimal parameter sets are depicted in Fig. 5-6. The efficiency of the simulation is evaluated using various metrics as presented in Table 5-2. In accordance with the standard criteria (ASABE, 2017; Moriasi et al., 2007) and the visual interpretation of the plots, the obtained statistics portray a ‘very-good’ model performance.

![Fig. 5-6 Time series simulation of Pareto-optimal parameter set for calibration period (a), (b) and validation period (c), (d)](image-url)
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Investigating the Role of Hydrological Model Parameter Uncertainty in Streamflow Projection

Table 5-2 Simulation statistics of the best performing parameter set

<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Monthly</td>
<td>Daily</td>
</tr>
<tr>
<td>NSE</td>
<td>0.83</td>
<td>0.72</td>
</tr>
<tr>
<td>PBIAS (%)</td>
<td>5.1</td>
<td>6.7</td>
</tr>
<tr>
<td>KGE</td>
<td>0.9</td>
<td>0.84</td>
</tr>
</tbody>
</table>

*NSE-Nash-Sutcliffe efficiency, KGE-Klinge Gupta efficiency, PBIAS – percentage bias

Apart from the statistical competence the simulation was also verified for the process adequacy of the model (Daggupati et al., 2015). The baseflow contribution to the total simulated streamflow is approximately two-thirds which is same for the observed flow, computed based on the baseflow separation program (Arnold and Allen, 1999). The ET simulated by the model has an annual median of 432 mm which is reasonable for this region of Northern Ontario.

The simulated low flows have been questioned several times in various SWAT studies (Guse et al., 2014; Pfannerstill et al., 2014a). Thus the authors considered it deemed important to verify the model performance for this flow segment. The segmentation of flow is carried out into four zones viz., peak (0-2%), high (2-20%), mid (20-70%) and low flows (70-100%) (Pfannerstill et al., 2014b), where the values in the parenthesis represent the flow exceedances. The volumetric efficiency (VE) (Criss and Winston, 2008) of each segment was evaluated. Table 5-3 presents the VE for each of the segment during calibration and validation period and found to be satisfactory; ideal value of VE shall be 1.

Table 5-3 Volumetric efficiency of various flow segments

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Monthly</td>
<td>Daily</td>
</tr>
<tr>
<td>Peak</td>
<td>0.95</td>
<td>0.7</td>
</tr>
<tr>
<td>High</td>
<td>0.69</td>
<td>0.6</td>
</tr>
<tr>
<td>Mid</td>
<td>0.65</td>
<td>0.59</td>
</tr>
<tr>
<td>Low</td>
<td>0.5</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Along with the time-series simulation, the calibration strength can be confirmed from the simulated FDC (Fig. 5-7). For the entire flow regime, the observed FDC is bounded by the simulated FDC corresponding to the optimal parameter set. Since FDC is one of the most informative ways of displaying the streamflow range (Smakhtin, 2001) and represents streamflow...
signature, the favorable reproduction of FDC is indicative of a model’s skill to render a good fit in different flow regimes (Euser et al., 2013).

![Flow duration curve (FDC) of the observed (solid line) and Pareto-optimal simulated parameters (shaded area); flow on y-axis is in log scale](image)

**Fig. 5-7** Flow duration curve (FDC) of the observed (solid line) and Pareto-optimal simulated parameters (shaded area); flow on y-axis is in log scale

5.5.3 Uncertainty assessment
The model calibration does not present a single best parameter set but multiple parameter sets giving similar and most rational output signal. The Pareto-optimal solution therefore presents these parameters that are equally likely simulator of the system based upon the chosen evaluation criteria (Bekele and Nicklow, 2007). The distribution of parameters is representative of the uncertainty of spatial watershed parameters. This assists in accepting that uncertainty is inherent in modeling the complex and non-linear watershed phenomena (Daggupati et al., 2015). Hydrologic models need to be forced with observed data as input and also for calibration, which make the models subjected to uncertainties at various stages of model development. Hence it is pertinent to accept, recognize and evaluate the model uncertainty through the ensemble of Pareto-optimal model parameters. As SWAT is a process based model, the results of different processes can be retrieved to judge the model simulation skill and the uncertainty in each of the sub-processes can be accessed. The ensemble values of surface water (SW), groundwater (GW), evapotranspiration (ET) and total water yield (WY) from Pareto-optimal SWAT simulation are presented in **Fig. 5-8**. The monthly and annual water yield is also compared with the observed yield which is computed from recorded streamflow data.

The narrow band of water yield prediction is indicative of the fact that the multi-objective calibration routine is successful in reducing the problem of parameter non-uniqueness and generating a crisp simulation.
Comparing the ensemble of surface water and groundwater, it is evident that there is greater uncertainty in the simulated groundwater flows. This could be attributed to the more complex nature of baseflow generation as it involves several minor processes, such as infiltration, evaporation, later subsurface flow and deep percolation. From these plots it is also apparent that the streamflow is baseflow dominant. Water balance is checked for monthly and annual period (Arnold et al., 2012). For most of the months, the simulated streamflow matches closely to the observed streamflow.
observed flows especially during the non-spring months. The first part of the spring (April) is simulated reasonably well while the second half i.e., the month of May which is the peak of spring period, the over-prediction by the model is substantial. Snowmelt dynamics play a key role in runoff generation during winter and spring periods.

5.5.4 Climate model data

The calibrated SWAT model is proposed to be extrapolated for assessing the streamflow in an altered climate scenario. The climate data is extracted for the two scenario periods from an ensemble of six RCMs. The bias factors for the monthly precipitation among all the models during the control period range from 0.68 to 1.67 with a mean of 1.02. The precipitation bias reported here as the ratio between average monthly observed and modeled values, while the temperature bias is reported in absolute value and computed as difference between observed and model, during the control period (1976-2005). Seasonally, the biases are found to be maximum during the late summer and early autumn period. Subsequent to computing the bias, the model data was corrected by adopting the quantile methodology as described in section 5.3.5.

Precipitation data

Subsequent to the bias correction, the mean annual increase in precipitation w.r.t the control period was found to be 9.4% over the mid-century and 10.6% over the end century period. This increase has a large variability across the seasons, with only 0.8% in summer while 15.9% in spring, for end of the century time horizon. Maximum increase in precipitation is expected during late winter and early spring months while a decrease is projected during the summer months. Fig. 5-9 presents the ensemble of monthly precipitation for mid and end of the century scenario period. The projected precipitation has larger uncertainty during middle of the year.

![Climate model ensemble bias corrected precipitation for the mid and end of the century period; dots represent the control period precipitation value](image)
Temperature data

Increased CO₂ concentration in the scenario period has a pronounced effect on global warming which is also reflected from the analysis of temperature data from the climate models. The increase in monthly average minimum air temperature, w.r.t. the control period, for end-century period is projected to be between -1.8°C to 11.1°C while that in the maximum temperature is -2.3°C to 14.7°C. The average increase in minimum temperature, for mid and end century period, are projected to be 2.8°C and 3.5°C, respectively. The corresponding statistics for the maximum temperature are 2.6°C and 3.4°C. Evidently, later time horizon is expected to have more warming than the earlier period given that rcp4.5 scenario is considered.

**Fig. 5-10** illustrates the seasonal pattern of temperature change of the model ensemble over the two time horizons. The highest increment in ensemble median minimum temperature is projected for the winter months followed by spring and the least for autumn. Spring period is expected to have the largest warming in terms of ensemble median maximum air temperature. First half of the year is projected to be warming more than the later. For majority of seasons, the rise in temperature is higher for end-century as compared to the mid-century except for autumn season, where the temperature increment with respect to the control period is the least. Also, there is a marginal decline in the temperature from mid towards the end century period for the autumn season. Few other climate change studies carried out in central and northern Canadian region have also reported large changes in the scenario temperature (Chen et al., 2011; Haguma et al., 2014; Li et al., 2016). The uncertainty in temperature projection is also noticeable. Winter and spring periods have maximum ensemble spread. This results from the varying simulation skill of each of the climate models in the ensemble.

![Fig. 5-10 Change in seasonal temperature for scenario periods with reference to the control period for (a) minimum temperature and (b) maximum temperature](image-url)
5.5.5 Hydrologic response to climate change

Bias corrected precipitation and temperature data are forced on to the pre-calibrated SWAT model to derive the hydrologic response of the watershed for the future scenarios. Fig. 5-11 presents the variation of mean monthly ensemble streamflow for end-century scenario. Increase in flow is projected during winter and substantial decrease during the summer period. The shift of spring peak towards winter months is also noteworthy. The shift corresponds to the increase in snowmelt during the winter months due to significant projected rise in both minimum and maximum air temperature. The uncertainty in scenario temperature during winter and spring months (Fig. 5-10) is also reflected in the streamflow projection. Similar trends in the streamflow projection have been reported by other researchers in this region (Chen et al., 2011; Haguma et al., 2014).

For the summer period, the projected temperature increase, to some extent, is counterbalanced by lower stomatal conductance in plants as the elevated atmospheric CO$_2$ leads to decreased stomatal conductance (Chakraborty et al., 2014; Field et al., 1995). Thus the reduced leaf loss of water potentially counterbalances the projected increases in temperature and PET.

Fig. 5-11 Projected streamflow for End century period; triangles indicate the average flow during the control period

5.5.6 Grouping of climate model ensemble

Fig. 5-11 reveals larger uncertainty in the flow projection during the late winter and spring months as compared to other months, which makes it very difficult to communicate the climate change results and the associated uncertainties with confidence. The plot indicates how the projections are impacted by climate model structural uncertainty (Parker, 2013). Hydrologic response is the cumulative effect of the forcing data and the model parameters. During the calibration period,
the model prediction was least certain for the months of April and May (refer Fig. 5-8e). The current model has some inherent uncertainties for predicting the spring flows. The increasing uncertainty for the month of March, during the scenario period, needs further investigation. The forcing climate data for the hydrologic model is an ensemble of bias-corrected precipitation and temperature data. Ensemble precipitation data (Fig. 5-9) has lesser uncertainty during winter and spring months, while the temperature data has a wider spread (Fig. 5-10) during the same period. The combined effect of model parameters and forcing data on hydrologic prediction is obvious. Since the forcing dataset is an ensemble of six data sets, the impact of each of the ensemble member is likely to disclose further insights. The model ensemble members M1, M2 and M3 have similar governing boundary conditions by virtue of same GCM. Therefore, it is likely that they lead to similar trends in projection. To further investigate this phenomenon, the model projections are grouped into two sets, group-1: M1 to M3 (bounded by same GCM) and group-2: M4 to M6.

Fig. 5-12 presents the ensemble of monthly bias-corrected minimum temperature. It is interesting to note that for all the months, results of the two groups are mostly identifiable. Group-1 projects higher increase in temperature during winter and spring period as compared to group-2. Also, the direction of projected change is different between the two groups during the autumn period. The difference in projection by the two groups is found to be statistically significant for most of the seasons as established by Mann-Whitney test.

Fig. 5-12 (a) Minimum temperature and (b) maximum temperature projection for end of the century period for two groups of models; solid circles indicate control period value

The p-value in Table 5-4 is indicative of the fact that only during the summer period, the projections by two model groups are similar; while for other seasons the null hypothesis, of the
sample being similar, can be easily rejected even at 1% level of significance. It is also evident that, moving from mid-century to end century period, the projection by two groups is becoming increasingly variable for the spring period (Table 5-4).

**Table 5-4** p-value of Mann-Whitney test between the projections by group-1 models (M1 to M3) and group-2 (M4 to M6) for the two study horizon

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Winter</th>
<th>Spring</th>
<th>Summer</th>
<th>Autumn</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mid century</td>
<td>$2.2 \times 10^{-16}$</td>
<td>$4.2 \times 10^{-4}$</td>
<td>0.92</td>
<td>$9.8 \times 10^{-7}$</td>
</tr>
<tr>
<td>End century</td>
<td>$2.2 \times 10^{-16}$</td>
<td>$2.2 \times 10^{-16}$</td>
<td>0.34</td>
<td>$2.4 \times 10^{-3}$</td>
</tr>
</tbody>
</table>

On the other hand, the autumn period projections by the two groups are gradually converging, as indicated by increased p-value. This indicates the different abilities of the two groups of models in projecting the future and thus causing larger uncertainty other than summer period.

The monthly projected streamflows are further examined to visualize the effect of individual ensemble members. **Fig. 5-13** presents the ensemble projection for each of the climate models. Each box plot represents projection corresponding to the Pareto-optimal HM parameter set. For the clarity sake results for the month of May are presented in inset plot. From the plot, the different range of projection by the two groups, especially during the winter and spring seasons, is evident. The large uncertainty in the spring streamflow projection (as in **Fig. 5-11**) is not as a result of uniform spread of the ensemble members, rather it corresponds to the differences in the two sets of projections. Group-1 projections indicated a higher increase in temperature (**Fig. 5-12**) during first half of the year causing an increased snow melt.

**Fig. 5-13** Monthly streamflow during the control and end-century scenario periods; each box plot represents an ensemble of 22 hydrological model parameters; dark fill box plots represent the control period flows; inset plot presents the results for the month of May
This possibly causes higher increase in streamflow projection during February and March as compared to a significantly lower increase by group-2 models during the same period (Fig. 5-12). The enhanced evapotranspiration is a likely reason for reduced streamflow during the spring and early summer period. For the months of January to July, the results of two groups are distinct.

