DEVELOPING ACRU UTILITIES FOR MODELLING FUTURE WATER AVAILABILITY: A CASE STUDY OF THE OLDMAN RESERVOIR WATERSHED, ALBERTA

CHARMAINE M. T. BONIFACIO

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Dr. Stefan W. Kienzle Thesis Supervisor	Professor	Ph.D.
Dr. Wei Xu Thesis Examination Committee Member	Professor	Ph.D.
Dr. John Zhang Thesis Examination Committee Member	Associate Professor	Ph.D.
Dr. Hester Jiskoot Chair, Thesis Examination Committee	Associate Professor	Ph.D.

ABSTRACT

A changing climate can seriously perturb hydrological response within a watershed. The potential impacts on the future water availability for the upper Oldman Reservoir Watershed (ORW) was investigated using the Agricultural Catchments Research Unit (ACRU) model. Due to the operational challenges of the model, several utility tools were developed. Once the limitations were addressed, the Klemeš (1986) model testing was applied to assess the performance of the ACRU model. The ACRU model performed very well using the standard split-sampling test; as the testing progressed, its performance decreased. The future hydrological response was then analysed using two regional climate projections by comparing the historical baseline and future period. Despite the inherent arid climate characteristics of the ORW, both projections indicated increasing summer temperatures and seasonal shifts in hydrology. The ORW is expected to experience a decrease of summer streamflow and an increase in spring and winter streamflow.

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LIST OF ABBREVIATIONS

AAFC	Agriculture and Agri-Food Canada
ACRU	Agricultural Catchments Research Unit
ANUSPLIN	Australian National University Splines
CCDST	Canadian Climate Data Scraping Tool
CRM3	Third Canadian Regional Climate Model
CRW	Castle River Watershed
d	Index of Agreement
DSST	Differential Split Sample Test
GCM	Global Climate Model
GFDL	Geophysical Fluid Dynamics Laboratory
GIS	Geographic Information System
HRM3	Hadley Regional Climate Model Version 3
km	kilometres
LNID	Lethbridge Northern Irrigation District
mm	millimetres
MODd	Modified Index of Agreement
MODnse	Modified Nash Sutcliffe Efficiency Index
NLWIS	National Land and Water Information Service
NSE	Nash-Sutcliffe Efficiency Index
ORB	Oldman River Basin
ORW	Oldman Reservoir Watershed
PBDSST	Proxy-Basin Differential Split Sample Test
PBIAS	Percent Bias
PBT	Proxy-Basin Test
PPT	Precipitation
PRISM	Parameter-elevation Regressions on Independent Slopes Model
Q	streamflow
r	Pearson's correlation coefficient
r^2	Coefficient of determination
RCM	Regional Climate Model
RMSE	Root Mean Square Error
RSR	RMSE-observed standard ratio
SSRB	South Saskatchewan River Basin
SST	Split Sample Test
Tmax	Maximum Temperature
Tmin	Minimum Temperature
UNSRB	Upper North Saskatchewan River Basin
VACEA	Vulnerability and Adaptation to Climate Extremes in the Americas

CHAPTER 1

INTRODUCTION

There is considerable uncertainty on the future of water resources in Canada. On the Prairies, an ever-increasing demand for water for agriculture, the industrial sector and a rapidly growing population have been present (Sauchyn et al., 2008). Various studies have already reported declining trends in mean annual streamflow from headwater streams in the Rocky Mountains within the last century (Byrne et al., 2006; Gan, 1998; Mote, 2006; Mote et al., 2005; Rood et al., 2008; Rood et al., 2005). Like many snowpack-dependent regions, the projected climate change impacts in southern Alberta's hydrological regimes include decreased snowpack accumulation, earlier spring runoff, increasing winter streamflow, decreasing summer streamflow, and decreasing glacial melt contributions (Barnett et al., 2005; Jiménez Cisneros et al., 2014; Mote et al., 2005; Romero-Lankao et al., 2014; Rood et al., 2008; Rood et al., 2005). Much of the uncertainty in the future of water resources is reflected in the Oldman River watershed, where projected hydrological impacts can affect current and future water demands. It is, therefore, crucial to understand the regional watershed balances in order to assess the current and future water resource in Canada.

For this very reason, hydrological models are one of the best tools to examine the impacts of climate change at a watershed scale. These models provide a conceptual framework to investigate the interactions and relationships between regional climate and components of the hydrological cycle for a given watershed

(Leavesley, 1994; Xu, 1999a). In this research study, the Agricultural Catchments Research Unit (ACRU) agro-hydrological modelling system is applied to assess the future water availability within the Oldman Reservoir Watershed by utilizing the available regional climate models (RCM) for the region (Teutschbein et al., 2010, 2012). RCMs have higher spatial resolution, temporal resolution and are considered to be representative of the regional hydrologic components (Teutschbein & Seibert, 2010). Thus, RCM projections are utilized in climate change impact studies using hydrological models, and will be used in this study in southern Alberta.

Moreover, this study focused on rigorously testing the ACRU agro-hydrological model using Klemeš (1986) four-level model testing scheme for operational validation for both gauged and ungauged watersheds within the Oldman Reservoir Watershed, a large upstream watershed of the Oldman River Basin. So far, only a number of hydrological studies have focused on the rigorous performance evaluations of hydrological models (Andreassian et al., 2009; Refsgaard et al., 1996; Seibert, 2003). Typically, the standard performance evaluations of hydrological models use the split-sampling technique, even under the context of a changing climate. This has been the case for validating the ACRU model in the recent studies of Canadian watersheds such as the Cline River Watershed in the upper North Saskatchewan River Basin (UNSRB); and of the Beaver Creek Watershed (BCW) and Castle River Watershed (CRW), in the Oldman River Basin (Anderson, 2014; Forbes et al., 2011; Nemeth, 2010). Thus, this is the first study that aims to rigorously evaluate the performance of the ACRU model under climate change impact studies.

Invariably, anyone tasked with a modelling exercise is faced with a number of limitations. In the operational use of the ACRU model, the lack of data pre-processing, model calibration, model validation and data post-processing tools, made the modelling exercise consisting of more than 1000 hydrological response units (HRU) to be ineffective. Originally, the ACRU modelling system operated on a maximum of 150 sub-units (Smithers et al., 1995). With the increasingly computer power, the ACRU model system was adapted to operate on larger snow dominated watersheds, with more than 150 sub-units (Forbes et al., 2011; Kienzle et al., 2009; Nemeth et al., 2012). This adaptation, however, meant that some of the original ACRU routines that aided in the data processing, calibration and validation could no longer be utilized. Thereby, potentially introducing human errors and decreasing the efficiency of data pre-processing and post-processing at the cost of having less time for validation analyses.

1.1 Research Objectives

The aim of this project is to evaluate the climate change impacts on the Oldman Reservoir Watershed (ORW) using the ACRU agro-hydrological modelling system. In order to evaluate the climate change impacts, the following objectives were completed:

- To implement a rigorous validation of the ACRU model using a four-level model testing scheme that incorporates the split-sampling test, the proxy-basin test, the differential split-sampling test and the proxy-basin differential split-sampling test.

- To investigate the assessment of climate change impacts using two bias-corrected Regional Climate Model (RCM) that represent a warmer/drier and cooler/wetter climate scenarios for the future (2041-2070) period. These future projections were compared to the historical baseline (1971-2000) period in order to determine the future changes within the region.

In addition, before the evaluation of the ACRU model could proceed, it was critical to overcome the modelling challenges that any distributed and physically-based hydrological models face. These challenges require the data management of large datasets consisting of bio-physical parameters and hydro-climatological time series and a more efficient data analysis as part of the ACRU modelling system. In order to overcome these challenges, it was necessary to develop a suite of utility tools that involved automated (1) data pre-processing, (2) model calibration/validation and (3) data post-processing:

- To develop automated data pre-processing tools that compile observed hydro-climatological data, and delineate hydrological response units within the study area.
- To develop utility tools to aid in automated model parameterization during calibration and validation of the hydrological model.

- To develop comprehensive verification analysis tools for temperature and streamflow results that allows the calculation of comparative statistics between observed and simulated data, create line graphs for seasonal changes over time, scatter plots for linear regression, as well as create annual hydrographs, mean monthly scatterplots and flow duration curves.

1.2 Thesis Organization

This research will be presented in six chapters, beginning with the introduction that describes the thesis topic and research objectives. The second chapter presents the current literature review of the major concepts, methods and background information on various topics of this research project. It covers topics on global climate change and its impacts on North America, particularly on the Prairie Provinces, use of hydrological modelling in climate change impact assessment, and the modelling framework in hydrological modelling. The third chapter describes the data and methods, which include the study area, hydrological model and data description as well as the methodological framework used in this study. The fourth chapter outlines the modelling challenges with the development of various ACRU utility tools. The fifth chapter presents and discusses the model performance results of the ACRU model and the climate models for the Oldman River Watershed. The sixth and final chapter, provides a summary of the findings and the significance of the research and further recommendations.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter will present a review of literature based on the subject of hydrological modelling of the Oldman Reservoir Watershed, Alberta using the ACRU modelling system and the regional climate impacts of climate change on water availability for the region. The review focuses on the climate change impacts in North America and the regional importance of water for southern Alberta. This topic is followed by the utilization of regional climate models in hydrological modelling studies. The next topic focuses on the hydrological modelling framework, summarizing of the hydrological models used in climate change studies followed by a description of the ACRU model and integrating GIS for climate change studies. Lastly, three hydrological modelling challenges are highlighted, especially on predicting in ungauged watersheds under changing climate as well as coding verification and model evaluation strategies used in hydrology.

2.2 Climate Change

2.2.1 Global Climate Change Impacts in North America

Climate change poses an increasing threat to sustainable freshwater resources. Many changes in the observed climate are unprecedented in the recent history, particularly with increasing atmospheric temperatures, rising global average sealevel, widespread melting of snow and glaciers and increased greenhouse gas concentrations (IPCC, 2013; Jiménez Cisneros et al., 2014; Romero-Lankao & Ruiz, 2014). According to the recent Intergovernmental Panel on Climate Change (IPCC) report, there is some robust evidence on the significant increase of freshwater-related risks with increasing greenhouse gas concentrations (IPCC, 2013; Jiménez Cisneros et al., 2014). These changes have been attributed to the increasing influence of anthropogenic greenhouse gas (GHG) concentrations since 1750 (IPCC, 2007, 2013). The concentrations of carbon dioxide, methane and nitrous oxide have already exceeded the pre-industrial levels by 40%, 150% and 20%, respectively (IPCC, 2013). Using information collected from ice cores, there is an unprecedented concentration of greenhouse gases within the last 22,000 years that have also exceeded the highest concentrations recorded within the last 800,000 years (IPCC, 2013). Thus, the continued increase in greenhouse gas concentrations will continue to negatively impact freshwater resources in the 21st century.

Climate change impact studies project a doubling of greenhouse gas emissions to increase temperatures (Barnett et al., 2005; Schindler, 2001). A warmer climate will result in increasing evaporation, ultimately reducing the availability of freshwater resources for the region. In many cases, a considerable shift from the amount of snow to rain, along with changes in the runoff patterns associated with earlier spring melt, can adversely affect the water availability for peak-flow demand (Burn, 1994; Jiménez Cisneros et al., 2014; Lapp et al., 2005). Adverse risks of climate change have been projected for snow-dependent regions that rely on winter snowpack and summer melt (Burn, 1994; Sauchyn & Kulshreshtha, 2008). The western alpine regions of North America are expected to experience increasing winter flows, reduced snowpack and reduced summer low flows (Barnett et al., 2005; IPCC, 2013; Jiménez Cisneros et al., 2014). Extreme weather and climate phenomena are likely to continue in the 21st century (IPCC, 2013). Therefore, the potential adverse impacts of climate change will exacerbate increasing water demand and supply in these regions.

2.2.2 Regional Hydrological Impacts

The water resources in the Canadian Prairie region are largely influenced by snow, glacier and ice fields in the Rocky Mountains. The Rocky Mountains are a considerable source of freshwater, contributing to 50-80% of the spring flows (Barnett et al., 2005; Mueller et al., 2011). Streamflow has already declined in the northern regions of the Rocky Mountains, with a projected 10% less flow by 2050 (Rood et al., 2005). A diminishing snowpack decline in the Rocky Mountains could mean altering the magnitude and the duration of peak spring flows for southern Alberta (Rood et al., 2008). In addition to increasing temperatures and decreasing volumes of snowpack, earlier snowmelt and decrease in summer soil moisture can also be expected (Barnett et al., 2005). Spring floods rejuvenate the riparian and floodplain areas within the region, where a variety of species depend on freshwater resources (Rood et al., 2008; Rood et al., 2005). Drought-risk regions that have experienced heavy precipitation events will continue to experience more frequent extreme events, and the expected increasing frequency and magnitude of droughts and flooding will subsequently affect the surface and groundwater quality of the region (Barrow et al., 2005; Jiménez Cisneros et al., 2014). Canada will likely experience some of the largest climate change impacts due to its geographic location in the mid-latitudes, and like many regions affected by drought and flooding, water-stress issues are likely to become a future trend.

2.2.3 From Global to Watershed Scale: Regional Climate Models

In order to project the hydrological impact of climate change, models require reliable sources of climatological data. Global Climate Models (GCMs) are commonly used to estimate the future climate change impacts on hydrological response in combination with a hydrological model. However, model outputs from GCMs have a much coarser resolution compared to the climate data available at a finer, e.g. 10-km, resolution. GCMs resolutions are at 100-250-km scale and, therefore, lack the detailed information needed in regional hydrological models (Fowler et al., 2007; IPCC, 2007; Salathe et al., 2007). Thus, there is a great need for a higher spatial resolution input for hydrologic models.

Table 2-1. Differences in spatial resolution between GCMs and RCMs

	RESOLUTION (km)	SOURCES
Global Climate Models	~125 – 600	Ali et al. (2014); Barrow and Yu (2005)
Regional Climate Models	~25 – 50	Barrow and Yu (2005); Graham, Andréasson, et al. (2007)

The downscaling of GCM output from global to watershed scale is typically carried out using either statistical or dynamical downscaling techniques. Previous studies have focused on comparing both downscaling techniques (Lapp et al., 2009; Murphy, 1999, 2000; Teutschbein et al., 2011; Wilby et al., 1997), emphasising the advantages and disadvantages of both. Statistical downscaling method utilizes statistics in order to build relationships between the large-scale data against the regional variables (Beckers et al., 2009; Fowler et al., 2007; Wilby et al., 2004). These methods are computationally efficient, thus, making it an attractive option for climate impact studies (Fowler et al., 2007; Teutschbein, 2013; Wilby et al., 2002). Conversely, the dynamical downscaling method focused on the development of limited-area models or regional climate models (RCMs) (Teutschbein & Seibert, 2010). The extraction of local climate information using GCM output data as a boundary condition allows the local scale climate processes to be captured (Teutschbein & Seibert, 2010; Wilby et al., 2002). Despite these advantages, the main disadvantage of the dynamical downscaling method is its relatively expensive computational requirement to extract useful climate data and its dependency on boundary conditions (Teutschbein & Seibert, 2010). Statistical downscaling, on the other hand, is more desirable in terms of required computational power. Wilby et al. (2002) recommended the use of statistical downscaling method for highly localized climate even if the reproduction of decadal and inter-annual climate variability is not quite appropriate (Fowler et al., 2007; Loukas et al., 2002).

Recently, much progress has been made with regional climate models (RCM) (Teutschbein & Seibert, 2010, 2012). RCMs have the ability to produce climate data at a much higher spatial and temporal resolution, using either downscaling techniques. Although most RCM output are at 25-60km spatial resolution, these datasets are still representative of the hydrologic components such as surface runoff (Jiménez Cisneros et al., 2014; Teutschbein & Seibert, 2010). Thus, RCM simulations attract more consideration for climate change impact studies using hydrologic models, and thus will be used in this study in southern Alberta.

Caution must be exercised, however, when dealing with the RCM data as these often have biases. Teutschbein and Seibert (2010) highlighted various RCM biases with a special focus on model errors. In particular, biases can occur with inaccurate conceptualisation framework used by the model itself as well as the discretization and the spatial averaging within grid cells. In order to correct these biases, it is recommended to apply a bias correction technique to an ensemble of RCM simulations (Teutschbein & Seibert, 2010, 2012). Previous studies have shown that uncorrected RCM simulations are a large source of uncertainty in modelling hydrological response to climate change. Recently, Teutschbein and Seibert (2012) have shown that the use of highly bias-corrected RCM climate data performed considerably better than other corrected RCM climate data. Therefore, the bias-corrected RCM data will be applied in this study in southern Alberta.

2.3 Irrigation and Agriculture in Alberta

Water demand continues to increase within Western Canada. In Alberta, irrigation and agriculture play an important part of its cultural history. The economic vitality of the region is reflected by the amount of water provided for irrigated agriculture. Nearly 50% of water use over the prairies has been used for agriculture through irrigation infrastructures (Barnett et al., 2005). According to Alberta Agriculture Rural Development (AARD) (2015), irrigation is formally organized into thirteen irrigation districts. In 2014, all irrigation districts provided water to

1,413,836 acres of agriculture within southern Alberta. There are currently ten major irrigation districts situated within the downstream of the Oldman River Basin (ORB) (AARD, 2013). Therefore, any perturbation in the hydrological system could have massive impacts for the irrigation and agriculture within southern Alberta.

Southern Alberta encompasses 60% of irrigated agriculture in Canada (Russenberger et al., 2012). More than 70% of the licensed water withdrawals are used to irrigate about approximately 4000 km^2 of land within this region (Russenberger et al., 2012; Schindler et al., 2006). According to the AARD (2014b) report on irrigation, the total volume of water diverted was approximately 3451 million m^3 and the total irrigated land has increased to 5017 km^2. If the future projected streamflow is expected to decline then future water availability for the irrigation districts is uncertain (Sauchyn & Kulshreshtha, 2008; Schindler & Donahue, 2006). For this reason, the distribution and availability of water under climate change between watersheds will be quite uncertain and may lead to increasing water conflicts between irrigation managers and consumers (Sauchyn et al., 2009). Therefore, it is essential to understand the watershed balances for the current and future water resources within the region.

The irrigation sector alone is a major economic stakeholder in the Province of Alberta. In 2002, it contributed approximately $832 million or 18.4% gross domestic product to the provincial economy (Irrigation Water Management Study Committee, 2002). Due to the inherent moisture deficiencies in the region, the utilization of irrigation is essential in the continued success of the region's intensive agricultural production. There are two provincially owned and operated reservoirs that supply the Lethbridge Northern Irrigation District (LNID). The Oldman Reservoir is the larger of the two reservoirs. It was built in order to regulate flow of the Oldman River (de Loë, 1999) and has the storage capacity of approximately 491 million m^3 of water. On the other hand, Keho Lake has the storage capacity of 96 million m^3 of water (AARD, 2014b). Although, the available water licence allocation for the LNID is approximately 413 million m^3, it has the capacity to store a total of 586 million m^3 of water. Although the average gross annual diversion of LNID from 1976-2014 operated at 50% of the water allocated for the district, the actual irrigated land within has steadily increased, with approximately 725.59 km^2 of irrigated land in 2014 (AARD, 2015). Thus, water in irrigation and agriculture play a significant role in southern Alberta.

Water is also an important aspect of rural communities and urban centres in southern Alberta. Commercial use of water only accounts for 4%, while municipal use accounts for 3% of the licensed water allocations within the Oldman River Basin. Meanwhile, habitat and recreation accounts for 0.5% of the total water allocations (Rock et al., 2007). Although agriculture and irrigation are significant consumers of water in the ORB, water quality for human consumption and sustaining a healthy aquatic are considered a priority for any watershed management.

2.4 Hydrological Modelling

2.4.1 Linking Hydrological Models to Climate Change Studies

Climate change can severely perturb the hydrological cycle. The substantial effects of climate change on the hydrological cycle should be an important focus for regional water resource assessment, because of the potential severe hydrological impacts to the cultural and economic vitality of any region. However, as a result of limitations on observed hydro-climatological data and data management techniques, the concept of utilizing models for climate change impact studies is proven to be attractive (Beckers et al., 2009; Beven, 2012; Warburton et al., 2010; Xu, 1999a). Xu (1999a) lists four characteristics of hydrological models when used in climate change impact studies: 1) the flexibility to allow for usage in various climatic conditions, spatial scales and hydrological representations; 2) the available data that can be tailored for the model; 3) the ease of manipulation of regional hydrological model compared to general circulation models, and 4) the evaluation of a watershed's sensitivity to climate changes and predictions.

Hydrological models attempt to predict the partitioning of water as it flows within and through the hydrologic cycle. A hydrological model consists of a simplified mathematical equation that represents components and processes at a watershed scale (Leavesley, 1994; Xu et al., 2004). According to Leavesley (1994), the water balance equation can be expressed as the following:

$$\boldsymbol{Q = P - ET \pm \Delta S}$$

where Q represents runoff, P represents precipitation, ET represents evapotranspiration and **Δ**S represents change in the water storage as reservoirs, snowpack, soil moisture or groundwater storage. A wide range of hydrological models has been developed in order to solve this water balance equation (Leavesley, 1994; Xu & Singh, 2004).

2.4.2 The Hydrological Modelling Framework

A hydrological modelling framework provides a way to investigate the relationships between climate and the hydrological processes within a watershed (Leavesley, 1994; Xu, 1999c). Indeed, the coupling of hydrological models with climate change projections is one of the best tools in order to determine the hydrological impacts of climate changes (Leavesley, 1994; Xu, 1999a, 1999c). Refsgaard (1997) best describes sequential steps to undertake climate change assessment on hydrological impacts, as illustrated in Figure 2-1. Beven (2001b), Wagener, Wheater, et al. (2004), and Bennett et al. (2013) have also discussed the modelling framework in detail. Typically, the climate scenario approach is used for modelling hydrological impacts under a changing climate (Chiew, 2010; Peel et al., 2011). This approach applies modelling techniques on a calibrated model with either downscaled or bias-corrected GCM or RCM data.

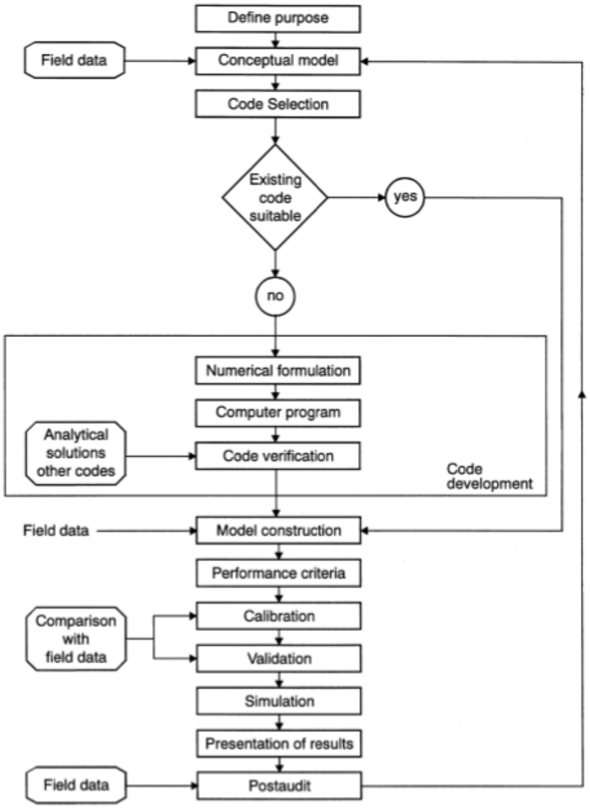


Figure 2-1. Hydrological Modelling Framework (Refsgaard, 1997)

2.4.3 Classifications of Hydrological Models

There are various modelling approaches used with hydrological models. Watershed-scale hydrological models can be classified according to their model spatial discretization, functionality and hydrologic process description (Beckers et al., 2009; Beven, 2012; Wagener, Wheater, et al., 2004). Beven (2012) describes that the first consideration when selecting a hydrological model is whether to use a *lumped* or *distributed* modelling approach. The second consideration is whether to use a *deterministic* or *stochastic* model (Refsgaard, 2007).

The basic classification of hydrological models is its spatial discretization approach (Beckers et al., 2009). A *lumped* model treats the watershed as a single unit.

In other words, this model does not take into consideration the bio-physical and hydro-climatological heterogeneity of the watershed. Conversely, a *distributed* model best represents the spatial variability of the input variables and the bio-physical parameters by dividing the unit into smaller, relatively homogenous units, which represents the overall heterogeneity of the watershed.

Deterministic models are described as permitting one outcome for one set of input variable and model parameter values, whereas, s*tochastic* models are described as permitting uncertainty in its outcomes (Beven, 2012). Refsgaard (2007) argues that deterministic models should be further classified according to their process description: *empirical*, *conceptual-lumped* and *physically-distributed (*or process-based*)* models.

Empirical models are statistical models that consider only the mathematical relations among the hydrological component of the water balance equation, rather than the physical laws between them (Leavesley, 1994). *Lumped-conceptual* models are simplistic in their attempt to account for the relationship between the physical laws of the hydrologic cycle (Beckers et al., 2009; Leavesley, 1994). These models use empirical process descriptions of the hydrological processes, and their parameters are not usually directly related to the physical observations for the region. *Distributed physically-based* models, on the other hand, represent the physical laws governing the watershed. These models have the ability to simulate the spatial patterns of hydrological responses within a watershed by using a grid cell or other topographic element (Beckers et al., 2009; Leavesley, 1994). It is important to note that there are major limitations for this type of model, which include the availability and the quality of data at finer spatial and temporal resolutions.

It needs to be emphasized that there is a plethora of hydrological models available in Canada. The choice simply depends on major factors such as the purpose of the project as well as the model and data availability for the researchers (Beckers et al., 2009; Xu, 1999a). The ability of the distributed process-based model has been acknowledged in various climate impact studies (Barnett et al., 2005; Barrow & Yu, 2005; Bathurst et al., 2004). Numerous hydrological models exist that focus on watershed hydrology. Beckers et al. (2009) reviewed a list of all models used for climate change and forest management studies for British Columbia and Alberta. In comparison to other models, the ACRU model has been extensively used in various climate change studies and water resource assessment studies (Forbes et al., 2011; Graham et al., 2011; Nemeth et al., 2012; Warburton et al., 2010). The ACRU model is described as a highly complex agro-hydrological model originally developed for South African condition since the late 1970s (Beckers et al., 2009). One of the key reasons for selecting the ACRU model in this study is the availability of the entire source code so that new routines can be created, when deemed necessary (Kienzle, 2008, 2011; Kienzle et al., 2008; Nemeth et al., 2012). Major improvements have been made with the addition of the snow routines developed for modelling in cold-climates such as Canada (Forbes et al., 2011; Kienzle et al., 2012; Nemeth et al., 2012). Ultimately, the selection of the ACRU model over other available models in Canada was its inherent ability to simulate under a distributed physically-based modelling environment.

2.4.4 The ACRU Agro-Hydrological Modelling System

The ACRU model is a multi-purpose, multi-level, integrated physical-conceptual model that has the capability of simulating total evapotranspiration, soil water and reservoir storages as well as land cover and climate change impacts on water resources. It can be operated as a lumped or distributed model, depending on the scale of the watershed in question (Beckers et al., 2009). The model is focused on a multi-layer soil water budget using specific variables that govern the atmosphere-plant-soil water interfaces. As such, runoff is generated as quickflow, which then corresponds to the magnitude of daily rainfall in relation to the multi-layer soil water budget.

In the 1970s, the School of Bioresources Engineering and Environmental Hydrology at the University of KwaZulu-Natal in South Africa originally developed the ACRU modelling system. By 2006, a snow model routine was added to ACRU version 300, which was developed by Dr. Stefan Kienzle in order to apply ACRU's modelling capabilities to snow-dominated regions. The snow model routine uses a novel approach in separating precipitation into snow and rain (Kienzle & Byrne, 2009). This version of the ACRU model (Version 336) simulates the principal hydrological processes of rain and snow interception, infiltration, snowpack accumulation and soil water storages as well as the unsaturated and saturated soil water redistribution and total evaporation. The subsequent snow processes that underlie the snow routine are simulated in a physical-based manner. These processes are described by Schulze (1995) include canopy interception, sublimation, metamorphosis, resulting in change in albedo and density. The snowmelt simulation is currently using a degree-day factor, which is dynamically determined daily from temperature, incoming solar radiation and albedo estimates.

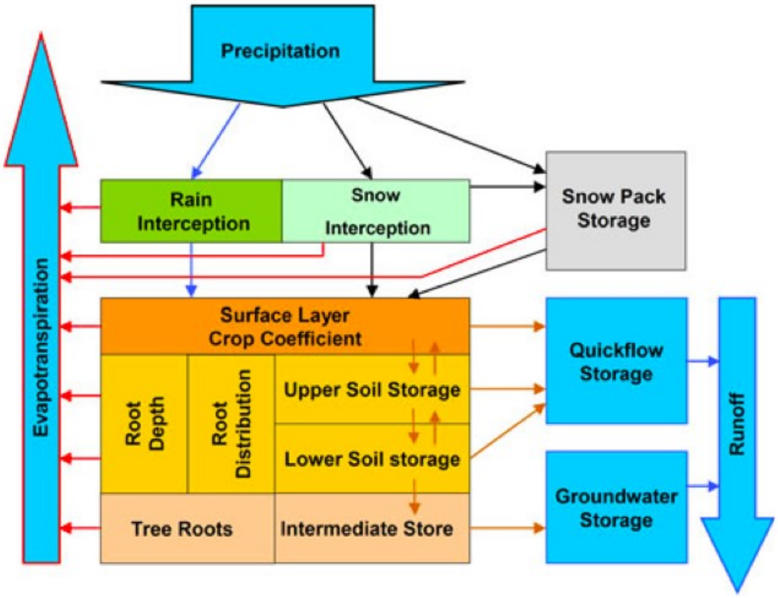


Figure 2-2. Major components of the ACRU agro-hydrological modelling system (Forbes et al., 2011)

The ACRU model has been widely used in climate change impact studies on water resources (Everson, 2001; Forbes et al., 2011; Kienzle & Schmidt, 2008; Schulze et al., 2004; Smithers et al., 1997; Tarboton et al., 1991). The model has been used in South Africa, Chile, Germany, Zimbabwe, USA and most recently in New Zealand and Canada. The major elements of the ACRU model have been revised to include snow routines (Forbes et al., 2011; Kienzle & Schmidt, 2008; Nemeth et al., 2012) and is illustrated in Figure 2-2. In Canada, the ACRU model was applied in the Cline River Watershed in the upper North Saskatchewan River Basin (UNSRB); parts of the Oldman River Basin which include the Beaver Creek Watershed and Castle River

Watershed (Anderson, 2014; Forbes et al., 2011; Nemeth, 2010; Nemeth et al., 2012). Therefore, this study aims to expand the scope of the ACRU model for the Oldman Reservoir Watershed in southern Alberta.

2.4.5 Integrating Geographical Information System with Hydrological Models for Water Resource Management

In the last few decades, the technological advancement of computers allowed the application of geographic information systems (GIS) along with hydrological models in water resource management. Tsihrintzis et al. (1996) described GIS as a system consisting of computer-based programs capable of "*capturing, storing, manipulating, analyzing and displaying spatial information in an efficient manner*." Significant progress in GIS consequently led to the advancement of many physical-based hydrological models (Kienzle, 1993; Leipnik et al., 1993; Tsihrintzis et al., 1996). Integrating GIS with hydrological models offers both front-end and back-end applications to model users. Front-end application involves watershed, topography, soil, and land cover parameter computations whereas back-end application involves the complex map layers as well as model output. Kienzle (1993) have previously linked GIS with the ACRU model, which usually require considerable spatial representation on the earth's surface and sub-surface information that includes topography, climate, soils, land cover, reservoirs, gauging station and sub-watersheds. Therefore, linking GIS with hydrological models is essential, as GIS enables the computation of a wide range of hydro-climatological and bio-physical parameters at a spatial scale required for distributed and physically-based hydrological models.

2.5 Current Challenges in Hydrological Modelling

Most physical-distributed hydrological models have underlying constraints inherent in their modelling application (Beven, 2012). These challenges emphasize the need for a better framework of analysis and a more efficient modelling experience for the ACRU model.

2.5.1 Predictions in Gauged vs Ungauged Watersheds

Most Canadian watersheds are typically poorly gauged or ungauged. In essence, a gauged watershed is one that has available streamflow measurements. On the other hand, an ungauged watershed is one where data is not available. The Prediction in Ungauged Basins (PUB) poses a hydrological challenge for hydrologists and the modeling community (Buytaert et al., 2009; Loukas et al., 2014; Sivapalan, 2003; Sivapalan et al., 2003). In 2003, the PUB initiative of the International Association of Hydrological Sciences (IAHS) was launched in order "*to improve scientific understanding of hydrological processes, as well as associated uncertainties and the development of models with increasing realism and predictive power*" (Hrachowitz et al., 2013). Typically, most PUB studies employed conceptual and lumped hydrological models. However, the challenge for hydrological modellers is to utilize physically-based distributed models as they account for heterogeneity of hydrological processed within a watershed (Athira et al., 2016; Cibin et al., 2014; Sivapalan, 2003). The diversity of these processes at finer resolutions is quite important for predictions in ungauged watersheds since they occur across a range of space and time. Sivapalan (2003) argues that in order to extrapolate predictions to ungauged watershed for a specific region, it is important to have a basic understanding of these hydrological processes and to have available data required to enable the predictions. The ACRU model is a physical-based agro-hydrological model that has been widely used in climate change impact studies on water resources. Interestingly, all current literature regarding the ACRU model in Canada is entirely based on gauged watersheds. This study in southern Alberta will be the first attempt to predict climate change impacts on an ungauged watershed in Canada using the ACRU model.

2.5.2 Model Code Verification

Another challenge to using a distributed and physically-based model, like the ACRU model, is the large data requirement that requires a high-level of expertise and, increasingly, a high level of effort for the model user (Beckers et al., 2009). The limited operational use of the ACRU model during data pre-processing and post-processing, model calibration and model validation can be an overwhelming experience to any untrained model user. Overcoming these operational challenges, however, is an impetus to make the ACRU model more accessible, particularly for the application in diverse and large watersheds, which require the delineation of thousands of hydrological response units (HRU). With these improvements, the new ACRU utility programs can be fully utilized in a distributed environment for a large watershed, thereby increasing the efficiency and accuracy of processing large input data and analysing large output data, as demonstrated in this study.

However, the development of utility programs require verification. Kleijnen (1995b) uses the term verification to determine whether a computer code or program performs the tasks or routines it was intended for. Essentially, the final version of the program should have no programming errors but still have room for improvement later on. Despite having a great number of original (1995) ACRU routines specifically designed for data pre-processing and post-processing for calibration and validation purposes, these routines were either no longer available or unsuitable for Canadian conditions, as they were coded specifically for South African conditions and datasets. In order to overcome these obstacles, the automation of several computer routines was severely needed.