5.5.7 Prediction uncertainty

Fig. 5-13 also provides a comparison of hydrological parameter uncertainty and the total uncertainty in the projected flows during the scenario period. The total spread during each month represents the cumulative uncertainty due to HM and climate models, whereas the individual box plot is representative of the HM parameter uncertainty. The total prediction uncertainty is found to be higher than the HM uncertainty during the scenario period, which is obviously owing to the inclusion of climate model ensemble. The increase in prediction uncertainty is significantly larger during the late winter and spring period than the other seasons. The HM parameter uncertainty corresponds to the uncertainty imposed by Pareto-optimal parameter set; the proportion of this uncertainty in the total prediction uncertainty is presented in Fig. 5-14. The plots indicate that the uncertainty contributed by the model parameters when compared to the total prediction uncertainty is very high during the drier summer months. This is also conclusive from the fact that all the climate models converge to similar projection during this period (Fig. 5-13). A similar conclusion was arrived at by Wilby (2005) and Mockler et al. (2016) in their studies.

![Fig. 5-14](image)

**Fig. 5-14** Proportion of hydrological model-parameter uncertainty in total projection uncertainty for (a) monthly and (b) seasonal streamflow

On the other hand, due to the difference in prediction skills of various climate models, the climate model uncertainty governs during winter and spring season. The dominance of climate model uncertainty during this period results from the fact that the streamflow is snowmelt driven which
in turn is controlled by the temperature. More uncertain temperature projections (Fig. 5-10) render higher climate model uncertainty. HM parameter uncertainty has a lesser role in total uncertainty during the later winter and spring months. The proportion of hydrological uncertainty is found to be higher for the end-century period than the mid-century during the summer months. This point towards stronger reaction of hydrological models to the larger changes in precipitation and temperature during later scenario period (Bosshard et al., 2013).

The result indicates a significant role of HM parameter uncertainty in the overall projection envelops and therefore should not be neglected in the climate change studies. A similar observation was also made by few other researchers (Bastola et al., 2011; Brigode et al., 2013; Mendoza et al., 2016; Mockler et al., 2016). Here we have shown its variation across the seasons. All the earlier studies that considered parameter uncertainty in the streamflow projection used single objective function for parameter selection. Even though some of the studies have adopted multiple objectives (Mendoza et al., 2016; Mockler et al., 2016; Brigode et al., 2013; Wilby, 2005) they were not in a strict Pareto sense. In conclusion, these studies have also recommended the use of multi-objective calibration to arrive at robust sets of model parameters (Brigode et al., 2013; Mockler et al., 2016). In the present study the parameter sets are obtained as a result of multi-objective process, therefore, they are more robust than considering a single optimal parameter set.

Some researchers (Deser et al., 2012; Lafaysse et al., 2014) have elaborated the need to evaluate the contribution of internal climate variability in the total projection uncertainty. Lafaysse et al. (2014) found that the role of internal variability for the precipitation cannot be neglected; while for temperature projections, especially after 2050, it is negligible and the GCM uncertainty only to be the main contributor. This aspect has not been explored in the current work and will be dealt with in future research.

5.5.8 Quantifying the streamflow change

In order to establish the statistical significance of the change between the control period flow ensemble and the projected flow ensemble the percentage change with respect to the control period is computed for each of the models (represented by Pareto-optimal parameter set) and for each months. The change is found to be significantly higher for the months February to May and for models 1-3 (representing group-1) as against other months. Fig. 5-15 presents the heat map plot of the streamflow change for each of the models and months.
Finally, the seasonal change in streamflow availability for the two scenario periods w.r.t. the control period is computed. On the basis of the mean model ensemble, the winter period will face the maximum change in the available flow, 91% increase for mid-century period and about 121% for end-of-the-century period. For the spring period, the overall variation in flow when compared to the control period is very low, but it shall be interpreted with caution. Variation in streamflow during this season is due to the increase in flow during the month of April, which gets compensated by decrease during May; but the shift in the spring peak by almost a month is very significant. This can impact agriculture, animal adaptation and hydropower generation. The most concerning impacts are projected during the summer period where the decrease in streamflow is projected to be of the order of 34% and 47% for the two study horizons, respectively. The results also indicate higher change for end of the century period as against the mid-century period (Fig. 5-16) for all the seasons.

Fig. 5-15 Heat map depicting the percentage change in flow between control period average monthly streamflow and projected streamflow projected by each climate model for (a) mid-century period and (b) end of the century period

Fig. 5-16 Projected average changes in seasonal streamflow with respect to the control period
5.6 Conclusions

In the present study, the climate change impacts and the associated uncertainties were evaluated for the streamflow of the Magpie River draining a highly forested watershed. As the river is exploited for hydropower generation, the results are important for the decision makers. The standard protocol generally adopted for the climate change studies in hydrology was also followed in the present work. A semi-distributed hydrological model, SWAT, was calibrated based on the multi-objective calibration strategy involving hydrological signatures. Prior to applying the model for a scenario period flow projection, the model was first tested for its simulation efficiency in mimicking the observed watershed hydrology. A good model calibration and validation was achieved as the evaluation period included both dry and wet periods, multiple evaluation techniques were adopted and all important model outputs such streamflow time-series, low flows and flow duration curves were well reproduced.

The model was then employed to simulate the scenario period hydrologic regime by forcing the calibrated model with the bias corrected daily climate scenario data extracted from an ensemble of six regional climate models. The hydrologic model was run with Pareto-optimal parameter sets, which were helpful in assessing the HM uncertainty along with the climate model uncertainty arising out of climate model ensemble. The extrapolation of models employing the Pareto-optimal parameter sets, derived through multi-objective process, fulfills the need for a robust parameter estimation methodology for a changing condition (Peel and Bloschl, 2011).

It was found out that the contribution of HM parameter uncertainty was significant and the same should not be neglected. The impact of model parameter uncertainty was evaluated across the seasons and found to be significantly varying. It was higher during the summer period and lower during other months of the year when climate model uncertainty dominates. The climate model uncertainty is primarily due to the varying simulation skill of the climate models in the ensemble. The projection by the models driven by similar boundary condition, by virtue of same GCM, were found to be similar. Accordingly, the models were divided into two groups. During the late winter and spring months, when the total projection uncertainty was very high, the differences in projections by the two groups of models were noticeable. This was found to be the primary cause of higher projection uncertainty during these months.

Finally, the average change in the mean streamflow was computed. The projection varied over the year and across different climate models. Members of the group-1 climate models have projected a very high increase in the late winter flows. On an average the streamflows in the
scenario period, in comparison to the baseline period, were found to be increasing during the winter period by 91% for mid-century period and by 121% for end of the century period. For the other seasons the streamflows were found to be decreasing. The most concerning impacts are projected during the summer period where the decrease is of the order of 34% and 47% for the two study horizons, respectively.

The limitations of present study are: (a) few other sources of uncertainty, such as uncertainty due to bias correction method, climate scenario and hydrological model structure have not been accounted for, and (b) more members in the climate model ensemble would be better, but it was limited by data availability. Knowledge about the contribution of the two uncertainty sources, studied here, may assist in improvising the future impact modeling studies. The results indicate that the uncertainty arising from the hydrological model parameters are not negligible and need to be suitably accounted for.

In order to reduce the uncertainty due to the varying skills of the climate models, it may call for providing different weights to the climate models in the ensemble. Even though there has been a debate in the scientific community on this issue (Chen et al., 2017; Christensen et al., 2010; Tebaldi and Knutti, 2007), the researchers stand divided. In the context of present results more work is proposed to be taken up on this issue of weighing the climate models.

5.7 Acknowledgements

The present research is funded by the Natural Sciences and Engineering Research Council (NSERC) of Canada through the Discovery grant programme to the senior author. The first author’s research is also supported through Ontario Graduate Scholarship and University of Windsor scholarship. We acknowledge the World Climate Research Programme’s Working Group on Regional Climate, and the Working Group on Coupled Modelling, former coordinating body of CORDEX and responsible panel for CMIP5. We also thank the climate modelling groups (listed in Table 1-1) for producing and making available their model output for the present research on impact assessment. The authors would like to thank Dr. David Hadka and Dr. Patrick M. Reed for providing the executable code of Borg used in this research for SWAT model calibration. The authors also extend their sincere thanks to the project authorities at Brookfield Renewable Power Limited for sharing the streamflow data required for hydrologic model development and holding discussions at various stages of this work.
Chapter 5

Investigating the Role of Hydrological Model Parameter Uncertainty in Streamflow Projection

5.8 References


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6.1 Chapter Synopsis
The climate change resulting from anthropogenic factors is pushing governments and policy-makers to provide additional thrust on renewable energy. Hydropower, which is the dominant renewable component of the energy-mix, is also under threat due to the changing climate conditions. The present study aims to quantify the impact of climate change on hydropower generation, the associated revenues and subsequently suggest the adaptation measures through adaptive reservoir management. Based on the modeling chain that consists of development of hydrologic and hydropower models, the impacts due to projected climate change on hydropower generation and the associated revenues are computed. The results show that the annual generation is not considerably affected but there is a significant seasonal redistribution on energy production. The changes in the hydropower revenues compared to the present level for the four seasons viz., winter, spring, summer and autumn are estimated to be 21.1%, 18.4%, -13.4% and -15.9%, respectively, for mid-century and 23.1%, 19.5%, -20.1% and -22.9% for end-century scenarios. Multi-objective optimization of reservoir level was found to be an effective approach to develop adaptation measures provided additional live storage is made available. It also reduced the vulnerability of the system to climate change by 24%. The seasonal alteration in the energy production will require the project owners to arrange modification in power purchase/sharing agreement with the buyers.

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5 This chapter has been submitted to Renewable Energy and is under review.
6.2 Introduction

Climate change is a growing concern for existing infrastructure. Hydropower generating facilities that constitute a significant part of energy infrastructure involve complex project components with huge capital investments. These projects are designed for service life that run into decades. Studies have pointed to a varying levels of impacts due to climate change on the water availability (Eisner et al. 2017; Karlsson et al. 2016; Li et al. 2016), the only fuel for hydropower, thus making hydropower generation projects very vulnerable to climate change (de Queiroz et al. 2019). All these reasons are making policy-makers, project owners and investors further anxious about the threats of future climate scenarios on hydropower generation and the associated revenues.

Canada has a huge hydropower infrastructure. The total hydropower installed capacity in Canada, by 2017 was 81 GW (Hydropower Status Report - Sector Trends and Highlights 2018) and it contributes 59% of the country’s total electricity generation. Canada ranks globally fourth in terms of total hydropower installed capacity. In addition to fulfilling energy needs, the hydropower industry contributes $37 billion annually to the gross domestic product (GDP) and supports 135,000 jobs (PRISM 2015). These statistics depict the importance of hydropower to the Canadian economy.

Governments across the globe are taking measures to reduce greenhouse gas (GHG) emissions. The United Nations Framework Convention on Climate Change (UNFCCC) is tasked with supporting the global response to the threat of climate change (“UNFCCC” 2019). It sets out a legal framework for stabilizing atmospheric concentrations of GHGs to limit the global temperature rise to an acceptable level. Under this, Canada has targeted a reduction of 30% GHG emission by the year 2030 from 2005 levels (“ECCC” 2019). Even tough the country has one of the cleanest electricity grids in the world, the electricity sector contributes about 11% of the total greenhouse gas emissions. The median life-cycle carbon equivalent intensity (gCO2-eq/kWh) for different electricity generation sources, such as coal, gas and solar are 820, 490 and 48 gCO2-eq/kWh, respectively (Hydropower Status Report - Sector Trends and Highlights 2018). While the same for hydropower generation is found to be much lower at around 18 gCO2-eq/kWh. This may call for phasing out the emission causing sources of generation and replacing them with cleaner options including hydropower, as part of climate change action strategy.
Considering the importance of hydropower to the Canadian electricity sector and its role in mitigating climate change (Berga 2016), it is important to assess the impacts of changing climate on hydropower generation. Various studies have been conducted that enlighten the community on this concerning issue (Ray et al. 2018; Chilkoti et al. 2017; Kopytkovskiy et al. 2015; Schaefli et al. 2007; Haguma et al. 2014; Huaringa Alvarez et al. 2014; Christensen and Lettenmaier 2007; Payne et al. 2004; Mimikou and Baltas 1997); these also include Canadian case studies (Haguma et al. 2014, 2017; Minville 2010; Oni et al. 2012). Most of these studies have appeared during last fifteen years.

The importance of such studies not only rests on quantifying the impacts, but also on formulating adaptation measures to reduce the vulnerability of hydropower system to climate change and consequently mitigate the impacts. Haguma et al. (2017) categorizes the hydropower adaptation strategies into two groups: structural and non-structural. The former involves modification to the physical system configuration, while the later focusses on operational alteration or adaptive reservoir management to minimize the impacts. Most of the studies focused on the later measures. The results of the research by Minville (2010) and Payne et al. (2004) concluded that reservoir operating rules need to be revisited to account for the modifications in hydrology anticipated due to climate change. Georgakakos et al. (2012) demonstrated the value of adaptive management for a Northern California water resources system that included hydropower projects. Haguma et al. (2014) formulated a revised weekly operating policy as an adaptation measure for a water resources system of the Manicouagan River, located in Quebec, Canada. Impacts of climate change on Columbia River basin were studied by Payne et al. (2004) and the authors also examined several alternative reservoir operating policies to mitigate reservoir system performance losses. These studies suggested that the adaptive management constitutes an effective mitigation measure for climate change impacts.