The challenge is to develop programs that follow common programming guidelines (Kleijnen, 1995a, 1995b; Kleijnen, 2001; Kleijnen et al., 2000; Sargent et al., 2000). First, general good programming practices are required and involve utilizing a number of approaches developed by software engineers. Modular programming was required so that modules can be divided and completed by developers one by one until the entire computer program has been verified. General documentation is also imperative, where developers provide information on model assumptions and test values. Secondly, the verification of computer code or program for intermediate simulation output should be undertaken. Many developers have utilized "*tracing*", which means manually calculating the intermediate results and compare these with simulation output. Thirdly, the comparison of simulation outputs with analytical results using statistical techniques. A variety of statistical techniques can be used in conjunction with hydrological models. Common statistics used in hydrology include the variance, standard deviation, regression coefficient (slope), the regression intercept, Pearson's correlation coefficient (r), coefficient of determination (r^2), index of agreement (d), Nash-Sutcliffe Efficiency index (NSE), and their modified versions, and numerous error index statistics such as root mean square error (RMSE) and percent bias to name a few. Graphical techniques enhanced the verification by providing output using hydrograph (daily and seasonal) and exceedance probability curves. Lastly, the assessment and credibility of the computer code or program is required. Assessment of the computer program allows for users who did not develop the program code to determine whether the model can be used with confidence. The credibility of the program code is also determined as the level of confidence increases with which the program can be used for. Consequently, only after the careful verification of the ACRU utility tools can a successful model evaluation be done, as required in this study.

2.5.3 Model Evaluation

The calibration and validation is part of an iterative modelling process. Model evaluation is an important part of the hydrological modelling framework. It starts with model calibration, which is the process of adjusting parameters until the simulation results match the observed data to a certain degree. It is recommended to have an equal split for long records, where calibration periods will include average, wet and dry years with an observed record, comprising of at least 3-5 years (Klemeš, 1986; Moriasi et al., 2007). However, if there is a sufficiently long available record, then the calibration period can be increased to provide a meaningful calibration. Parameters are initially derived from the previous study of watersheds that have similar topography, land cover and climatology. Then, some of the parameters are adjusted based on the visual inspection of the hydrographs. Advanced visualization tools are often used to support the calibration process. Parameterization is tied within this because the process of defining a set of parameter values reflects the heterogeneous characteristic of the watershed. The complexity of the parameter interactions is considered in the final stages of the model calibration. A range of statistical criteria and visualization tools are combined to find the most suitable parameter set for the study area. The optimal parameter set is a trade-off between the different periods of the hydrograph. The calibration process is terminated once the parameter set is suitable over a number of iterations. Therefore, in order to reduce uncertainty in model simulations, proper model calibration procedures should be undertaken.

On the other hand, the ability of a hydrological model to demonstrate its predictive prowess is done through validation. This process is often the operational testing of the model on a dataset independent from the dataset used in the calibration period (Klemeš, 1986; Wagener, Wheater, et al., 2004). Essentially, once the model is validated under a testing scheme, the accuracy and its predictive capability are proven to be acceptable within the common benchmark. Some of the most common performance criteria are shown in Table 2-2.

Table 2-2. Common performance criteria for hydrological studies (Moriasi et al., 2007)

	Nash-Sutcliffe efficiency index (NSE)	Percent BIAS (Streamflow)
Excellent	0.75 < NSE ≤ 1.00	PBIAS < ±10
Good	0.65 < NSE ≤ 0.75	±10 ≤ PBIAS ≤ ±15
Satisfactory	0.5 < NSE ≤ 0.65	±15 ≤ PBIAS ≤ ±25
Unsatisfactory	NSE ≤ 0.5	PBIAS ≥ ±25

One of the proposed rigorous testing methods is the Klemeš' hierarchical scheme for operational testing of simulation models. It requires the use of the simple split-sample test (SST), which for simulating streamflow in an ungauged watershed, it is usually inadequate. The proxy-basin test (PBT) can then be utilized to examine the ability to spatially simulate streamflow between two similar regions, usually gauged watershed into an ungauged watershed. For climate change studies where a model is required to simulate streamflows under a different climate condition, Klemeš (1986) emphasised the importance of using the differential split-sample test (DSST). If the model is required to simulate streamflow for a wet climate scenario, then it should be calibrated on the dry period within the time series and validation on the wet period within the time series. This test is used to demonstrate the model's ability to simulate streamflows under changing climate conditions. The proxy-basin differential split-sample test (PB-DSST) is applied when a model is required to simulate streamflow in ungauged watershed under changing climate conditions. The test is quite lengthy, and consist of two parts to the model testing. Unfortunately, in most climate change studies, the common model calibration and validation techniques are inadequate.

The most commonly known model validation strategy used is the simple split-sample test (Moriasi et al., 2012). After running the model simulations, a comparison is made between the observed and predicted hydrographs (Beven, 1989). Most model calibration only use the simple split sampling test means of evaluating model, which ultimately leads to accepting reasonable but non-rigorous model testing (Klemeš, 1986; Refsgaard, 1997; Seibert, 2003; Semenova et al., 2015; Xu & Singh, 2004). The

ACRU model has been validated extensively in a number of applications in various climates around the world (Chetty et al., 2011; Forbes et al., 2011; Jewitt et al., 1999; Kienzle, 2010; Kienzle et al., 2012; Nemeth et al., 2012; Schulze, 1995; Smithers et al., 2013; Smithers & Schulze, 1995; Smithers et al., 1997; Tarboton & Schulze, 1991; Wangusi et al., 2013; Warburton et al., 2010, 2012). Yet, interestingly, the ACRU model has not yet been tested using the differential split-sample test, proxy-basin test or proxy-basin differential split-sample test. Therefore, the four-level Klemeš (1986) model testing scheme will be applied in this study in southern Alberta.

The need for improved model evaluation strategies have been emphasized in many hydrological modelling studies (Bárdossy, 2007; Bennett et al., 2013; Beven, 2012; Gupta et al., 2006; Gupta et al., 1998; Hornberger et al., 1985; Kirchner et al., 1996; Lamb, 1999; Perrin et al., 2001; Refsgaard, 1997; Refsgaard & Knudsen, 1996; Sahoo et al., 2006; Wagener, Wheater, et al., 2004; Winsemius et al., 2009; Xu, 1999b). However, there are currently no universally accepted guidelines for evaluating hydrological models in climate change studies using performance criteria (Moriasi et al., 2012). There is still much debate on the acceptance of evaluation guidelines for both model calibration and validation in the modelling community. For this study, a multi-objective performance criteria will be applied during the calibration and validation of the ACRU model.

2.6 Summary

Hydrological models provide an important conceptual framework for climate change studies. Utilizing global climate scenarios is still a large source of uncertainty in modelling hydrological response to climate change. However, regional climate scenarios have been proven to be more reliable. Moreover, a fundamental understanding of the crucial steps in model evaluations is required in order to simulate the regional climate scenarios appropriately. In addition, linking hydrological models with GIS allows for the surface and sub-surface hydrological application due to the large spatial data requirement. The rigorous testing of hydrological models under changing climate conditions is crucial but often neglected in many climate change studies. The current literature on ACRU model is not an exception, focusing on standard simple-sampling test on gauged watershed but not in an ungauged watershed. Furthermore, the utilization of the hierarchical (Klemeš)' model testing scheme allows the prediction of the ACRU model in ungauged watershed, like the Oldman Reservoir Watershed in southern Alberta. Thereby, a thorough understanding of the framework and challenges for using hydrological models are essential for reducing modelling uncertainty in climate change studies.

CHAPTER 3

STUDY AREA, DATA AND METHODS

3.1 Introduction

This chapter introduces the data and methods used in this study. Firstly, the Oldman Reservoir Watershed is presented as the study area. Secondly, the utilization of the ACRU agro-hydrological model is presented. Thirdly, various model input data are discussed. Lastly, the hydrological modelling framework is discussed in this chapter, particularly, the extensive calibration and validation procedures as well as sampling procedure undertaken in a large-size watershed study. Hence, it is important to outline the importance of utilizing the ACRU model in this study, as well as the various data properties and modelling procedures used in this study.

3.2 Study Area

The Oldman Reservoir Watershed, which is defined here as the watershed upstream of the Water Survey Canada stream gauging station 05AA024 (Oldman River near Brocket), is located in southwestern Alberta, Canada. It is comprised of sub-alpine landscapes located on the eastern slopes of Alberta’s Rocky Mountains and gradually transitions into a foothill region. It is approximately 4,380 km^2, with elevation ranging from 1037 m to 3099 m asl. The western part of the watershed mainly consists of coniferous and deciduous forests and barren rock (Rock et al., 2006). In contrast, the eastern part of the watershed predominantly consists of grassland and agricultural areas.

3.2.1 Regional Climate and Hydrology

The Oldman Reservoir Watershed (ORW) is an important upstream watershed of the Oldman River Basin (ORB). The ORB is a major sub-basin of the South Saskatchewan River Basin (SSRB) with an area of approximately 26,000 km^2 and predominantly semi-arid climate. (Alberta Environment, 2007; Byrne et al., 2006; Rock & Mayer, 2006). According to the available Parameter-elevation Regressions on Independent Slopes Model (PRISM) surfaces developed by Daly (2006; 2008; 1997), the mean annual precipitation (1971-2000) is 755 mm, ranging from 1665 mm to 511 mm at the outlet. Although precipitation increases with elevation, accurate observed precipitation data is difficult to determine due to the data measurement uncertainty and scarce data measurements found in mountainous regions, where the mean annual precipitation could reach more than 1500 mm at higher elevations.

The importance of mountain hydrology is quite evident for this study since the ORW represents about 17 percent of the total ORB area. However, it contributes approximately 39 percent of water for the entire region of the ORB (Kienzle et al., 2013). The tributaries that originate in the Canadian Rocky Mountains are the Oldman River, the Crowsnest River and the Castle River, which eventually flow into the Oldman Dam reservoir (Environment Canada, 2014; Glenn, 2000). These upper tributaries along with the Waterton and Belly Rivers contribute to the surface and groundflow of water through snowmelt, and rainfall runoff across the entire region (Byrne et al., 2006; Glenn, 2000; Jokinen et al., 2011; Rock & Mayer, 2006, 2007). The St. Mary River, a major tributary originating in Glacier National Park in Montana, joins the Oldman River south of the City of Lethbridge. The easterly flow of the Oldman

River converges with the Bow River to form the South Saskatchewan River, which eventually drains into Hudson Bay. Therefore, it is critical to study the ORW and the implication of potential impacts of climate change on a critical upstream watershed within the ORB and SSRB.

3.2.2 Importance of Water for Irrigation and Agriculture

Water storage is necessary for irrigation purposes in the semi-arid regions like the Canadian prairies. According to Environment Canada (2004) report, agriculture represents 70% of the water withdrawals from rivers, streams and reservoirs and 75% of all agricultural withdrawals occurred in the Prairie Provinces (Environment Canada, 2004). Due to the moisture deficiencies inherent in semi-arid climate, irrigation became essential in a region that focuses on agriculture and agriculture-related activities (Sauchyn & Kulshreshtha, 2008). Evidently, the eastern slopes of the Canadian Rocky mountains that cover the Oldman Reservoir Watershed provided 79% of water within the Oldman River Basin during the period 1971-2000 (Kienzle & Mueller, 2013). In southern Alberta, more than 1,248,000 acres of land are serviced by 13 irrigation districts (Oldman Watershed Council, 2013). Irrigation provides water to many intensive livestock operations, rural towns and major urban centres as well as wildlife and recreational facilities within southern Alberta (AARD, 2014a). Following its completion in 1992, the Oldman Reservoir was commissioned to regulate flow of the Oldman River Basin. It is located upstream of the LNID, where the Oldman, Crowsnest, and Castle rivers converge. It has a capacity to store 491 million m^3 of water. Therefore, any future changes in the availability of water will have serious implication on agriculture and irrigation for this region.

3.3 ACRU Agro-Hydrological Modelling System

In 2006, a snow model routine was added to the ACRU model. This new version is able to simulate snow melt routines in snow-dominated regions like the Oldman Reservoir Watershed (ORW). The primary objective of this study is to estimate the future water availability under climate change conditions by simulating streamflow under historical and future climate change scenarios using two RCM time-series from 1971-2000 and 2041-2070. However, a hydrological model can only be applied after a successful validation of the model is completed. In order to apply the RCM using the ACRU agro-hydrological model, it is important to validate the model performance within the ORW. Like other hydrological models, the ACRU model requires an extensive calibration and validation analyses in order to assess the model performance. The ACRU model calibration requires the refinement of model parameters within the physical constraints of the watershed in order to optimize the fit between the observed and simulated variables within physically meaningful boundaries. On the other hand, the model validation requires the comparison of observed temperature and streamflow data with simulated data in order to confirm the acceptable representation of the ACRU model. Once there is reasonable confidence with multiple model simulation, the ACRU model is then applied for future simulations using two regional climate model data (Loukas et al., 2002; Nemeth et al., 2012).

3.3.1 Model Structure of the ACRU Model

The spatial variability of rainfall, soils and land cover are considered when the ACRU model is used in a distributed mode. By taking into account the spatial variability of these variables, a more accurate representation of where the hydrological responses are occurring within the watershed and the magnitude of the hydrological response within the watershed is provided. The ACRU model uses a cell-type discretization approach to divide the watershed into smaller cell units. Each of the cell unit is regarded as a sub-catchment. The entire watershed is comprised of sub-catchments numbered sequentially, where each one flows into another and reflects a stream pattern as shown in Figure 3-1a. It is therefore important that the sequence of the flow of the cell units is defined accurately.

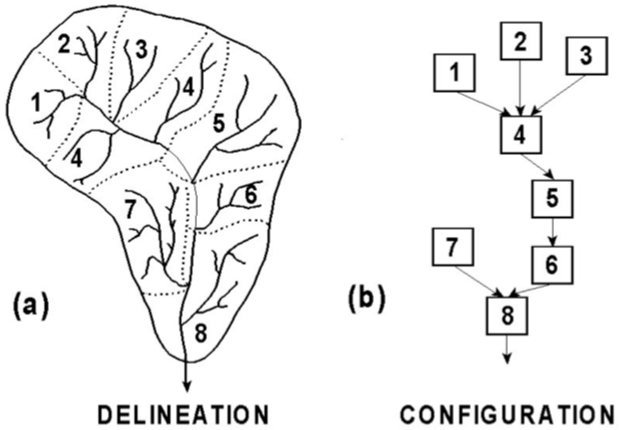


Figure 3-1. Spatial discretisation of a hypothetical watershed using the distributed version of the ACRU Model: a) Delineation of watershed boundaries and b) Simplified cell configuration of the sub-watershed as found in Schulze (1995).

The inter-sub-watershed flow is depicted in Figure 3-1b of a hypothetical cell configuration that follows the watershed delineation. The method for directing streamflow, which is made up of stormflow and baseflow expressed in mm, is illustrated in Figure 3-2. Schulze (1995) presents an explanation on the method of directing streamflow downstream between cell units within the ACRU model, where:

- A_i represents the area in km^2 of the sub-watershed Cell i
- q_i represents the streamflow in mm generated within the sub-watershed Cell i, without any possible flows from upstream sub-watersheds
- q_i' represents the equivalent depth of streamflow in mm distributed over the entire upstream sub-watershed Cell i
- Q_i represents the total volume of streamflow in m^3 leaving sub-watershed Cell i. This means Q_4 represents the total volume of streamflow in m^3 leaving the upstream sub-watersheds Cells 1+2+3+4

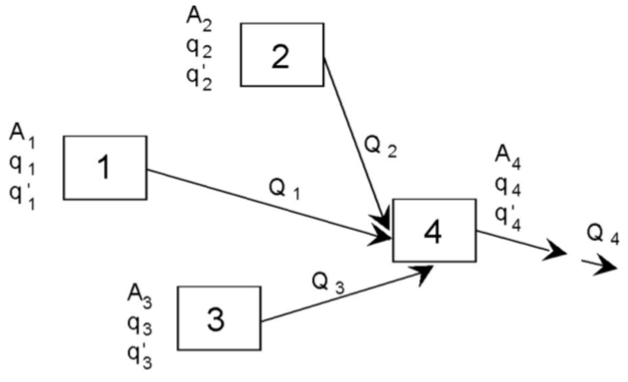


Figure 3-2. Directing streamflow downstream in distributed mode of ACRU model found in Schulze (1995)

3.3.2 Watershed Delineation

The model structure of the distributed version of the ACRU model allows for the spatial discretization of the Oldman Reservoir Watershed. The Oldman Reservoir Watershed was divided into six sub-watersheds. The delineation was undertaken by utilizing the locations of the Water Survey of Canada (WSC) gauging stations within the Oldman River Basin. Essentially, the ACRU model allows the sub-watersheds to be run as an independent watershed for validation purposes. The entire Oldman Reservoir Watershed was further subdivided into hydrological response units (HRUs), which are relatively homogeneous units that are based on similar physical and spatial characteristics (Flügel, 1995).

The delineation process required a combination of available spatial data that included: sub-watershed boundaries, digital elevation model (Figure 3-3), climate grids (Figure 3-4), land cover data (Figure 3-5) and mean annual solar radiation. A 100 m digital elevation model (DEM) was classified into 14 elevation bands by incorporating two different intervals: 100 m intervals for 1000 m to 2000 m and 200 m intervals for elevations over 2000 m. Climate grids were included, as the area inside each grid is fed by the climate time series (Agriculture and Agri-Food Canada, 2013). The landcover shapefile was reclassified into eight categories of land cover classes. Lastly, the mean annual solar radiation was calculated using the Solar Radiation tool in ArcGIS 10.1, aggregated from quarter-hour intervals for the entire year for each 100 m grid cell. The output was then reclassified into four quartiles.

A total of 1706 hydrological response units were created, based on 6 sub-watershed boundaries, 36 climate grids, 14 elevation bands, 8 land cover classes and

4 mean annual radiation classes. Although theoretically 96,768 possible combinations exist, only 1706 individual HRUs were defined, because, for example certain land covers only are associated with certain elevation bands.

Table 3-1. Overview of the sub-watershed in the Oldman Reservoir Watershed

Sub-Watershed	Area (KM^2)	Min Elevation (M)	Max Elevation (M)	Mean Elevation (M)	Total Number of HRUs
1	825.5	1187	2719	1710	314
2	403	1273	2736	1702	178
3	217.8	1448	2716	1854	121
4	142.7	1482	3051	1901	103
5	1086.6	1267	3018	1850	395
6	1702.4	1098	2580	1423	595

The use of HRUs as a spatial unit is a better representation of the regional characteristics found within the watershed (Beven, 2001a). Both the watershed and hydrological response unit approaches have been applied in Alberta. The cell-type spatial discretization approach has been applied for the hydrological impacts of climate change on the Beaver Creek Watershed in the Oldman River Basin (ORB) (Forbes et al., 2011). Meanwhile, the HRU spatial discretization approach was applied to the Cline River Watershed in the Upper North Saskatchewan River Basin (UNSRB) (Nemeth et al., 2012) and the Castle River Watershed (CRW) in the ORB (Anderson, 2014; Nemeth et al., 2012). All three studies have used the ACRU model in a distributed mode to simulate the impact of climate change on future runoff. Therefore, the spatial discretization approach based on HRUs is used for our study of the Oldman Reservoir Watershed in southern Alberta.

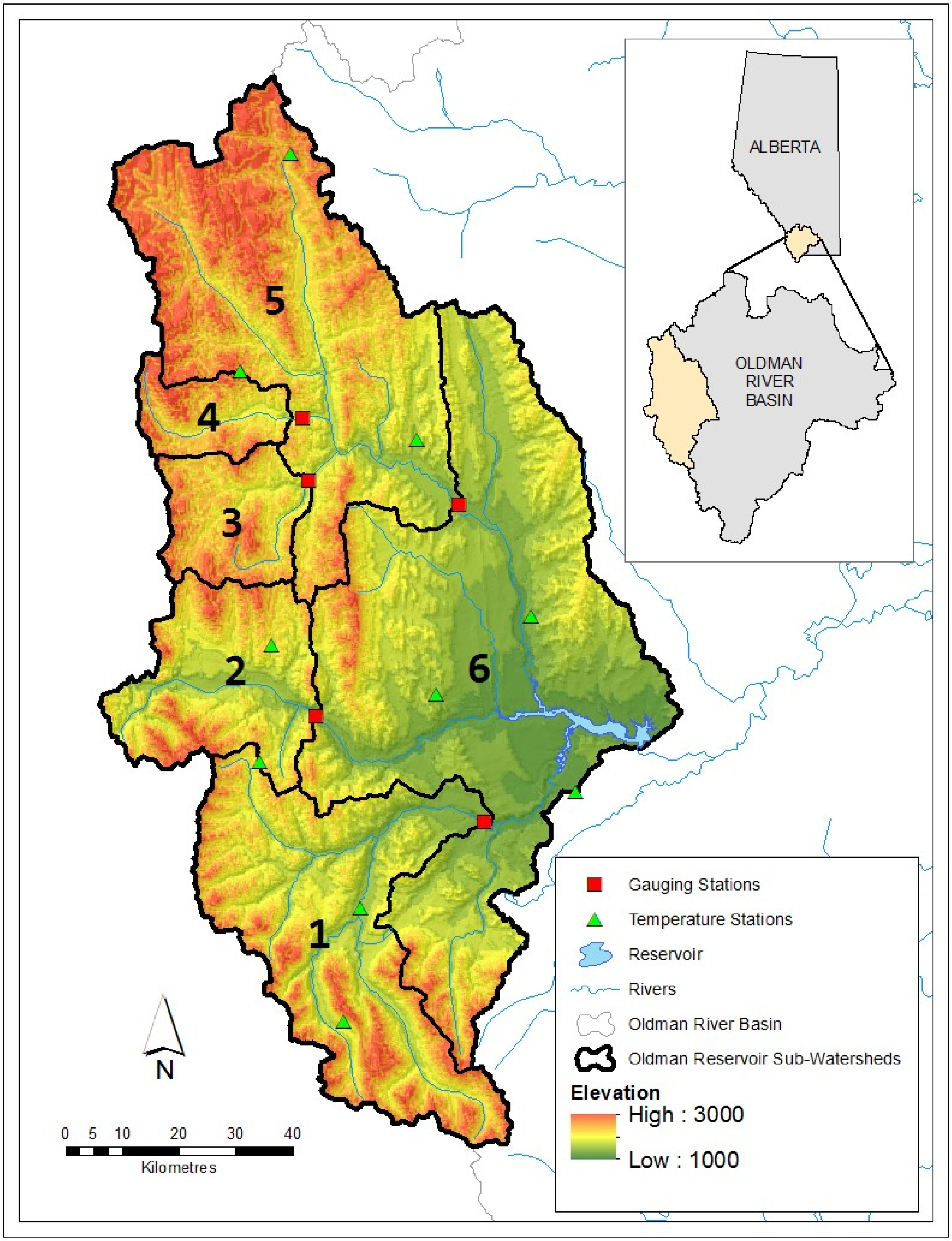


Figure 3-3. Map of the Oldman Reservoir Watershed

Table 3-2. Data Sources for the Oldman Reservoir Watershed

DATA DESCRIPTION	TEMPORAL RESOLUTION	SPATIAL RESOLUTION	VARIABLES OF INTEREST	SOURCE
Continuous Gridded Dataset (1951-2010)	Daily	10 x 10 km grids (100 km^2)	Tmin (°C), Tmax (°C), Precipitation (mm/day)	National Land and Water Information Service (NLWIS), Agriculture and Agri - Foods Canada (AAFC) (Hutchinson et al., 2009)
Observed time series data from stations of varying length	Monthly Averages	Point	Wind speed (m/s), Relative Humidity (%), Sunshine Hours (hr/day)	Environment Canada
Observed time series data from stations of varying length	Daily	Point	Tmin (°C), Tmax (°C),	Environment Canada using CCDST as an extraction tool (Bonifacio et al., 2014)
Hydrometric Data	Daily	Point	Streamflow discharge (m^{3}s^{-1})	Water Survey of Canada
Temperature Lapse Rates	Monthly	Point	Min and Max Lapse Rates	Literature Review (Anderson, 2014; Forbes et al., 2011; Nemeth, 2010; Nemeth et al., 2012; Shea et al., 2004)
Land Cover Data	-	Raster	Land cover	National Land and Water Information Service (NLWIS) through GeoBase portal
Bias-corrected Regional Climate Model data	Daily	22 – 44 km^2	Tmin (°C), Tmax (°C), Precipitation (mm/day)	VACEA under Dr. Sauchyn and Elain Barrow (University of Regina) (Barrow & Yu, 2005)
Simulated solar radiation for Alberta	Monthly	Raster	Solar Radiation (WH/m^2)	ESRI ArcGIS Software using Area Solar Radiation

3.4 ACRU Data Input Requirements

The ACRU agro-hydrological modelling system generally requires two types of input: 1) hydro-climatological data and 2) bio-physical parameters values for model parameterization and calibration. The next two sections discuss the data required for watershed delineation, hydro-climatological input as well as the biophysical parameters for the model parameterization of the ACRU model. A list of all the data required to run the ACRU model for the Oldman Reservoir Watershed is presented in Table 3-2.

3.4.1 Daily 10K Gridded Climate Dataset

Large datasets are required for hydrological model simulations. Often, models rely on the availability of hydro-climatological data such as maximum temperature, minimum temperature and precipitation. For regional climate change impact studies, high-resolution climatological data is further required. After much modelling effort, Hutchinson et al. (2009) produced the daily grids of daily maximum temperature (°C), minimum temperature (°C) and precipitation for 1961-2003. In 2007, the National Land and Water Information Service, under the Agriculture and Agri-Food Canada (AAFC), released the original *Daily 10KM Gridded Climate Dataset for Canada* for 1961-2003, known as the 10K-GCDC (Agriculture and Agri-Food Canada, 2013). The original dataset contained daily maximum temperature, minimum temperature and precipitation for Canada (south of 60°N). These data, along with elevation data, were obtained from Environment Canada's Meteorological Service of Canada (MSC) from 1891-2004 for 7514 climate stations across Canada (Hutchinson et al., 2009; Newlands et al., 2010). The available climate station data were used to create an interpolated surface using a thin-plate smoothing spline surface that has been implemented by Australian National University Splines (ANUSPLIN) 4.3 (Hutchinson et al., 2009; Sun, 2011). Error estimates for southern Canada were found to be low, but Hutchinson et al. (2009) reported that the occasional minor errors were caused by differences in climatological days. Hopkinson et al. (2011) improved on the daily climate data by aligning the climate days on the original daily gridded dataset for maximum temperature, minimum temperature and precipitation. The adjusted daily gridded dataset now covers the period of 1950-2010. Therefore, utilizing this high-resolution, gridded climate dataset will be valuable to this study.

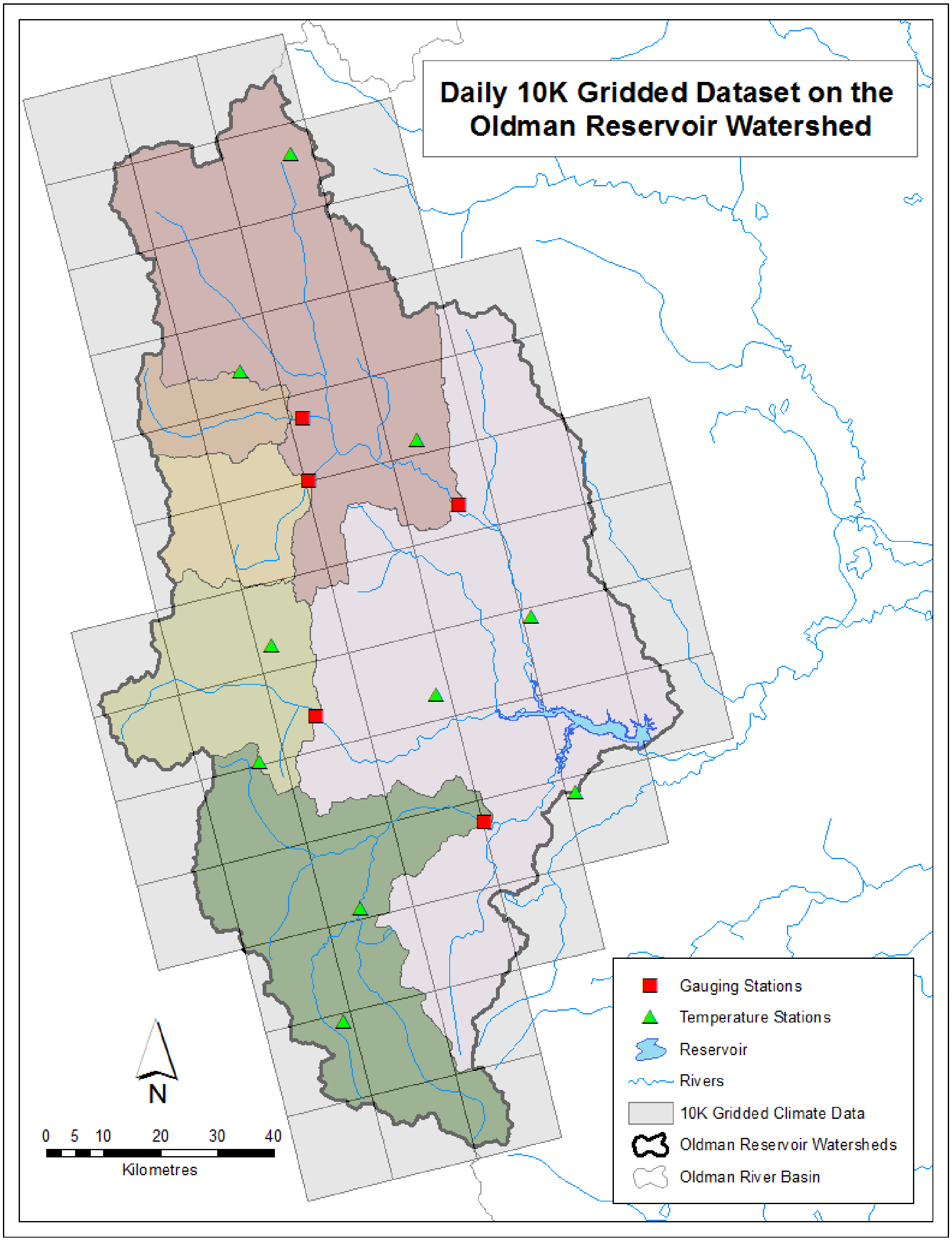


Figure 3-4. Daily 10K gridded dataset map for the Oldman Reservoir Watershed

Interestingly, the ANUSPLIN dataset could not be easily downloaded anywhere else except for the selected Canadian institutions that received the dataset in the first place (McGill University, 2013; University of Waterloo, 2010). The original and adjusted *Daily 10KM Gridded Climate Dataset* only contained three climate information: maximum temperature, minimum temperature and precipitation. The spatially interpolated surfaces for solar radiation, sunshine hours, relative humidity, and wind speed were created. Estimated daily values were added into the gridded dataset for the entire province of Alberta in order to estimate daily reference evaporation using Penman-Monteith equation. The revised dataset contains seven hydro-climatological variables: daily maximum temperature (°C), minimum temperature (°C), total daily precipitation (mm), solar radiation (MJ $m^{-2}day^{-1}$), sunshine hours (hr day^{-1}), relative humidity (fraction), and wind speed (km day^{-1}) for the entire province of Alberta. This study will apply the extended climate grid dataset for the Oldman Reservoir Watershed.

3.4.2 Reference Evapotranspiration Data

The Penman (1948) method for estimating daily A-Pan equivalent evaporation has been the most widely used equation for estimating potential reference evaporation. This method requires incoming radiation, sunshine hours, relative humidity and wind speed observed data. Climate normal values for sunshine hours, relative humidity and wind speed were collected mostly from Environment Canada (2012a). Data were collected for British Columbia, Alberta and Saskatchewan. Some data were collected from the US National Atmospheric and Oceanic Administration (NOAA) from the State of Montana. These monthly data points were spatially interpolated to create 100 m monthly raster data across the province of Alberta using spline interpolation tool in ArcGIS. However, there are no available solar radiation data found for the ORW. Monthly solar radiation data were extensively calculated using the Area Solar Radiation Tool in ArcGIS for Desktop. The Area Solar Radiation tool only allows a single latitude input for the entire province of Alberta (ESRI, 2012a, 2012b). Therefore, it was crucial to calculate the increasing over-estimation of solar radiation at 49°N and 60°N. The corrections were calculated by combining these two datasets into twelve correction surfaces. Overall, all four datasets provided monthly mean data that were eventually converted to daily values using the Fourier Transformation method through the Harmonic Analysis tool, a tool originally provided by the ACRU model. These daily values were combined with the Daily 10K gridded dataset for the entire province of Alberta.

Table 3-3. Summary of Evapotranspiration Data Sources using various climate station data

	ENVIRONMENT CANADA STATIONS			**NOAA STATIONS**
	British Columbia	**Alberta**	**Saskatchewan**	**State of Montana**
Sunshine Hours	-	7	-	-
Relative Humidity	17	29	15	6
Wind Speed	26	48	25	7

3.4.3 Observed Temperature Data

Ten additional minimum and maximum temperature data were obtained from the Environment Canada's National Climate Data and Information Archive (NCDIA) using the Canadian Climate Data Scraping Tool (Bonifacio et al., 2014). The daily air temperature data were used to calibrate the temperature within the ACRU model for the Oldman Reservoir Watershed, using monthly lapse rates.

Table 3-4. List of Climate stations downloaded from Environment Canada

CLIMATE STATION	LAT	LONG	ELEVATION	GRID ELEVATION	ELEVATION DIFFERENCE	N
Castle	49.4	-114.34	1360	1657.1	297.1	7447
Carbondale Lo	49.43	-114.37	1798	1514.3	283.7	5317
Gardiner Creek	49.3611	-114.5158	1920	1704	216	3035
West Castle	49.2833	-114.3667	1524	1827.4	303.4	2797
Connelly Creek	49.62	-114.22	1249	1462.2	213.2	10914
Willoughby Ridge	49.55	-114.5	1783	1721.3	61.7	2888
Sugarloaf Lo	49.95	-114.53	2514	1874.5	639.5	3439
Hailstone Butte Lo	50.17	-114.45	2372.9	2070.5	302.4	5329
Bob Creek	49.88	-114.25	1371.6	1536.2	164.6	3889
Pelletier Creek	49.67	-114.48	1646	1781.6	135.6	2293

3.4.4 Hydrometric Data

Discharge mean daily (Q_d) data for the Canadian hydrometric sites were obtained from the Water Survey of Canada's hydrometric database (HYDAT) (Environment Canada, 2012b). The hydrometric daily data were converted from $m^3 s^{-1}$ units to mm day^{-1}, which is a requirement as an input for the ACRU model.

Table 3-5. HYDAT Gauging Stations from Environment Canada

GAUGING STATION NAME	YEARS	LATITUDE	LONGITUDE
Crowsnest River at Frank	1910 - 2012	49.6	-114.4
Castle River near Beaver Mines	1945 - 2013	49.5	-114.1
Oldman River near Waldron's Corner	1949 - 2008	49.8	-114.2
Oldman River near Brocket	1966 - 2012	49.6	-113.8
Dutch Creek near the mouth	1966 - 1995	49.9	-114.48
Racehorse Creek near the mouth	1966 - 2012	49.8	-114.4
Castle River at Ranger Station	1967 - 2012	49.4	-114.3

3.4.5 Air Temperature Lapse Rates

In most hydrological studies, the lack of available measurements of climate stations at various elevations is a common problem. The interpolation of near-surface temperature is made possible with the use temperature lapse rate(Blandford et al., 2008). However, due to a number of influences common in mountainous regions such as inversions, katabatic winds, anabatic winds and diurnal temperature fluctuations, deriving air temperature lapse rates can be highly complicated (Pigeon et al., 2008). Due to various regional climatological studies, the most commonly used environmental temperature lapse rates also vary. The range of single environmental temperature lapse rate starts with 6.5°C km^{-1} (Blandford et al., 2008; Pigeon & Jiskoot, 2008). However, other regional mean monthly lapse rates for maximum and minimum temperatures were assumed to be at 6°C km^{-1} (Gardner et al., 2009; Shea et al., 2009). Mostly recently, the first application of the ACRU model in Canada assumed the mean monthly lapse rates for maximum and minimum temperatures at 6.2 km^{-1} for the Beaver Creek Catchment (Forbes et al., 2011). However, temperature adjustments using lapse rates are made from the location of the base station and away from mountain peaks. For this study, the following approach was incorporated from the Castle River Watershed (CRW) where the mean monthly lapse rates were derived through the application of a weighted distance calculation to PRISM-based lapse rates previously determined for the upper Northern Saskatchewan River Basin (UNSRB) (Kienzle et al., 2012) and St. Mary River Watershed (Kienzle, 2011). The calculated temperature lapse rates for the CRW were found to be similar to those calculated by Blandford et al. (2008). For this reason, the same maximum and minimum temperature lapse rates were used in the Oldman Reservoir Watershed study, as seen in Table 3-6.

Table 3-6. Monthly maximum and minimum temperature lapse rates for each month used in the Castle River Watershed

	Maximum Temperature Lapse Rate in °C/KM	Minimum Temperature Lapse Rate in °C/KM
January	-5.73	-0.56
February	-5.74	-0.75
March	-5.75	-2.39
April	-6.56	-4.05
May	-6.85	-3.83
June	-7.16	-4.2
July	-7.09	-3.7
August	-6.9	-2.95
September	-6.72	-2.89
October	-6.9	-3.38
November	-6.48	-2.38
December	-6.14	-1.35

3.4.6 Land cover-based data

The National Land and Water Information Service (NLWIS) produced the land cover data at 30 m resolution. The data were comprised of 36 groups and sub-groups of land cover classes and were combined according to their classification for the purposes of reducing the number of hydrological response units for the study area. The land cover-based classifications were combined into eight categories: cropland, grassland, herb, wetland, deciduous forests, coniferous forest, shrubland, barren and water, as shown in.

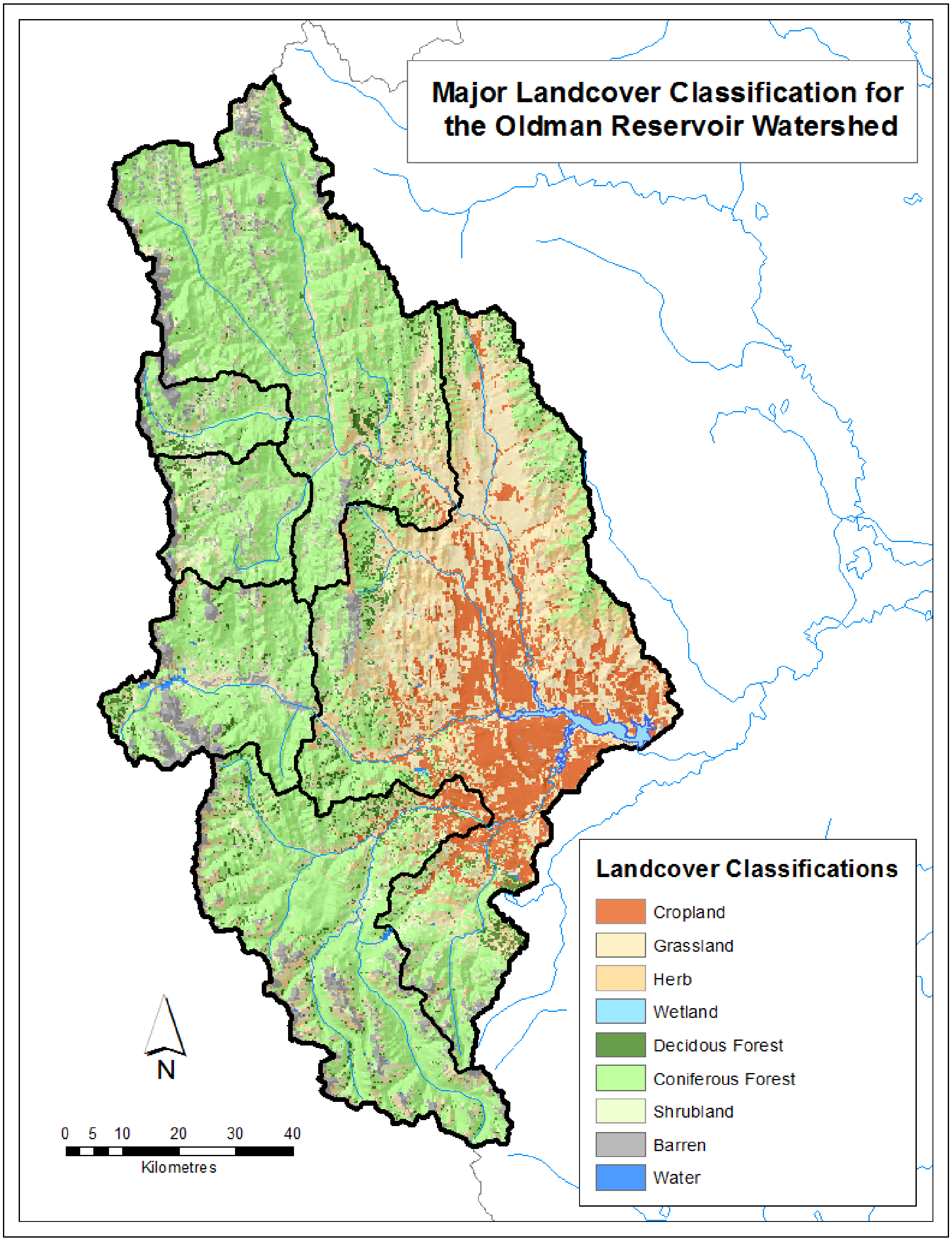


Figure 3-5. Final land cover classification for the Oldman Reservoir Watershed

The establishment of a land-cover based database for the Castle River Watershed was a crucial step in developing a database that can be applied for the wider region of the Oldman River Basin. Anderson (2014) described the utilization of various parameter values such as albedo, rooting depth, plant transpiration coefficients, leaf area index, forest canopy and soil data in detail. Therefore, the same data were incorporated into the study of the Oldman Reservoir Watershed.

Table 3-7. Percent of each land cover found for each sub-watershed in the ORW

	SUB-WATERSHED					
	1	**2**	**3**	**4**	**5**	**6**
Water	0.22%	0.77%	0.04%	0.02%	0.01%	1.21%
Barren	9.25%	14.43%	10.36%	13.39%	7.50%	2.27%
Shrubland	10.64%	12.67%	17.59%	14.92%	10.55%	6.44%
Coniferous Forest	59.09%	62.52%	63.60%	62.73%	64.68%	21.11%
Deciduous Forest	4.32%	3.09%	2.17%	4.04%	2.92%	4.01%
Wetland	0.15%	0.00%	0.00%	0.00%	0.00%	0.01%
Herb	6.39%	2.56%	1.89%	1.16%	4.67%	13.42%
Grassland	6.72%	3.95%	4.35%	3.74%	9.10%	29.09%
Cropland	3.23%	0.00%	0.00%	0.00%	0.57%	22.44%
TOTAL	100%					

3.4.7 Bias-Corrected Regional Climate Model Dataset

Lastly, to simulate the climate change impacts on the Oldman Reservoir Watershed, regional climate scenarios must be selected. The Intergovernmental Panel on Climate Change (IPCC) recommends a range of future climate scenarios within a region (IPCC-TGICA, 2007). The global climate models (GCMs) are downscaled into bias-corrected regional climate models (RCMs) projections. The first scenario focused on a cooler/wetter regional climate projection and was based on the Regional Climate Model Version 3 (RCM3), which was developed in University of Carolina-Santa Cruz, in USA. The Third Canadian Regional Climate Model (CRCM3) GCM drives this RCM. The other RCM is the Hadley Regional Climate Model Version 3 (HRM3) developed at the Hadley Centre, UK and is driven by the Geophysical Fluid Dynamics Laboratory (GFDL), a GCM developed at Princeton University, USA. In partnership with the VACEA project, prior agreement was made with Dr. David Sauchyn (University of Regina) to provide multiple regional climate model scenarios for the region. Due to the scope of this study, only two regional climate model projections are presented (see Table 3-8).

Table 3-8. List of Regional Climate Model Sources and Future Projections used in ORW

Global Climate Model	Regional Climate Model	Regional Climate Projection	Climate Scenario
Third Generation Coupled Global Model (CGCM3)	Regional Climate Model 3 (RCM3)	RCM3-cgcm3	Cooler/wetter
Geophysical Fluid Dynamics Laboratory (GFDL)	Hadley Regional Climate Model 3 (HRM3)	HRM3-gfdl	Warmer/Drier

The regional climate model data have spatial resolutions of 22 to 44 km^2. Each of the five regional climate model data has two datasets: one historical time-series ranging from 1971-2000, and one future time-series ranging from 2041-2070. All 10 datasets were further downscaled to match the daily 10 km^2 climate grid dataset that was used to drive historical climate simulations in this study, thus ensuring that the ACRU parameters resulting from the calibration and validation analysis are valid for hydrological simulations under a range of future climates.

3.5 The ACRU Agro-Hydrological Modelling Framework

Utilizing Refsgaard (1997) hydrological modelling framework as a key reference, the modelling framework for the ACRU model is comprised of the same model processes; however, additional processes were required in order to fulfill the objectives of this study (see Figure 3-6). The scenario approach to hydrological modelling governs the assessment of climate change impact in an ungauged catchment. Therefore, the scenario approach will be applied in this study. In order to make the future climate projections similar to observations, the climate projections were adjusted through a variety of methods. The delta method is commonly used, where the differences between recorded baseline and simulated historical climate are compared. For further downscaling the bias-corrected RCM data, the delta change method will be applied in this study.

The Modelling Framework:

1.) *Define the purpose of the study*: The Oldman Reservoir Watershed, southwestern Alberta, Canada and approximately 4400 km^2.

2.) *Model Input data construction and management*: Development of data pre-processing utility tools that were used in the setting up the ACRU model for a large-size watershed study.

3.) *Model Calibration*: Development of missing calibration and parameterization utility tools that enabled faster model calibration for a large-size watershed study.

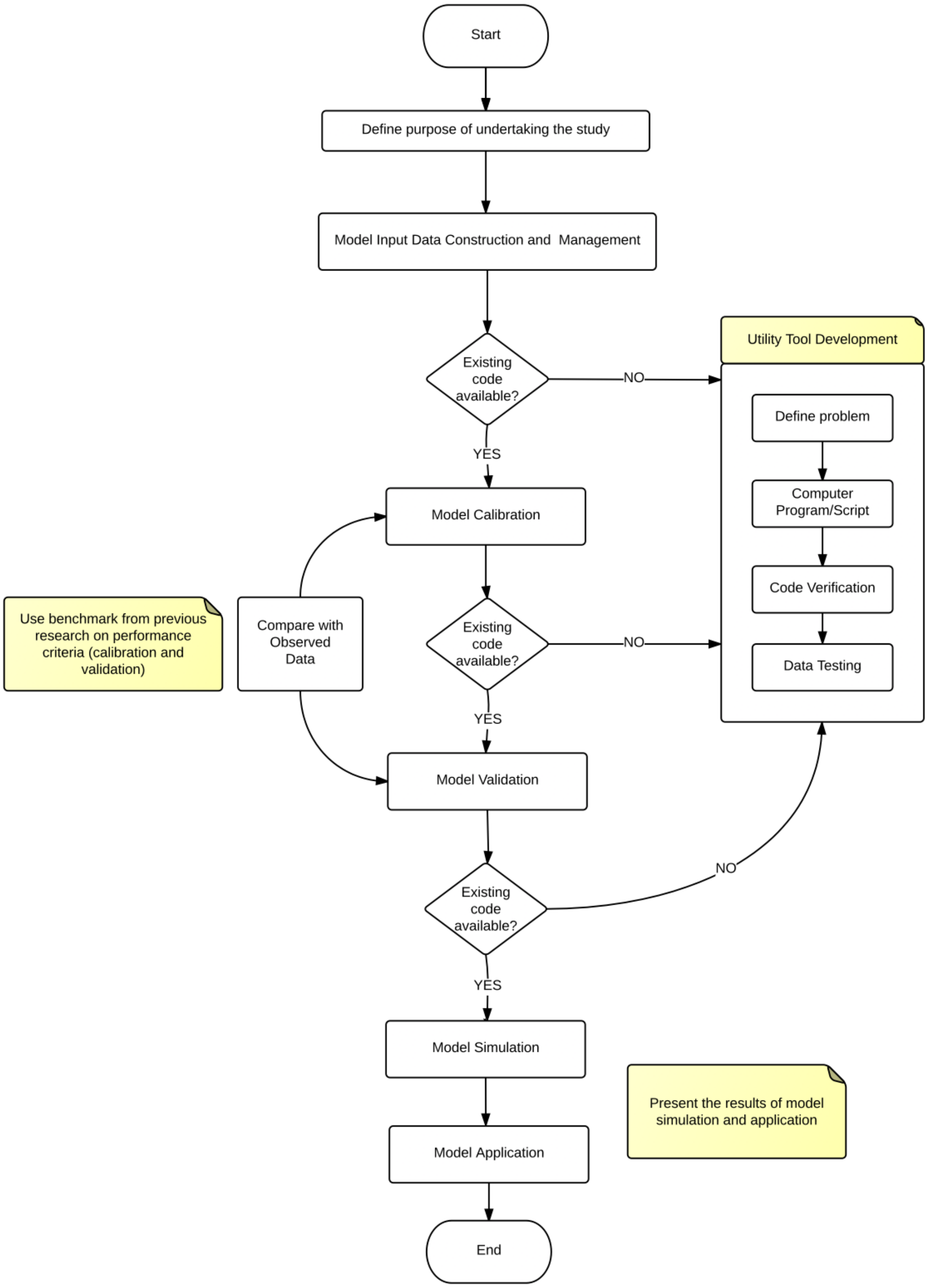


Figure 3-6. Modelling Framework for the Oldman Reservoir Watershed using the ACRU agro-hydrological model (yellow boxes are comments)

4.) *Model Validation*: Validating the ACRU model using historical observed data, often calibrated. Development of comprehensive validation package tools that enabled accurate statistical reporting as well as visual graphical techniques.

5.) *Model Simulation*: Simulation of historical and future regional climate model projections, after satisfactory model validation.

Much emphasis is placed on the development of crucial utility tools for the ACRU modelling system, especially for a large-sized watershed with more than a thousand hydrological response units. This step was essentially completed for data construction and management, model calibration and model validation phases of the ACRU hydrological modelling framework. Additional in-depth modelling details are presented in this section.

3.5.1 Model Performance Strategy

Two approaches were used to evaluate the ACRU model performance in this study. First, emphasis was placed on an improved rigorous assessment of the ACRU model. Second, the implementation of a multi-objective model performance criteria during model calibration and validation.

3.5.1.1 Klemeš Model Testing Scheme

The ACRU model was evaluated based on its ability to simulate temperature and streamflow data on a daily and monthly time scale in the Oldman Reservoir Watershed. First, the air temperature values were compared to mean air temperature values from Environment Canada. The temperature lapse rates of 6°C km^{-1}, 6.2°C km^{-1} and 6.5°C km^{-1} are typically used in these studies. These temperature lapse rates were compared against the multi-lapse rate approach used in previous studies (Pigeon & Jiskoot, 2008). Unfortunately, due to time constraints, further investigation regarding influences of inversions were not considered.

Second, the streamflow values were compared to observed HYDAT data from the Water Survey of Canada Hydrometric Program. Next, Klemeš (1986) four-level model testing scheme for operational validation was applied to the ACRU model for the study area. The testing scheme is comprised of four tests: 1) the split-sampling test for all five gauged watersheds in this study, 2) the proxy-basin test for two gauged watersheds, 3) the differential split-sampling test and 4) the proxy-basin differential split-sampling test using the same gauged watersheds in order to simulate results for the entire Oldman Reservoir watershed.

The split-sample test (SST) required the splitting of the available streamflow record into two parts; one segment is used for calibration while the other is used for validation. Here, the model is considered acceptable if the results are reasonable according to various statistical and graphical benchmarks. Annual comparison of observed and simulated streamflow for 1961-2000 period revealed the best calibration period to have low, average and high peak flows to be 1971-1980. Therefore, the selected calibration period for all five sub-watersheds was a 10-year period from 1971-1980 and the selected validation period was 1981-1990. All five gauged watersheds will be used to test the temperature and streamflow. However, due to the limited scope of this study, Sub-Watershed 1 and Sub-Watershed 5 were used in the model evaluation of the ACRU model for the remaining tests.

The proxy-basin test (PBT) required the ACRU model to be calibrated on watershed A and validated on watershed B and then vice versa if streamflow in an ungauged watershed C is to be simulated. Since the outlet of the Oldman Reservoir Watershed falls within the reservoir and is ungauged, this test should examine the concept of non-stationary concept of spatial transferability of the ACRU model (Klemeš, 1986). Here, Sub-Watershed 1 was considered as watershed A, and Sub-Watershed 5 was considered as watershed B for a period of 10-years beginning in 1981. According to Table 3-1, these two watersheds were similar in size and total number of hydrological response units within their boundaries. As shown in Figure 3-5, the dominant land cover classes between these two sub-watersheds were quite similar.

The differential split-sample test (DSST) is required for gauged watersheds since the ACRU model is used to simulate streamflows under changing climate conditions. Two streamflow periods were identified as high and low-average precipitation periods. The period between 1974 and 1976 were identified as the high-average precipitation period whereas the period between 1982 to 1984 were identified as low-average precipitation period. The ACRU model was required to simulate streamflow for a wet climate scenario and was calibrated under the dry period and then validated on the wet period. Low average precipitation period (LAPP) is used in the calibration run, whereas high average precipitation period (HAPP) is used in validation of the model.

This proxy-basin differential split-sample test (PBDSST) was required to simulate streamflows for the ungauged Oldman reservoir under changing climate conditions. The test was implemented where the same two streamflow periods were identified as high and low-average precipitation periods from previous tests. Essentially, the ACRU model was required to simulate streamflow for a wet climate scenario, test requires the model to be calibrated under dry period from Watershed #1 and then validated on a wet period from Watershed #5. Additionally, the dry period for Watershed #5 was calibrated and then validated using wet period for Watershed #1. Furthermore, the ACRU model is also required to simulate streamflow for a dry climate scenario, the test required that the model to be calibrated under a wet period for Watershed #1 and then validated on a dry period for Watershed #5. In addition, the wet period for Watershed #5 is calibrated and validated on a dry period for Watershed #1.

3.5.1.2 Performance Criteria

The recommended performance criteria by Schulze et al. (1995), Smithers and Schulze (1995) and Moriasi et al. (2007) were combined for the calibration of the ACRU model in this study. The percentage difference between the sum of simulated daily flows ($\sum Q_s$) and observed daily flows ($\sum Q_o$), percentage difference between standard deviations of simulated daily flows ($\sum \sigma_s$) and observed daily flows ($\sum \sigma_o$), were combined with RMSE-observations standard deviation ratio (RSR), Nash-Sutcliffe Efficiency Index (NSE), and percent bias for streamflow (PBIAS) were during the calibration phases of the performance assessment.

The Nash-Sutcliffe Efficiency index (NSE) is used to evaluate hydrological model performance (Gupta et al., 2009; Legates et al., 1999), as it is one of the criteria most widely used in model calibration and evaluation of hydrologic models, where the coefficient indicates how much of percentage of the observed variance can be explained by the simulated data (Gupta et al., 2009). Nash et al. (1970) initially proposed the equation to be as follows:

$$\mathrm{NSE_f} = \frac{\sum_{i=1}^{N}\left(\hat{Y} - Y_i\right)^2}{\sum_{i=1}^{N}(Y_i - \overline{Y})^2}$$

where $\hat{Y}$ represents the simulated data, Y_i represents the observed data and $\overline{Y}$ represents the mean of the observed values (McCuen et al., 2006). A value of E_f equal or close to zero indicates that the simulated data are not better than the mean observed streamflow for the entire period used in the analysis. McCuen et al. (2006) evaluated the Nash-Sutcliffe coefficient and concluded that its structure is similar to the Pearson product-moment correlation coefficient. Overall, the Nash-Sutcliffe coefficient is a useful index, however, it should be used with caution as it is sensitive to a number of factors such as sample size, outliers, magnitude bias and time-offset bias. Unfortunately, the failure to recognize the limitations of the Nash-Sutcliffe coefficient index may lead to reject a good hydrological model on the basis of a less than ideal index value as it may not be indicative of a poor model.

Another criterion similar to NSE is the RMSE-observations standard deviation ratio (RSR). It is a ratio of the RMSE and standard deviation of observed data. This measure was initially proposed by Singh et al. (2005) and is defined as follows:

$$\mathrm{RSR} = \frac{\sqrt{\sum_{\mathrm{i}=1}^{\mathrm{N}}\left(\mathrm{Y_i} - \widehat{\mathrm{Y}}_{\mathrm{i}}\right)^2}}{\sqrt{\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{Y_i} - \overline{\mathrm{Y}})^2}}$$

where $\mathrm{Y_i}$ represents the observed data, $\widehat{\mathrm{Y}}$ represents the simulated data and $\overline{\mathrm{Y}}$ represents the mean of the observed values (Moriasi et al., 2007). RSR is recommended as a model evaluation statistic as it normalizes RMSE using observed standard deviation (Bennett et al., 2013; Moriasi et al., 2007; Singh et al., 2005).

In addition, the percent bias can be used to indicate whether the model performance had an underestimation or overestimation bias, meanwhile, the index of agreement indicated the degree of model prediction error. Moriasi et al. (2007) found that NSE and PBIAS statistics were both used in model calibration and validation. Legates and McCabe (1999) reported on the index of agreement's over-sensitivity to high extreme values and suggested the modified index as an alternative. Unfortunately, Moriasi et al. (2007) found that this improved statistic is not extensively used in literature. Although, regression statistics are usually the standard objective criteria used in most hydrological studies, these objective measures indicate the linear relationship of the simulated data fits the observed data. Therefore, due to the nonlinear relationship of hydrological modelling, regression statistics were only considered during the final calibration runs of the ACRU model.

Moreover, graphical techniques, usually considered subjective measures of goodness of fit, were coupled with multiple-objective performance criteria for the Oldman Reservoir Watershed. These evaluation techniques provide a visual comparison of observed and simulated data. Two most commonly used graphical techniques in hydrology are hydrographs and flow duration curves. Hydrographs identify the model bias by providing a visual comparison of observed and simulated time series plot. Differences in timing and magnitude of peak flows are identified. Meanwhile, flow duration curves illustrate the frequency of measured daily flows throughout the calibration and validation periods (Booker et al., 2012).

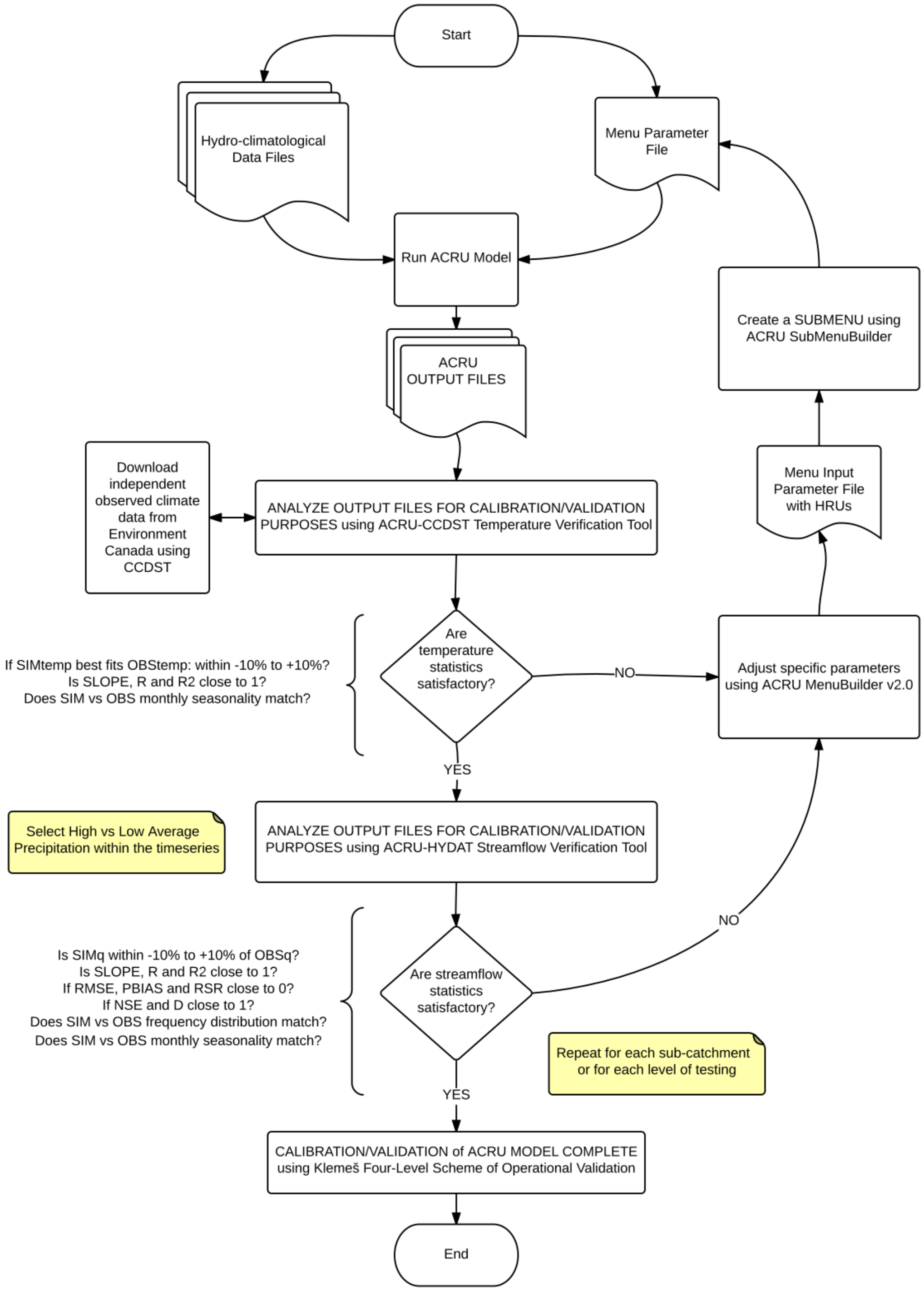


Figure 3-7. Model Calibration Procedure of the ACRU model (yellow boxes are comments)

3.5.2 Future Climate Change Projection

After the model testing is completed, the regional climate projections are applied to the ACRU model. The second framework (see Figure 3-8) describes the process of applying bias-corrected regional climate model data using the calibrated ACRU model. The application of a hydrological model is described as the process where the validated model must demonstrate it is capable of making accurate projections in the future. No further calibration or validation is required during this step.

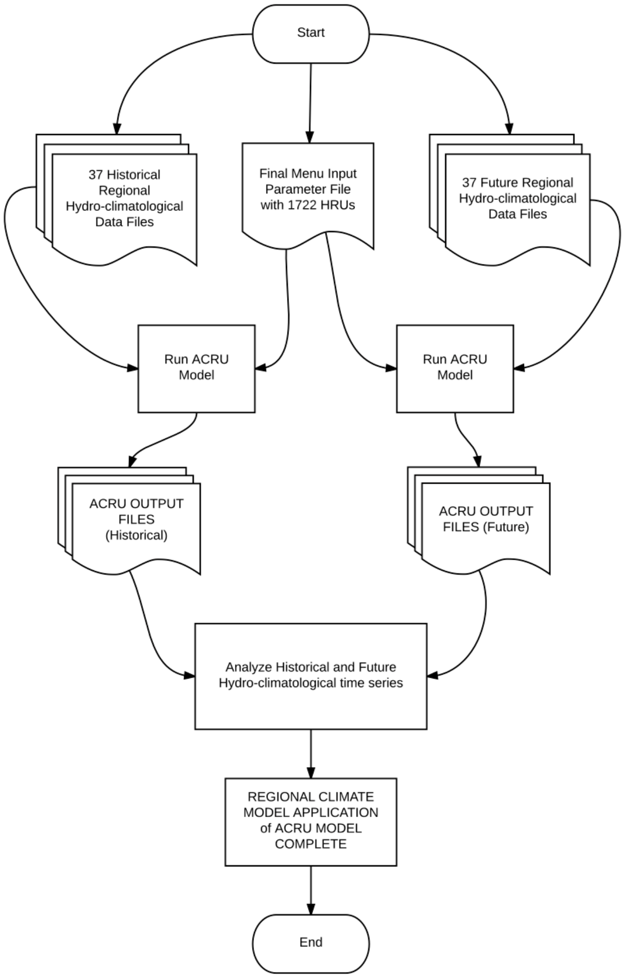


Figure 3-8. Regional Climate Model Application using ACRU Model

3.6 Summary

The application of the ACRU model to the Oldman Reservoir Watershed, a large-sized semi-arid watershed, was described in this chapter. The spatial delineation technique of sub-watershed, elevation data, climate data, land cover, solar radiation was applied in this study, resulting in a total of 1706 hydrological response units. In addition, a rigorous four-level model testing was chosen for the study and was incorporated in the model evaluation of the ACRU model. Furthermore, the additional components for modelling hydrological processes within a large-catchment required the utilising a multiple-objective performance criteria. This allowed for a more efficient and accurate model calibration and validation of the ACRU agro-hydrological model. Thus, the data and methods presented in this chapter effectively allowed a more rigorous testing of the ACRU model under a changing climate.

CHAPTER 4

UTILITY TOOLS FOR THE ACRU MODEL

4.1 Introduction

This chapter presents the utilization of the distributed version of the ACRU model. Most physical-distributed hydrological models have underlying constraints inherent in their modelling application (Beven, 2012). The current version of the ACRU model in a distributed environment presents a few constraints. According to Smithers and Schulze (1995) manual of the ACRU modelling system, the model was configured to operate on a maximum of 150 sub-units before it was configured due to increasing computation power. In 2006, the model was adapted to work with up to 9999 sub-units. This has led to increasing challenges in utilizing the ACRU model for regional climate modelling. A distributed and physically-based model requires a large number of data, high-level of expertise, and an increasingly high level of effort for the model user (Beckers et al., 2009). Thus, the development of key ACRU model utility tools became necessary.

4.2 The Need for Improved Utility Tools

Many physically-based hydrological model users face overwhelming challenges. These challenges require the processing and management of large datasets, as well as efficient data analysis. In improving the ACRU modelling system, the main consideration in developing tools has been to enable efficient data management, processing and analysis through user friendly interface and faster processing time.

The ArcGIS for Desktop environment uses ArcPy, which is a site package for the software that productively aids in the automatic spatial data analysis, data conversion, data management, and map creation (ESRI, 2014). It contains a large library of spatial analysis tools for integration using Python, thus incorporating ArcGIS analytical tools in Python without having to run ArcGIS software. On the other hand, Microsoft Excel is a widely used spreadsheet program, which is commonly used in commercial and academic enterprises (Walkenbach, 2010). Academics usually, gravitate towards tools that are free to use (e.g. Python, and R); while others rely on software programs that have costly annual licenses (e.g. SPSS, MATLAB). It is important to note that the level of computing skill can be minimized with the operation of the program and a graphical user interface that is intuitive and user-friendly. Moreover, the original ACRU modelling system was written in Fortran77, which has been freely available since the 1970s (Schulze, 1995; Smithers & Schulze, 1995). Many programs written in Fortran77 have been updated to use more modern or object oriented friendly languages such as C, C++ and C# (Ferland, 2000). Unforeseen challenges were faced in adapting Fortran77 script to Fortran95 standards, especially due to compiler availability issues. Therefore, the development of a variety of utility tools using Python, Visual Basic for Applications (VBA) and Fortran resolved some of these constraints in order to facilitate the ACRU model with increasing efficiency of data processing and analysis several thousand hydrological response units for this study. See Appendix I for a detailed look at the code developed for each utility tool.

4.3 Data Processing Tools

The automation of various data processing procedures was crucial in the model construction of the ACRU model. Since the ACRU model required daily time-step input, all hydro-climatological input files were pre-processed accordingly. This involved assembling the observed hydro-climatological input time series to incorporate the following daily climate variables: relative humidity, sunshine hours, wind speed and solar radiation variables into the 100 km^2 resolution climate grids. It also involved the development of a GIS-based utility to facilitate and standardize the delineation of hydrological response units (HRUs) for the Oldman Reservoir Watershed. The calculation of correction factors was also required for precipitation, solar radiation, sunshine hours, relative humidity and wind speed, in order to transfer average data values from the 100km^2 resolution climate grids to the much smaller HRUs. Before the application of the ACRU model is undertaken, two bias-corrected Regional Climate Model (RCM) time series were further downscaled to the existing 100 km^2 resolution grids and properly formatted for the ACRU model. The next sub-sections will discuss the several procedures used to create the data management utility tools for this study.