The above studies focus on the reservoir adaptation to mitigate the adverse impacts on the water availability and energy generation. From a business perspective, it is vital to optimize the revenues along with the energy generation. Incorporating revenue generation while formulating the adaptation measures will bring forth the economic perspective and be more appropriate for the decision-makers. de Queiroz et al. (2019) analyzed the impact of climate change on the revenues of Brazilian hydropower plants. Buttle et al. (2004) estimated the electricity generating capacity
of the hydropower facilities on the Grate Lakes watershed (Canadian side) under several climate change scenarios. These estimates were then evaluated using a selection of pricing options on the basis of economic assumptions concerning adaptation and time frame for impacts and adaptation. Gaudard et al. (2014) evaluated the climate change effects on hydropower revenue by including an electricity pricing model. Even though there are some studies that place emphasis on hydropower revenue, more work will benefit the end users.

Several researchers have provided assessments of general trends of impact over large region. Climate change impacts on Brazilian hydropower industry were presented by de Queiroz et al. (2016). Boehlert et al. (2016) computed the impacts of various emission projections on hydropower generation and then analyze the physical and economic effects of changes in hydropower generation for the contiguous U. S. in future. Impacts of changing climate on the Portuguese electrical system particularly focusing on the impacts on water resources availability and hydropower generation was assessed by Teotônio et al. (2017). As pointed out by Gaudard et al. (2014) and Schaefli (2015a), the effect of the changing trends in climate cannot be generalized for hydropower and will vary based on the individual project location, size and configuration. Two projects of different configuration, for example one being a run-of-the-river and other being a storage type, but located in same area, could have different impacts from changing scenarios. Therefore, from a business perspective it is deemed important to evaluate the impact on individual projects. To this end, the current study focuses on one hydropower facility in Northern Ontario.

The objectives of present study are to: (a) assess the impacts of climate change on hydropower energy and revenue generation, and (b) formulate adaptation measures based on multi-objective reservoir optimization.

### 6.3 Study Area

The climate vulnerability study was carried out for a hydroelectric facility located on Magpie River in Northern Ontario. Although the River is utilized by more than one hydropower generating station, the result of the present work focuses only on one of them. Fig. 6-1 represents the location map of the study area. The Magpie River drains into Lake Superior near the Town of Wawa and is primarily a south flowing river. The catchment area at the project dam site is 1772 km². The watershed lies in the Boreal shield region in accordance with the Canada’s terrestrial
ecozones (Ecological Stratification Working Group (Canada) 1996). The area is primarily a forested region comprising of deciduous, evergreen and mixed type of forests covering almost 70% of the total catchment area.

The previous studies on Magpie River include climate change impact assessment (Oni et al. 2012) and adaptive management study to assess the impacts of flow rate on ecology (Murchie and Smokorowski 2004; Smokorowski et al. 2011). Uncertainty in the streamflow projection under climate change for this river has been carried out by (Chilkoti et al. Submitted) and the present study is an extension of the same study.

![Fig. 6-1 Study Area](image)

6.3.1 Climatic and streamflow characteristics

Based on the climate and flow data from years 2000-2012, the annual average precipitation and streamflow depth over the catchment are 925 mm and 329 mm, respectively giving an average runoff ratio of 0.35. The climate and flow characteristics can be summarized for four seasons: Winter (Dec, Jan-Mar), Spring (Apr-May), Summer (Jun-Aug) and Autumn (Sep-Nov). The average monthly hydrograph has a bi-modal distribution and is depicted in Fig. 6-2. The peak during the first half of the year results from the spring snowmelt while the smaller peak during autumn is precipitation driven. The daily Magpie River flow varies from an extreme low value of 0.64 m$^3$/s to 250 m$^3$/s with a mean daily value of 17.7 m$^3$/s and median of 9.9 m$^3$/s.
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Assessment of climate change impacts and operational adaptation for a hydroelectric facility in Northern Ontario

6.3.2 Hydropower potential

About 11% of the Canada’s total installed capacity lies in the province of Ontario. The Boreal Shield region, wherein the Magpie river basin lies, contains 48% of the country’s total hydropower potential (Global Forest Watch). The Magpie River is utilized by three hydroelectric facilities: Mission Station, Harris Station and Steep Hill Falls. The present study pertains to the 15.5 MW capacity project located at Steep Hill Falls which is upstream of the three projects and is owned by Brookfield Renewable Power Limited (BRPL). The lake behind the dam stretches upstream up to 34 km with a maximum water spread area of approximately 1860 ha. The project began operation in 1990 and the average annual energy generation since then is about 57 GWhr.

6.4 Methodology

In order to arrive at a suitable adaptation strategy against climate change, it is imperative to first assess the extent of the anticipated change in hydropower generation. To this end, first the hydrologic regime of the watershed is simulated through hydrological modeling approach. This provides the required inflow series for power computations. The hydropower model is then applied to compute the monthly energy generation; this is also validated with the limited period data of the actual generation by the hydropower facility. In the next step, the projected streamflows for future scenarios are obtained by forcing the climate data extracted from the climate model ensemble into the hydrological model. Assessment of variation in energy production is then evaluated. Lastly, as an adaptation measure, optimization of reservoir levels is carried out to maximize the revenue generation during the scenario period. The methodology for the different analyses is further discussed in the following sub-sections.
6.4.1 Hydrological modeling

The hydrological modeling was carried out to simulate the hydrologic regime of the study watershed. The model was first calibrated and validated for the historic streamflow conditions and later extrapolated to simulate for the projected future scenarios. A hydrologic model acts as a transfer function between the climate data and streamflow. The relevance of undertaking a hydrological-model based climate change impact assessment (CCIA) study for the hydropower system has been highlighted in (Schaeffli 2015a). In the present study the semi-distributed hydrologic model, Soil and Water Assessment Tool (SWAT) (Arnold et al. 1998), is used to develop a model for the Magpie watershed. The model has been successfully used in other climate change related studies (Haguma et al. 2014; Reshmidevi et al. 2018; Wu and Johnston 2007). The daily precipitation and minimum and maximum temperature data required to drive the SWAT model were extracted from the gridded climate datasets from Natural Resources Canada (Hopkinson et al. 2011; Hutchinson et al. 2009). Streamflow data observed upstream of the project dam site is adopted for model calibration and validation. The model was calibrated using multi-objective evolutionary algorithm (MOEA). The robust calibration strategy incorporating hydrological signatures was introduced by (Chilkoti et al. 2018). The detailed hydrologic modeling of the watershed is presented in (Chilkoti et al. Submitted). The same may be referred to for further details.

6.4.2 Power generation

The hydropower generation is computed based on the available streamflow, driving water head on the turbine and the reservoir volume-elevation relationship. The computations were carried out at daily time step and then summarized on monthly scale. The power and energy produced were evaluated using Eq. 6-1 and Eq. 6-2, respectively.

\[
P(t) = \frac{1}{10^6} Q(t) H_{net} \gamma_w \eta
\]

\[
E(y) = \sum_{t=1}^{365} 24P(t)
\]

where,

\[P(t)\] - power generated at time step ‘t’ (MW)

\[Q(t)\] - flow rate at time ‘t’ (m³/s)
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\[ H_{\text{net}} - \text{net head on turbine (m)} \]
\[ \gamma - \text{specific weight of water (} = 9810 \text{ KN/m}^3\text{)} \]
\[ \eta - \text{turbine-generator efficiency (} = 0.9\text{)} \]
\[ E(y) - \text{annual energy generation (GWhr)} \]

Due to very small variation of water level between minimum and maximum reservoir levels, the head was considered constant at any given water elevation across the live storage. Thus, power generated is directly proportional to the streamflow rate, while the energy generated is proportional to the volume of available water in a given time step. The volume is constrained by the governing upper and lower reservoir water levels.

The water flowing through the reservoir was computed by using a reservoir routing model (Chow et al. 2010) at a daily time step. Eq. 6-3 describes the routing phenomena.

\[ V_j = (I_j - Q_j)\Delta t + V_{j-1} \quad \text{Eq. 6-3a} \]
\[ Q_j = Q_p + Q_{\text{dam}} \quad \text{Eq. 6-3b} \]
\[ V_{\text{min}} \leq V_j \leq V_{\text{max}} \quad \text{Eq. 6-3c} \]

where,
\[ V_j - \text{reservoir volume at the end of time period 'j'} \]
\[ I_j - \text{inflow into the reservoir during time step 'j'} \]
\[ Q_j - \text{outflow from the reservoir during time step 'j'} \]
\[ Q_p - \text{discharge for power generation passing through the turbines} \]
\[ Q_{\text{dam}} - \text{outflow from the dam when } V_j > V_{\text{max}}, \text{this is in addition to } Q_p \]
\[ V_{\text{min}}, V_{\text{max}} - \text{minimum and maximum reservoir storage corresponding to MDDL and FRL, respectively.} \]

The flow required for power generation, \( Q_p \), during normal operating condition is 44 m\(^3\)/s. As per the operating policy of the project, the plant generates at full capacity only during the weekdays. During the weekends, only the minimum environmental flow, as required for sustaining the downstream ecology, passes through the turbine (Smokorowski et al. 2011). The basic reservoir information used in the present study and other parameters required for energy generation are provided in Table 6-1.
Table 6-1 Basic parameters required for energy generation

<table>
<thead>
<tr>
<th>S.No</th>
<th>Information</th>
<th>Value</th>
<th>Unit</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Full Reservoir Level (FRL)</td>
<td>El. 318.5</td>
<td>m</td>
<td>Project authorities</td>
</tr>
<tr>
<td>2</td>
<td>Minimum Draw Down Level (MDDL)</td>
<td>El. 315.0</td>
<td>m</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Minimum storage</td>
<td>42.5</td>
<td>MCM</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Maximum storage</td>
<td>110.5</td>
<td>MCM</td>
<td>(Oni et al. 2012; Smokorowski et al. 2011)</td>
</tr>
<tr>
<td>5</td>
<td>Design turbine discharge</td>
<td>44</td>
<td>m³/s</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Minimum environmental flow</td>
<td>7.5 m³/s</td>
<td>m³/s</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Net head</td>
<td>39.9 m</td>
<td>m</td>
<td>Computed</td>
</tr>
</tbody>
</table>

IESO is the Crown Corporation responsible for operating the electricity market and directing the operation of the bulk electrical system in the province of Ontario. It is one of seven Independent System Operators in North America. The actual generation data is available from the year 2010 onwards. Five-year period from 2011 to 2015, is considered for model validation.

6.4.3 Climate change projection

The climate projections for future scenarios are acquired using the climate models. General Circulation Models (GCMs) are the primary sources of future climate data (North et al. 2015). But the resolution of these models is not appropriate for watershed scale impact assessment study. A Regional Climate Model (RCM) provides data at a finer resolution, and therefore, are functional alternatives to GCM (Teutschbein and Seibert 2010). Data set from six RCM’s that are part of Coordinated Regional Downscaling Experiment (CORDEX) (Giorgi et al. 2009; Mearns 2017), has been extracted. The RCM projections are dynamically downscaled products that derive their boundary conditions from GCMs. The GCMs in the CORDEX are part of the Coupled Model Inter-comparison Project Phase 5 (CMIP5) (Asrar 2011). Use of a multi-model ensemble approach in an impact assessment study provides greater reliability (Schaeфli 2015a) and the same has been adopted in the current study (Table 6-2). For the sake of simplicity, the climate models will be described by their respective numbers henceforth in the manuscript.

Two different future time horizons are considered for impact assessment, the mid-century (2041-1970) and end-century (2071-2100) period. Data extracted corresponds to the Representative Concentrated Pathways (RCP) 4.5, that represents one of the intermediate greenhouse gas emission scenarios (GHGES) as per the latest IPCC guidelines (Pachauri et al. 2014). The raw model
data for the two scenario periods, mid-century and end-century periods, is first bias-corrected using the commonly used quantile mapping method (Piani et al. 2010).

Table 6-2 List of the climate models as part of NA-CORDEX and adopted in the present study

<table>
<thead>
<tr>
<th>Model No</th>
<th>Regional Climate Model (RCM)</th>
<th>Driving General Circulation Model (GCM)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RCM</td>
<td>Modeling Agency*</td>
</tr>
<tr>
<td>M1</td>
<td>CanRCM4</td>
<td>CCCma</td>
</tr>
<tr>
<td>M2</td>
<td>RCA4</td>
<td>SMHI</td>
</tr>
<tr>
<td>M3</td>
<td>CRCM5</td>
<td>UQAM</td>
</tr>
<tr>
<td>M4</td>
<td>RCA4</td>
<td>SMHI</td>
</tr>
<tr>
<td>M5</td>
<td>HIRHAM5</td>
<td>DMI</td>
</tr>
<tr>
<td>M6</td>
<td>CRCM5</td>
<td>UQAM</td>
</tr>
</tbody>
</table>

* CCCma - Canadian Center for Climate Modeling and Analysis, SMHI – Swedish Meteorological and Hydrological Institute, DMI – Danish Meteorological Institute, ICHEC – Irish Center for High End Computing, UQAM-Université du Québec à Montréal, MPI – Max Planck Institute of Meteorology

6.4.4 Reservoir optimization for climate change adaptation

Based on the results of the climate change impact assessment, the suitable adaptation measures need to be undertaken. The primary goal of adaptation is to reduce the adverse impacts of the anticipated changes due to modification in hydrologic regime. For a hydropower project, the adaptation should aim to reduce the energy deficit with respect to the historical generation while also maximizing revenues. There are different possible adaptation measures for various infrastructure projects. The present study focuses only on the operational adaptations for the hydropower under study. The operational adaptation is attempted to maximize the revenue generation by modifying the existing reservoir rule curve. A simulation-optimization approach is adopted to achieve the same. A multi-objective computational algorithm is coupled with a simulation model to carry out the optimization process (Fig. 6-3).

6.4.5 Multi-objective optimization

A multi-objective problem is generally formulated as described in Eq. 4-1(Deb 2001). Multi-objective optimization has been applied in various fields of engineering and sciences (Eriksson and Gray 2019; Reed et al. 2013; Zhou et al. 2011) and has gained a wide popularity in the water
resources applications including reservoir optimization (Ashofteh et al. 2015a; b; Sarzaeim et al. 2018).

In the present research the Borg multi-objective algorithm (Hadka and Reed 2013) is adopted to constrain the objectives for attaining an optimal solution. Borg belongs to the class of evolutionary algorithms that evolves solution on the basis of genetic operators leading to an optimal Pareto solution set. Since its inception, the Borg algorithm has attained popularity due to the various advantages it possesses over other conventional algorithms such as NSGA-II. Borg has been applied in variety of water resources application (Chilkoti et al. 2018, Kasprzyk et al. 2016, Hadka et al. 2015, Reed et al. 2014).

In the present work, the objective of the optimization is to maximize the revenue from hydropower production. The decision variables are the minimum reservoir levels, as they can be optimized for certain periods, especially the low flow period. The water for energy generation is drawn from the reservoir live storage and thus, the minimum water level governs the quantum of available water and the hydropower production. Although the computations are carried out at daily time step, the water level constraints (decision variable) are being imposed at monthly time scale. If the constraint is provided on a daily scale the system operator may not be able to handle frequently changing water level constraints.

Considering monthly water levels as the decision variable will result in twelve variables. More variables adversely affect the performance of the optimization algorithm. Moreover, in multi-objective optimization the objectives should be compromising. The energy generation in a given month is dependent only on the water level for that month and the previous month. Since the

**Fig. 6-3 Reservoir simulation-optimization model**
reservoir under study does not have over-the-season storage, the energy generation in a month, say June, is not dependent on the water levels in the reservoir during January. This is the main reason for not considering all the months as decision variables and hence only three variables are optimized.

Since the objective is to maximize the revenue, the months having the higher energy sale price need to be targeted. Fig. 6-4 presents the average monthly energy sale rate based on 2002-2018 (Independent Electricity Systems Operator (IESO) 2018). It is assumed that the sale rate remains same in a future scenario. There are many factors affecting the price of electricity at any given time, like market demand, planned or unplanned plant outages, location of supply, among others (Buttle et al. 2004). A stochastic model can be incorporated for future electricity rates, but it will also introduce additional uncertainty in the analysis. It is beyond the scope of the present work to project the electricity prices and its variations.

![Electricity sale price based on average monthly values for 2002-2018](Image)

**Fig. 6-4** Electricity sale price based on average monthly values for 2002-2018 (Independent Electricity Systems Operator (IESO) 2018)

Based on the plot it is evident that the energy prices are maximum during peak summer months (July and August) and peak winter months (January and February). Enhancing the energy generation during these months would lead to maximizing the total revenue. We propose to carry three-objective optimization in two stages, first for the summer months and followed by the winter period, keeping the summer optimal water levels. For the other months, the allowable MDDL is kept the same as during the control period operation. **Table 6-3** presents the objective function and the decision variables used in the optimization. The table also presents the two different options for adaptation as considered on the basis of additional live storage. In the first
option no additional storage is provided and thus the MDDL remains the same as present. Whereas in the second option, 15% additional live storage is proposed by making the MDDL lower by 1 m below the present level.

**Table 6-3** Objective function and decision variables proposed for multi-objective optimization; two different options considered for adaptation

<table>
<thead>
<tr>
<th>Stages</th>
<th>Objectives</th>
<th>Decision variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stage-1</td>
<td>( f_1 = 1/Rev_{June} )</td>
<td>MDDL for May, June</td>
</tr>
<tr>
<td></td>
<td>( f_2 = 1/Rev_{July} )</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( f_3 = 1/Rev_{Aug} )</td>
<td></td>
</tr>
<tr>
<td>Stage-2</td>
<td>( f_1 = 1/Rev_{Dec} )</td>
<td>MDDL for Nov, Dec</td>
</tr>
<tr>
<td></td>
<td>( f_2 = 1/Rev_{Jan} )</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( f_3 = 1/Rev_{Feb} )</td>
<td></td>
</tr>
</tbody>
</table>

\( f \) – objective function, \( Rev_{June} \) – hydropower revenue during June month

<table>
<thead>
<tr>
<th>Adaptation Option</th>
<th>Additional Storage</th>
<th>MDDL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Option-1</td>
<td>0</td>
<td>No change</td>
</tr>
<tr>
<td>Option-2</td>
<td>15%</td>
<td>1m below existing MDDL</td>
</tr>
</tbody>
</table>

6.4.6 Vulnerability

The adaptation measure aims at mitigating the adverse impacts of climate change and thus reducing the vulnerability of the system to the changing conditions. Vulnerability indicates the severity of an unsatisfactory state (Minville 2010). It can be quantified using Eq. 6-4.

\[
v = \frac{\sum_{i=1}^{N} v_i}{N} \quad \text{Eq. 6-4a}
\]

\[
v_i = \begin{cases} 
0 & \text{if } E_{sce} < 0.9E_{control} \\
1 & \text{if } E_{sce} \geq 0.9E_{control}
\end{cases} \quad \text{Eq. 6-4b}
\]

where, \( v \) – vulnerability, \( E_{sce}, E_{control} \) – energy generated during scenario and control period, respectively, for each month and each climate model, \( N \) – total number of periods tested = 12 x
number of climate models. Vulnerability varies between 0 to 1, with 0 indicating that the system is not vulnerable. It will be determined for scenario climate conditions without and with adaptation measures.

6.5 Results

This section presents the results of the hydrological model simulation, hydropower energy generation, climate change impacts on energy and associated revenue and the adaptation options to mitigate the effects of climate change.

6.5.1 Historical period model simulation

Hydrologic model simulation

As explained in the methodology, the SWAT model is adopted to simulate the streamflow of Magpie River. As SWAT is a semi-distributed model, there are a large number of parameters that play a role in simulating the various process associated with runoff generation. Thirteen relevant parameters affecting the streamflow were selected for calibration. The model performance was measured in terms of Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe 1970), percentage bias (PBIAS) (Moriasi et al. 2007) and Kling-Gupta efficiency (KGE) (Gupta et al. 2009). During the calibration and validation periods, the statistics were found to be very good: NSE as 0.83 and 0.81, PBIAS as 5.1% and 2.6% and KGE as 0.9 and 0.89, respectively. Fig. 6-5 presents the summary of model streamflow simulation. Time series during the calibration period (2003-2008) is presented in Fig. 6-5(a); the shaded region represents the simulated model streamflow corresponding to the Pareto-optimal solution set. The average monthly flow volumes during the same period are compared in Fig. 6-5(b).

![Streamflow calibration from SWAT model](image)

**Fig. 6-5** Streamflow calibration from SWAT model (a) monthly time series of observed and ensemble simulation, and (b) comparison of average monthly flow volume
Chapter 6
Assessment of climate change impacts and operational adaptation for a hydroelectric facility
in Northern Ontario

The relatively inferior model performance for the month of May should not be a cause of concern, as the flow during this month always exceeds the design discharge for power generation. Any additional flow would be spilled through the dam.

Apart from these metrics, the model was also tested for its efficiency to simulate the flow in various flow zones and overall water budget. The model was found to be satisfactory on all these efficiency considerations. A good model simulation is imperative for the analysis, as streamflow is the key input in estimating the hydropower generation. For further details on parameter selection, the calibration scheme and various efficiency metrics, Ref. (Chilkoti et al. Submitted) may be referred.

Energy generation
For the available inflow series, hydropower production and corresponding energy is computed. The installed capacity of the project is 15.5 MW and design discharge through the turbines is 44.0 m³/s. Considering the turbine-generator efficiency as 90%, the design head works out to 39.9 m. Applying these values along with the daily inflow rate to Eq. (1) and (2), the power and daily energy generation are obtained. Cumulative monthly and annual generation is then confirmed against available actual generation data. Fig. 6-6 presents the performance of energy generation model. The comparison of monthly values is shown as scatter plot in Fig. 6-6(a). The annual generation for control period are presented in bar plot from 1991 to 2015. Since the observed generation data is available only after 2010, the same are indicated in the plot.

Fig. 6-6 Actual and modeled hydropower generation (a) Scatter plot of monthly energy generation for the period 2011-2015 (b) Simulated annual energy generation during control period (1991-2015), circles represent the actual energy generation
The model performance for monthly generation is reasonable with coefficient of correlation ($r^2$) as 0.71, while that for annual generation is excellent at 0.97. The prime reason for lower monthly performance is non-inclusion of market energy-demand in the simulation. Due to non-availability of the data on flow release through the dam, a generic rule is applied in the model. Accordingly, the turbines generate energy only during the day time on the weekdays (Smokorowski et al. 2011). During other times (nights and weekends) only the minimum environmental flow of 2 m$^3$/s, as required to maintain the downstream ecology (Smokorowski et al. 2011), passes through the turbine and then released back into the river. On the other hand, in real scenario the energy generated may be deviating from these rules. For example, during some of the months, in spite of water being available for generation, the lesser market demand restricts the operators to generate electricity. On the other hand, the greater market demand during some periods, forces the facility to generate more. These could not be strictly accounted for in the model.

Reservoir Simulation

**Fig. 6-7** (a) presents the daily inflow into the reservoir and variation of reservoir water level between the live storage during a typical year, as computed based on Eqs. 1, 2 & 3. Typically the reservoir is refilled during the spring snowmelt season. Subsequently when the inflows reduce, the reservoir level depletes while supplying the deficit volume for hydropower generation. By the end of summer, the reservoir is lowered to its minimum live storage level. During the late winter and early autumn months, when the inflows are at minimum, the energy production also remains the lowest (**Fig. 6-7** b) as the reservoir is at minimum drawdown level and cannot further contribute water for electricity generation.

![Fig. 6-7 Monthly reservoir simulation for a typical year (2015) (a) reservoir inflows vs. variation of reservoir water level; (b) reservoir inflows vs. hydropower generation](image-url)
Based on the computations for each of the years during the control period (1991-2015), the average reservoir level maintained during each month is presented in Fig. 6-8. The reservoir remains at the highest level during the spring months. Autumn period precipitation also leads to filling of the reservoir but not as high as the spring levels. The reservoir remains at the lowest level at the start of spring and end of summer. It has only a limited live storage and does not have any annual or long-term storage. Once the reservoir is full, it depletes within couple of months depending on the available inflow. The hydropower production is affected by this annual cycle of filling and depleting, as also evident from Fig. 6-7(b).

**Fig. 6-8** Monthly average reservoir level during the control period (1991-2015)

Hydropower Revenue

Based on the hydropower simulated for 25 years (1991-2015), the average monthly energy production is presented in Fig. 6-9 (as bars). The plot also presents the corresponding hydropower revenue which is computed using the average monthly electricity sale rate as presented in Fig. 6-4. It is evident from the plot that the revenue during July is greater than that of previous two months despite less electricity production. This is due to higher market value of the energy during that period. Similar observation can be made for December when compared to November. These numbers play an important role from an economic perspective. It is not only important to generate more energy during a given time, but that energy should fetch commensurate returns. This feature of revenue generation will be later exploited in formulating the adaptation measure for climate change conditions. Even though the electricity rates vary across the day, the adoption of rates will depend on the scale of planning. For long term planning such as, for climate change scenario, the average monthly rates are justified.
6.5.2 Climate change impact

This section presents the results for climate change impacts on (a) the streamflow using the hydrological model and (b) hydropower energy and revenue generation.

![Monthly average hydropower production and revenue generation](image)

**Fig. 6-9** Monthly average hydropower production (bars) during the control period (1991-2015); solid line indicates the monthly revenue generation

**Impact on Streamflow**

For evaluating the impacts of changing climate on hydropower generation, the variation in the streamflow for a scenario period is first computed. Based on the data analysis, the change in average precipitation during mid-century and end-century periods is projected to be 9.4% and 10.6%, respectively. The average increase in minimum and maximum temperature is projected to be 2.8°C and 2.6°C, respectively for the mid-century scenario; while for end-century, these values are 3.5°C and 3.4°C, respectively. Even though an overall increase in key climatic parameter is found, a considerable seasonal variation also expected. For further details Ref. (Chilkoti et al. Submitted) may be referred.

The scenario period climate data, on a daily time-scale, is then forced into the calibrated hydrological model to generate the runoff projection. **Fig. 6-10** presents the comparison between the control period and both the scenario periods average monthly streamflow. The shaded region represents the projected scenario streamflow due to the climate model ensemble. Some significant trend can be interpreted for the scenario streamflow when compared to the control period flows. First, the annual peak flows are projected to occur earlier by about a month for mid-century and by two months for end-century. Second, the winter flows will substantially increase. Third, the summer period flows are projected to reduce for both the scenario periods, with the
change more severe for the later scenario. Similar conclusions for streamflow projection have been made by the other research studies carried out in the regions that are climatically similar to the current study area (Seiller and Anctil 2014; Chen et al. 2011a; Poulin et al. 2011).