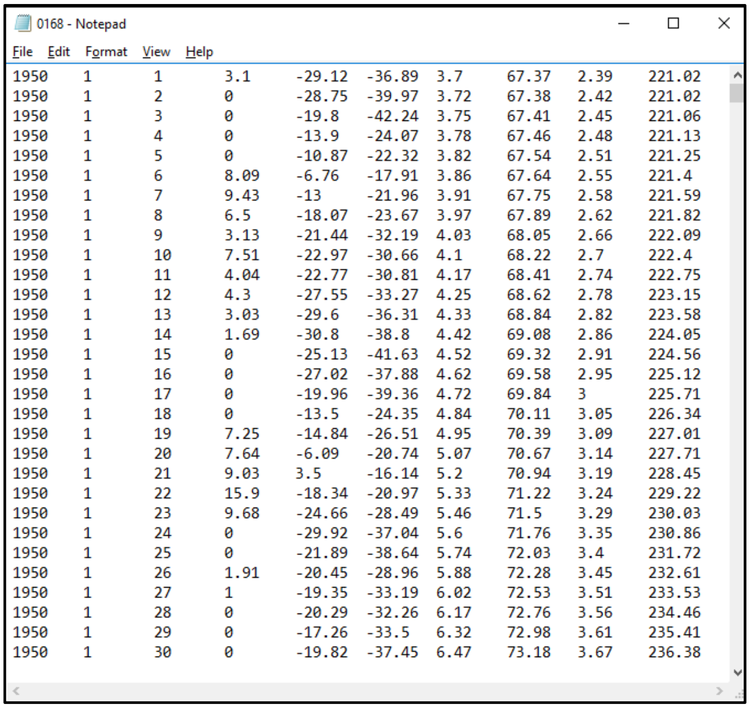
4.3.1 ACRU Hydro-Climatological Data File Generator

The original version of the Daily 10km Gridded Climate Dataset from 1961-2003 (AAFC, 2008) contained climate information such as daily maximum temperature (°C), minimum temperature (°C) and total daily precipitation (mm), (Hutchinson et al., 2009), which was further improved by Hopkinson et al. (2011). The spatially interpolated surfaces for solar radiation, sunshine hours, relative humidity, and wind speed have been appended into the original data for the entire province of Alberta. The revised dataset now contains additional 4 hydro-climatological variables: solar radiation (MJ m^{-2} day^{-1}), sunshine hours (hr day^{-1}), relative humidity, and wind speed (km day^{-1}) for the calculation of Penman Monteith (Penman, 1948). This tool compiles seven variables for each 10km climate grid in an ACRU specific file format. Before compiling all seven variables into an ACRU formatted input file, it was important to create a spatially interpolated climate data surface pertaining to relative humidity, sunshine hours and wind speed. This process was automated by utilizing the ArcPy modules through Microsoft© Excel graphical user interace. The following outlines the procedures used for this tool:

1.) The Zonal Statistics tool is initiated using ArcPy module for each spatial data for 12 months. There should be 48 DBF files found in the folder at the end of this step (one for each of the four variables and each month).
2.) The Fourier Transformation method is applied using the Harmonic Analysis tool in order to transform the observed 12 monthly values into daily values. This tool uses the original ACRU Fortran77 code. Therefore, no changes were made to code during this project.

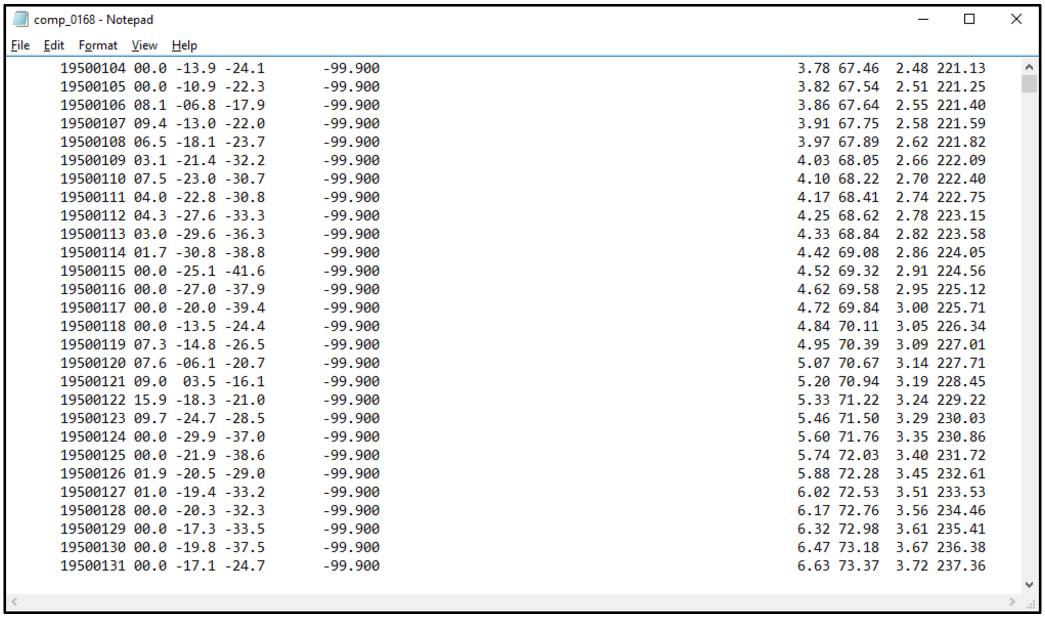
3.) Calculations are saved in an unformatted output, as a .TXT file (Figure 4-1).

4.) *Composite File* subroutine is initiated to format the .TXT file into the appropriate ACRU input file (Figure 4-2).



```
1950    1       1       3.1     -29.12  -36.89  3.7     67.37   2.39    221.02
1950    1       2       0       -28.75  -39.97  3.72    67.38   2.42    221.02
1950    1       3       0       -19.8   -42.24  3.75    67.41   2.45    221.06
1950    1       4       0       -13.9   -24.07  3.78    67.46   2.48    221.13
1950    1       5       0       -10.87  -22.32  3.82    67.54   2.51    221.25
1950    1       6       8.09    -6.76   -17.91  3.86    67.64   2.55    221.4
1950    1       7       9.43    -13     -21.96  3.91    67.75   2.58    221.59
1950    1       8       6.5     -18.07  -23.67  3.97    67.89   2.62    221.82
1950    1       9       3.13    -21.44  -32.19  4.03    68.05   2.66    222.09
1950    1       10      7.51    -22.97  -30.66  4.1     68.22   2.7     222.4
1950    1       11      4.04    -22.77  -30.81  4.17    68.41   2.74    222.75
1950    1       12      4.3     -27.55  -33.27  4.25    68.62   2.78    223.15
1950    1       13      3.03    -29.6   -36.31  4.33    68.84   2.82    223.58
1950    1       14      1.69    -30.8   -38.8   4.42    69.08   2.86    224.05
1950    1       15      0       -25.13  -41.63  4.52    69.32   2.91    224.56
1950    1       16      0       -27.02  -37.88  4.62    69.58   2.95    225.12
1950    1       17      0       -19.96  -39.36  4.72    69.84   3       225.71
1950    1       18      0       -13.5   -24.35  4.84    70.11   3.05    226.34
1950    1       19      7.25    -14.84  -26.51  4.95    70.39   3.09    227.01
1950    1       20      7.64    -6.09   -20.74  5.07    70.67   3.14    227.71
1950    1       21      9.03    3.5     -16.14  5.2     70.94   3.19    228.45
1950    1       22      15.9    -18.34  -20.97  5.33    71.22   3.24    229.22
1950    1       23      9.68    -24.66  -28.49  5.46    71.5    3.29    230.03
1950    1       24      0       -29.92  -37.04  5.6     71.76   3.35    230.86
1950    1       25      0       -21.89  -38.64  5.74    72.03   3.4     231.72
1950    1       26      1.91    -20.45  -28.96  5.88    72.28   3.45    232.61
1950    1       27      1       -19.35  -33.19  6.02    72.53   3.51    233.53
1950    1       28      0       -20.29  -32.26  6.17    72.76   3.56    234.46
1950    1       29      0       -17.26  -33.5   6.32    72.98   3.61    235.41
1950    1       30      0       -19.82  -37.45  6.47    73.18   3.67    236.38
```

Figure 4-1. Unformatted output file from the ACRU Composite File Generator Tool. It includes: year, month, day, precipitation, Tmax, Tmin, solar radiation, relative humidity, sunshine hours and wind speed.



```
    19500104 00.0 -13.9 -24.1      -99.900                                      3.78 67.46  2.48 221.13
    19500105 00.0 -10.9 -22.3      -99.900                                      3.82 67.54  2.51 221.25
    19500106 08.1 -06.8 -17.9      -99.900                                      3.86 67.64  2.55 221.40
    19500107 09.4 -13.0 -22.0      -99.900                                      3.91 67.75  2.58 221.59
    19500108 06.5 -18.1 -23.7      -99.900                                      3.97 67.89  2.62 221.82
    19500109 03.1 -21.4 -32.2      -99.900                                      4.03 68.05  2.66 222.09
    19500110 07.5 -23.0 -30.7      -99.900                                      4.10 68.22  2.70 222.40
    19500111 04.0 -22.8 -30.8      -99.900                                      4.17 68.41  2.74 222.75
    19500112 04.3 -27.6 -33.3      -99.900                                      4.25 68.62  2.78 223.15
    19500113 03.0 -29.6 -36.3      -99.900                                      4.33 68.84  2.82 223.58
    19500114 01.7 -30.8 -38.8      -99.900                                      4.42 69.08  2.86 224.05
    19500115 00.0 -25.1 -41.6      -99.900                                      4.52 69.32  2.91 224.56
    19500116 00.0 -27.0 -37.9      -99.900                                      4.62 69.58  2.95 225.12
    19500117 00.0 -20.0 -39.4      -99.900                                      4.72 69.84  3.00 225.71
    19500118 00.0 -13.5 -24.4      -99.900                                      4.84 70.11  3.05 226.34
    19500119 07.3 -14.8 -26.5      -99.900                                      4.95 70.39  3.09 227.01
    19500120 07.6 -06.1 -20.7      -99.900                                      5.07 70.67  3.14 227.71
    19500121 09.0  03.5 -16.1      -99.900                                      5.20 70.94  3.19 228.45
    19500122 15.9 -18.3 -21.0      -99.900                                      5.33 71.22  3.24 229.22
    19500123 09.7 -24.7 -28.5      -99.900                                      5.46 71.50  3.29 230.03
    19500124 00.0 -29.9 -37.0      -99.900                                      5.60 71.76  3.35 230.86
    19500125 00.0 -21.9 -38.6      -99.900                                      5.74 72.03  3.40 231.72
    19500126 01.9 -20.5 -29.0      -99.900                                      5.88 72.28  3.45 232.61
    19500127 01.0 -19.4 -33.2      -99.900                                      6.02 72.53  3.51 233.53
    19500128 00.0 -20.3 -32.3      -99.900                                      6.17 72.76  3.56 234.46
    19500129 00.0 -17.3 -33.5      -99.900                                      6.32 72.98  3.61 235.41
    19500130 00.0 -19.8 -37.5      -99.900                                      6.47 73.18  3.67 236.38
    19500131 00.0 -17.1 -24.7      -99.900                                      6.63 73.37  3.72 237.36
```

Figure 4-2. Formatted input for the ACRU Model. The file includes: Year, month, day, precipitation, Tmax, Tmin, observed streamflow, solar radiation, relative humidity, sunshine hours, and wind speed

4.3.2 HRU Delineation Tool

The ArcPy module was utilized in order to develop a stand-alone script that did not require ArcGIS software to be used, which decreased the overall data processing time. The delineation of the hydrological response units required the following steps:

1.) Five spatial raster layers were selected in order to delineate hydrological response units for the watershed.

2.) A category of values for each data was created. For instance, there were six sub-watersheds for this study and, therefore, analyses required the processing to be resampled to six categories.

3.) Data were resampled into the same resolution. For this study, most of the raster images had already been resampled into 100 m resolution. This process repeated for all the layers.

4.) The stand-alone Python script were used to automatically delineate the hydrological response units. Note, that some units are too small to be considered as an HRU. For instance, the creation of an HRU, which is one ha in size represents less than a 1000s of one percent, and is thus insignificant. That specific HRU is then aggregated into a neighbouring HRU. This step is important as it reduced the total amount of HRUs for the Oldman Reservoir Watershed.

4.3.3 ACRU Correction Factors Tool

The spatial variability of precipitation, solar radiation, sunshine hours, relative humidity, and wind speed in the mountainous regions can be significant. Kienzle (2008) notes the underestimation of rainfall measurements in Canada. Therefore, correction factors needed to be calculated in order to make up for the differences due to elevation as outlined below. The calculation of the correction factors are outlined below:

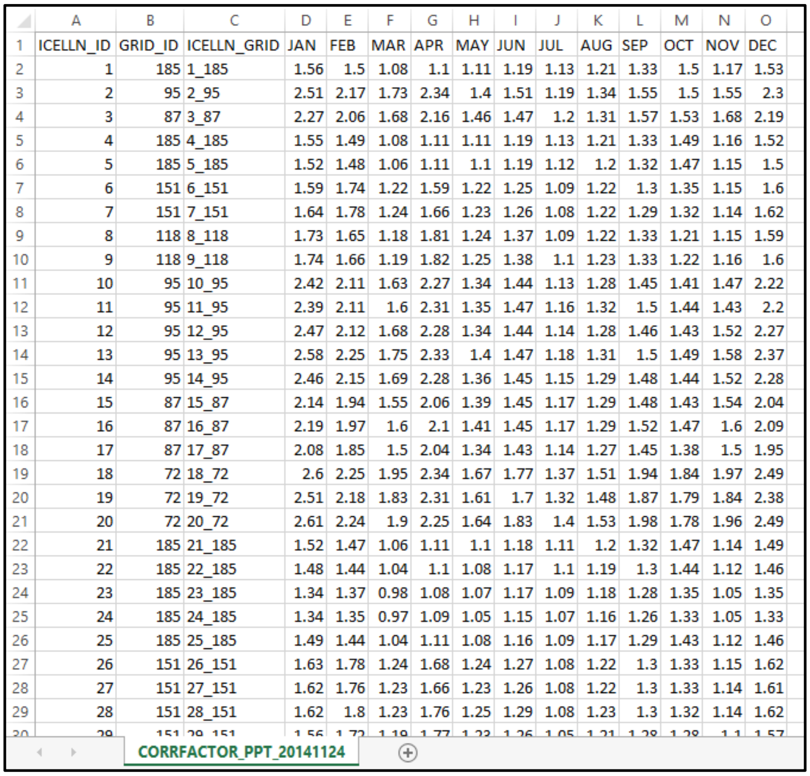
1.) Calculate X_{HRU-I} mean value using the Zonal Statistics module for the HRU shapefile and the specific variable for each month (i.e. precipitation, solar radiation, sunshine hours, relative humidity, and wind speed).

2.) Calculate X_{10K-i} mean value for the daily 10km gridded dataset using the same variable for each month.

3.) Calculate correction factors as monthly mean value for each HRU by dividing them by the monthly means value for each 10 KM grids.

$$CORFAC_i = X_{HRU\text{-}i} / X_{10K\text{-}i}$$

4.) The results are saved in an .XLSX file, which contains corresponding monthly values for each HRU (Figure 4-3).



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	ICELLN_ID	GRID_ID	ICELLN_GRID	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2	1	185	1_185	1.56	1.5	1.08	1.1	1.11	1.19	1.13	1.21	1.33	1.5	1.17	1.53
3	2	95	2_95	2.51	2.17	1.73	2.34	1.4	1.51	1.19	1.34	1.55	1.5	1.55	2.3
4	3	87	3_87	2.27	2.06	1.68	2.16	1.46	1.47	1.2	1.31	1.57	1.53	1.68	2.19
5	4	185	4_185	1.55	1.49	1.08	1.11	1.11	1.19	1.13	1.21	1.33	1.49	1.16	1.52
6	5	185	5_185	1.52	1.48	1.06	1.11	1.1	1.19	1.12	1.2	1.32	1.47	1.15	1.5
7	6	151	6_151	1.59	1.74	1.22	1.59	1.22	1.25	1.09	1.22	1.3	1.35	1.15	1.6
8	7	151	7_151	1.64	1.78	1.24	1.66	1.23	1.26	1.08	1.22	1.29	1.32	1.14	1.62
9	8	118	8_118	1.73	1.65	1.18	1.81	1.24	1.37	1.09	1.22	1.33	1.21	1.15	1.59
10	9	118	9_118	1.74	1.66	1.19	1.82	1.25	1.38	1.1	1.23	1.33	1.22	1.16	1.6
11	10	95	10_95	2.42	2.11	1.63	2.27	1.34	1.44	1.13	1.28	1.45	1.41	1.47	2.22
12	11	95	11_95	2.39	2.11	1.6	2.31	1.35	1.47	1.16	1.32	1.5	1.44	1.43	2.2
13	12	95	12_95	2.47	2.12	1.68	2.28	1.34	1.44	1.14	1.28	1.46	1.43	1.52	2.27
14	13	95	13_95	2.58	2.25	1.75	2.33	1.4	1.47	1.18	1.31	1.5	1.49	1.58	2.37
15	14	95	14_95	2.46	2.15	1.69	2.28	1.36	1.45	1.15	1.29	1.48	1.44	1.52	2.28
16	15	87	15_87	2.14	1.94	1.55	2.06	1.39	1.45	1.17	1.29	1.48	1.43	1.54	2.04
17	16	87	16_87	2.19	1.97	1.6	2.1	1.41	1.45	1.17	1.29	1.52	1.47	1.6	2.09
18	17	87	17_87	2.08	1.85	1.5	2.04	1.34	1.43	1.14	1.27	1.45	1.38	1.5	1.95
19	18	72	18_72	2.6	2.25	1.95	2.34	1.67	1.77	1.37	1.51	1.94	1.84	1.97	2.49
20	19	72	19_72	2.51	2.18	1.83	2.31	1.61	1.7	1.32	1.48	1.87	1.79	1.84	2.38
21	20	72	20_72	2.61	2.24	1.9	2.25	1.64	1.83	1.4	1.53	1.98	1.78	1.96	2.49
22	21	185	21_185	1.52	1.47	1.06	1.11	1.1	1.18	1.11	1.2	1.32	1.47	1.14	1.49
23	22	185	22_185	1.48	1.44	1.04	1.1	1.08	1.17	1.1	1.19	1.3	1.44	1.12	1.46
24	23	185	23_185	1.34	1.37	0.98	1.08	1.07	1.17	1.09	1.18	1.28	1.35	1.05	1.35
25	24	185	24_185	1.34	1.35	0.97	1.09	1.05	1.15	1.07	1.16	1.26	1.33	1.05	1.33
26	25	185	25_185	1.49	1.44	1.04	1.11	1.08	1.16	1.09	1.17	1.29	1.43	1.12	1.46
27	26	151	26_151	1.63	1.78	1.24	1.68	1.24	1.27	1.08	1.22	1.3	1.33	1.15	1.62
28	27	151	27_151	1.62	1.76	1.23	1.66	1.23	1.26	1.08	1.22	1.3	1.33	1.14	1.61
29	28	151	28_151	1.62	1.8	1.23	1.76	1.25	1.29	1.08	1.23	1.3	1.32	1.14	1.62

Figure 4-3. Precipitation Correction Factor for each of the 1706 HRUs; ICELLN-ID is the HRU number, GRID-ID is the 10K grid number, and ICELLN-GRID is concatenating the two individual numbers

4.3.4 RCM Downscaling Tool

All of the regional climate model data have two datasets: one historical period ranging from 1971-2000 and one future period ranging from 2041-2070. The regional climate model data have spatial resolutions of 22 to 44 km^2. One of the requirements to effectively use the RCM projections is to spatially match the observed data's spatial resolution. Essentially, the reasons for matching the spatial resolution of the observed 10k climate grid time series are to replicate (a) the seasonality and magnitude of the 1971-2000 climate normal streamflow behaviour, (b) the use of the established parameter input files for the historical and future RCM simulations, and (c) enable the comparison of all future RCM projections. Since the regional climate model data and hydro-climatological data are available in spatially separated time series, it was important to spatially downscale the regional climate data using an area-weighting ratio based on the spatial overlay of the 10K climate grids and the RCM climate grids (see Figure 4-4). The following outlines the procedure for downscaling each of the regional climate model datasets:

1.) The 10K climate gridded dataset and the RCM grid file are spatially overlayed.
2.) The area for the 10K climate grid and the RCM grid files are calculated.
3.) The average for each temperature (minimum and maximum) and precipitation for the 10K climate grid are calculated by spatially overlaying the PRISM grid with the respective RCM grid, resulting in spatially averaged grids for determination of correction factors (variable P_{10K-i} and T_{10K-i},with i=1-12).
4.) The 1971-2000 mean RCM precipitation and temperature were calculated for each month (variable P_{RCM-i} and T_{RCM-i} with i=1-12). The ArcGIS© Zonal

Statistics as Table tool is run for each month and each variable on both spatial data (e.g. 12 months for each maximum temperature, minimum temperature, and precipitation) for each regional climate data.

5.) The climate grid spatial data and regional climate grid spatial data are permanently joined. The ArcGIS UNION command results in a spatial overlay containing both input grids, and containing all associates data.

6.) Any polygons that were not part of the spatial overlay are deleted. You can distinguish these polygons from the rest when the column contains a value of 0.

7.) The monthly precipitation ratio and temperature differences between the RCM value and the 10K-grid based value are calculated as follows:

$$P_{ratio\text{-}i} = P_{10K\text{-}i} / P_{RCM\text{-}i}$$

$$T_{ratio\text{-}i} = T_{10K\text{-}i} - T_{RCM\text{-}i}$$

8.) The area of the union polygons in meters squared and the percent area are calculated as follows:

$$P_{perArea} = P_{areaUNION} / P_{areaRCM\text{-}i}$$

$$T_{perArea} = T_{areaUNION} / T_{raareaRCM\text{-}i}$$

9.) The percent ratio is calculated as follows:

$$P_{perRatio} = P_{perArea} * P_{ratio\text{-}i}$$

$$T_{perRatio} = T_{perArea} + T_{ratio\text{-}i}$$

10.) The RCM-based daily precipitation time series (P_{RCM}) and daily temperature time series (T_{RCM}) for each 10K climate grid are calculated using the equation:

$$P_{RCMcorr} = P_{RCM} * P_{ratio\text{-}i}$$

$$T_{RCMcorr} = T_{RCM} + T_{ratio\text{-}i}$$

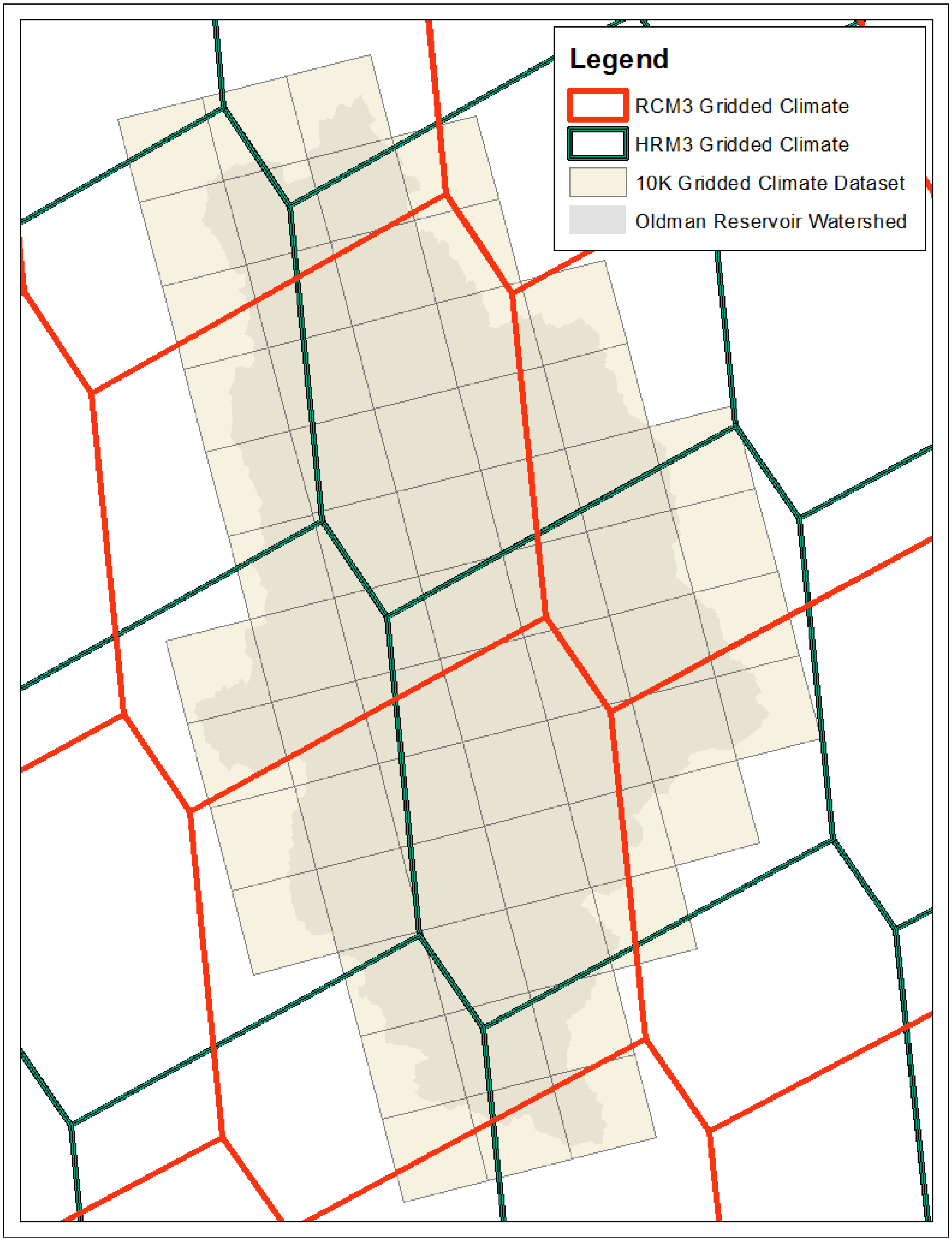


Figure 4-4. Two regional climate data: 1) HRM3 (warmer/drier) climate projection driven by GFDL and 2) RCM3 (cooler/wetter) climate projection driven by CGCM3.

4.4 Parameterization Tools

The development of parameterization utility tools was a crucial step in creating an efficient model parameterization for any ACRU model user. The previous version of the modelling system had the ACRU MenuBuilder program, an interactive and user friendly program that allowed user prompts for direct information input on the parameter file called MENU (Smithers & Schulze, 1995). It operated independently of the ACRU model and contained 250 subroutines. The original MenuBuilder was rather a teaching tool than an operational tool, as data input was very time consuming, and filling in data for more than a few HRUs was not practical. When the ACRU model was adapted to include snowmelt routines and a range of other new variables a combination of spreadsheet (Excel) and Textpad software approach was used to manipulate the MENU file. Each variable needed to be filled in by the user for all HRUs at a time. The next sub-sections will discuss the procedures used to create the new model parameterization utility tools, which allows for a significantly faster, and automated creation of the MENU file.

4.4.1 ACRU MenuBuilder v2.0 Program

The newly developed ACRU MenuBuilder v2.0 program enables the seamless manipulation of the MENU file without having to manually manipulate the file. The manual manipulation of the MENU file typically takes several minutes to set-up for each variable, one variable at a time. It already required testing the file against the ACRU model, to check whether the MENU file has not lost its fixed format, a limitation ushered by the original fixed-format Fortran code. The new utility tool enables a much more seamless approach to model calibration and parameterization of the ACRU model. The selection of a new parameter set is obtained by changing the parameter values in the menu input parameter (MIP) file. Once the Fortan script was called, the task of manipulating the MENU file was completed within a few seconds. Essentially, overcoming this challenge means that the calibration of the ACRU model is now possible for larger watersheds, especially with more than a thousand hydrological response units. Table 4-1 and Table 4-2 list the parameters used in ACRU MenuBuilder v2.0. The ACRU model parameterization is far more efficient, thus allowing more calibration runs, and consequently better simulation results within a given time frame. The Microsoft Excel© spreadsheet is utilized for the MIP file, instead of relying on other software (e.g. R, SPSS, MATLAB). This leads to a reduction of training of the ACRU model user. For accuracy purposes, the Microsoft Excel© macro calls the initialization and parameterization scripts and contains a log file system used to verify the parameterization process. The following outlines the procedure for the automated initialization and parameterization of the variables for this study:

1.) An empty MENU file is created with *X* number of hydrological response units.
2.) The MIP file is initiated with *X* number of rows.
3.) All parameters that need to be initialized once are defined (see Table 4-1) using the *MENU_INIT* worksheet (e.g. area of HRU, slope of HRU, land cover code, associated climate file name, etc.)
4.) The Fortran initialization script is initiated using the Microsoft Excel© macro. The initialization script adjusts 46 parameters all at once.

5.) Specific calibration parameters are defined using *MENU_PARAM* worksheet (e.g. flow routing parameters for surface and groundwater flows, soil depth, snow melt variable, and many more), which may be required to change more than once (see Table 4-2). Typically, parameters are updated one parameter at a time for manual calibration.

6.) The parameterization script based on Fortran through the Microsoft Excel© macro is initiated. The parameterization script is capable of adjusting 23 parameters all at once within 2 seconds.

Table 4-1. List of hydro-climatological parameters in the MENU file.

HYDRO-CLIMATOGLOGICAL INPUT DATA	DATA / INFORMATION DESCRIPTION	UNITS
ICELL	mode of simulation : lumped or distributed	-
ISUBNO	total number of subcatchments	-
CLAREA	area of subcatchment (km2)	km^2
SAUEF	slope area under estimation factor	-
ELEV	average elevation (m) of subcatchment	M
TMAX(I)	monthly means of daily maximum temperatures	°C
TMIN(I)	monthly means of daily minimum temperatures	°C
TELEV	altitude of base temperature station (m)	M
TMAXLR	mean regional lapse rate (+/-ec.1000m-1) for maximum temperature	°C
TMINLR	mean regional lapse rate (+/-ec.1000m-1) for minimum temperature	°C
WINCOR	wind speed correction factor relative to base station	m
RHUCOR	relative humidity correction factor relative to base station	-
SUNCOR	actual sunshine hours correction factor relative to base station	hours/day
SLORAD	radiation adjustment factor for sloped surfaces	
RADCOR	radiation correction factor relative to base station	-

Table 4-2. List of biophysical parameters in the MENU file

BIO-PHYSICAL PARAMETERS	DATA / INFORMATION DESCRIPTION	UNITS
MINSUB	first subcatchment of simulation	-
MAXSUB	last subcatchment of simulation	-
ICELLN	variables to specify layout of subcatchments	-
IDSTRM	variables to specify layout of subcatchments	-
HEAD	header information of simulation	-
IRAINF	name of rainfall or climate data file	-
FORMAT	option to specify the format of the input data file	-
IOBSTQ	variable which specifies availability of observed	-
ISTRMF	daily streamflow data	mm/day
DNAMIC	name of streamflow data file	-
IDYNFL	indicator whether a dynamic input file is to be used name of dynamic input file	-
IOBSPK	variable which specifies availability of observed peak discharge data	-
IYSTRT	first year of simulation	-
IYREND	last year of simulation	-
IOBOVR	option to replace simulated with observed streamflow	-
PPTCOR	option to invoke rainfall adjustment factors	-
CORPPT(I)	rainfall adjustment factors, given month-by-month	-
FOREST	option to invoke enhanced wet canopy evaporation	-
VEGINT(I)	interception loss, input on a monthly basis	mm^{-1}
CAY(I)	average crop coefficient, input on a monthly basis	-
ROOTA(I)	fraction of roots active in the topsoil, input on a monthly basis	-
ELAIM(I)	leaf area index, input on monthly basis	-
DEPAHO;DEPBHO	thicknesses of a and b horizon	m
WP1;WP2	permanent wilting point of a and b horizon	m.m^{-1}
FC1;FC2	drained upper limit of a and b horizon	m.m^{-1}
PO1;PO2	porosity of a and b horizon	m.m^{-1}
ABRESP	"saturated" redistribution fraction from a to b horizon	-
BFRESP	"saturated" redistribution fraction from b horizon to intermediate/groundwater store	-
COIAM(I)	monthly input coefficient of initial abstraction	-
QFRESP	same day stormflow response fraction	-
COFRU	coefficient of groundwater response baseflow	-
SMDDEP	effective depth of soil for stormflow response	m
TPCRIT	critical base temperature	°C
TRANGE	temperature range for snow/rain	°C
ICC	for Forest HRUs one: monthly values for canopy coverage	-
TMCRIT	critical temperature for the onset of melt	°C
SNOMC	snow melt factor for open areas	-
SNEREL	fraction of upper 5m snow that can evaporate	-

4.4.2 ACRU SubMenuBuilder Program

Smithers and Schulze (1995) reported that in order to run all variables within the ACRU model, it requires approximately 100 Kb per year of model simulations. Running the model for 1706 hydrological response units for 60 years is not an efficient way to calibrate the model, despite the increasing computer power of available desktop and laptop hardware today. The additional development of the ACRU SubMenuBuilder program enabled the model calibration of sub-watersheds within the Oldman Reservoir Watershed in a less amount of time. This tool enhanced the ACRU model run times for each sub-watershed. The following outlines the procedure for creating a sub-MENU file for this study:

1. User input is required for first HRU line, last HRU line, total HRUs, HRU outlet, and the last HRU outlet it is connected to.
2. The Fortran script automatically checks if the MENU file exists. If the file exists, the MENU file is opened and the following variables are read: isubno (Number of HRUs), minsub (Lowest HRU ID number), maxsub (Highest HRU ID number) and loopbk values (Lookback option, required for simulating irrigation scheduling). Otherwise, the program exits.
3. The header lines for the first parameter block that contains X number of HRU lines is copied and followed by the range of lines that includes the first HRU line up to the last HRU line. The HRU at the outlet is changed to reflect the new HRU outlet.
4. New sub-MENU file is created. This new file can be used to run the ACRU model for a smaller sub-watershed.