![Fig. 6-10](image)

**Fig. 6-10** Comparison of average monthly streamflow between control and scenario period (a) mid-century (b) end-century. Firm line represents the control period flow and shaded region represents the climate model ensemble projection.

Climate change impacts on streamflow are quantified and are presented in **Table 6-4**. The table provides the median and the range of flow change for both the scenarios with respect to the control period. The range of values (Min and Max) in the table, as evaluated using each of the climate models, demonstrate the uncertainty in the projection. As can be interpreted from the median change values, the changes in streamflow during winter and summer periods are projected to be more severe moving from mid-century to end-century; while that for spring and autumn periods, the change w.r.t the control period does not vary significantly.

**Table 6-4** Percentage change in streamflow for the mid-century (2041-2070) and End-century (2071-2099) with respect to the control period (1991-2015). The table provides the minimum, median and maximum % change by the ensemble of six climate models.

<table>
<thead>
<tr>
<th>Season</th>
<th>Mid-century</th>
<th>End-century</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Median</td>
</tr>
<tr>
<td>Winter</td>
<td>9.4</td>
<td><strong>62.4</strong></td>
</tr>
<tr>
<td>Spring</td>
<td>-18.2</td>
<td>-3.7</td>
</tr>
<tr>
<td>Summer</td>
<td>-45.1</td>
<td><strong>-28.7</strong></td>
</tr>
<tr>
<td>Autumn</td>
<td>-14.6</td>
<td><strong>-6.1</strong></td>
</tr>
</tbody>
</table>
Impact on Energy and Revenue generation

The effect of climate change on energy generated may not be the same as that on the streamflow, as the hydropower energy is limited by the installed capacity and the volume of available water in the reservoir live storage. Fig. 6-11 presents the comparison of energy generated by Steephill Falls hydroelectric facility during the control and end-century period. Similar to the streamflow trend, the energy production is projected to increase during winter months and decrease during the summer and autumn months. On the other hand, the spring period flow was found to decrease (Table 6-4) but the hydropower energy is estimated to increase in the future scenario. This is because the reservoir is filled by the winter months’ inflow, which provides an adequate supply of water for electricity generation leading to the enhanced spring period generation. Autumn period energy reduction is consequent to the reduced availability of streamflow. The maximum energy generation through the turbines is limited by the turbine sizes, i.e., the project installed capacity. For Steephill Falls this is approximately 6.8 GWhr for a month, given that the design flow is available throughout the month. Therefore, despite additional water available during the winter period, the monthly energy is limited by installed capacity.

For the future planning of resources, the quantification of the expected change in the hydropower production is essential. The median (model ensemble) change in generation for winter, spring, summer and autumn periods are 44.9%, 17.3%, -14.9% and -18.4, respectively for the mid-century and 53.1%, 18.4%, -25.5% and -19.4, respectively for end-century. There is a clear trend of seasonal redistribution in hydropower production. The project-authorities need to be aware of
these changing trends in order to take further decisions on adaptation either technically, financially or otherwise.

Seasonal changes in hydropower production in the present case were found to have similar trends as in the study by Minville et al. (Minville 2010), their study also being in a Canadian snow-fed watershed at a similar latitude. While, in the study of hydropower project lying in much lower latitude (Chilkoti et al. 2017), resulted in increased autumn period generation, in contrast to the projections presented here. In spite of two projects being of similar size and configuration, the regional differences in the two study areas could be the reason for this. Thus, the climate change impacts on each hydropower facility will be different depending on its location, type and size (Schaefli 2015b).

Consequent to the impacts on hydropower production, the revenue is also affected. Fig. 6-12 presents the percentage change in the hydropower revenue between the historical period and the two scenario periods with respect to the control period revenue. The plot clearly indicates the first two seasons of the year are projected to perform well for the business due to the enhanced generation as determined earlier. The latter half of the year will face the negative impacts of climate change due to decreased generation. It is significant to note that the changes are amplified for the later scenario with the biggest change for the summer season.

**Fig. 6-12** Percentage change in the hydropower revenues between control and the two scenario periods. Each box plot represents the change values computed by the climate model ensemble for the specific month or season.

For long term planning, the total annual revenue is relevant for the decision-makers. Table 6-5 presents the annual average revenue during the control period, and the two scenario periods.
There is no adverse impact expected on annual revenue for the mid-century while for end-century the revenues reduce by about 2.2%. The decrease in hydropower energy and revenue during second half of the year gets mostly compensated by the increase during the first half of the year. The study of the hydropower project located in Rhone River sub-catchment in Switzerland in (Gaudard et al. 2014), also indicated minor increase in revenue for mid-century and decline for end-century scenario. But as discussed earlier, the seasonal impacts are more concerning.

Table 6-5 Climate change impact on annual hydropower revenue generation. The scenario values represent the mean values of the climate model ensemble

<table>
<thead>
<tr>
<th>Period</th>
<th>Annual Revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>$2,063,000</td>
</tr>
<tr>
<td>Scenario</td>
<td></td>
</tr>
<tr>
<td>Mid-century</td>
<td>$2,071,000</td>
</tr>
<tr>
<td>End-century</td>
<td>$2,019,000</td>
</tr>
</tbody>
</table>

Projection Uncertainty

The projections from the climate model ensemble portray significant uncertainty, as evident from Figs. 10 and 11. The magnitude of the uncertainty can be assessed from the error bars and box plots in the respective plots. Even though the monthly uncertainty is found to be maximum in the winter month of March (Fig. 6-11a and Fig. 6-12a), the seasonal uncertainty is found to be highest for the summer period. For other months, all the models suggest similar range of energy generation, thus giving better confidence of the projections to the decision makers. The uncertainty arises as a result of different level of projections by the individual member in the ensemble. There are other possible sources of uncertainty in the modeling chain (Chen et al. 2011b; Clark et al. 2016), but the contribution of climate models is generally found to be the maximum in the overall uncertainty (Chen et al. 2011b; Prudhomme and Davies 2009). Hence, the other sources have not been explicitly accounted for in the present work. Some of the research studies point out towards the role of hydrological model parameter uncertainty in the modeling chain (Bastola et al. 2011; Chilkoti et al. Submitted). The authors find it relevant to present an additional analysis for the same.

The Pareto-optimal solution of the hydrological model calibration resulted in 22 sets of feasible parameters (Chilkoti et al. Submitted). For the sake of simplicity, the median parameter set was considered in the analysis up to this point. Now the analysis considering each of the parameter
sets is presented. 22 number of flow series are obtained (equal to the number of parameter sets). On computing the hydropower energy generation using each of the flow series and for each of the six climate models, resulted in 132 values for each of the month. **Fig. 6-13** presents a comparison of the uncertainty in the hydropower energy projection due to the two data sets. The first set only includes the uncertainty due to climate models (six values), while the other includes the hydrological model uncertainty as well (132 values).

No significant difference in the median values is observed for most of the months. As the second set of box plot represents a larger sample size, it is found to have a larger spread for all the months. For winter and spring months, this spread does not vary substantially between the two data sets. While for the summer period, the larger spread in the second set is indicative of the hydrological modeling uncertainties being prominent. Neglecting this uncertainty source may not result in significant differences in the mean value and hence no substantial error in computing the change over the scenario period (w.r.t the control period). But it may not provide a true picture for the overall modeling uncertainty.

**Fig. 6-13** Comparison of projection uncertainty in hydropower generation due to inclusion of hydrological model parameter ensemble. White box presents uncertainty due to climate models (CM) and grey box presents uncertainty due to both climate models and hydrological model (HM) parameters

The projection uncertainty is quantified in terms of percentage with respect to control period values and are presented in **Table 6-6**. For the winter and summer periods, the uncertainty is found to increase from mid-century to end-century; while for the spring and autumn months it is found to reduce, indicating more confident projections. For the managers, it is not only important
to be informed about the projected changes over a period but also how significant is the uncertainty in relation to the change. This can be judged by using the data presented in Table 6-6.

In order to demonstrate the relative importance of uncertainty in the changes occurring, a factor termed as ‘uncertainty signal’ is defined. It is computed as the ratio of the percentage change to the percentage uncertainty. A high value of uncertainty signal represents a low error in projection. Therefore, ‘Uncertainty signal’ thus measures the confidence of projection.

Table 6-6 Percentage change in hydropower revenue and projection uncertainty during the two climate change scenario periods. All are computed with respect to the control period revenues.

<table>
<thead>
<tr>
<th>Season</th>
<th>Mid-century</th>
<th>End-century</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Change</td>
<td>Uncertainty</td>
</tr>
<tr>
<td>Winter</td>
<td>21.1</td>
<td>12.5</td>
</tr>
<tr>
<td>Spring</td>
<td>18.4</td>
<td>7.6</td>
</tr>
<tr>
<td>Summer</td>
<td>(-13.4)</td>
<td>15.5</td>
</tr>
<tr>
<td>Autumn</td>
<td>(-15.9)</td>
<td>11.7</td>
</tr>
</tbody>
</table>

Fig. 6-14 shows its seasonal variation for both the scenario periods. It is found to be lowest for the summer season than the other seasons. During this period, its values close to one implies that the uncertainty in the projection is almost equal to the projected change (even higher for the mid-century period). End-century projections are found to better than the mid-century in terms of uncertainty signal.

Fig. 6-14 Uncertainty signal - ratio of percentage change to percentage uncertainty in revenues for the two scenario periods
6.5.3 Climate change adaptation

Operational adjustment of the optimal reservoir minimum levels is carried out to enhance the annual revenue generation. Fig. 6-15 presents the variation of average monthly energy and corresponding revenue between the control and end-century period. The plot has two key regions, one during July and August (summer) and other during the February (winters), marked as (A) and (B), respectively. Both the regions have higher sale price compared to the immediate previous months. Energy generation in region (A) is projected to decline, while in region (B) it is expected to increase during future period. By enhancing generation during these periods will fetch better revenues. This idea is exploited to formulate the adaptation measure. For each of the two-adaptation option (Table 6-3), the optimization of minimum permissible water level during the month is carried out. As explained in the methodology earlier, this is done in two stages.

Adaptation Option-1

In this option the optimization of monthly revenues is carried out in two stages, with the permissible MDDL for any month kept same as at present.

![Figure 6-15](image)

**Fig. 6-15** Comparison of hydropower energy between control and end-of-the-century scenario period. The firm line indicates the electricity sale rate. The relevant regions on the plot are marked as (a) and (b)

In the three-objective optimization, revenue is maximized for July, August and September months (region A) by varying the MDDL for June, July and August months, as the first stage. The second stage solution for optimizing the revenues for December, January and February months (region B) did not improve total annual revenue. The overall optimization led to only marginal
improvement in the annual revenues. The optimization is not very effective due to the physical system limitations. During the summer period the reservoir is unable to supply the required volume for generation due significant reduction in inflow (Table 6-4) and limited storage capacity; while during the winter period the installed capacity of the system restricts it to utilize the additional available flows. For the system to adapt to the changing scenario, the barriers caused by any of these two i.e., limited reservoir capacity and limited installed capacity need to be removed.

Adaptation Option-2

This adaptation option is formulated against the barrier of limited reservoir capacity. It is proposed to enhance the reservoir live storage by about 15%, which requires to lower the MDDL by 1 m from the present level. With this relaxed constraint on lower reservoir level, the optimization is again performed for both the stages. Fig. 6-16 depicts the Pareto optimal fronts of the solutions generated during each of the optimization stages.

**Fig. 6-16** 3-D Pareto fronts generated for adaptation option-2 by optimizing revenue in (a) Stage-1: July, August and September months, and (b) Stage-2: December, January and February months

**Table 6-7** presents the estimates for annual revenue generation for the control and both the scenario periods, with and without adaptation measures. Maintaining the reservoir MDDL levels the same as during the control period, the revenue generation during the end-century period is projected to decline by 3% due to climate change. The operational adaptation is able to counter this and further escalate the annual revenue by 4%. Even though the mid-century period had no
impact on the annual revenue, carrying out the operational adjustment will enhance the revenue by similar amount. Clearly option-2 outperforms option-1.

**Table 6-7** Effect of adaptation options on annual hydropower revenue generation

<table>
<thead>
<tr>
<th>Period</th>
<th>Control Revenue in $</th>
<th>Adaptation Option-1 Revenue generation in $ after</th>
<th>Adaptation Option-2 Revenue generation in $ after</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>2,063,000</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Mid-century</td>
<td>2,071,000*</td>
<td>2,082,000</td>
<td>2,148,000</td>
</tr>
<tr>
<td>End-century</td>
<td>2,019,000*</td>
<td>2,030,000</td>
<td>2,097,000</td>
</tr>
</tbody>
</table>

*Computed by maintaining the reservoir level same as during the control period

Since the impact was primarily felt on the seasonal hydropower performance (Fig. 6-12), it is deemed relevant to analyze the impact on the seasonal basis. Since adaptation option-2 is more effective on an annual scale, its seasonal performance is presented in Fig. 6-17. The plot presents the percentage change in revenue with respect to the revenue generated without adaptation measure. Increase in revenue during summer and autumn indicates the good performance of the adaptation measure. The end-century scenario has the strongest optimization effect on the summer period, which is a good sign from the business prospective. Kim et al. (2017) also found, based on a South Korean hydropower project, that the existing storage is inadequate for future scenarios and needs upgrade to mitigate the impacts of climate change.
6.5.4 Vulnerability

The vulnerability in hydropower production during each month is verified for each of the climate models (Eq. 6-4). Fig. 6-18 presents the vulnerability matrix before and after imposing the adaptation measures under the future climate scenario. Adaptation option-1 has only nominal effect in reducing the vulnerability whereas, option-2 is able to reduce the vulnerability by 24% from 0.42 to 0.32. Summer and autumn months remain vulnerable even after implementing the adaptation measures.

<table>
<thead>
<tr>
<th></th>
<th>Adaptation Option 1</th>
<th>Adaptation Option 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Month</td>
<td>M1</td>
<td>M2</td>
</tr>
<tr>
<td>Jan</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Feb</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Mar</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Apr</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>May</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Jun</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Jul</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Aug</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Sep</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Oct</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Nov</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Dec</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Vulnerability = 0.42 Vulnerability = 0.4 Vulnerability = 0.32

Fig. 6-18 Vulnerability of the hydropower generation under climate change for end-century scenario; in the matrix, 0 represents not-vulnerable period and 1 is vulnerable period

6.5.5 Reservoir levels

The optimization carried out as operational adaptation, provides the reservoir MDDL to be maintained at the end of each month. Based on the results for adaptation option-2, the modified rule curves (for minimum reservoir levels) are presented in Fig. 6-19. The plot presents the monthly minimum levels as maintained during the control period and the required levels during both the scenario periods. All the levels are presented w.r.t. the present MDDL. The scenario period values correspond to the median of the Pareto-optimal solution. Even though there is uncertainty in the projections as indicated by the error bars, the trend is evident. The reservoir should be kept at significantly higher level during the summer time to generate higher revenue. In the control period, the reservoir is allowed to be lowered up to the given MDDL during summer; but in future scenarios, the limiting reservoir level need to be maintained higher during these months to maximize the profits. On the other hand, during the late autumn and early winter months, the reservoir should be lowered compared to the present level. For the end century
period the January level needs to be significantly lower than the present operational level. Similar inferences for the reservoir level were also found by the other researchers (Haguma et al. 2014).

**Fig. 6-19** Comparison of reservoir rule curve during control and scenario periods (after adaptation). The scenario period levels correspond to the median of the Pareto-optimal solutions

### 6.6 Conclusions

The climate change resulting from the anthropogenic factors is driving interest in renewable energy. Hydropower, which is the dominant component of the renewable proportion, is facing threat due to the changing climate scenarios. The present study has quantified the impact of climate change on hydropower energy generation and the associated revenues and subsequently suggested the adaptation measure through adaptive reservoir management.

The modeling framework for the work comprised of four stages. First, the assessment of modification in streamflow hydrology due to changing climatic variables has been carried out. The hydrologic regime is simulated using a hydrologic model, SWAT, which is first calibrated and validated for the historic period observed flows and later used to simulate the scenario period streamflow. Second, the hydropower generation of Steephill Fall generating station was simulated by applying the basic equations on power computation and reservoir routing. The energy generated was then verified on monthly and annual scale with the five years of actual generation data. Next, the impact of climate change on streamflow and energy generation was evaluated. The bias-corrected climate data from six regional climate models were forced into the hydrologic model to obtain the projected streamflow at the hydropower site. Using these flow series in the energy model, the future period energy and revenues were computed. Lastly, based on the extent and direction of deviation computed in the hydropower revenue due to climate
change, the adaptation measure is proposed. Adaptive management of the reservoir through multi-objective optimization is carried out to counter the adverse impacts.

The hydrologic model had very good performance during the calibration and validation period which was assessed based on the different statistical indices. The hydropower model simulated the annual hydropower with 97% accuracy, but its performance was only satisfactory for the monthly timescale. The non-inclusion of market electricity demand in the model was found to be the key reason for this under-performance. The impact assessment due to climate change on streamflow (model median) was found to increase the available flow during winter season while it decreased during all other months. The decrease in summer flows is concerning for watermanagers. The annual hydropower generation was found to reduce by 2.2% for end-century but had no adverse impact during the mid-century period. A significant seasonal redistribution in hydropower production was observed, with the increase during the first half of the year and the decrease in the later half. Correspondingly, the median percentage change in hydropower revenues for the four seasons, winter, spring, summer and autumn, are 21.1%, 18.4%, -13.4% and -15.9%, respectively, for mid-century and 23.1%, 19.5%, -20.1% and -22.9% for end-century scenario. The severity of change is found to be more for the later period scenario. The model projection had significant uncertainty which was also quantified.

Optimization of reservoir levels, which was carried out in two stages first for summer months and then for winter, led to an improved performance for future climate scenarios. Without adding any live storage, the adaptation measure was not very effective due to the significantly reduced summer inflows. Also, the limitation of fixed installed capacity hinders the utilization of increased winter flows. Enhancing the live storage by 15% requires MDDL to be lower by 1 m and improves the generation both annually and seasonally. The adaptation measure also reduces the vulnerability of the project by 24% from 0.42 to 0.32. Even though the hydropower infrastructure remains vulnerable, with the suggested adaptation measure, the project managers and investors can be confident of assured annual returns. The key aspect requiring attention is the seasonal alteration in the energy production which would require suitable modification in power purchase/sharing agreements with the buyers.

The present work did not include the market demand variation anticipated in the future. This may play a vital role in assessing the future vulnerability of hydropower. The market electricity prices
are unlikely to be stationary. The trend of the revenue generation will be very different from the presented results, only if the monthly trend varies from the current trends. This is not very likely as the reduced power availability during summer will keep the prices higher as also in the present scenario. But, inclusion of the market dynamics of price and demand will assist in better overall projection of electricity and the revenues. It is proposed to consider these issues in the future work.

### 6.7 Acknowledgements

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6.8 References


Chapter 6

Assessment of climate change impacts and operational adaptation for a hydroelectric facility in Northern Ontario


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CHAPTER 7 SUMMARY, CONCLUSIONS AND FUTURE WORK

7.1 Summary

Climate change is driving thrust on cleaner sources of energy. Hydropower is the dominant renewable source of electricity generation that is dependent on the natural hydrologic system. Changing climate is projected to alter the hydrologic regime, thus affecting the hydropower generation. This dissertation is an effort towards quantifying the impacts of climate change on hydropower generation and the associated uncertainties, over a long period of time.

Hydrologic models are vital tools for carrying out various assessments for water resources, including hydropower. The present investigation holds hydrologic simulation as pivotal to the entire analysis. The reliability of hydrologic model predictions is of paramount importance while extrapolating the model results for a scenario condition. This research provides direction for an enhanced model performance leading to robust future projections.

The major contributions of the present research are:

- quantified the impact of climate change on hydropower energy generation and revenues (Chapter 2 and Chapter 6)
- demonstrated need for improved diagnostic assessment approaches for hydrological models (Chapter 3)
- improved the model performance by incorporating hydrologic signature based multi-objective calibration (Chapter 4)
- quantified the contribution of hydrologic-model-parameter-uncertainty in total uncertainty of the climate change impacts (Chapter 5 and Chapter 6)
- suggested the adaptation measure for hydropower facilities through adaptive reservoir management (Chapter 6)

The present dissertation is a compilation of five independent research papers elaborating the above ideas. Three of these have already been published and remaining two are submitted to different peer-reviewed journals.
The major contribution of the present study is establishing the importance of hydrologic simulation for climate change impact assessment studies. Two key aspects were investigated: superior model evaluation and robust parameter estimation.

A hydrologic simulation necessitates appropriate diagnosis. The idea of model diagnostic evaluation was explored further. Flow duration curve (FDC) was employed as a tool to assist in better model evaluation. The idea was applied in modeling seventeen watersheds of varying climatic conditions located in Southern United States through a conceptual hydrologic model. The model performance improved subsequent to parameter generation based on the division of FDC into various flow zones.

Multi-objective calibration was adopted for robust model parameter estimation. Coupling of Soil and Water Assessment Tool (SWAT) with Borg multi-objective evolutionary algorithm (MOEA) was found to effectively enhance the model performance. The improvement in the low-flow simulation was observed to be 135% in terms of volume efficiency and 65% for flow time series simulation. Inclusion of hydrological signatures, that are more representative for various streamflow processes, was demonstrated to be an important element in accurate model simulation. This research also investigated the use of multiple evaluation measures in enhancing the model performance. The idea that was first presented for Saugeen River watershed (Chapter 4), was later efficiently adopted in the Magpie River watershed simulation (Chapter 5).

The knowledge on improved model simulation was then applied in assessing the streamflow under altered climate scenario for the Magpie River watershed in Northern Ontario. The hydrologic model developed based on the gridded climate data for control period was forced with data from an ensemble of climate models for two scenario periods, a) Mid-century (2041-2070) and b) End-century (2071-2099). The extrapolation of the model suggests a significant variation in the streamflow quantity in comparison to the control period. In projecting the scenario, two key sources of uncertainties, the climate models and the hydrological model parameters, were taken into account. It was shown that the climate models led to maximum uncertainty in projection, in line with the literature. But a seasonal variation in the prediction uncertainty was also found. Uncertainty emanating from model parameters was also found significant in the range of 16% - 83% of the total uncertainty during the year.
Utilizing the streamflow projection for future period rendered by the hydrologic simulation, the impacts on hydropower generation were evaluated. A hydropower simulation model was adopted to compute the energy generation. Two case studies were presented, a) C.H.Corn Hydroelectric project on Ochlockee River (Florida, USA) in Chapter 2, and b) Steep Hill Falls hydroelectric project on Magpie River (Northern Ontario) in Chapter 6. The later study applied the concepts of improved hydrologic simulation using a semi-distributed hydrological model. The results indicated the vulnerability of the hydropower facilities to climate change. A significant change in generation during most periods with varying uncertainty is projected. The annual variation in the energy is not significant, as the increase during the first half gets compensated by the decrease during the later half. But, the seasonal variation in the energy and revenue generation requires attention of the project authorities. Median changes in hydropower revenue during winter, spring, summer and autumn seasons are estimated to be 21.1%, 18.4%, -13.4% and -15.9%, respectively, for mid-century and 23.1%, 19.5%, -20.1% and -22.9% for end-century scenarios.

In order to reduce the impacts, adaptation of the project through optimal reservoir management is suggested. Multi-objective optimization of the monthly governing water levels was found an effective way of adaptation. It was also found that in spite of the operational adaptation measure, the vulnerability of the project reduces by 24%, from 0.42 to 0.32.

7.2 Conclusions
Evaluating the impacts of changing climate on infrastructure has gained an immense focus in the engineering world. Robust scientific principles are essential to confidently depend upon such an analysis. Estimates of hydropower production are function of reliable hydrological inputs. A good hydrological modeling framework thus underpins a bankable hydropower computation for a scenario period.

Evaluating the hydrologic model performance only based on few statistical metrics computed on aggregate flow simulation may not reflect a models’ true simulation ability. As demonstrated in this research, the simulations that had acceptable performance under conventional evaluation scheme, were found to underperform on further diagnosis. It is thus suggested to effectively diagnose the underperforming periods or flow zones in a model, in order to avoid model
misrepresentations and erroneous judgements. This also implies a step-forward beyond the conventional curve-fitting approach for model assessment.

Accurate parameter values hold a key for a reliable model performance. Strong parameter estimation methodology is therefore pertinent. Multi-objective calibration methodology incorporating hydrologic signatures were found to be effective in arriving the hydrological optimum along with the statistical optimum. Signature measures, that provide insights into the catchment functioning, are good way to evaluate the catchment response to different levels of inputs. They should be increasingly adopted in the analysis. Following such an approach is mandatory for finding parameters and their range that faithfully represent the governing hydrologic process.

Uncertainties are inherent in any impact assessment methodology. The imprecise nature of future climate projections coupled with high climate sensitivity of the hydrologic systems are relevant in characterizing uncertainty in the hydrologic impacts of climate change. In the impact modeling chain, different sources of uncertainties are known. The uncertainties emanating from the climate model are reported to be the maximum, but this may not always be true. This research demonstrated the variation of uncertainties across different seasons. Thus accounting hydrologic model uncertainty is found to be vital for providing a good assessment.

Climate change impacts on hydropower will not be same for all projects. The impacts will vary depending on the project location, type, and configuration. The results of the two different studies presented in this dissertation validate the same. In order to know about the climate change impacts, the project owners can take some guidance from any study in their project area, but an independent investigation of the specific project is recommended.

Climate change will permanently alter the hydrologic regime. For the northern latitudes, the summer period flows are projected to reduce significantly, with good confidence, as found in this dissertation and by other researchers too. This makes hydropower vulnerable to climate change. Increases in live storage, wherever possible, along with adaptive reservoir management are found to be effective adaptation measures. But they are not adequate enough to fully mitigate the projected impacts. The project owners should be prepared to face this effect of the anthropogenic climate change. The respite comes from the compensatory increment during the earlier part of the year. The changing scenario of hydropower generation requires a well-crafted and suitably-
altered power selling arrangement for each of the generation facility. The present study lays a foundation for carrying out those kinds of adaptation approaches.

The present methodology consisted of a modeling chain. There are some weak links in the overall impact assessment process. The assumption of time-invariance for various parameters, in each of the modeling steps, may be considered as model weakness. These variables in the modeling chain respectively, are: hydrological model parameters, climate model bias and electricity sale rate. The non-stationarity of these parameters enhances the projection uncertainty.

7.3 Recommendations for Future Work
As scientists are intensely studying various impacts of climate change, hydrologists need to continue their investigations on the response of watersheds under changing climate conditions. The temporal variation of parameters is a promising area of research that can significantly impact the projection results. The role of signatures as information agents of temporal evolution can be examined in detail in future.