4.5 Evaluation Tools

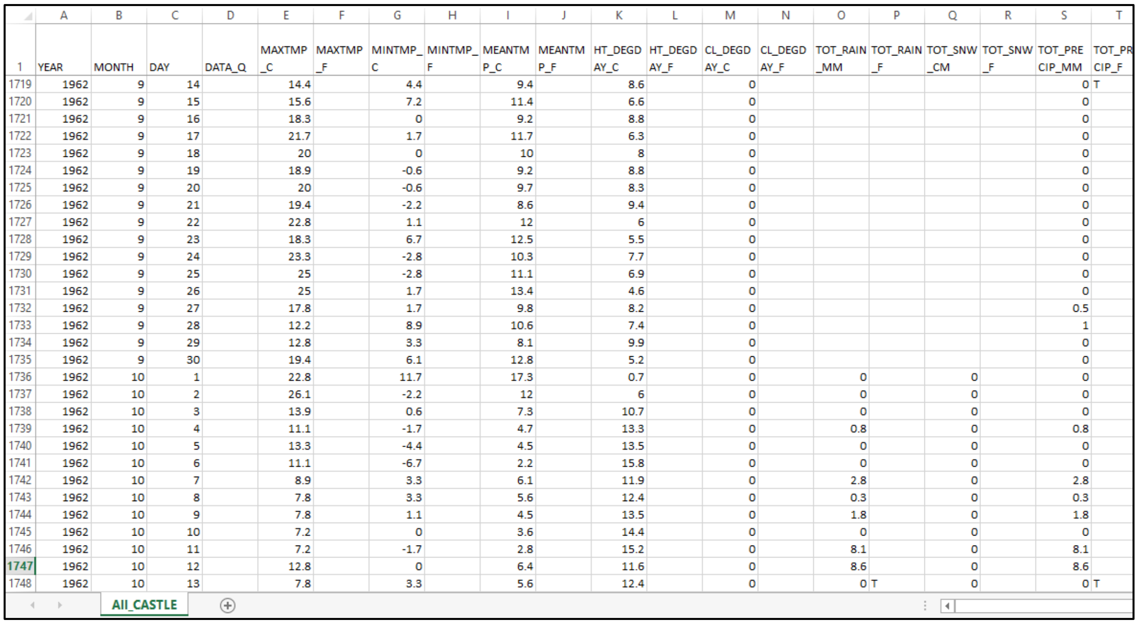
In order to verify the hydrological processes using the ACRU model, the simulated hydrological variables were statistically compared with the observed variables in terms of seasonal changes, and daily and monthly time series. The development of two comprehensive verification analysis tools for temperature and streamflow data was important in the efficient analysis of simulation results. The previous version of ACRU model included the ACRU Output Utilities, which contained a variety of statistical performance criteria for comparing observed and simulated streamflow values (Smithers & Schulze, 1995). With the adoption of running the model in distributed mode, this program was rendered obsolete.

The Canadian Climate Data Scraping Tool (CCDST) was used to automate the download of all independent station temperature data that were used to verify simulated temperature data (Bonifacio et al., 2014). The ACRU-CCDST Temperature Verification Tool was developed to work with the CCDST and verify simulated temperature against observed temperature. On the other hand, the ACRU-HYDAT Streamflow Verification Tool was developed to verify the simulated streamflow against observed streamflow data from the Water Survey of Canada. Both verification tools use a multitude of statistical and graphic analysis used in hydrological studies. The next sub-sections discussed the procedures used to create the model validation utility tools.

4.5.1 The Canadian Climate Data Scraping Tool

The Canadian Climate Data Scraping Tool (CCDST) was published in the Computers & Geosciences Journal (Bonifacio et al., 2014). It automatically fetches, downloads and consolidates climate data from a Web database where the data are contained on multiple Web pages. It was developed to enhance access and simplify analysis of climate data from Canada's National Climate Data and Information Archive (NCDIA). The CCDST deconstructs a URL for a particular climate station in the NCDIA and then iteratively modifies the data parameters to download large volumes of data, remove individual file headers, and merge data files into one output file. This automated sequence enhances access to climate data by substantially reducing the time needed to manually download data from multiple Web pages. Below we present the procedure used for downloading climate data using CCDST for this study:

1.) User is required to enter station name and URL link. Enter specified start and end date or leave this option blank. Visit Environment Canada Climate Data website at http://climate.weather.gc.ca. and find the station to download. Go the address bar on any Internet browser and copy the URL address. The URL address is necessary to download all the data in the time series, if available.
2.) A diagnostic summary will inform the user when the program has finished download and merging all data into one file (Figure 4-5).



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	YEAR	MONTH	DAY	DATA_Q	MAXTMP_C	MAXTMP_F	MINTMP_C	MINTMP_F	MEANTMP_C	MEANTMP_F	HT_DEGDAY_C	HT_DEGDAY_F	CL_DEGDAY_C	CL_DEGDAY_F	TOT_RAIN_MM	TOT_RAIN_F	TOT_SNW_CM	TOT_SNW_F	TOT_PRECIP_MM	TOT_PR CIP_F
1719	1962	9	14		14.4		4.4		9.4		8.6		0						0	T
1720	1962	9	15		15.6		7.2		11.4		6.6		0						0	
1721	1962	9	16		18.3		0		9.2		8.8		0						0	
1722	1962	9	17		21.7		1.7		11.7		6.3		0						0	
1723	1962	9	18		20		0		10		8		0						0	
1724	1962	9	19		18.9		-0.6		9.2		8.8		0						0	
1725	1962	9	20		20		-0.6		9.7		8.3		0						0	
1726	1962	9	21		19.4		-2.2		8.6		9.4		0						0	
1727	1962	9	22		22.8		1.1		12		6		0						0	
1728	1962	9	23		18.3		6.7		12.5		5.5		0						0	
1729	1962	9	24		23.3		-2.8		10.3		7.7		0						0	
1730	1962	9	25		25		-2.8		11.1		6.9		0						0	
1731	1962	9	26		25		1.7		13.4		4.6		0						0	
1732	1962	9	27		17.8		1.7		9.8		8.2		0						0.5	
1733	1962	9	28		12.2		8.9		10.6		7.4		0						1	
1734	1962	9	29		12.8		3.3		8.1		9.9		0						0	
1735	1962	9	30		19.4		6.1		12.8		5.2		0						0	
1736	1962	10	1		22.8		11.7		17.3		0.7		0		0		0		0	
1737	1962	10	2		26.1		-2.2		12		6		0		0		0		0	
1738	1962	10	3		13.9		0.6		7.3		10.7		0		0		0		0	
1739	1962	10	4		11.1		-1.7		4.7		13.3		0		0.8		0		0.8	
1740	1962	10	5		13.3		-4.4		4.5		13.5		0		0		0		0	
1741	1962	10	6		11.1		-6.7		2.2		15.8		0		0		0		0	
1742	1962	10	7		8.9		3.3		6.1		11.9		0		2.8		0		2.8	
1743	1962	10	8		7.8		3.3		5.6		12.4		0		0.3		0		0.3	
1744	1962	10	9		7.8		1.1		4.5		13.5		0		1.8		0		1.8	
1745	1962	10	10		7.2		0		3.6		14.4		0		0		0		0	
1746	1962	10	11		7.2		-1.7		2.8		15.2		0		8.1		0		8.1	
1747	1962	10	12		12.8		0		6.4		11.6		0		8.6		0		8.6	
1748	1962	10	13		7.8		3.3		5.6		12.4		0		0	T	0		0	T

Figure 4-5. Merged data file for Castle climate station using CCDST.

4.5.2 ACRU-CCDST Temperature Verification Tool

The ACRU-CCDST Temperature Verification Tool (ATVT) was developed to work with the CCDST and verify simulated against observed temperature data. The tool is developed using Visual Basic for Applications using Microsoft Excel©. It contains a multitude of statistical and graphic analysis used in hydrological studies such as regression coefficient (slope), the regression intercept, Pearson's correlation coefficient (r) and coefficient of determination (r^2), scatter plot graphs and linear regression graphs that visualize the standard regression statistics in space. Below is the procedure for verifying temperature data for this study:

1.) The daily CCDST data that corresponds to the simulated ACRU output data is required to be selected. The number of observations must match the simulated entries.

2.) A summary statistics worksheet is created to compare the observed and simulated results in daily and monthly time-steps.

3.) A series of linear graphs are created to show the comparison between minimum, maximum and mean temperatures (see Chapter 5, Figure 5-2).

4.) A series of scatter plot graphs are created to show how each of the simulated temperature data correlates with the observed values (see Chapter 5, Figure 5-3).

4.5.3 ACRU-HYDAT Streamflow Verification Tool

The ACRU-HYDAT Streamflow Verification Tool was developed to verify the simulated streamflow against observed streamflow data from the Water Survey of Canada. This tool also contains a variety of statistical as well as graphic analysis used in hydrological studies. It contains standard regression statistics such as regression coefficient (slope), the regression intercept, Pearson's correlation coefficient (r) and coefficient of determination (r^2). These also included dimensionless statistics such as index of agreement (d), Nash-Sutcliffe efficiency (NSE), and their modified versions. It is also important to include error index statistics such as root mean square error (RMSE), percent bias (PBIAS), the ratio of the RMSE to the observed standard deviation (RSR), the percent differences between simulated and observed variances, standard deviations, and means. Graphical techniques were included such as analysing hydrograph and flow duration curves. Below is the procedure for verifying streamflow data for this study:

1.) A summary statistics worksheet is created to compare the observed and simulated results in daily and monthly time-steps (Figure 4-6). The number of observations must match the simulated entries for daily and monthly time-steps.

2.) A daily and monthly scatter plot is created to show linear relationship between the observed and predicted values (see Chapter 5, Figure 5-7).

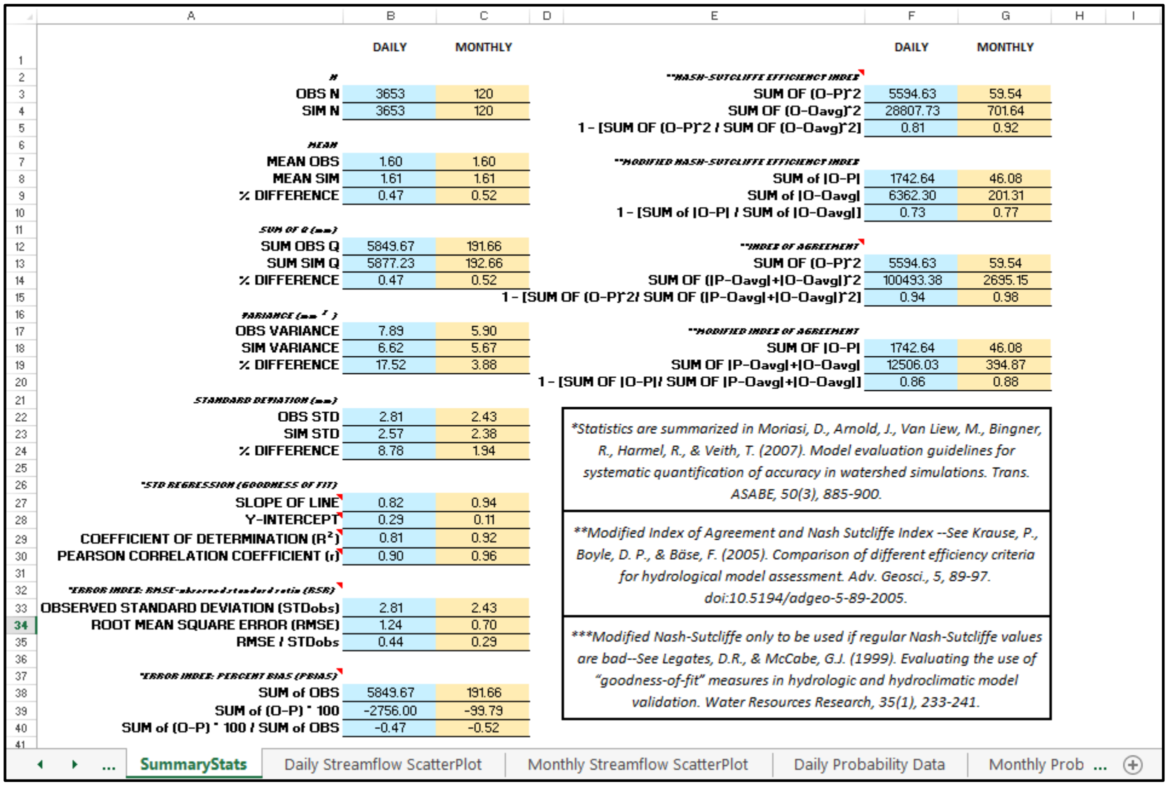
e) Two hydrographs is created to show the comparison between peak and low flows as well as the magnitude and frequency of runoff (see Chapter 5, Sub-Watershed 5

3.) Figure 5-4).

4.) A seasonal line graph is created to show how each of the simulated streamflow data correlates with the monthly-observed trends.

5.) An annual graph is created for the duration of the model simulation that shows the sum of runoff for each year.

6.) A series of annual hydrographs are created for the duration of the model simulations. For instance, if the calibration period is 10 years, this tool creates 10 annual hydrographs. In ACRU modelling system, the first year is considered as a simulation year where groundwater storage is zero and leads to the under-simulation of the baseflow (Schulze, 1995; Smithers & Schulze, 1995).



	DAILY	MONTHLY
N		
OBS N	3653	120
SIM N	3653	120
MEAN		
MEAN OBS	1.60	1.60
MEAN SIM	1.61	1.61
% DIFFERENCE	0.47	0.52
SUM OF Q (mm)		
SUM OBS Q	5849.67	191.66
SUM SIM Q	5877.23	192.66
% DIFFERENCE	0.47	0.52
VARIANCE (mm ^{2})		
OBS VARIANCE	7.89	5.90
SIM VARIANCE	6.62	5.67
% DIFFERENCE	17.52	3.88
STANDARD DEVIATION (mm)		
OBS STD	2.81	2.43
SIM STD	2.57	2.38
% DIFFERENCE	8.78	1.94
**STD REGRESSION (GOODNESS OF FIT)*		
SLOPE OF LINE	0.82	0.94
Y-INTERCEPT	0.29	0.11
COEFFICIENT OF DETERMINATION (R^2)	0.81	0.92
PEARSON CORRELATION COEFFICIENT (r)	0.90	0.96
**ERROR INDEX: RMSE-observed standard ratio (RSR)*		
OBSERVED STANDARD DEVIATION (STDobs)	2.81	2.43
ROOT MEAN SQUARE ERROR (RMSE)	1.24	0.70
RMSE / STDobs	0.44	0.29
**ERROR INDEX: PERCENT BIAS (PBIAS)*		
SUM of OBS	5849.67	191.66
SUM of (O-P) * 100	-2756.00	-99.79
SUM of (O-P) * 100 / SUM of OBS	-0.47	-0.52

	DAILY	MONTHLY
***NASH-SUTCLIFFE EFFICIENCY INDEX*		
SUM OF (O-P)^2	5594.63	59.54
SUM OF (O-Oavg)^2	28807.73	701.64
1 – [SUM OF (O-P)^2 / SUM OF (O-Oavg)^2]	0.81	0.92
***MODIFIED NASH-SUTCLIFFE EFFICIENCY INDEX*		
SUM of |O-P|	1742.64	46.08
SUM of |O-Oavg|	6362.30	201.31
1 – [SUM of |O-P| / SUM of |O-Oavg|]	0.73	0.77
***INDEX OF AGREEMENT*		
SUM OF (O-P)^2	5594.63	59.54
SUM OF (|P-Oavg|+|O-Oavg|)^2	100493.38	2695.15
1 – [SUM OF (O-P)^2/ SUM OF (|P-Oavg|+|O-Oavg|)^2]	0.94	0.98
***MODIFIED INDEX OF AGREEMENT*		
SUM OF |O-P|	1742.64	46.08
SUM OF |P-Oavg|+|O-Oavg|	12506.03	394.87
1 – [SUM OF |O-P|/ SUM OF |P-Oavg|+|O-Oavg|]	0.86	0.88

**Statistics are summarized in Moriasi, D., Arnold, J., Van Liew, M., Bingner, R., Harmel, R., & Veith, T. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE, 50(3), 885-900.*

***Modified Index of Agreement and Nash Sutcliffe Index --See Krause, P., Boyle, D. P., & Bäse, F. (2005). Comparison of different efficiency criteria for hydrological model assessment. Adv. Geosci., 5, 89-97. doi:10.5194/adgeo-5-89-2005.*

****Modified Nash-Sutcliffe only to be used if regular Nash-Sutcliffe values are bad--See Legates, D.R., & McCabe, G.J. (1999). Evaluating the use of “goodness-of-fit” measures in hydrologic and hydroclimatic model validation. Water Resources Research, 35(1), 233-241.*

Figure 4-6. Summary sheet created by the ACRU-HYDAT Streamflow Tool

4.5.4 ACRU-RCM Analysis Tool

The ACRU-RCM Analysis Tool was developed to verify the simulated streamflow against the future projected regional streamflow values from the Vulnerability and Adaptation to Climate Extremes in the Americas (VACEA) project. This tool also contains a variety of statistical as well as graphic analysis used in hydrological studies. It contains graphical techniques that compare observed and predicted values as well distribution clearly. The following outlines the procedure for comparing two different simulated data for this study:

1.) The baseline ACRU simulated output file or the baseline RCM simulated output file is required in order to compare against the future RCM simulated output data.

2.) The simulation values are compared using pivot tables.

3.) A series of line graphs are created (see Chapter 5, section 5.3).

4.6 Synthesis

The challenges of hydrological modelling are apparent in distributed physical-based hydrological models. The utilization of the ACRU model in distributed environment presents a few challenges that concern data management, processing, and analysis. The adoption of finer hydrological response units has led to the increasing operational challenges in utilizing the ACRU model for regional climate modelling. The model requires an ever-increasingly high level of effort for the model user. The development of a suite of utility tools resolved these constraints for this study. The tools discussed in this chapter included (1) the ACRU Composite File Generator Tool, (2) the Hydrological Response Unit Delineation Tool, (3) the ACRU Correction factors, (4) the Regional Climate Downscaling Tool, (5) the ACRU MenuBuilder v2.0 and (6) ACRU SubMenuBuilder programs, (7) the Canadian Climate Data Scraping Tool, (8) the ACRU-CCDST Temperature Verification Tool, (9) the ACRU-HYDAT Streamflow Verification Tool, and (10) the ACRU-RCM Analysis Tool. With the development of these automated tools, model users can utilize the ACRU model in increasingly efficient, consistent, and accurate manner.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Introduction

The performance of the ACRU model primarily focused on the magnitude and seasonality of temperature and streamflow data for the Oldman Reservoir Watershed (ORW). By utilizing the Klemeš (1986) testing scheme, all simulated results for each subsequent sub-watershed were compared with its corresponding observed data. The effectiveness of the model simulations during calibration was determined by using multiple objective functions as well as graphical techniques common to hydrological modelling (Krause et al., 2005; Legates & McCabe, 1999; Moriasi et al., 2007). These objective functions included (1) standard regression statistics such as regression coefficient (slope), the regression intercept, Pearson's correlation coefficient (r) and coefficient of determination (r^2) which are quite often used (Moriasi et al., 2007), (2) dimensionless statistics such as index of agreement (d), Nash-Sutcliffe efficiency (NSE), and their modified versions, and (3) error index statistics such as root mean square error (RMSE), percent bias (PBIAS), RMSE-observations standard deviation ratio (RSR), and percent difference between the mean, variance, standard deviation. On the other hand, graphical techniques are often used to analyse the predicted streamflow response using hydrograph and flow duration curves. These evaluations were combined, therefore, to provide acceptable benchmarks.

Hydrological modelling objectives were outlined for an acceptable model simulation during the calibration phase of this study. The first benchmark was set according to Moriasi et al. (2007) with a good performance ratings for Percent Bias (PBIAS) value of less than ±15%, RMSE-observations standard deviation ratio (RSR) value of less than 0.6 and Nash-Sutcliffe Efficiency Index (NSE) value of more than 0.65 were considered as acceptable for adequate simulation. The second benchmark for an adequate simulation was set as a percentage difference between the sum of simulated daily flows ($\sum Q_s$) and observed daily flows ($\sum Q_o$) of less than 15% (Smithers & Schulze, 1995). The third benchmark was set using graphical techniques that compared observed and simulated data using hydrographs and flow duration curves. Only after careful consideration of the abovementioned statistics and graphical techniques of the streamflow data was the R^2 value of 0.7 for simulated daily flows considered as an additional benchmark in this study, however, a detailed summary can be found in Moriasi et al. (2007) and Bennett et al. (2013). The performance criteria used in this study are summarized in Table 5-1.

Table 5-1. Combined performance criteria for daily and monthly time series (Moriasi et al., 2007; Schulze & Smithers, 1995)

	PBIAS of Streamflow	RSR	NSE	$\%\Sigma_{diff}Q$
Excellent	PBIAS < ±10	0 ≤ RSR ≤ 0.5	0.75 < NSE ≤ 1.00	$0 < \%\Sigma_{diff}Q \leq 5$
Good	±10 ≤ PBIAS ≤ ±15	0.5 < RSR ≤ 0.6	0.65 < NSE ≤ 0.75	$5 < \%\Sigma_{diff}Q \leq 10$
Satisfactory	±15 ≤ PBIAS ≤ ±25	0.6 < RSR ≤ 0.7	0.5 < NSE ≤ 0.65	$10 < \%\Sigma_{diff}Q \leq 15$
Unsatisfactory	PBIAS ≥ ±25	RSR > 0.7	NSE ≤ 0.5	$\%\Sigma_{diff}Q > 15$

5.2 Model Validation Results

5.2.1 Temperature

The observed daily maximum and minimum temperature data from ten climate stations were used to verify that the daily and monthly temperatures were reasonably simulated. These climate stations were downloaded using the Canadian Climate Data Scraping Tool (CCDST) created by Bonifacio et al. (2014). In order to eliminate the elevations bias, the r^2 results of all the climate stations used were compared against the station elevations (see Figure 5-1). The result show that there are no elevation bias with climate stations used.

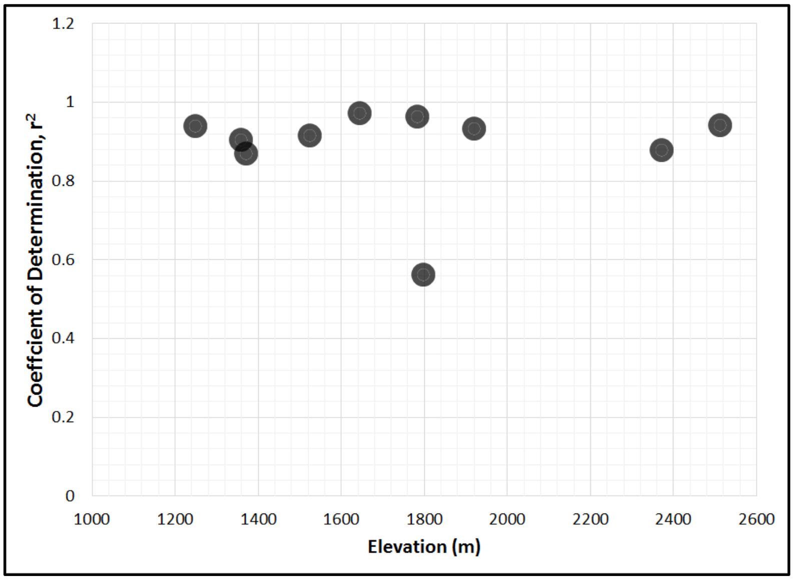


Figure 5-1. Results of the ACRU model output of mean monthly simulated and observed temperatures for 10 climate stations in the Oldman Reservoir Watershed.

The multiple-lapse rate approach used in Castle River Watershed were compared to the single temperature lapse rates (see Table 5-2 and Table 5-3). Although there were essentially no difference between each of the temperature parameter sets when comparing the daily and monthly performance statistics of the linear regression as evidenced by the slope, coefficient of determination (r^2), Pearson Correlation coefficient (r) and root mean square error (RMSE). The multiple lapse rate approach produced slightly stronger results when examining the daily percentage difference for mean temperature (3.59%), variance (4.06%) and standard deviation (2.04%), as evidenced by previous work done by Anderson (2014). Essentially, the daily performance for the mean temperatures was slightly over-simulated. Subsequently, the percentage difference for the mean monthly temperature (-18.77%) was under simulated, and both the variance (17.69%) and standard ddeviation (8.49%) were over simulated. There is an overall slight under-simulation of air temperature in the winter months (as seen in Figure 5-2). Therefore, the multiple parameter approach used in temperature verification for Oldman Reservoir produced relatively excellent results (see Figure 5-3) and was chosen for this study.

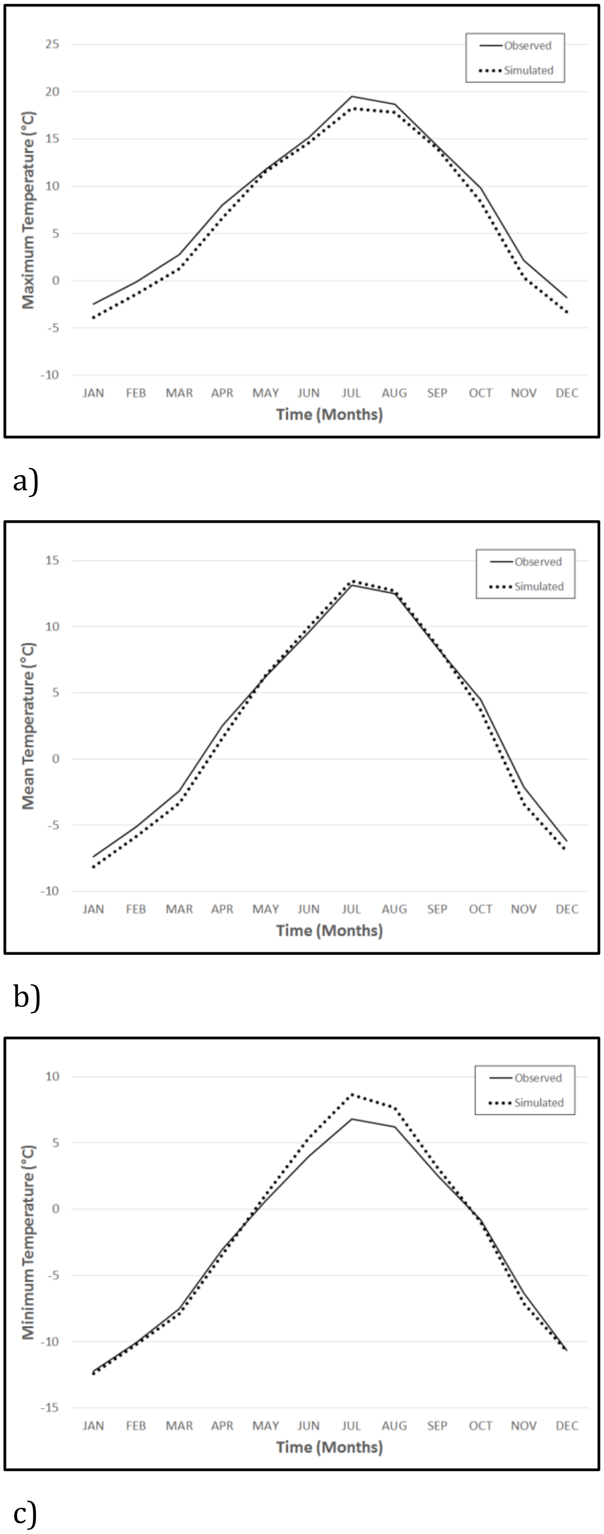


Figure 5-2. Results of the ACRU model output of monthly a) maximum, b) mean and c) minimum simulated and observed temperatures for 10 climate stations in the Oldman Reservoir Watershed.

Table 5-2. Daily performance statistics for air temperatures using ten climate stations for four different lapse rate parameters.

	Lapse Rate (Castle Parameters)	Lapse Rate (-6°C)	Lapse Rate (-6.2°C)	Lapse Rate (-6.5°C)
Sample Size	47343	47343	47343	47343
Observed Mean	5.57	5.57	5.57	5.57
Simulated Mean	5.37	5.31	5.31	5.29
% Difference	3.59	4.67	4.67	5.03
Observed Variance	77.76	77.76	77.76	77.76
Simulated Variance	80.92	81.70	81.81	81.98
% Difference	-4.06	-5.07	-5.21	-5.43
Observed Standard Deviation	8.82	8.82	8.82	8.82
Simulated Standard Deviation	9.00	9.04	9.04	9.05
% Difference	-2.04	-2.49	-2.49	-2.61
Slope	0.99	0.99	0.99	0.99
Coefficient of Determination (r^2)	0.94	0.93	0.93	0.93
Pearson Correlation Coefficient (r)	0.97	0.97	0.97	0.96
Root mean square error (RMSE)	0.01	0.01	0.01	0.01

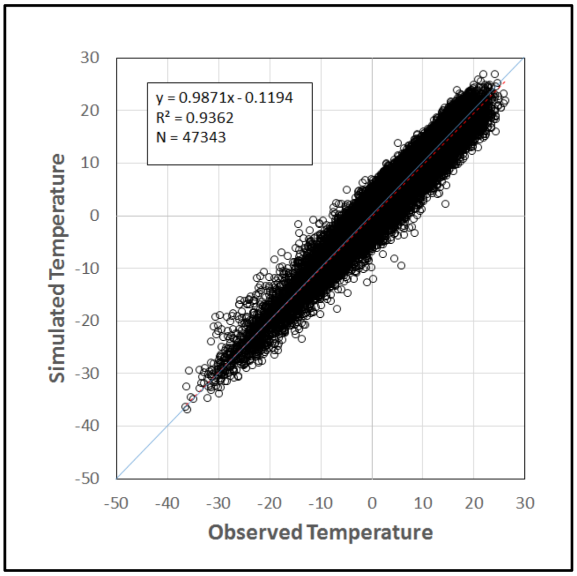


Figure 5-3. Regression scatter plot results for simulated and observed mean daily air temperature. The solid blue line represents the 1:1 line. The red dotted line is the slope of the regression.

Table 5-3. Monthly performance statistics for air temperatures using ten climate stations for different lapse rate parameters.

	Lapse Rate (Castle Parameters)	Lapse Rate (-6°C)	Lapse Rate (-6.2°C)	Lapse Rate (-6.5°C)
Sample Size	575	575	575	575
Observed Mean	3.09	3.09	3.09	3.09
Simulated Mean	2.51	2.45	2.45	2.43
% Difference	18.77	20.71	20.71	21.36
Observed Variance	56.81	56.81	56.81	56.81
Simulated Variance	66.86	67.52	67.61	67.76
% Difference	-17.69	-18.85	-19.01	-19.27
Observed Standard Deviation	7.54	7.54	7.54	7.54
Simulated Standard Deviation	8.18	8.22	8.22	8.23
% Difference	-8.49	-9.02	-9.02	-9.15
Slope	1.07	1.07	1.07	1.07
Coefficient of Determination (r^2)	0.97	0.97	0.97	0.97
Pearson Correlation Coefficient (r)	0.99	0.98	0.98	0.98
Root mean square error (RMSE)	0.07	0.07	0.07	0.07

5.2.2 Streamflow

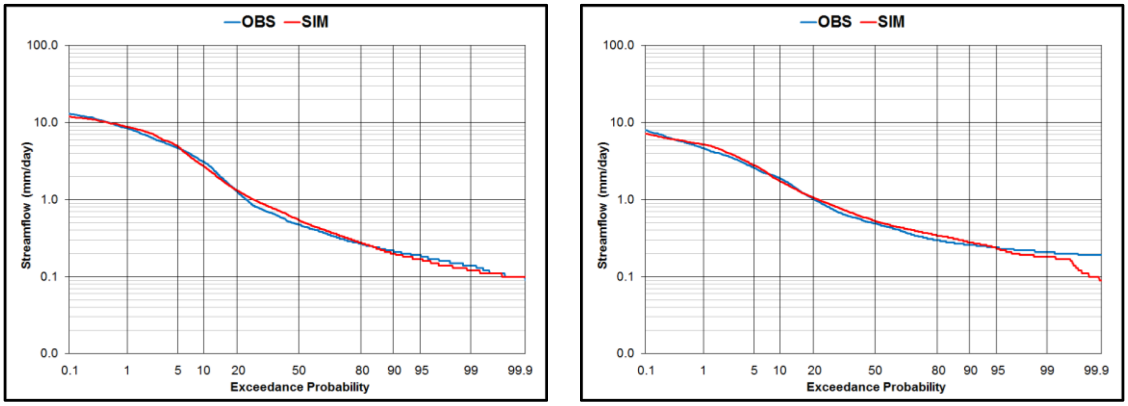
The observed daily streamflow discharge data from five hydrometric stations were used to verify that the daily and monthly streamflow values were reasonably simulated. The observed data from the hydrometric climate stations were initially converted to mm/day as a pre-requisite before using the ACRU model. The ACRU-HYDAT Streamflow Verification Tool (AHSVT) allowed the efficient comparison between all calibration model runs for the Oldman Reservoir Watershed. The streamflow verification was expanded to utilize a more robust model testing procedure. Klemeš (1986) scheme was selected to establish a rigorous testing that involved four different sampling tests for the entire Oldman Reservoir watershed for its ability to test model performance under spatial and climatic transferability. It was found that the percentage difference between the sum of simulated daily flows ($\sum Q_s$) and observed daily flows ($\sum Q_o$) was similar to percent bias values and was removed as termination criterion during model calibration and validation.

5.2.2.1 The Split-sample Test

The split-sample test results for calibrating all five gauged watersheds are listed in Table 5-4 and Table 5-5. Based on the calibration runs for the Oldman Reservoir Watershed, the ACRU model has shown to simulate streamflow well, where the PBIAS is less than 10% for most of the sub-watersheds, although there is a slight over-estimation in the daily flows in Sub-Watershed 4 (12.086%). The results of the split-sample test showed that the percentage difference between standard deviations to be mostly under 10% between the daily and monthly output for all sub-watersheds, with exception of Sub-Watershed 5. Overall, the ACRU model performed with a slight overestimation bias between daily and monthly flows based on the negative values across all gauged watersheds. The daily flow duration curves showed the best simulation runs for Sub-Watershed 1 (see Figure 5-4). Calibration results for Sub-Watershed 3 revealed a slightly less than ideal simulation with an underestimation of low flows. The validation results showed how the ACRU model performed with relatively good ratings. The results of the daily and monthly validation performance ratings are shown in Table 5-6 and Table 5-7. Indeed, the trends that occurred are similar to the calibration runs. The daily flow duration curves during the validation run revealed similar patterns during the calibration run with an exception to Sub-Watershed 2 with an over simulation of high peak flows (see Figure 5-5).

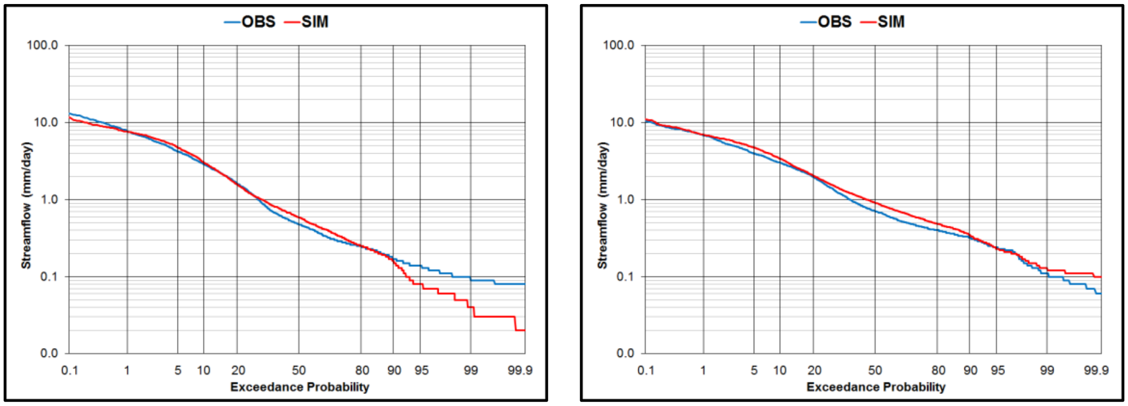
Table 5-4. Daily model performance results of all five gauged sub-watersheds using the split-sample test under calibration period, 1971-1980.

	SUB-WATERSHED				
	1	2	3	4	5
Sample Size	3653	3653	2379	2145	3653
Observed Mean	1.601	1.065	1.557	1.608	1.051
Simulated Mean	1.609	1.114	1.587	1.802	1.118
Observed Q	5849.670	3889.550	3704.560	3449.360	3839.060
Simulated Q	5877.230	4070.640	3774.770	3866.260	4082.450
Observed Variance	7.888	2.065	6.160	4.174	3.104
Simulated Variance	6.617	2.117	5.489	4.764	2.305
% Difference of Variance	16.111	-2.524	10.895	-14.136	25.762
Observed Standard Deviation	2.809	1.437	2.482	2.043	1.762
Simulated Standard Deviation	2.572	1.455	2.343	2.183	1.518
% Difference of STD	8.409	-1.254	5.604	-6.835	13.839
Slope	0.822	0.927	0.855	0.889	0.751
Y-Intercept	0.292	0.127	0.256	0.373	0.328
Coefficient of Determination R^2	0.806	0.839	0.820	0.693	0.760
Correlation Coefficient, R	0.898	0.916	0.905	0.832	0.872
Root mean square error, RMSE	1.238	0.596	1.059	1.246	0.865
RMSE-observed standard ratio, RSR	**0.441**	**0.414**	**0.427**	**0.610**	**0.491**
Percent Bias, PBIAS	**-0.471**	**-4.656**	**-1.895**	**-12.086**	**-6.340**
Nash Sutcliffe Efficiency Index, NSE	**0.806**	**0.828**	**0.818**	**0.628**	**0.759**
Modified NSE	0.726	0.677	0.697	0.498	0.640
Index of Agreement, D	0.944	0.956	0.950	0.906	0.926
Modified D	0.861	0.838	0.847	0.751	0.814



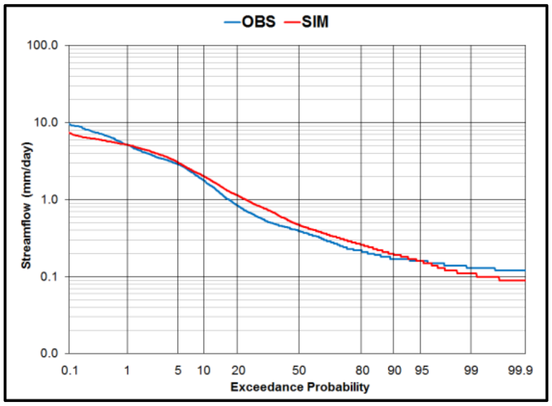
a) Sub-Watershed 1

b) Sub-Watershed 2



c) Sub-Watershed 3

d) Sub-Watershed 4



f) Sub-Watershed 5

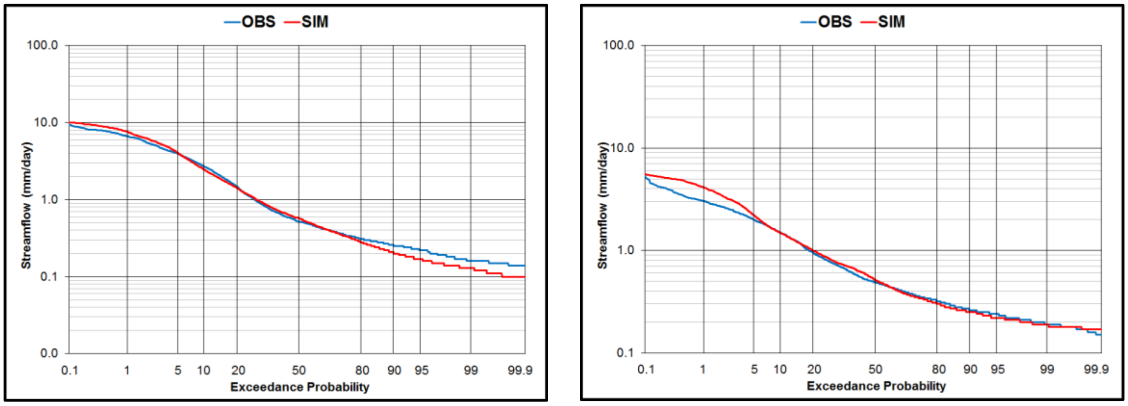
Figure 5-4. Comparison of five daily flow duration curves of the gauged sub-watersheds during the 1970-1980 calibration period

Table 5-5. Monthly model performance results of all five gauged sub-watersheds using the split-sample test under calibration period, 1971-1980.

	WATERSHED				
	1	**2**	**3**	**4**	**5**
Sample Size	120	120	89	82	120
Observed Mean	1.597	1.061	1.423	1.466	1.048
Simulated Mean	1.605	1.111	1.435	1.611	1.115
Observed Q	191.658	127.344	126.674	120.237	125.792
Simulated Q	192.656	133.359	127.737	132.067	133.752
Observed Variance	5.896	1.677	3.964	2.868	2.317
Simulated Variance	5.671	1.764	3.890	3.473	1.993
% Difference of Variance	3.811	-5.152	1.845	-21.092	13.967
Observed Standard Deviation	2.428	1.295	1.991	1.693	1.522
Simulated Standard Deviation	2.381	1.328	1.972	1.863	1.412
% Difference of STD	1.924	-2.543	0.927	-10.042	7.246
Slope	0.939	0.961	0.944	0.969	0.857
Y-Intercept	0.107	0.091	0.091	0.189	0.217
Coefficient of Determination, R^2	0.916	0.879	0.908	0.776	0.853
Correlation Coefficient, R	0.957	0.937	0.953	0.881	0.923
Root mean square error, RMSE	0.704	0.466	0.604	0.890	0.585
RMSE-observed standard ratio, RSR	**0.290**	**0.360**	**0.303**	**0.525**	**0.385**
Percent Bias, PBIAS	**-0.521**	**-4.723**	**-0.839**	**-9.839**	**-6.328**
Nash Sutcliffe Efficiency Index, NSE	**0.915**	**0.869**	**0.907**	**0.721**	**0.851**
Modified NSE	0.771	0.720	0.776	0.579	0.698
Index of Agreement, D	0.978	0.967	0.976	0.933	0.958
Modified D	0.883	0.859	0.887	0.790	0.845

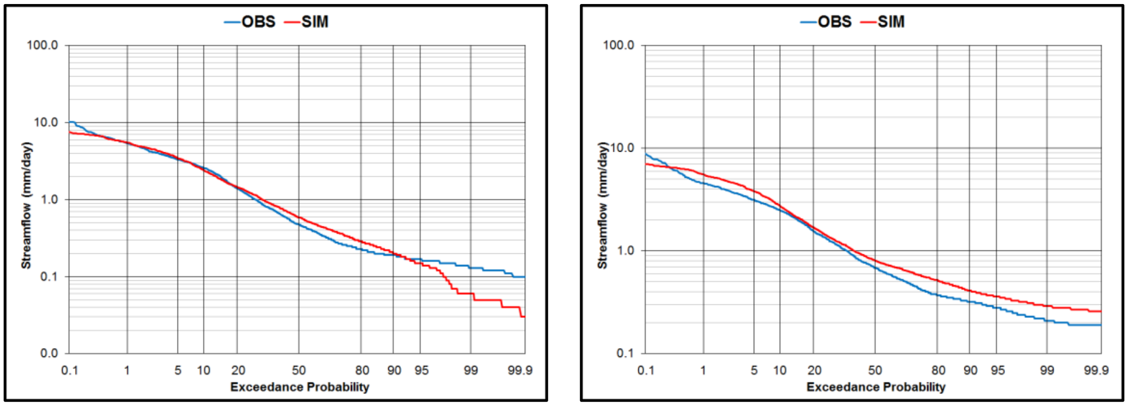
Table 5-6. Daily model performance results of all five gauged sub-watersheds using the split-sample test under validation period, 1981-1990.

	WATERSHED				
	1	**2**	**3**	**4**	**5**
Sample Size	3652	3652	2215	1942	3652
Observed Mean	1.413	0.870	1.281	1.332	0.811
Simulated Mean	1.454	0.954	1.283	1.506	0.836
Observed Q	5159.280	3179.010	2838.330	2587.080	2962.010
Simulated Q	5308.280	3483.980	2842.440	2925.300	3054.610
Observed Variance	3.867	0.924	3.587	2.484	1.841
Simulated Variance	4.539	1.264	2.628	2.529	1.219
% Difference of Variance	-17.398	-36.761	26.742	-1.822	33.788
Observed Standard Deviation	1.966	0.961	1.894	1.576	1.357
Simulated Standard Deviation	2.131	1.124	1.621	1.590	1.104
% Difference of STD	-8.351	-16.945	14.409	-0.907	18.629
Slope	1.015	1.054	0.735	0.884	0.710
Y-Intercept	0.020	0.037	0.341	0.329	0.260
Coefficient of Determination, R^2	0.877	0.812	0.738	0.767	0.762
Correlation Coefficient, R	0.937	0.901	0.859	0.876	0.873
Root mean square error, RMSE	0.749	0.497	0.970	0.808	0.667
RMSE-observed standard ratio, RSR	**0.381**	**0.517**	**0.512**	**0.512**	**0.491**
Percent Bias, PBIAS	**-2.888**	**-9.593**	**-0.145**	**-13.073**	**-3.126**
Nash Sutcliffe Efficiency Index, NSE	**0.855**	**0.733**	**0.738**	**0.737**	**0.758**
Modified NSE	0.713	0.589	0.611	0.589	0.665
Index of Agreement, D	0.966	0.941	0.918	0.931	0.922
Modified D	0.859	0.805	0.798	0.796	0.829



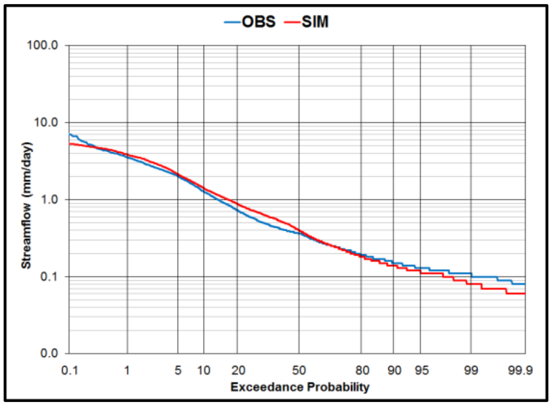
a) Sub-Watershed 1

b) Sub-Watershed 2



c) Sub-Watershed 3

d) Sub-Watershed 4



e) Sub-Watershed 5

Figure 5-5. Comparison of five daily flow duration curves of the gauged sub-watersheds during the 1981-1990 validation period

Table 5-7. Monthly model performance results of all five gauged sub-watersheds using the split-sample test under validation period, 1981-1990.

	WATERSHED				
	1	2	3	4	5
Sample Size	120	120	84	76	120
Observed Mean	1.410	0.868	1.164	1.253	0.809
Simulated Mean	1.450	0.951	1.169	1.385	0.834
Observed Q	169.154	104.175	97.794	95.239	97.046
Simulated Q	173.966	114.095	98.168	105.236	100.035
Observed Variance	2.968	0.722	2.177	1.463	1.199
Simulated Variance	3.648	0.996	1.839	1.583	0.999
% Difference of Variance	-22.907	-37.851	15.534	-8.207	16.689
Observed Standard Deviation	1.723	0.850	1.476	1.209	1.095
Simulated Standard Deviation	1.910	0.998	1.356	1.258	1.000
% Difference of STD	-10.863	-17.410	8.095	-4.023	8.725
Slope	1.068	1.085	0.839	0.957	0.850
Y-Intercept	-0.055	0.009	0.192	0.186	0.147
Coefficient of Determination R^2	0.928	0.854	0.833	0.846	0.866
Correlation Coefficient, R	0.963	0.924	0.913	0.920	0.931
Root mean square error, RMSE	0.526	0.395	0.599	0.510	0.400
RMSE-observed standard ratio, RSR	**0.305**	**0.464**	**0.406**	**0.422**	**0.365**
Percent Bias, PBIAS	**-2.845**	**-9.523**	**-0.383**	**-10.497**	**-3.080**
Nash Sutcliffe Efficiency Index, NSE	**0.906**	**0.782**	**0.833**	**0.820**	**0.866**
Modified NSE	0.766	0.633	0.692	0.640	0.730
Index of Agreement, D	0.978	0.952	0.953	0.955	0.962
Modified D	0.886	0.825	0.839	0.820	0.863

5.2.2.2 The Proxy-basin Test

The daily performance results for the proxy-basin test for the calibration run produced quite excellent results based on the PBIAS values for Sub-Watershed 1 (-0.471%) and Sub-Watershed 5 (-6.34%), as shown in Table 5-8. Similarly, the daily performance ratings of RSR and NSE proved to be quite excellent with RSR and NSE values for Sub-Watershed 1 (RSR=0.441 and NSE=0.806) and for Sub-Watershed 5 (RSR=0.491 and NSE=0.759). The monthly performance ratings performed better, when compared to the daily performance ratings (see Table 5-9). The validation results of the proxy-basin test showed similar trends with excellent performance ratings. There is an over-estimation bias on validating Sub-Watershed 5 (-7.208 %) compared to Sub-Watershed 1 (-0.399%). The total accumulated flows at a daily time step (Figure 5-6a) revealed median flows are slightly over simulated but the high and low flows are simulated well for Sub-Watershed 1. Conversely, Sub-Watershed 5 flows (Figure 5-6b) showed a slight over simulation of high and median flow and under-simulation of low flows.

Table 5-8. Daily performance calibration and validation for two proxy-basin test of Sub-Watershed 1 and Sub-Watershed 5 for an ungauged watershed$_6$

	Watershed 1		Watershed 5	
	Calibration	Validation	Calibration	Validation
Sample Size	3653	3652	3653	3652
Observed Mean	1.601	1.413	1.051	0.811
Simulated Mean	1.609	1.418	1.118	0.870
Observed Q	5849.670	5159.280	3839.060	2962.010
Simulated Q	5877.230	5179.880	4082.450	3175.500
Observed Variance	7.888	3.867	3.104	1.841
Simulated Variance	6.617	3.817	2.305	1.457
% Difference of Variance	16.111	1.298	25.762	23.301
Observed Standard Deviation	2.809	1.966	1.762	1.357
Simulated Standard Deviation	2.572	1.954	1.518	1.207
% Difference of STD	8.409	0.649	13.839	11.690
Slope	0.822	0.931	0.751	0.777
Y-Intercept	0.292	0.103	0.328	0.240
Coefficient of Determination R^2	0.806	0.878	0.760	0.762
Correlation Coefficient, R	0.898	0.937	0.872	0.873
Root mean square error, RMSE	1.238	0.697	0.865	0.665
RMSE-observed standard ratio, RSR	**0.441**	**0.354**	**0.491**	**0.490**
Percent Bias, PBIAS	**-0.471**	**-0.399**	**-6.340**	**-7.208**
Nash Sutcliffe Efficiency Index, NSE	**0.806**	**0.874**	**0.759**	**0.760**
Modified NSE	0.726	0.742	0.640	0.642
Index of Agreement, D	0.944	0.967	0.926	0.928
Modified D	0.861	0.868	0.814	0.824

Table 5-9. Monthly performance for the proxy-basin test of Sub-Watershed 1 and Sub-Watershed 5 for an ungauged watershed[6]

	Watershed 1		**Watershed 5**	
	Calibration	**Validation**	**Calibration**	**Validation**
Sample Size	120	120	120	120
Observed Mean	1.597	1.410	1.048	0.809
Simulated Mean	1.605	1.415	1.115	0.867
Observed Q	191.658	169.154	125.792	97.046
Simulated Q	192.656	169.763	133.752	103.992
Observed Variance	5.896	2.968	2.317	1.199
Simulated Variance	5.671	3.133	1.993	1.195
% Difference of Variance	3.811	5.400	13.967	0.377
Observed Standard Deviation	2.428	1.723	1.522	1.095
Simulated Standard Deviation	2.381	1.770	1.412	1.093
% Difference of STD	1.924	2.701	7.246	0.189
Slope	0.939	0.988	0.857	0.930
Y-Intercept	0.107	0.022	0.217	0.114
Coefficient of Determination R^2	0.916	0.925	0.853	0.869
Correlation Coefficient, R	0.957	0.962	0.923	0.932
Root mean square error, RMSE	0.704	0.483	0.585	0.406
RMSE-observed standard ratio, RSR	**0.290**	**0.280**	**0.385**	**0.370**
Percent Bias, PBIAS	**-0.521**	**-0.360**	**-6.328**	**-7.158**
Nash Sutcliffe Efficiency Index, NSE	**0.915**	**0.921**	**0.851**	**0.862**
Modified NSE	0.771	0.785	0.698	0.708
Index of Agreement, D	0.978	0.980	0.958	0.964
Modified D	0.883	0.892	0.845	0.857

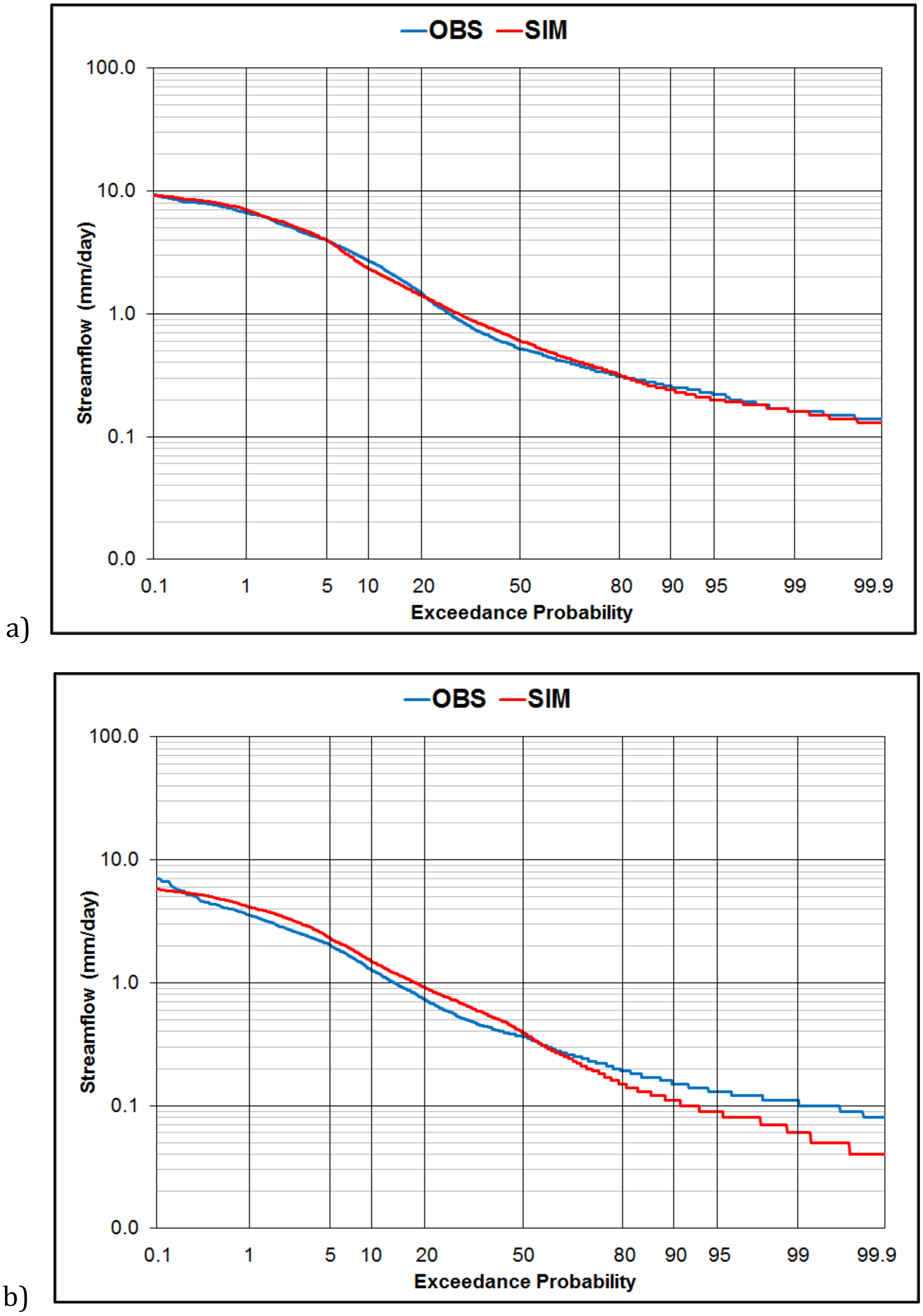
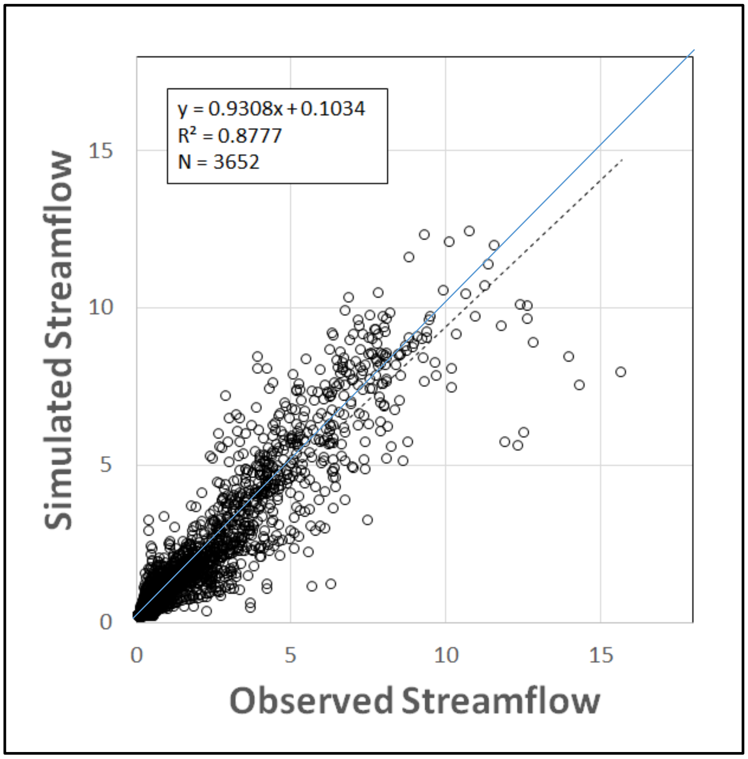


Figure 5-6. Daily flow duration curves for a) Sub-Watershed 1, validated at Sub-Watershed 5 and b) Sub-Watershed 5, validated at Sub-Watershed 1.

a)



b)

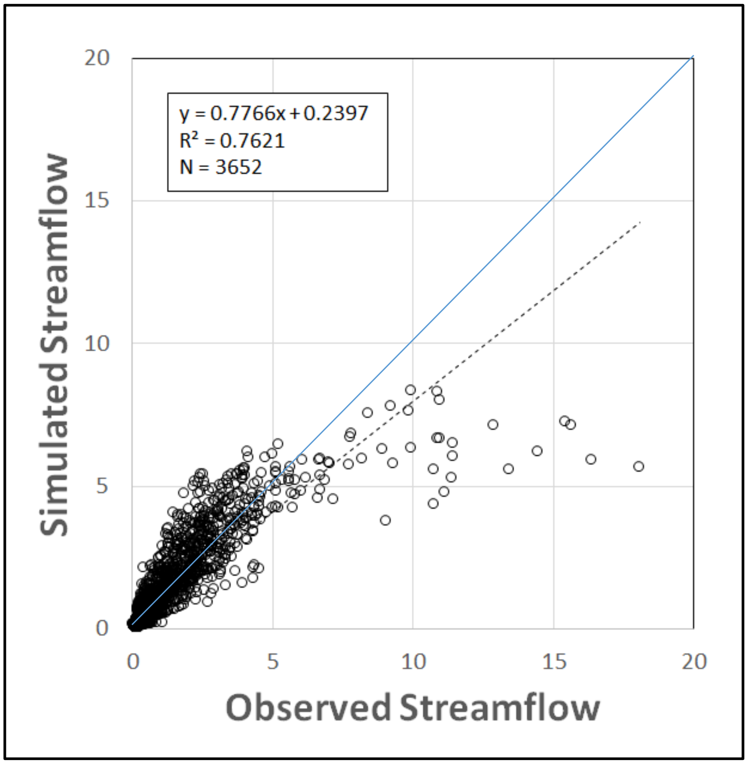


Figure 5-7. Regression scatter plot for simulated and observed streamflow for a) Sub-Watershed 1 and b) Sub-Watershed 5. The solid blue line represents the 1:1 line. The black dotted line is the slope of the regression.

5.2.2.3 The Differential Split-Sample Test

Firstly, the ACRU model was required to simulate streamflow for a wet climate scenario. The daily and monthly performance calibration run for Sub-Watershed 1 (see Table 5-10) and Sub-Watershed 5 (see Table 5-11) showed excellent results with PBIAS values for Sub-Watershed 1 (-6.705%, -6.798%) and Sub-Watershed 5 (-8.278%, -8.170%) during calibration. Moreover, the daily performance for the calibration runs for both watersheds are quite excellent where Sub-Watershed 1 RSR value is 0.253 and NSE value is 0.936. Meanwhile, Sub-Watershed 5 RSR value is 0.344, and NSE value is 0.882. In addition, the validation runs showed the decrease in model performance ratings for these criteria (Sub-Watershed 1: RSR=0.54, NSE=0.74 and Sub-Watershed 5: RSR=0.53, NSE=0.72). Similar trends occurred in the monthly results, with slightly better results. There is an overall slight overestimation bias with the predicted data based on the PBIAS values.

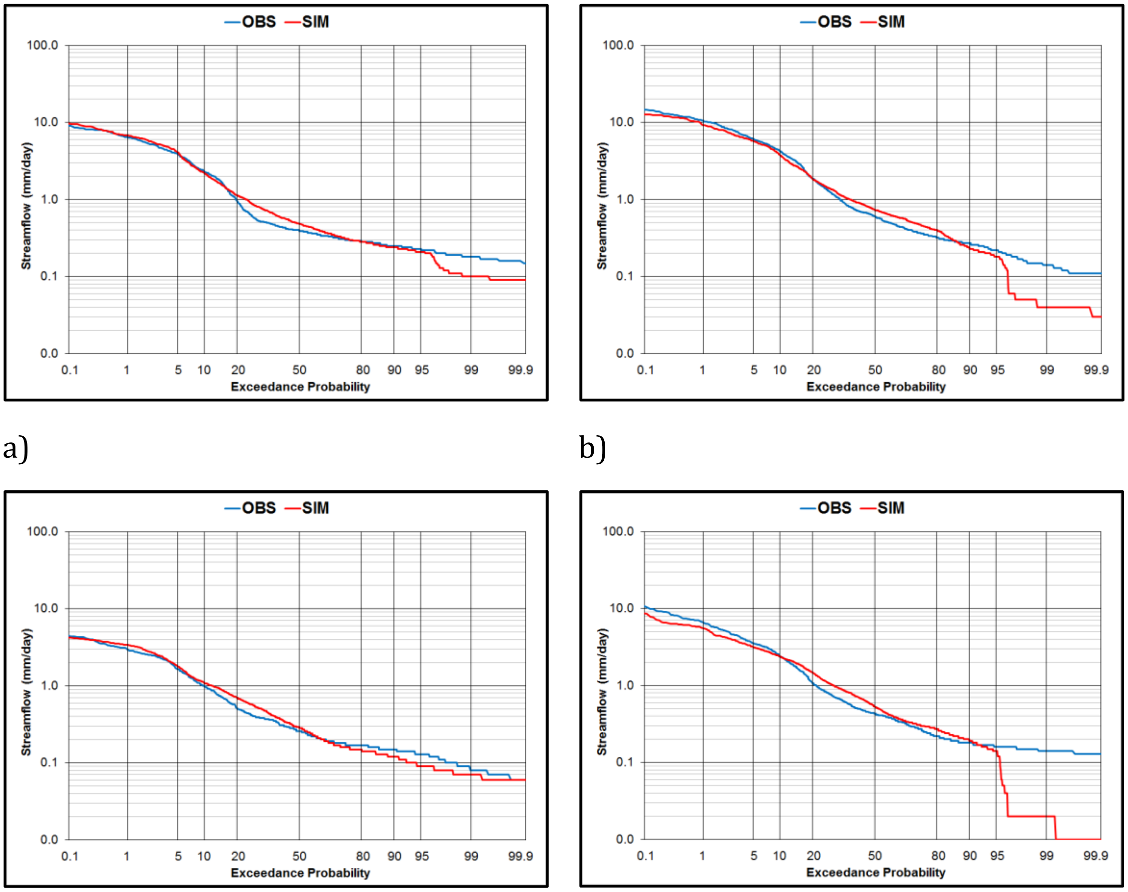
Secondly, the ACRU model is also required to simulate streamflow for a dry climate scenario. The daily and monthly performance results for Sub-Watershed 1 and Sub-Watershed 5 are listed in Table 5-12 and Table 5-13, respectively. The daily performance ratings showed excellent results based on the PBIAS values during calibration for Sub-Watershed 1 (5.849%) and Sub-Watershed 5 (3.279%) There is an overall slight under-estimation bias with the predicted data as compared to the over-estimation during validation run of Sub-Watershed 1 (-8.11%) and Sub-Watershed 5 (-11.823%). Furthermore, the RSR and NSE values for Sub-Watershed 1 (RSR=0.484, NSE=0.765) and Sub-Watershed 5 (RSR=0.527, NSE=0.722) were good. The monthly performance result for this test also showed similar trends.

Table 5-10. Daily and monthly performance results for the differential split-sample test for simulating a wet climate scenario for Sub-Watershed 1.

	Daily Sub-Watershed 1 Calibration	Daily Sub-Watershed 1 Validation	Monthly Sub-Watershed 1 Calibration	Monthly Sub-Watershed 1 Validation
Sample Size	1096	1096	36	36
Observed Mean	1.242	2.103	1.240	2.100
Simulated Mean	1.326	1.940	1.325	1.937
Observed Q	1361.730	2304.910	44.654	75.594
Simulated Q	1453.030	2126.740	47.690	69.748
Observed Variance	3.537	13.503	2.888	9.654
Simulated Variance	3.942	7.630	3.261	6.950
% Difference of Variance	-11.454	43.496	-12.923	28.015
Observed Standard Deviation	1.881	3.675	1.699	3.107
Simulated Standard Deviation	1.986	2.762	1.806	2.636
% Difference of STD	-5.572	24.831	-6.265	15.156
Slope	1.026	0.656	1.051	0.822
Y-Intercept	0.051	0.562	0.021	0.212
Coefficient of Determination R^2	0.945	0.761	0.978	0.938
Correlation Coefficient, R	0.972	0.872	0.989	0.968
Root mean square error, RMSE	0.476	1.858	0.292	0.864
RMSE-observed standard ratio, RSR	**0.253**	**0.506**	**0.172**	**0.278**
Percent Bias, PBIAS	**-6.705**	**7.730**	**-6.798**	**7.734**
Nash Sutcliffe Efficiency Index, NSE	**0.936**	**0.744**	**0.970**	**0.921**
Modified NSE	0.797	0.709	0.852	0.754
Index of Agreement, D	0.985	0.911	0.993	0.976
Modified D	0.898	0.845	0.926	0.870

Table 5-11. Daily and monthly performance results for the differential split-sample test for simulating a wet climate scenario for Sub-Watershed 5.

	Daily Sub-Watershed 5 Calibration	Daily Sub-Watershed 5 Validation	Monthly Sub-Watershed 5 Calibration	Monthly Sub-Watershed 5 Validation
Sample Size	1096	1096	36	36
Observed Mean	0.620	1.294	0.619	1.291
Simulated Mean	0.671	1.228	0.670	1.225
Observed Q	679.120	1417.700	22.291	46.460
Simulated Q	735.340	1346.290	24.112	44.107
Observed Variance	0.782	4.366	0.672	3.377
Simulated Variance	0.836	2.581	0.681	2.296
% Difference of Variance	-6.949	40.870	-1.345	32.023
Observed Standard Deviation	0.884	2.089	0.820	1.838
Simulated Standard Deviation	0.914	1.607	0.825	1.515
% Difference of STD	-3.416	23.104	-0.670	17.552
Slope	0.977	0.658	0.981	0.782
Y-Intercept	0.065	0.377	0.062	0.216
Coefficient of Determination R^2	0.893	0.732	0.949	0.899
Correlation Coefficient, R	0.945	0.856	0.974	0.948
Root mean square error, RMSE	0.304	1.098	0.191	0.622
RMSE-observed standard ratio, RSR	**0.344**	**0.526**	**0.233**	**0.338**
Percent Bias, PBIAS	**-8.278**	**5.037**	**-8.170**	**5.064**
Nash Sutcliffe Efficiency Index, NSE	**0.882**	**0.723**	**0.944**	**0.882**
Modified NSE	0.714	0.652	0.789	0.722
Index of Agreement, D	0.971	0.905	0.986	0.964
Modified D	0.859	0.813	0.895	0.851



a)

b)

c)

d)

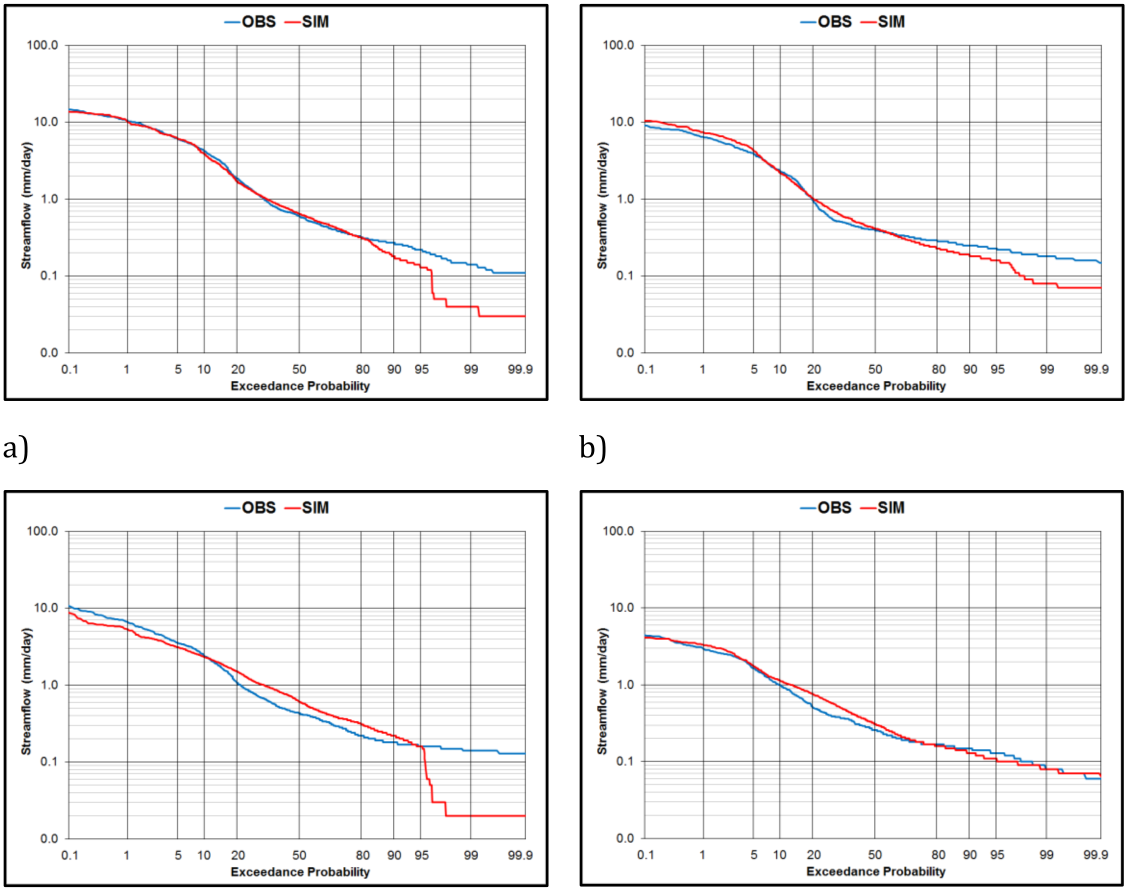
Figure 5-8. Daily flow duration curves for simulating a wet climate scenario, showing a) calibration on LAPP and b) validation on HAPP for Sub-Watershed 1 and the c) calibration on LAPP and d) validation HAPP for Sub-Watershed 5

Table 5-12. Daily and monthly performance results for the differential split-sample test for simulating a dry climate scenario for Sub-Watershed 1 (Castle Watershed).