Non-stationarity in bias correction of climate model data is also under intense research. Proper accounting of non-stationarity should assist in reducing the projection uncertainty.

A hydropower system should be tested for various stresses it may have to face such as, climate scenarios, natural hazards and financial risks. As the electricity sale price may significantly vary in future, the stochasticity of the same may be accounted for using a suitable pricing model. There are various sources of uncertainties in the climate change projections. Efforts should be made to accurately quantify the uncertainties and reduce them in order to assist a decision-maker to reasonably account for the climate change impacts in the operational models. Contribution of natural variability is one of the key aspects that can be investigated for deriving climate change projections with reduced uncertainty.
Annexure – 1 Borg-SWAT coupling code (in ‘R’)

*r_Input_MO.R*

# All the INPUTS required to run SWAT-BORG coupled simulation

## Hydrology Inputs ######
BASIN<-‘Saugeen’
ObjFcn<-‘NSE_RSRLow_Sign’
CA = 312 #Catchment area in SqKm

## MOEA BORG Inputs ######
nobjs = 3 # No. of objective functions
nvars = 18 # No. of decision variables (SWAT models parameters)
nconstr = 0
ITERATIONS = 1000
epsilon = c(0.01,0.1,0.01)

### SWAT Simulation Inputs ####

analysis<-’Daily’
simStartYear=1985
simYears=9
skipYears=2 # No of initial years to skip
myReachNos=16 # Reach where observed Q is taken
totalReaches=21

paramEdit <- c("CH_N2","CH_K2","SOL_AWC(1)","CN2","ESCO","EPCO","OV_N",
"GWQMN","GW_DELAY","GW_REVAP","REVAPMN","ALPHA_BF",
"SFTMP","SMTMP","SMFMN","SMFMX","TIMP","SNOCOVMX")

paramSWATFile <- c(".rte",".rte",".sol",".mgt",".hru",".hru",".gw",".gw",
".gw",".gw",".bsn",".bsn",".bsn",".bsn",".bsn")

paramRangeLow <- c(0.01, 0, -0.2, -0.2, 0.7, 0.5, 0, 0, 0,
0.02, 0, 0, -3, -2, 0, 0, 0, 0) # Lower value for each parameter

paramRangeHigh <- c(0.05, 200, 0.4, 0.2, 1.0, 1.0, 0.3, 2000, 200,
0.2, 1000, 0, 0, 0, 0, 0, 0) # Higher value for each parameter

# FDC Inputs
Exceedance1<-seq(0,2,by=0.2)
Exceedance2<-seq(2,20,by=1)
Exceedance3<-c(20,70)

if(analysis==’Monthly’)
simPrint<-0
if(analysis=='Daily')
    simPrint<-1
if(analysis=='Annually')
    simPrint<-2

r_BORG_MOEA.R

#########################################################################
# Program calling the main Borg function and writing the final output
#########################################################################

startTime<-Sys.time()
source("r_borg.R")
source("r_Input_MO.R")
source("r_FDC.R")
source("r_fun_parameters.R")
source("r_FDC_Signatures.R")
source("r_fun_readingDailySimQ.R")
source("r_fun_readingMonthlySimQ.R")
source("r_RSR_LowHigh.R")
source("r_SWATRun.R")

result <- borg(nvars, nobjs, nconstr, HydroModel, ITERATIONS, epsilons,
    paramRangeLow,paramRangeHigh)
setwd("D:/Chilkoti/SWAT_Saugeen_MOEA")
names(result)<-c(paramEdit,paste("Obj-",seq(1:nobjs),sep=""))
write.table(round(result,2),"results.txt",sep='\t')

plot(result[,1],result[,2],"p",xlab="ObjFun-1",ylab="ObjFun-2")

endTime<-Sys.time()
simTime<-round(endTime-startTime,2)
simTime

r_fun_parameters.R

#########################################################################
# Function to define parameters to be modified
#########################################################################

source("r_Input_MO.R")

parameters <- function(parValue)
{
    paramChange<-parameterEdits(1:nvars,2)
    paramEdit<-parameterEdits(1:nvars,3)
    paramSWATFile<-parameterEdits(1:nvars,4)
    par<-matrix(NA,nrow=nvars,ncol=1)
for(i in 1:nvars)
{
  par[i]<-paste(paramChange[i],"+'_',paramEdit[i],paramSWATFile[i],"\t",parValue[i],sep="")
}
write(par,file="model.in")

r_SWATRun.R

################################################
# Function to create link between BORG and SWAT
################################################
source("r_Input_MO.R")
setwd(paste(myDirectory,"/TxtInOut",sep=""))

#### Editing file.cio for simulation period and duration details####
cioFile<readLines("file.cio")
editStartYear<-paste("               ",simYears,"    | NBYR : Number of years simulated",sep="")
editYears <- paste("            ",simStartYear,"    | IYR : Beginning year of simulation",sep="")
editSkip <- paste("              ",skipYears,"   | NYSKIP: number of years to skip output printing/summarization")
editSimPrint <-paste("              ",simPrint,"   | IPRINT: print code (month, day, year")
cioFile[c(8:9,59,60)]<-c(editStartYear,editYears,editSimPrint,editSkip)
writeLines(cioFile,"file.cio")

HydroModel <- function(x)
{
  setwd(paste(myDirectory,"/TxtInOut",sep=""))
  parameters(x)
  system("SWAT_Batch.bat")

  simulationYears<-simYears-skipYears
  readSimYear<-simStartYear+skipYears # starting year of data reading
  while (analysis=='Monthly'){
    simFlow<-readingMonthlySimQ(myReachNos,totalReaches,simulationYears)
    obsQData<-read.table("obsMonthlyData.txt",header=T)
    dataPeriod<-data.frame(simFlow[,c(1,2)])
    obsFlow<-join(dataPeriod,obsQData,by=c("Year","Month"))
    break }
  while (analysis=='Daily'){
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simFlow <- readingDailySimQ(myReachNos, readSimYear, simulationYears)
obsQData <- read.table("obsDailyData.txt", header=T)
dataPeriod <- data.frame(simFlow[,c(1,2)])
obsFlow <- join(dataPeriod, obsQData, by=c("Year", "Day"))
break

simQ <- simFlow[,3]
obsQ <- obsFlow[,3]

## Computing disaggregate flow statistics
RSR <- RSR_lowHigh(obsQ, simQ)

## Computing Hydrologic Objectives - Runoff coefficient ####
avgSimQ <- tapply(simFlow$Flow, simFlow$Year, mean)
avgObsQ <- tapply(obsFlow$Obs, obsFlow$Year, mean)
RoC <- mean(abs(avgSimQ/avgObsQ - 1)) # Runoff coefficient = mean(abs(Qs/Qo - 1))

## Computing Hydrologic Objectives - FDC Signature ####
fdc_obs <- fdc(obsQ)
fdc_sim <- fdc(simQ)
peakFlowSign <- flowSignatures(obsQ, simQ, Exceedance1)
highFlowSign <- flowSignatures(obsQ, simQ, Exceedance2)
lowFlowSign <- flowSignatures(obsQ, simQ, Exceedance4)

midFlow_obs <- quantile(fdc_obs[,2], probs=(100 - Exceedance3)/100)
midFlow_sim <- quantile(fdc_sim[,2], probs=(100 - Exceedance3)/100)

signatureBias <- mean(peakFlowSign, highFlowSign, lowFlowSign, vlowFlowSign, midSegmentSlope)

## Water Yield computation
annualWY <- function(dataSet)
{
  yield <- sum(dataSet/CA*86.4*30.5)
  return(yield)
}
annualObsWY <- tapply(obsFlow$Obs, obsFlow$Year, annualWY)
annualSimWY <- tapply(simFlow$Flow, simFlow$Year, annualWY)
deltaWY <- mean(abs(annualObsWY-annualSimWY))

#### Computing the Objective Functions #######
a=2
NS <- sum((obsQ-simQ)^a)/sum((obsQ-mean(obsQ))^a)
NSlog <- sum((log(obsQ)-log(simQ))^a)/sum((log(obsQ)-mean(log(obsQ)))^a)
MAE <- mean(abs(obsQ-simQ))
PBIAS <- -100*mean(obsQ-simQ)/mean(obsQ)
#RoC<- abs(RoC_Obs-RoC_Sim)
#RSRMean<- mean(RSR_lowHigh(obsQ,simQ))

objectives<- rep(NA,nobjs)
o
objectives[1]<- NS
#objectives[2]<- NSlog
#objectives[2]<- PBIAS
objectives[3]<- signatureBias
#objectives[3]<- RoC

#########################################
#setwd("E:/Projects/SWAT-BORG Link/R")
return(objectives)
}

r_fun_readingDailySimQ.R

########################################################################
# Function to extract the simulated data
########################################################################

readingDailySimQ <- function(myReachNos,startYear,simYears)
{
  library(plyr)
  library(chron)
  # Creating data frame for Reach No, in order to 'join' with Reach Data
  ReachNo<- rep(myReachNos,1)
  SNos<- seq(1:1)
  reachNoDF<- data.frame(SNos,ReachNo)

  #Reading the simulated Q data from rch file
  reach_Q<- read.table("output.rch",skip=9)
  reach_Q1<- reach_Q[,c(2,4,7)]
  colnames(reach_Q1)=c("ReachNo","Day","Flow")

  #Extracting the data for given reach
  reach_Q2<- join(reachNoDF,reach_Q1,by="ReachNo")
  start<- as.Date(paste(startYear,"/1/1",sep=""))
  endYear<- startYear+simYears-1
  end<- as.Date(paste(endYear,"/12/31",sep=""))
  simDays<- end-start+1
  a<- seq(as.Date(paste(startYear,"/1/1",sep="")),by="day",length.out=simDays)
  Years<- years(a)
  simQ<- cbind(Years,reach_Q2[,c(3,4)])
  return(simQ)
}
**r_RSR_LowHigh.R**

# Generates the FDC of observed flow
# Computes the RSR for the High flow and Low flow

```r
RSR_lowHigh <- function(qobs, qsim) {
  totalValues <- length(qobs)
  seqMatrix <- matrix(NA, nrow=totalValues, ncol=2)
  #obsQ <- as.character(as.numeric(qobs))
  #simQ <- as.character(as.numeric(qsim))
  data <- data.frame(qobs, qsim)
  colnames(data) <- c("Obs", "Sim")
  flowData <- data[order(data$Obs, decreasing=TRUE),]

  seqMatrix[,1] <- seq(1:totalValues)
  seqMatrix[,2] <- round(seqMatrix[,1]/(max(seqMatrix[,1])+1)*100,3)
  colnames(seqMatrix) <- c("SNo", "Exceedance")
  fdcMatrix <- data.frame(seqMatrix, flowData)

  a2 <- fdcMatrix[which(fdcMatrix[,2]>70),3] - mean(fdcMatrix[which(fdcMatrix[,2]>70),3])
  RSRlow <- round(sqrt(sum(a1^2)/sum(a2^2)),2)

  b2 <- fdcMatrix[which(fdcMatrix[,2]<20),3] - mean(fdcMatrix[which(fdcMatrix[,2]<20),3])
  RSRhigh <- round(sqrt(sum(b1^2)/sum(b2^2)),2)

  RSR <- c(RSRlow, RSRhigh)
  return(RSR)
}
```

**r_FDC.R**

# Generating FDC from given flow series

```r
fdc <- function(flowValues) {
  n <- length(flowValues)
  fdcMatrix <- matrix(NA, nrow=length(flowValues), ncol=3)
  fdcMatrix[,2] <- as.matrix(sort(flowValues, decreasing=TRUE))
  fdcMatrix[,1] <- order(-fdcMatrix[,2])
  fdcMatrix[,3] <- round(fdcMatrix[,1]/(n+1)*100,3)
  colnames(fdcMatrix) <- c("SNo", "Flow", "Exceedance")
  return(fdcMatrix)
}
```
r_FDC_Signature.R
## Computes the FDC volume bias b/w observed and simulated flow for given flow exceedances

```r
flowSignatures <- function(obs_flowValues, sim_flowValues, pTile)
{
  fdc_obs <- fdc(obs_flowValues)
  fdc_sim <- fdc(sim_flowValues)
  fdcFlow_obs <- quantile(fdc_obs[,2], probs=(100-pTile)/100)
  fdcFlow_sim <- quantile(fdc_sim[,2], probs=(100-pTile)/100)
  signature <- sum(abs(fdcFlow_obs - fdcFlow_sim))/sum(fdcFlow_obs)
  return(signature)
}
```
Annexure-2a Gridded Precipitation

A2.1.1 Methodology

The availability of observed climate data was very limited for the Magpie watershed. Therefore, the available gridded climate dataset from NRCan has been adopted. Application of a gridded data product has been proved to be useful in the absence of the actual observation record (Vu et al., 2012).

The dataset is prepared by fitting standard trivariate smoothing splines to the available observation data points. The gridded temperature was obtained following this methodology directly, whereas the precipitation was evaluated in a two-stage approach, to model precipitation occurrence and positive precipitation separately (Hutchinson et al., 2009). Although the method of interpolation used for preparing the data is reported to be most accurate among the available methods (Jarvis and Stuart, 2001; Xia et al., 2001), the dataset is verified before its application for the current study region. Any bias in the data w.r.t. the observed data is computed and subsequently applied the correction.