	Daily Sub-Watershed 1 Calibration	**Daily Sub-Watershed 1 Validation**	**Monthly Sub-Watershed 1 Calibration**	**Monthly Sub-Watershed 1 Validation**
Sample Size	1096	1096	36	36
Observed Mean	2.103	1.242	2.100	1.240
Simulated Mean	1.980	1.343	1.977	1.342
Observed Q	2304.910	1361.730	75.594	44.654
Simulated Q	2170.100	1472.160	71.187	48.324
Observed Variance	13.503	3.537	9.654	2.888
Simulated Variance	9.195	4.816	8.410	3.958
% Difference of Variance	31.899	-36.155	12.892	-37.057
Observed Standard Deviation	3.675	1.881	3.107	1.699
Simulated Standard Deviation	3.032	2.195	2.900	1.990
% Difference of STD	17.477	-16.685	6.668	-17.071
Slope	0.724	1.135	0.910	1.159
Y-Intercept	0.458	-0.067	0.066	-0.095
Coefficient of Determination R^2	0.769	0.947	0.951	0.979
Correlation Coefficient, R	0.877	0.973	0.975	0.990
Root mean square error, RMSE	1.779	0.576	0.699	0.400
RMSE-observed standard ratio, RSR	**0.484**	**0.306**	**0.225**	**0.235**
Percent Bias, PBIAS	**5.849**	**-8.110**	**5.830**	**-8.219**
Nash Sutcliffe Efficiency Index, NSE	**0.765**	**0.906**	**0.948**	**0.943**
Modified NSE	0.736	0.777	0.797	0.809
Index of Agreement, D	0.925	0.980	0.986	0.988
Modified D	0.865	0.893	0.897	0.908

Table 5-13. Daily and monthly performance results for the differential split-sample test for simulating a dry climate scenario for Sub-Watershed 5.

	Daily Sub-Watershed 5 Calibration	**Daily Sub-Watershed 5 Validation**	**Monthly Sub-Watershed 5 Calibration**	**Monthly Sub-Watershed 5 Validation**
Sample Size	1096	1096	36	36
Observed Mean	1.294	0.620	1.291	0.619
Simulated Mean	1.251	0.693	1.248	0.692
Observed Q	1417.700	679.120	46.460	22.291
Simulated Q	1371.210	759.410	44.930	24.897
Observed Variance	4.366	0.782	3.377	0.672
Simulated Variance	2.467	0.816	2.163	0.645
% Difference of Variance	43.497	-4.394	35.952	3.970
Observed Standard Deviation	2.089	0.884	1.838	0.820
Simulated Standard Deviation	1.571	0.903	1.471	0.803
% Difference of STD	24.831	-2.173	19.970	2.005
Slope	0.644	0.950	0.760	0.946
Y-Intercept	0.419	0.104	0.267	0.106
Coefficient of Determination R^2	0.733	0.864	0.902	0.931
Correlation Coefficient, R	0.856	0.930	0.950	0.965
Root mean square error, RMSE	1.101	0.344	0.629	0.224
RMSE-observed standard ratio, RSR	**0.527**	**0.389**	**0.342**	**0.274**
Percent Bias, PBIAS	**3.279**	**-11.823**	**3.293**	**-11.689**
Nash Sutcliffe Efficiency Index, NSE	**0.722**	**0.849**	**0.879**	**0.923**
Modified NSE	0.640	0.670	0.703	0.756
Index of Agreement, D	0.903	0.962	0.962	0.980
Modified D	0.802	0.837	0.837	0.877



a)

b)

c)

d)

Figure 5-9. Daily flow duration curves for simulating a dry climate scenario, showing a) calibration on HAPP and b) validation on LAPP for Sub-Watershed 1 and the c) calibration on HAPP and d) validation on LAPP for Sub-Watershed 5

5.2.2.4 The Proxy-Basin Differential Split-Sample Test

For simulating a wet climate scenario, the daily performance ratings of the calibration runs was excellent for both the first test (6.89%) and the second test (-8.278%), as shown in Table 5-14 and Table 5-15. During validation, the daily performance ratings of PBIAS values remained excellent for the first test (3.279%) and satisfactory for the second test (18.461%). Similarly, ACRU's daily performance ratings were very well for RSR and NSE values for the first test (RSR=0.247

NSE=0.939) whereas second test results were slightly reduced performance (RSR=0.344 NSE=0.882). During the validation phase, the performance ratings showed better results for the first test and less than ideal for second test. The LAPP validation of Sub-Watershed 1 using Sub-Watershed 5 HAPP calibration runs were satisfactory. The underestimation of low peak flows are apparent in the validation runs (Figure 5-10). The monthly performance result for simulating wet scenario also showed similar trends (see Table 5-15).

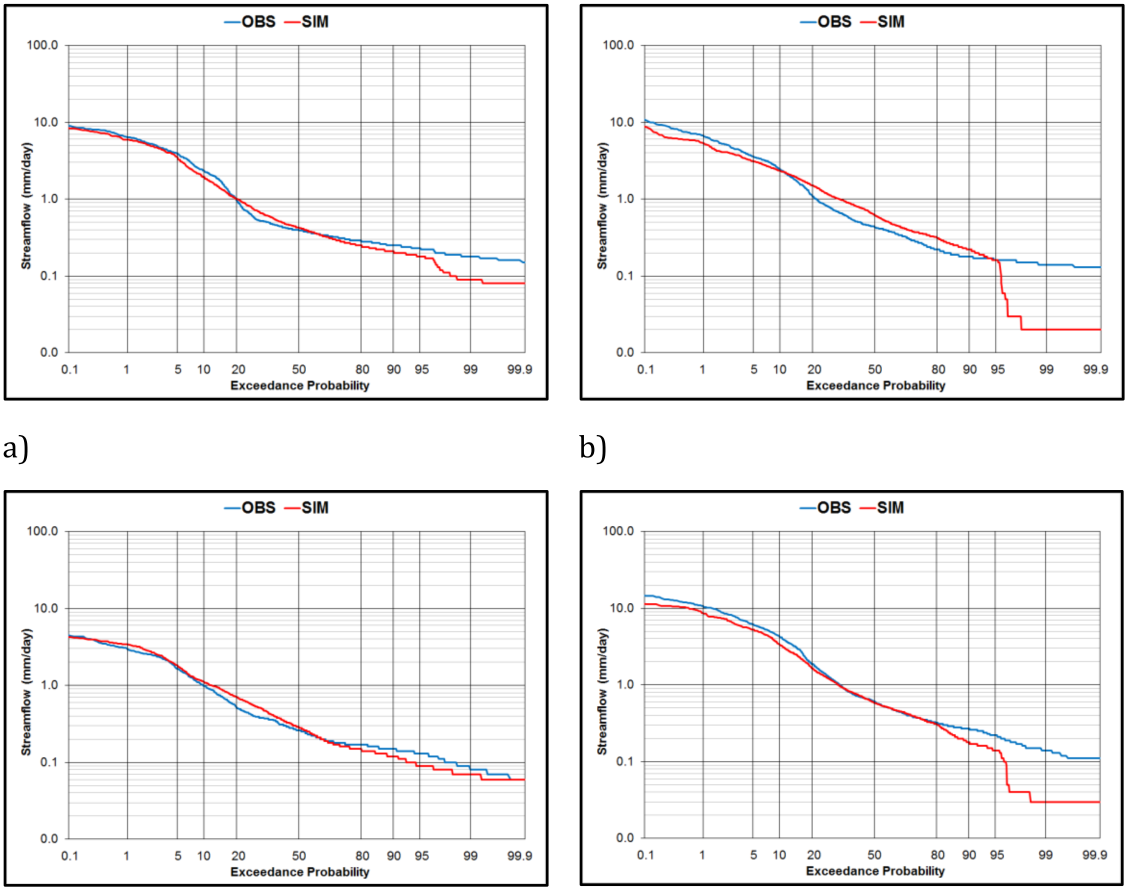
For simulating a dry climate scenario, the daily performance ratings of the calibration runs was excellent for both the first test (5.849%) and the second test (5.037%), as shown in Table 5-16. During validation, the daily performance ratings of PBIAS values were unsatisfactory for the first test (-34.389%) and excellent for the second test (8.902%). Similarly, ACRU's daily performance ratings were very well for RSR and NSE values for the first test (RSR=0.484 NSE=0.765) whereas second test results were slightly reduced performance (RSR=0.526 NSE=0.723). During the validation phase, the performance ratings for the first test revealed similar trends where the HAPP validation of Sub-Watershed 5 using Sub-Watershed 1 LAPP calibration runs were unsatisfactory. The underestimation of low peak flows are apparent during the calibration runs (Figure 5-11). The monthly performance result for this test also showed similar trends (see Table 5-17).

Table 5-14. Daily performance results for the proxy-basin differential split-sample test for simulating a wet climate scenario

	Daily Sub-Watershed 1 HAPP Calibration	Daily Sub-Watershed 5 LAAP Validation	Daily Sub-Watershed 5 HAPP Calibration	Daily Sub-Watershed 1 LAAP Validation
Sample Size	1096	1096	1096	1096
Observed Mean	1.242	1.294	0.620	2.103
Simulated Mean	1.157	1.251	0.671	1.715
Observed Q	1361.730	1417.700	679.120	2304.910
Simulated Q	1267.910	1371.210	735.340	1879.410
Observed Variance	3.537	4.366	0.782	13.503
Simulated Variance	3.026	2.467	0.836	6.314
% Difference of Variance	14.465	43.497	-6.949	32.656
Observed Standard Deviation	1.881	2.089	0.884	3.675
Simulated Standard Deviation	1.739	1.571	0.914	2.513
% Difference of STD	7.515	24.831	-3.416	31.618
Slope	0.898	0.644	0.977	0.599
Y-Intercept	0.041	0.419	0.065	0.455
Coefficient of Determination R^2	0.943	0.733	0.893	0.767
Correlation Coefficient, R	0.971	0.856	0.945	0.876
Root mean square error, RMSE	0.464	1.101	0.304	1.946
RMSE-observed standard ratio, RSR	**0.247**	**0.527**	**0.344**	**0.530**
Percent Bias, PBIAS	**6.890**	**3.279**	**-8.278**	**18.461**
Nash Sutcliffe Efficiency Index, NSE	**0.939**	**0.722**	**0.882**	**0.719**
Modified NSE	0.814	0.640	0.714	0.713
Index of Agreement, D	0.983	0.903	0.971	0.895
Modified D	0.903	0.802	0.859	0.846

Table 5-15. Monthly performance results for the proxy-basin differential split-sample test for simulating a wet climate scenario

	Monthly Sub-Watershed 1 HAAP Calibration	Monthly Sub-Watershed 5 LAAP Validation	Monthly Sub-Watershed 5 HAAP Calibration	Monthly Sub-Watershed 1 LAAP Validation
Sample Size	36	36	36	36
Observed Mean	1.240	1.291	0.619	2.100
Simulated Mean	1.156	1.248	0.670	1.712
Observed Q	44.654	46.460	22.291	75.594
Simulated Q	41.603	44.930	24.112	61.629
Observed Variance	2.888	3.377	0.672	9.654
Simulated Variance	2.443	2.163	0.681	5.814
% Difference of Variance	15.406	35.952	-1.345	23.873
Observed Standard Deviation	1.699	1.838	0.820	3.107
Simulated Standard Deviation	1.563	1.471	0.825	2.411
% Difference of STD	8.025	19.970	-0.670	22.399
Slope	0.913	0.760	0.981	0.755
Y-Intercept	0.024	0.267	0.062	0.126
Coefficient of Determination R^2	0.984	0.902	0.949	0.947
Correlation Coefficient, R	0.992	0.950	0.974	0.973
Root mean square error, RMSE	0.256	0.629	0.191	1.007
RMSE-observed standard ratio, RSR	**0.151**	**0.342**	**0.233**	**0.324**
Percent Bias, PBIAS	**6.833**	**3.293**	**-8.170**	**18.474**
Nash Sutcliffe Efficiency Index, NSE	**0.977**	**0.879**	**0.944**	**0.892**
Modified NSE	0.875	0.703	0.789	0.752
Index of Agreement, D	0.994	0.962	0.986	0.966
Modified D	0.935	0.837	0.895	0.868



a)

b)

c)

d)

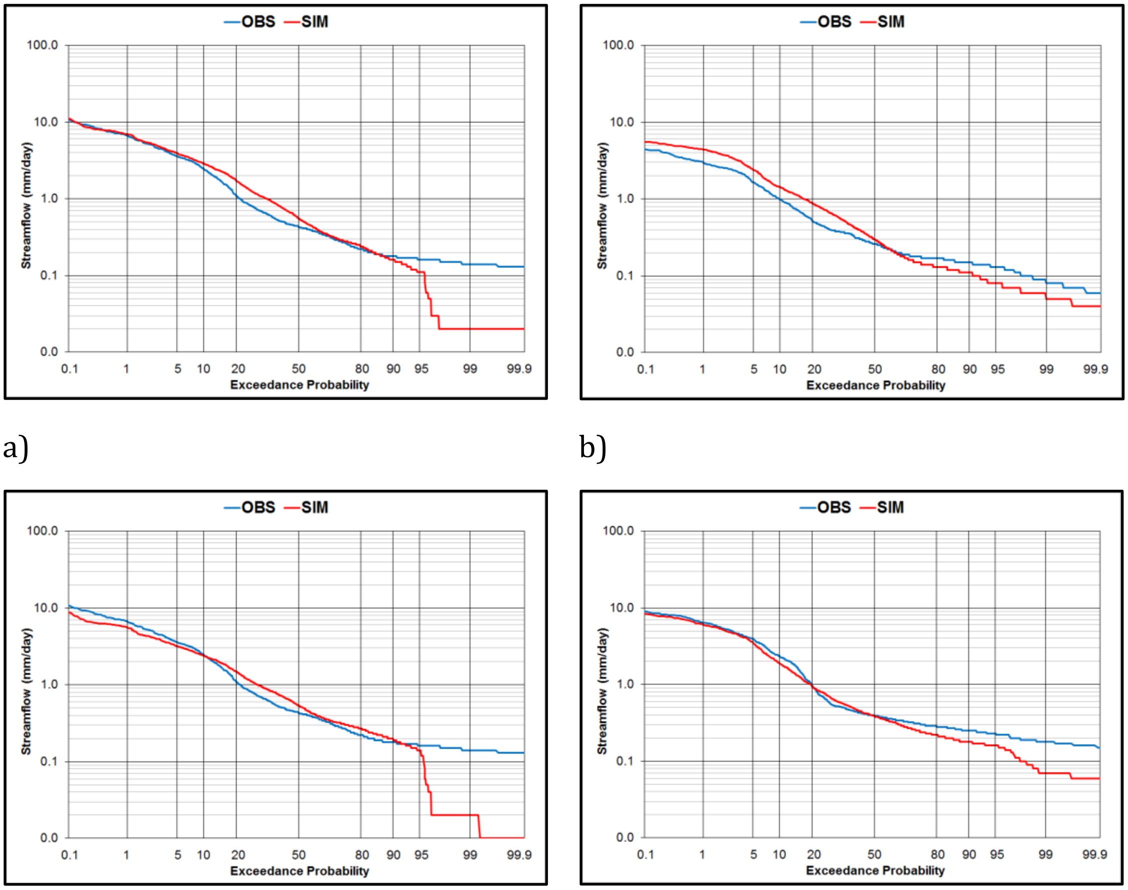
Figure 5-10. Daily flow duration curves for simulating a wet climate scenario under the PBDSS test using a) calibration of LAPP on Sub-Watershed 1 and b) validation of HAPP on Sub-Watershed 5 and c) calibration of LAPP on Sub-Watershed 5 and d) validation of HAPP on Sub-Watershed 1

Table 5-16. Daily performance results for the proxy-basin differential split-sample test for simulating a dry climate scenario

	Daily Sub-Watershed 1 LAPP Calibration	Daily Sub-Watershed 5 HAAP Validation	Daily Sub-Watershed 5 LAPP Calibration	Daily Sub-Watershed 1 HAAP Validation
Sample Size	1096	1096	1096	1096
Observed Mean	2.103	0.620	1.294	1.242
Simulated Mean	1.980	0.836	1.228	1.132
Observed Q	2304.910	679.120	1417.700	1361.730
Simulated Q	2170.100	915.720	1346.290	1240.510
Observed Variance	13.503	0.782	4.366	3.537
Simulated Variance	9.195	1.495	2.581	3.072
% Difference of Variance	31.899	-91.254	40.870	7.515
Observed Standard Deviation	3.675	0.884	2.089	1.881
Simulated Standard Deviation	3.032	1.223	1.607	1.753
% Difference of STD	17.477	-38.294	23.104	6.806
Slope	0.724	1.322	0.658	0.909
Y-Intercept	0.458	0.016	0.377	0.003
Coefficient of Determination R^2	0.769	0.914	0.732	0.951
Correlation Coefficient, R	0.877	0.956	0.856	0.975
Root mean square error, RMSE	1.779	0.507	1.098	0.439
RMSE-observed standard ratio, RSR	**0.484**	**0.573**	**0.526**	**0.234**
Percent Bias, PBIAS	**5.849**	**-34.839**	**5.037**	**8.902**
Nash Sutcliffe Efficiency Index, NSE	**0.765**	**0.671**	**0.723**	**0.945**
Modified NSE	0.736	0.545	0.652	0.821
Index of Agreement, D	0.925	0.942	0.905	0.985
Modified D	0.865	0.802	0.813	0.908

Table 5-17. Monthly performance results for the second part of the proxy-basin differential split-sample test for simulating a dry climate scenario

	Monthly Sub-Watershed 1 LAAP Calibration	Monthly Sub-Watershed 5 HAAP Validation	Monthly Sub-Watershed 5 LAAP Calibration	Monthly Sub-Watershed 1 HAAP Validation
Sample Size	36	36	36	36
Observed Mean	2.100	0.619	1.291	1.240
Simulated Mean	1.977	0.834	1.225	1.131
Observed Q	75.594	22.291	46.460	44.654
Simulated Q	71.187	30.030	44.107	40.704
Observed Variance	9.654	0.672	3.377	2.888
Simulated Variance	8.410	1.236	2.296	2.519
% Difference of Variance	12.892	-84.044	32.023	8.025
Observed Standard Deviation	3.107	0.820	1.838	1.699
Simulated Standard Deviation	2.900	1.112	1.515	1.587
% Difference of STD	6.668	-35.663	17.552	6.600
Slope	0.910	1.330	0.782	0.927
Y-Intercept	0.066	0.011	0.216	-0.019
Coefficient of Determination R^2	0.951	0.961	0.899	0.984
Correlation Coefficient, R	0.975	0.980	0.948	0.992
Root mean square error, RMSE	0.699	0.405	0.622	0.256
RMSE-observed standard ratio, RSR	**0.225**	**0.494**	**0.338**	**0.151**
Percent Bias, PBIAS	**5.830**	**-34.720**	**5.064**	**8.846**
Nash Sutcliffe Efficiency Index, NSE	**0.948**	**0.749**	**0.882**	**0.977**
Modified NSE	0.797	0.554	0.722	0.870
Index of Agreement, D	0.986	0.955	0.964	0.994
Modified D	0.897	0.803	0.851	0.934



a)

b)

c)

d)

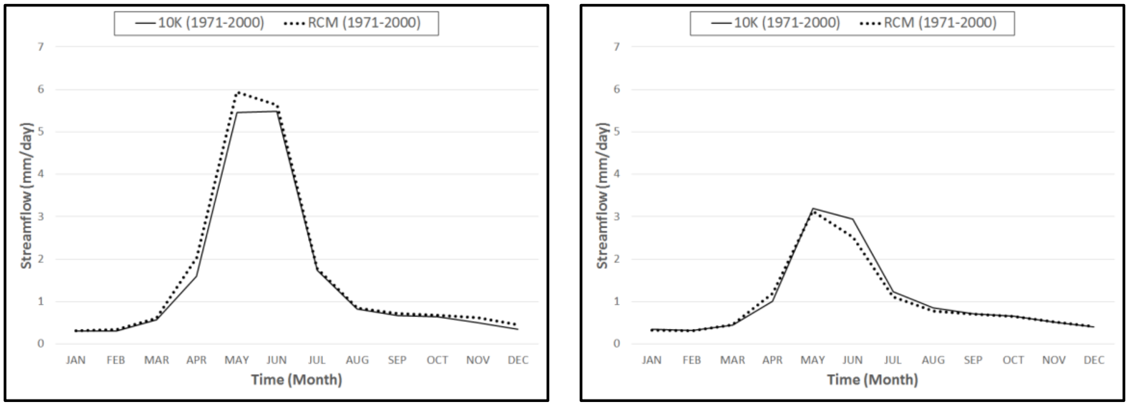
Figure 5-11. Daily flow duration curves for simulating a dry climate scenario under the PBDSS test using for a) calibration of HAPP on Sub-Watershed 1 and b) validation of LAPP on Sub-Watershed 5 and c) calibration of HAPP on Sub-Watershed 5 and d) validation of LAPP on Sub-Watershed 1

5.3 Model Simulation Results

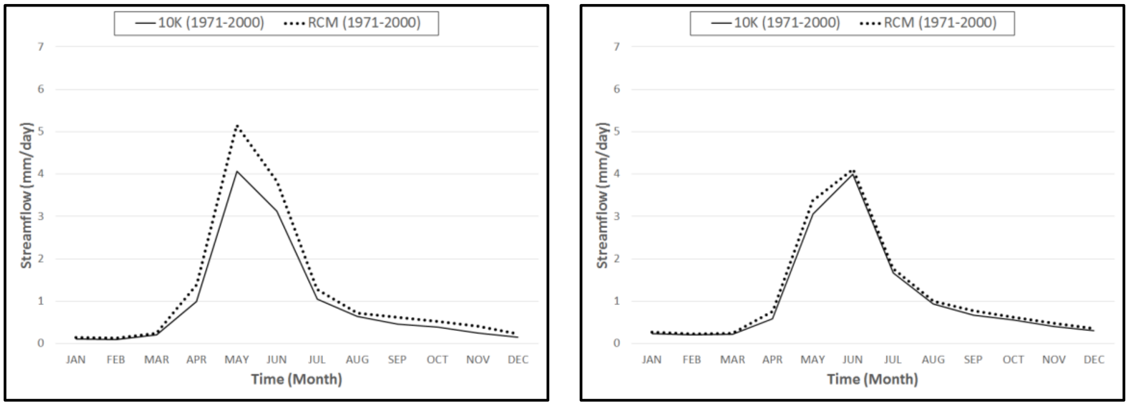
The process of simulating future climate on a rigorously calibrated ACRU model using selected bias-corrected regional climate model data is described in Chapter 3, Section 3.5.2. In this section, the simulation results of using the RCM3 cooler/wetter (CW) and HRM3 warmer/drier (WD) regional climate scenarios for the Oldman Reservoir Watershed are presented. First, the observed baseline (1971-2000) period is compared against the regional climate model historical (1971-2000) period. Second, the regional climate model historical (1971-2000) period is compared against the regional climate model future (2041-2070) period.

5.3.1 Comparison of Baseline and RCM projection for 1971-2000 period

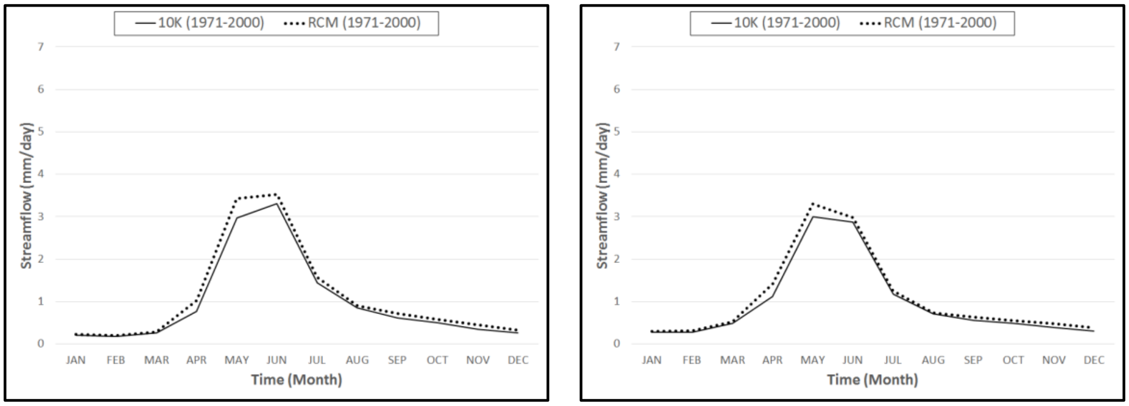
The RCM-based historical (1971-2000) and future (2041-2070) time series required further downscaling in order to match the 10K climate grid. The comparison showed the successful spatial and temporal downscaling of the bias-corrected RCM-based historical (1971-2000) period against the 10K baseline time period, as shown in Figure 5-12 and Figure 5-13. The magnitude and seasonality are comparable for both regional projections, however, the bias-corrections for each of the regional climate models shows pronounced differences in late spring and summer months.



a) Sub-Watershed 1 b) Sub-Watershed 2

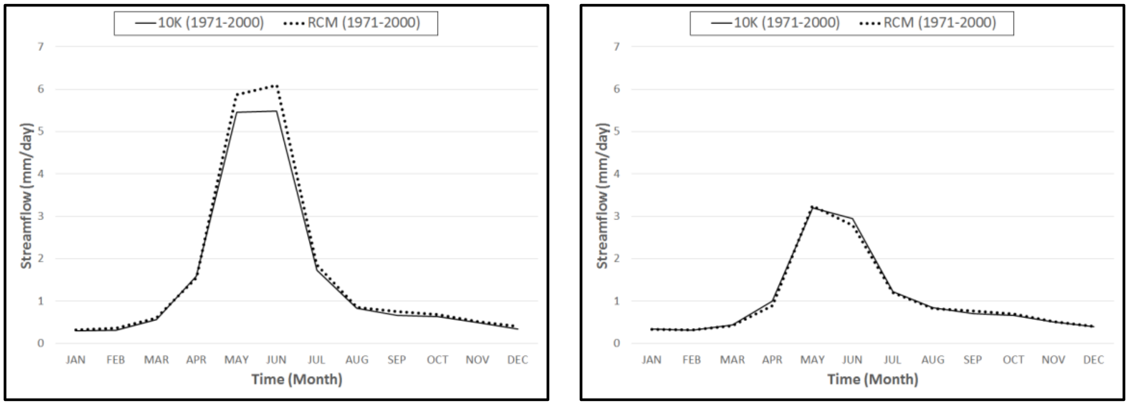


c) Sub-Watershed 3 d) Sub-Watershed 4

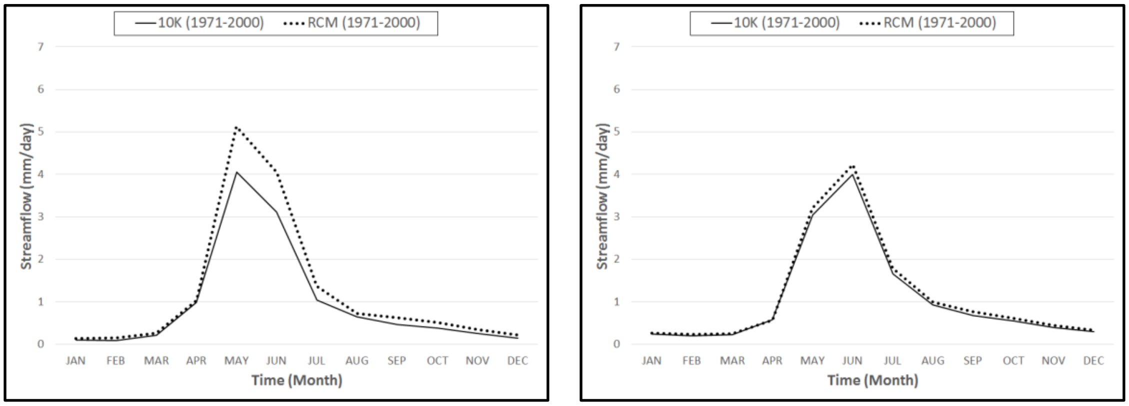


e) Sub-Watershed 5 f) Sub-Watershed 6

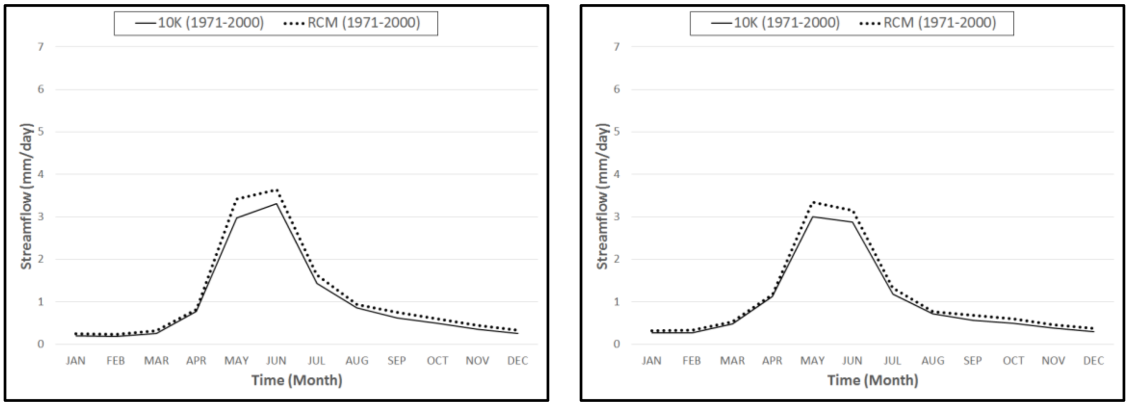
Figure 5-12. Comparison of baseline and historical (1971-2000) RCM time series for all six sub-watershed using the RCM3 (cooler/wetter) regional climate projection, driven by CGCM3 global climate model.



a) Sub-Watershed 1 b) Sub-Watershed 2



c) Sub-Watershed 3 d) Sub-Watershed 4



e) Sub-Watershed 5 f) Sub-Watershed 6

Figure 5-13. Comparison of baseline and historical (1971-2000) RCM time series for all six sub-watersheds using the HRM3 (warmer/drier) regional climate projection, driven by GFDL global climate model

5.3.2 Projected changes using the RCM Historical (1971-2000) and Future (2041-2070) periods

The predicted changes in the future 2041-2070 period for temperature, precipitation and streamflow were compared against historical 1971-2000 period for the Oldman Reservoir Watershed.

5.3.2.1 Temperature

Predicted changes in temperature for each sub-watershed, relative to the historical regional climate period, are reflected in absolute temperature differences for each month. Both regional climate scenarios predicted increased in maximum and minimum temperatures for the future 2041-2070 period. The RCM3 (cooler/wetter) scenario predicted increases in maximum temperature in spring and summer months with ranges from 0.5°C to 3°C and from 2.2°C to 4.5°C, respectively. Whereas the HRM3 (warmer/drier) scenario predicted increases in maximum temperature in spring and summer months with similar ranges, from 0.5°C to 3.2°C and 2.5°C to 5.4°C, respectively. On the other hand, both climate projections predicted increases in minimum temperature in spring and summer months with ranges from 0.5°C to 2.4°C and from 1.9°C to 4°C, respectively. Interestingly, the largest predicted temperature increases occur in the July and December months.

Table 5-18. Monthly absolute maximum temperature differences (in °C) for 2040-2070 period relative to the 1971-2000 period for the RCM3 (cooler/wetter) regional climate scenario for all watersheds for each month.

	SUB-WATERSHED					
	1	**2**	**3**	**4**	**5**	**6**
J	1.63	1.35	1.27	1.80	1.72	1.69
F	1.71	1.62	1.54	2.30	2.11	2.01
M	1.06	0.48	0.45	0.93	0.52	0.47
A	2.30	0.71	0.69	0.76	0.87	0.81
M	3.17	0.90	0.89	1.05	0.95	0.91
J	4.01	2.54	2.39	1.92	2.22	2.27
J	5.07	3.51	3.36	2.68	3.09	3.07
A	4.49	2.98	2.85	2.24	2.71	2.73
S	3.15	2.50	2.19	2.00	1.99	2.12
O	3.17	2.36	2.25	1.86	2.50	2.42
N	1.32	1.47	1.43	1.86	1.70	1.68
D	3.66	2.94	2.91	3.93	3.82	3.61

Table 5-19. Monthly absolute minimum temperature differences (in °C) for 2040-2070 period relative to the 1971-2000 period for the RCM3 (cooler/wetter) regional climate scenario for all watersheds for each month.