WawaA is the only climate station within the study area having the observation record commensurate to the evaluation period, its dataset is used for bias evaluation. The mean monthly precipitation and temperature from NRCan are compared to those with the observed data to determine the systematic biases present. The precipitation bias is computed as the ratio while temperature bias as the difference between the observed and gridded data, as given by Eqs. (1) through (4). The daily gridded climate data is subsequently corrected by applying the computed monthly factors, with multiplicative correction for precipitation and additive correction for the temperature. The similar methodology of improvising the gridded data product has been adopted in earlier studies (Monteiro et al., 2016; Vu et al., 2012)

\[
\text{bias}_{P,m} = \frac{\sum_{i=1}^{n} P_{i,\text{Obs}}}{\sum_{i=1}^{n} P_{i,\text{Grid}}} \quad \cdots(1)
\]

\[
P_{\text{GridCorr},m} = \text{bias}_{P,m} P_{\text{Grid},m} \quad \cdots(2)
\]

\[
\text{bias}_{T,m} = \frac{1}{n} \sum_{i=1}^{n} T_{i,\text{Obs}} - \frac{1}{n} \sum_{i=1}^{n} T_{i,\text{Grid}} \quad \cdots(3)
\]
\[ T_{\text{GridCorr}, m} = \text{bias}_{T, m} + T_{\text{Grid}, m} \]  

...(4)

Here,

\[ \text{bias}_{P, m} \] - bias in precipitation (P) for month m
\[ P_{i, \text{Obs}} \] - observed precipitation for \( i^{th} \) day of a given month
\[ P_{i, \text{Grid}} \] - Gridded precipitation for \( i^{th} \) day of a given month
\[ P_{\text{GridCorr}, m} \] - corrected grid precipitation of month m
\[ P_{\text{Grid}, m} \] - gridded precipitation of month m

\[ T \] - temperature; other notations for temperature are similar to precipitation

A2.1.2 Results

Out of the eight grid locations (Fig. A1) Grid1 falls closest to the observation station of Wawa A maintained by Environment Canada. Therefore, the two datasets are compared in terms of their mean. It was found that on the average, the gridded precipitation data is underestimated by about 12%, ranging between 2% to 20% for different months except in December where it is overestimated by about 4%. The bias is minimum during the winter period. The minimum air temperature in the gridded dataset is lower than the observed temperature for all the months while the maximum temperature for different months has a varying bias pattern. The monthly biases for precipitation and temperature are presented in Fig. A1. Based on these bias factors, the gridded data are corrected using appropriate equations from Eqs. (1) through (4).

![Fig. A1 Bias in the gridded climate data w.r.t the observed data at station Wawa A for (a) precipitation (b) minimum (Tmin) and maximum (Tmax) air temperature](image_url)
A2.1.3 References


Annexure-2b SWAT Calibration

A2.2.1 Objective Functions

Formulations of the three objective functions used in the multi-objective calibration are presented in Eq. (S1) through Eq. (S3).

\[ NSE = 1 - \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2} \]  
...(S1) (Nash and Sutcliffe, 1970)

\[ RSR = \sqrt{\frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}} \]  
...(S2) (Moriasi et al., 2007)

\[ S_{FDC} = \frac{1}{4} \left( s_{peak} + s_{high} + s_{mid} + s_{low} \right) \]  
...(S3) (Chilkoti et al., 2019)

\[ S = \frac{\sum_{j=1}^{m} |O_j - S_j|}{\sum_{j=1}^{m} O_j} \]  
...(S3a)

\[ S_{ms} = \frac{|(O_{E3} - S_{E3}) - (O_{E4} - S_{E4})|}{(O_{E3} - O_{E4})} \]  
...(S3b)

Here, \( S_i \) is simulated values by model, \( O_i \) is observed values at time step ‘i’, \( \bar{O} \) is the mean of observed values and \( n \) is number of observations. \( S_{FDC} \) represents FDC signature, \( S \) is signature for peak, high and low segment of FDC, \( j \) indicates flow exceedance; for peak flows \( j=0, 0.2, 0.4 \ldots 1.8, 2.0 \% \), for high flow \( j=2, 3, 4, \ldots, 18, 20 \% \), for mid flow \( j=20, 70 \% \) and for low flows \( j=70, 71, 72 \ldots, 99, 100 \% \). \( E3 \) is exceedance at the start of segment-3 i.e., 20% and \( E4 \) is exceedance at start of segment-4 i.e., 70%.

A2.2.2 Preliminary parameter filtering

SWAT model was calibrated based on the described methodology in the main text. A semi-automatic approach for the calibration was adopted. First the underperforming portions of the hydrograph are identified by visual inspection. This was followed by identifying the associated parameters and their range. Subsequently, the optimal sets of parameter values are obtained through a multi-objective algorithm.

The default model run was found to generate excessive base flow, very low annual ET of about 250 mm and mismatch in the peak flow events which were primarily the snowmelt-induced peaks (Fig. A2a). Based on these observations, it was concluded that some of the parameters affecting
the groundwater process, evapotranspiration and snow melt process required tuning. The available water capacity (SOL_AWC) is the model parameter that affects both ET and groundwater (GW). The AWC of the reclassified soils from the FAO database had a very low default value; therefore, this parameter was increased in the first iteration. In the subsequent trials the six snow parameters and two groundwater parameters were altered. Fig. A2 shows the progressive improvement in the simulation by stepwise alteration of the parameters, which is based on the physics of the streamflow generation (Malagò et al., 2015). Sequentially recognizing the model parameters assist in a logical understanding of the hydrological phenomena and also avoids the unwanted burden of throwing several parameters to the automatic calibration routine.

![Fig.A2 Monthly flow time series depicting progressive improvement in the SWAT simulation during calibration period (2003-2008). The plot indicates the default parameter simulation and effects of increasing SOL_AWC ( ), six snow parameters (all together) and increasing GW_REVAP; broken line represents the observed flow and firm line the simulated flow](image)

Based on this preliminary analysis, 13 SWAT parameters were identified as sensitive and were subsequently optimized using the MOEA for deriving the final optimal parameter set. Of the 13 parameters, as presented in Table 2, six are snow parameters, four are surface water (SW) and remaining three are groundwater (GW) parameters.
A2.2.3 References


Annexure – 3 Code for Hydropower computation (in ‘R’)

**r_input.R**

```r
source('Elevation-Volume.R')
source('reservoirOperation.R')
library(plyr)

myDir<-'D:/Chilkoti/Magpie/Hydropower with 22 sets'
minLevel<-read.table('targetLevel_hist.txt',header=T)
period<-'Mid'  #End or Mid (century)
allEnergy<-matrix(NA,nrow=length(dateCol),ncol=1)
for(i in 1:6){
  model<-paste('M',i,sep='')
  setwd(paste(myDir,'/Scenario Flows',sep=''))
  flows<-read.csv(paste('simQ_Pareto_Daily_',model,'_',period,'.csv',sep=''),header = T)
  allFlowData<-flows[,c(1:3)]
  energy<-hydroGeneration(allFlowData,period)
  allEnergy<-data.frame(allEnergy,energy)
}
allEnergy1<-allEnergy[,1]
setwd(myDir)
View(allEnergy1)
```

**r_reservoirOperation.R**

```r
source('Elevation-Volume.R')
source('reservoirOperation.R')
library(plyr)

myDir<-'D:/Chilkoti/Magpie/Hydropower with 22 sets'
minLevel<-read.table('targetLevel_hist.txt',header=T)
period<-'Mid'  #End or Mid (century)
allEnergy<-matrix(NA,nrow=length(dateCol),ncol=1)
for(i in 1:6){
  model<-paste('M',i,sep='')
  setwd(paste(myDir,'/Scenario Flows',sep=''))
  flows<-read.csv(paste('simQ_Pareto_Daily_',model,'_',period,'.csv',sep=''),header = T)
  allFlowData<-flows[,c(1:3)]
  energy<-hydroGeneration(allFlowData,period)
  allEnergy<-data.frame(allEnergy,energy)
}
allEnergy1<-allEnergy[,1]
setwd(myDir)
View(allEnergy1)
```
Qdesign<-44.0 # in cumec
Qmin<-7.5 # in cumec
dailySecs<-24*3600
dailyGenFactor<-0.8
FRL<-318.5
resVolume<-function(level)
{
.vol<-(6243312.617+62213.94284*level-206.82946112*level^2+0.22936700302*level^3)*86400
return(vol)
}
Vmax<-resVolume(FRL)
Vinitial<-Vmax # Reservoir volume at start of operation

eff<-0.9 # Turbine efficiency
gamma<-9810 # in KN/m3
netHead<-39.9 # in meters
ts<nrow(flowData) # ts – timestep

Qp<-matrix(NA,nrow=ts,ncol=1)
Qdam<-matrix(NA,nrow=ts,ncol=1)
Vinflow<-matrix(NA,nrow=ts,ncol=1)
Voutflow<-matrix(NA,nrow=ts,ncol=1)
Storage<-matrix(NA,nrow=ts,ncol=1)
Energy<-matrix(NA,nrow=ts,ncol=1)
Time<-matrix(NA,nrow=ts,ncol=1)
resElev<-matrix(NA,nrow=ts,ncol=1)

for(setNo in 1:ncol(flowData))
{
for(i in 1:ts)
{
Qts<-flowData[i, setNo] # Q for time step 'i'
tsMonth<-months(as.POSIXlt(dateCol[i], format="%m/%d/%Y"), abbreviate = T)
MDDL<-unlist(minLevel[minLevel$Month==tsMonth,][2])
Vmin<-resVolume(MDDL)
Vinflow[i]<-Qts*dailySecs
doDay<-ifelse(dayCol[i]=="Saturday",0,ifelse(dayCol[i]=="Sunday",0,1)) # # while(doDay==1) {
while(Vinitial<Vmax & Vinitial>Vmin)
{
Qp[i]<-Qdesign
Qdam[i]<-0
Voutflow[i]<-Qp[i]*dailySecs*dailyGenFactor
Storage[i]<-Vinitial+(Vinflow[i]-Voutflow[i])
if(Storage[i]<Vmin)
{
Voutflow[i]<-Storage[i-1]-Vmin


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Qp[i]<-Voutflow[i]/(dailySecs*dailyGenFactor)
Storage[i]<-Vinitial+(Vinflow[i]-Voutflow[i])
}
if(Storage[i]>Vmax)
{
  Vout<-Storage[i]-Vmax
  Qdam[i]<-Vout/(dailySecs*dailyGenFactor)
  Voutflow[i]<-(Qp[i]+Qdam[i])*dailySecs*dailyGenFactor
  Storage[i]<-Vinitial+(Vinflow[i]-Voutflow[i])
}
resElev[i]<-elevation(Storage[i])
break
}
while(Vinitial<=Vmin)
{
  Qp[i]<-ifelse(Qts<Qdesign,Qts,Qdesign)
  Qdam[i]<-0
  Voutflow[i]<-Qp[i]*dailySecs*dailyGenFactor
  Storage[i]<-Vinitial+(Vinflow[i]-Voutflow[i])
  resElev[i]<-elevation(Storage[i])
  break
}
while(Vinitial>=Vmax)
{
  Qp[i]<Qdesign
  Qdam[i]<-ifelse(Qts>Qdesign,(Qts-Qdesign),0)
  Voutflow[i]<-(Qp[i]+Qdam[i])*dailySecs
  Storage[i]<-Vinitial+(Vinflow[i]-Voutflow[i])
  resElev[i]<-elevation(Storage[i])
  break
}
break

###########################################################################
while(theDay==0){
  while(Vinitial<Vmax & Vinitial>Vmin)
  {
    Qp[i]<Qmin
    Qdam[i]<0
    Voutflow[i]<-Qp[i]*dailySecs*dailyGenFactor
    Storage[i]<-Vinitial+(Vinflow[i]-Voutflow[i])
    if(Storage[i]>Vmax)
    {
      Vout<-Storage[i]-Vmax
      Qdam[i]<-Vout/(dailySecs*dailyGenFactor)
      Voutflow[i]<-(Qp[i]+Qdam[i])*dailySecs*dailyGenFactor
      Storage[i]<-Vinitial+(Vinflow[i]-Voutflow[i])
    }
    resElev[i]<-elevation(Storage[i])
    break
  }
  while(Vinitial<=Vmin)
  {
  }
}
```r
Qp[i]<-ifelse(Qts<Qmin,Qts,Qmin)
Qdam[i]<-0
Voutflow[i]<-Qdam[i]*dailySecs*dailyGenFactor
Storage[i]<-Vinitial+(Vinflow[i]-Voutflow[i])
resElev[i]<-elevation(Storage[i])
break }
while(Vinitial>=Vmax)
{
  Qp[i]<-Qmin
  Qdam[i]<-ifelse(Qts>Qmin,(Qts-Qmin),0)
  Voutflow[i]<-(Qp[i]+Qdam[i])*dailySecs
  Storage[i]<-Vinitial+(Vinflow[i]-Voutflow[i])
  resElev[i]<-elevation(Storage[i])
  break }
break }

################################################################
Energy[i]<-round(ef*gamma*netHead*Qp[i]*24*dailyGenFactor/10^9,3)
Vinitial<-Storage[i]
}
Qp<-matrix(Qp)
Qout<-Qp+Qdam
summary<-cbind(dateCol,flowData[,setNo],Qp,Qdam,Qout,Vinflow,Voutflow,Storage,resElev,Energy)
resElvALL[,setNo]<-resElev
energyALL[,setNo]<-Energy
spillALL[,setNo]<-Qdam
#View(summary)
Vinitial<-Vmax
}
return(energyALL)
}
#################################################################```
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LANGUAGES: English, Hindi