	SUB-WATERSHED					
	1	**2**	**3**	**4**	**5**	**6**
J	2.00	1.72	1.75	1.33	2.06	1.99
F	2.18	2.23	2.23	1.61	2.93	2.88
M	1.44	0.92	0.89	0.48	1.27	1.21
A	2.18	0.66	0.80	0.73	0.99	0.87
M	2.41	1.02	1.03	0.86	1.05	1.09
J	3.10	1.90	1.92	2.36	1.99	2.11
J	4.00	2.59	2.70	3.34	2.75	2.60
A	3.40	2.28	2.27	2.83	2.36	2.42
S	2.49	1.87	1.93	2.02	1.82	1.94
O	2.44	1.96	2.01	2.32	2.16	2.12
N	1.50	1.91	1.81	1.48	2.14	2.14
D	4.19	3.84	3.83	3.00	4.71	4.65

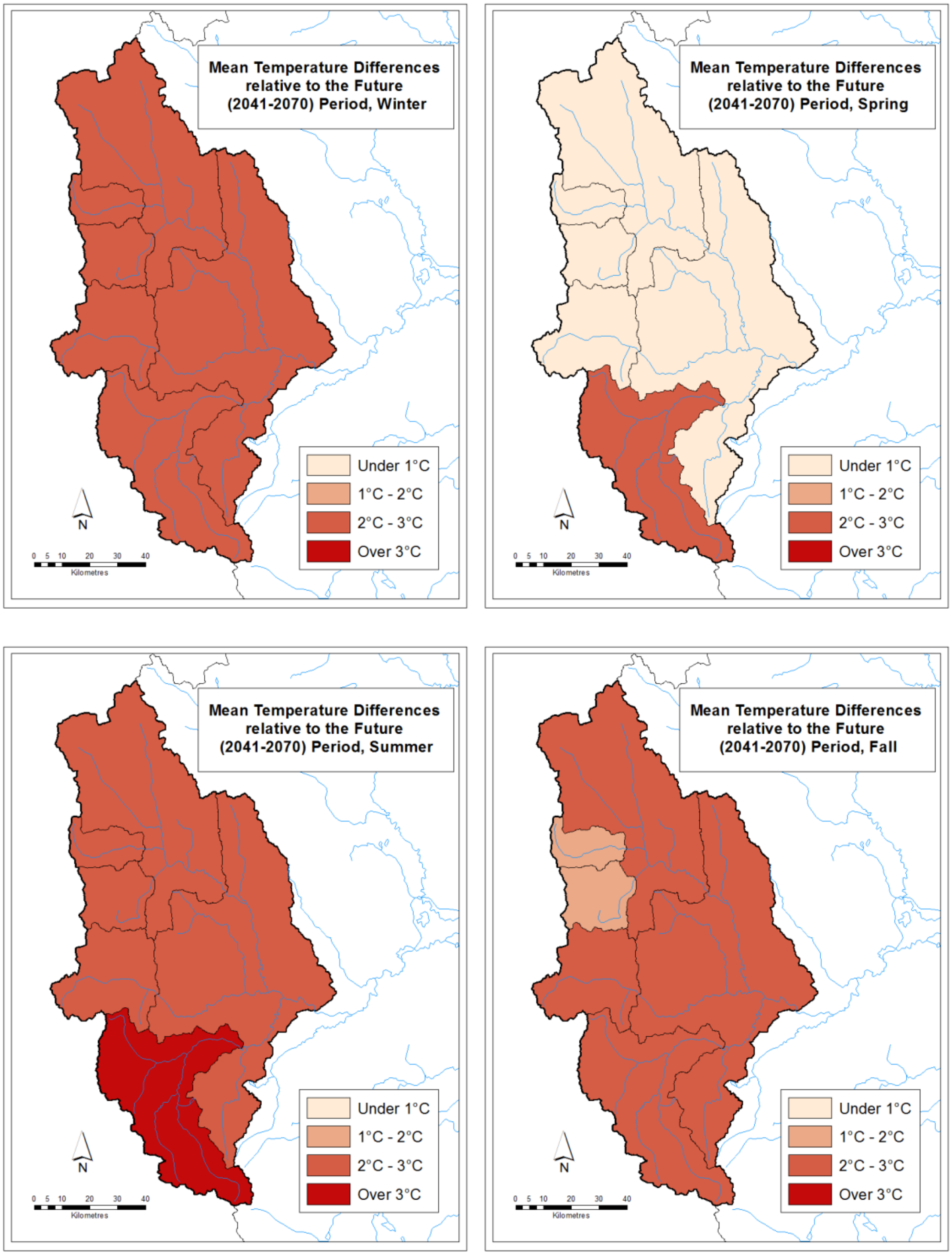


Figure 5-14. Mean temperature differences (in °C) maps of RCM3 (cooler/wetter) climate projection for the winter, spring, summer and fall months

Table 5-20. Monthly absolute maximum temperature differences (in °C) for 2040-2070 period relative to the 1971-2000 period for the HRM3 (warmer/drier) regional climate scenario for all watersheds for each month

	SUB-WATERSHED					
	1	**2**	**3**	**4**	**5**	**6**
J	1.37	1.53	1.57	1.62	1.66	1.65
F	1.64	1.68	1.76	1.79	1.81	1.74
M	0.49	1.12	0.91	0.92	0.93	1.08
A	0.70	2.84	2.24	2.08	2.08	2.31
M	0.90	3.24	3.09	3.16	3.16	3.18
J	2.53	4.23	4.02	3.99	4.00	4.08
J	3.43	5.35	5.31	5.35	5.25	5.17
A	2.94	4.73	4.76	4.75	4.66	4.55
S	2.52	3.34	3.32	3.26	3.28	3.16
O	2.34	3.21	3.21	3.13	3.24	3.17
N	1.47	1.40	1.54	1.57	1.45	1.29
D	2.89	3.47	3.38	3.45	3.57	3.67

Table 5-21. Absolute minimum temperature differences (in °C) for 2040-2070 period relative to the 1971-2000 period for the HRM3 (warmer/drier) regional climate scenario for all watersheds for each month

	SUB-WATERSHED					
	1	**2**	**3**	**4**	**5**	**6**
J	1.70	1.62	1.64	1.68	1.93	2.03
F	2.20	1.93	2.08	2.13	2.25	2.21
M	0.93	1.43	1.45	1.50	1.49	1.48
A	0.61	2.08	2.00	1.89	2.01	2.17
M	1.03	2.27	2.23	2.20	2.21	2.36
J	1.97	2.93	2.86	2.87	2.88	3.00
J	2.68	3.73	3.99	4.02	3.96	3.85
A	2.36	3.27	3.38	3.34	3.33	3.26
S	1.96	2.47	2.59	2.56	2.43	2.41
O	2.02	2.23	2.44	2.36	2.43	2.39
N	1.92	1.62	1.73	1.72	1.61	1.48
D	3.76	3.94	3.81	3.93	4.05	4.22

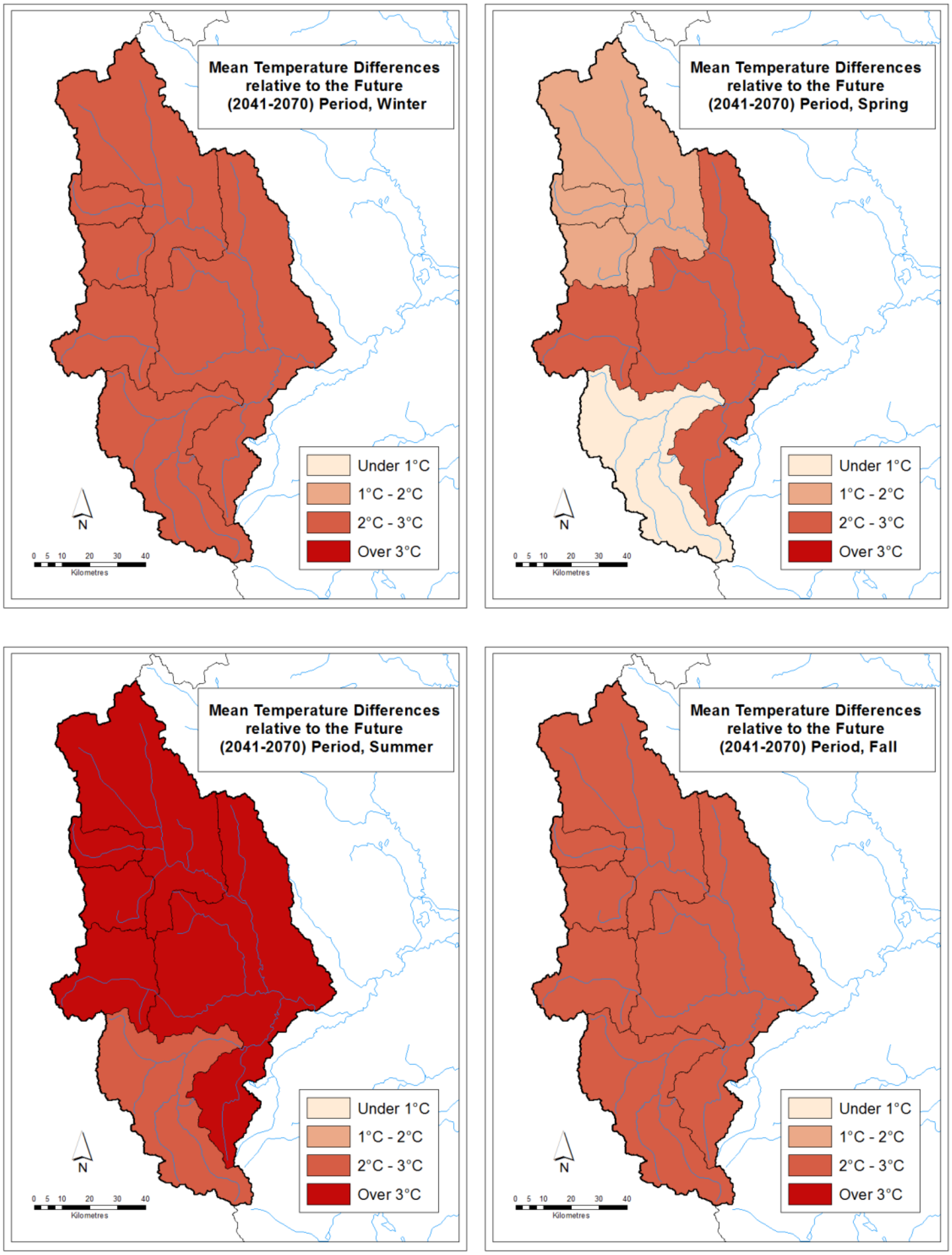


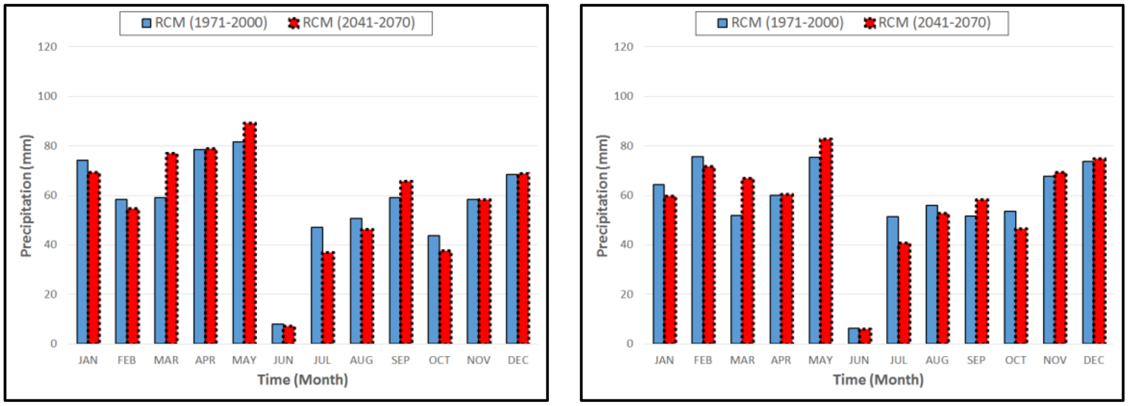
Figure 5-15. Mean temperature differences (in °C) maps of HRM3 (warmer/drier) climate projection for the winter, spring, summer and fall months

5.3.2.2 Precipitation

Predicted changes in precipitation for each sub-watershed, relative to the historical regional climate period, are reflected as monthly averages, as illustrated in Figure 5-17 and Figure 5-19. Both regional climate scenarios predicted seasonal shift in hydrology with increased spring precipitation, decreased summer precipitation and increased early fall precipitation for the future 2041-2070 period, as shown in Figure 5-16 and Figure 5-18. Overall, the RCM3 (cooler/wetter) scenario projected increase of up to 5.2% of precipitation for the upstream gauged sub-watersheds within the Oldman Reservoir Watershed, as shown in Table 5-22. Similarly, the HRM3 (warmer/drier) scenario projected reductions of precipitation with up to 8.6% for some sub-watersheds.

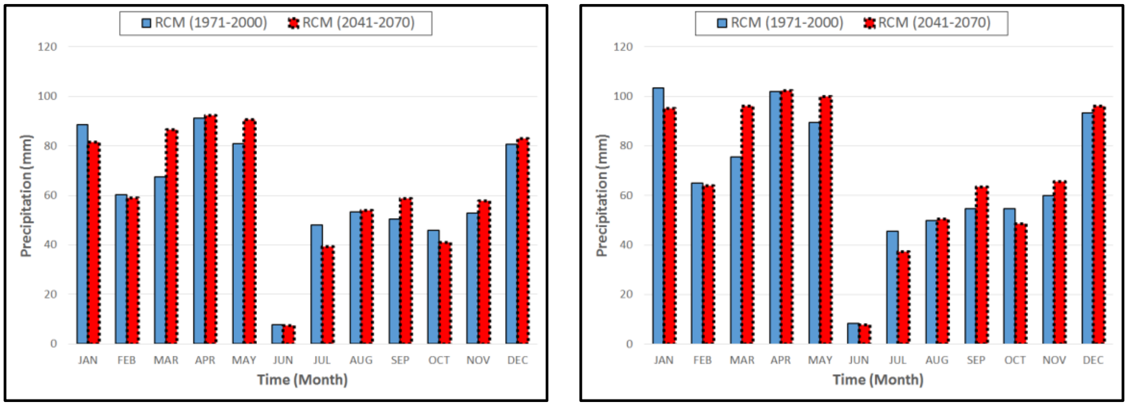
Table 5-22. Mean monthly percent change in precipitation (mm) changes for both regional climate projections for the Oldman Reservoir Watershed.

	SUB-WATERSHED					
	1	2	3	4	5	6
RCM3 (wetter/cooler)	0.3	0.3	3.2	3.0	5.2	0.3
HRM3 (warmer/drier)	-6.3	-8.6	-4.2	-3.9	-4.4	-6.4



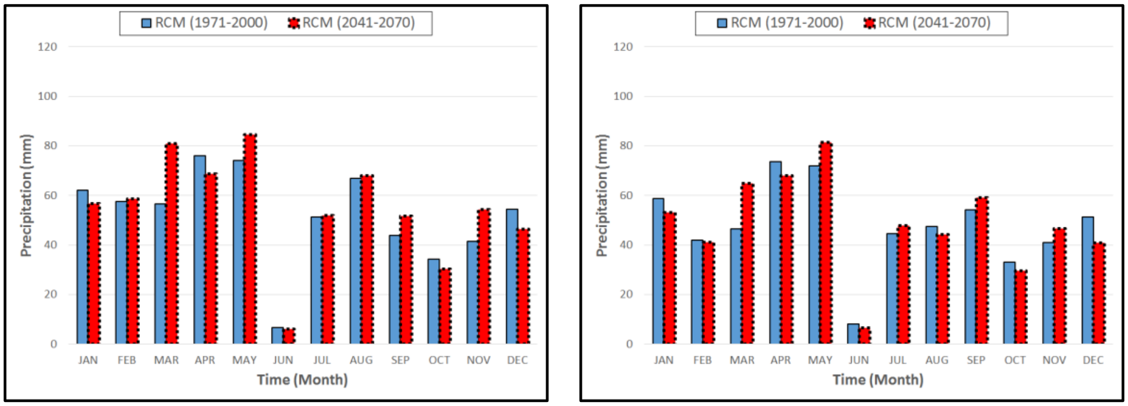
a) Sub-watershed 1

b) Sub-watershed 2



c) Sub-watershed 3

d) Sub-watershed 4



e) Sub-watershed 5

f) Sub-watershed 6

Figure 5-16. Comparison of monthly precipitation average for historical (1971-2000) and future (2041-2070) period for all six sub-watersheds using the RCM3 (cooler/wetter) regional climate projection, driven by CGCM3 global climate model.

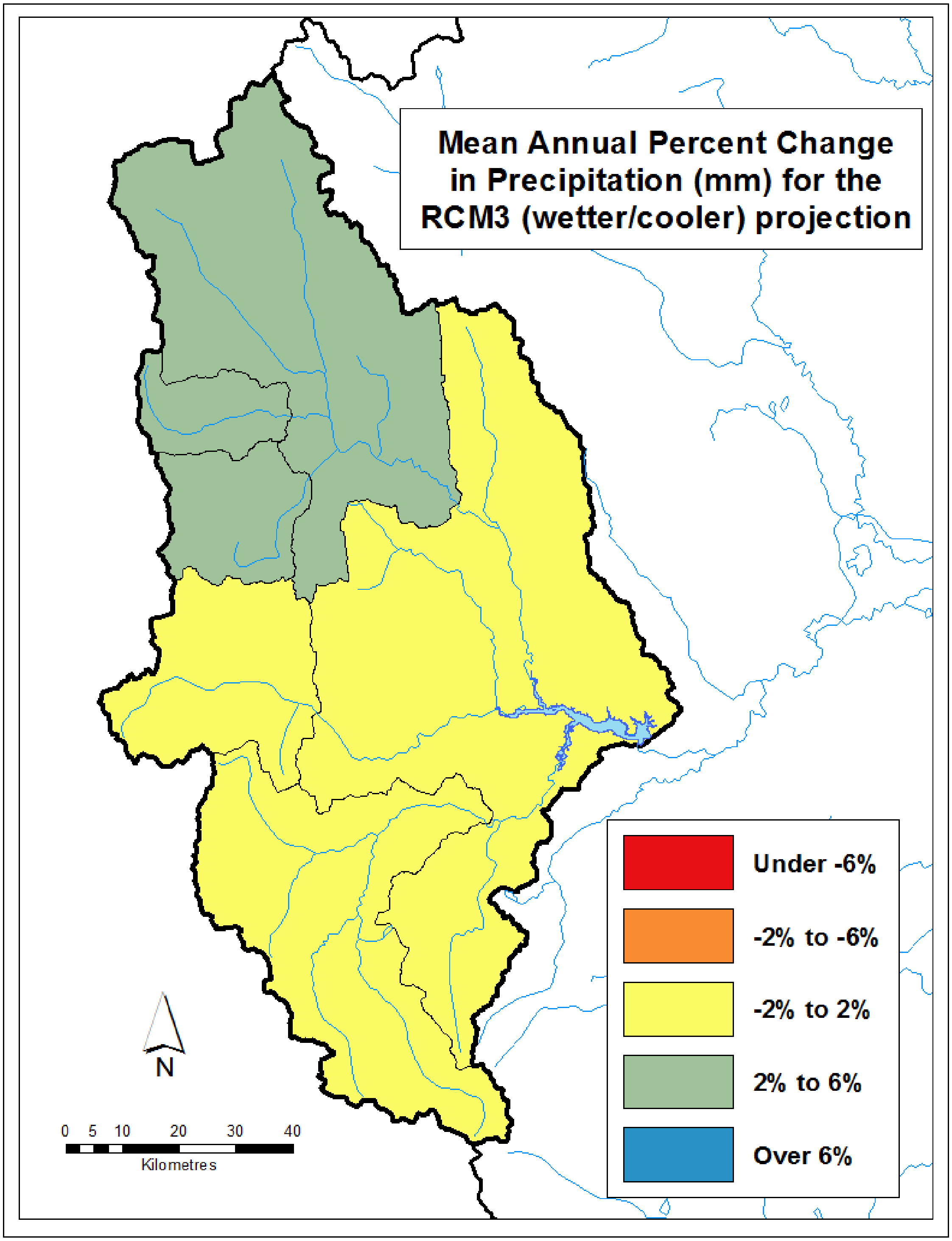
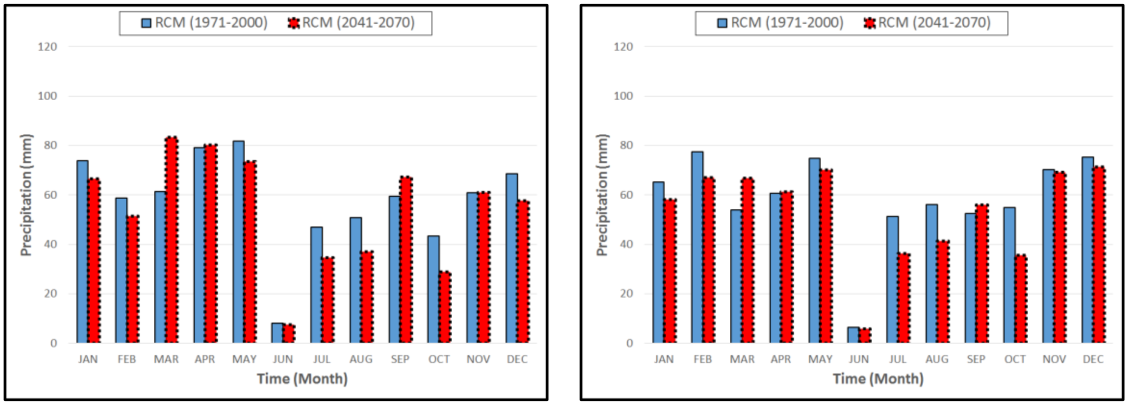
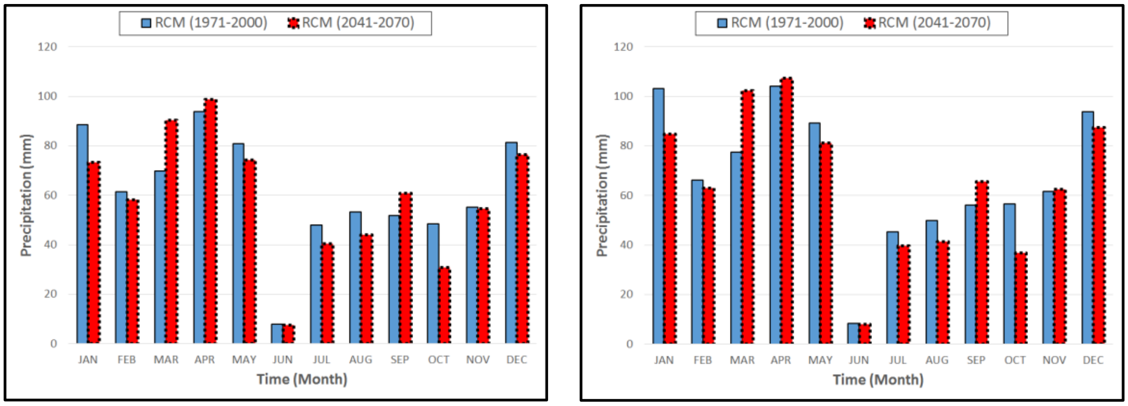


Figure 5-17. Mean annual percent change in precipitation (mm) of RCM3 (cooler/wetter) climate projection for the Oldman Reservoir Watershed



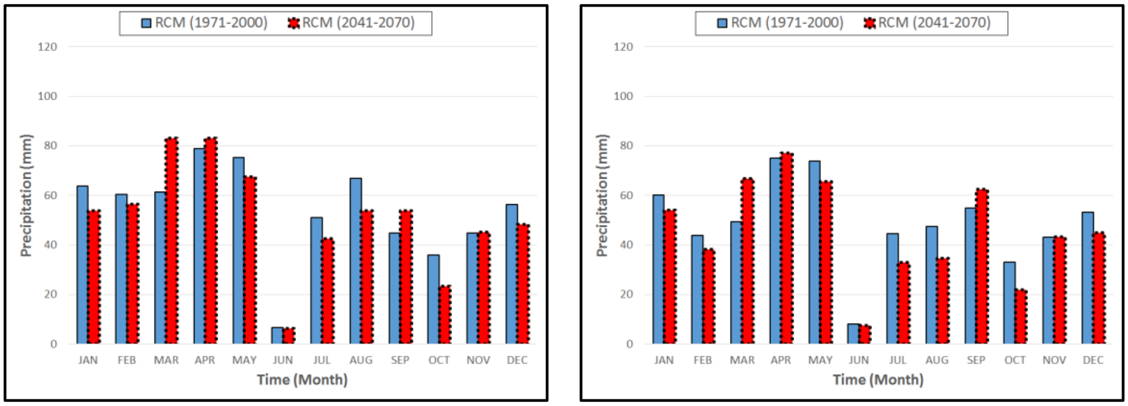
a) Sub-watershed 1

b) Sub-watershed 2



c) Sub-watershed 3

d) Sub-watershed 4



e) Sub-watershed 5

f) Sub-watershed 6

Figure 5-18. Comparison of monthly precipitation average for historical (1971-2000) and future (2041-2070) period for all six sub-watersheds using the HRM3 (warmer/drier) regional climate projection, driven by GFDL global climate model

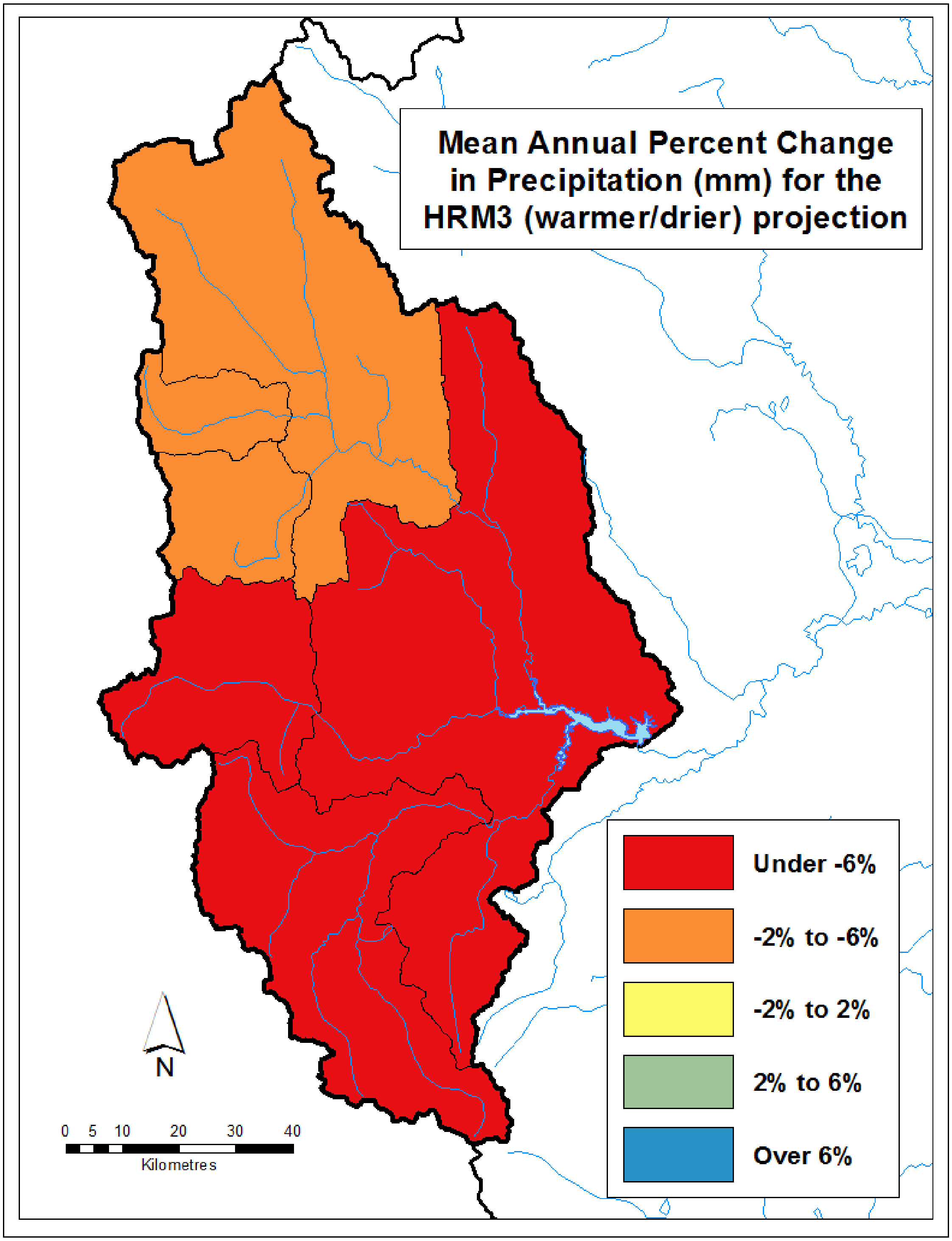


Figure 5-19. Mean annual percent change in precipitation (mm) of HRM3 (warmer/drier) climate projection for the Oldman Reservoir Watershed

5.3.2.3 Streamflow

The predicted changes in streamflow (Q) for the Oldman Reservoir Watershed are shown in Figure 5-21 and Figure 5-23. The RCM3 (cooler/wetter) scenario projected significant reductions of streamflow for the Castle River Watershed (Sub-Watershed 1) of -7.4%, as shown in Table 5-23. However, it projected an increase in streamflow for the rest of the sub-watersheds, ranging from 0.1% to 7.5%. For the HRM3 (warmer/drier), significant reductions of streamflow is projected for the entire watershed, with range of -1.4% to 9.7%. In both scenarios, earlier shifts in timing of mean monthly runoff were predicted across all sub-watersheds, as illustrated in Figure 5-20 and Figure 5-22. More pronounced increases in the winter and early spring flows and considerable reductions in the summer flows for the HRM3 (warmer/drier) climate scenario (see Table 5-25). Although there were considerable increases of winter and spring flows, the RCM3 (wetter/cooler) climate scenario also predicted reductions of summer flows (see Table 5-24). However, these changes are less pronounced compared to the HRM3 (warmer/drier) climate scenario.

Table 5-23. Mean annual percent change in streamflow (Q) changes for both regional climate projections for the Oldman Reservoir Watershed.

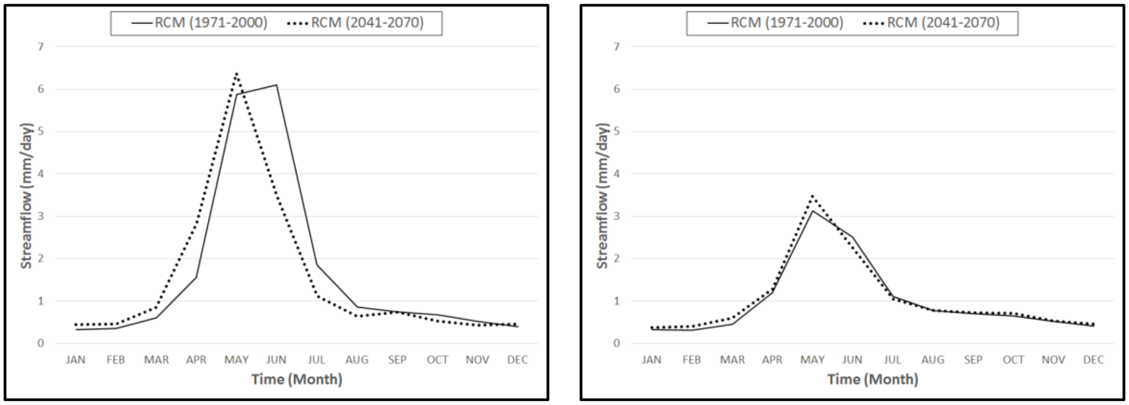
	SUB-WATERSHED					
	1	2	3	4	5	6
RCM3 (wetter/cooler)	-7.4	4.4	2.8	7.5	5.4	0.1
HRM3 (warmer/drier)	-1.4	-9.7	-5.5	-4.2	-3.9	-6.7

Table 5-24. Monthly percent change of streamflow (mm) for 2040-2070 period relative to the 1971-2000 period for the RCM3 (cooler/wetter) regional climate scenario.

	SUB-WATERSHED					
	1	**2**	**3**	**4**	**5**	**6**
J	27.83	12.78	11.42	14.47	12.38	4.07
F	22.54	21.79	32.67	17.76	21.76	17.53
M	29.15	23.62	32.20	26.93	27.11	19.79
A	45.07	7.91	6.22	8.67	8.01	4.64
M	7.92	9.87	11.46	18.03	14.99	9.63
J	-74.66	-11.42	-10.85	-0.82	-3.45	-11.07
J	-65.30	-6.35	-14.79	-5.73	-9.43	-17.03
A	-32.69	-0.25	-5.52	1.19	-0.10	-7.45
S	-0.42	3.05	-0.66	4.23	1.44	-4.20
O	-28.88	9.83	12.32	10.87	8.21	0.02
N	-22.40	0.22	-17.58	2.84	-3.66	-15.48
D	13.51	10.32	12.07	10.66	8.69	-1.10

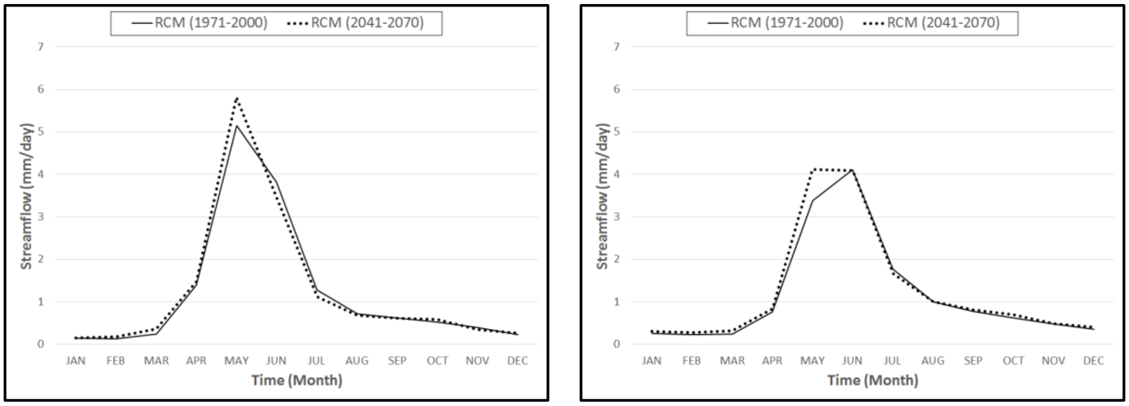
Table 5-25. Monthly percent change of streamflow (mm) for 2040-2070 period relative to the 1971-2000 period for the HRM3 (warmer/drier) regional climate scenario.

	SUB-WATERSHED					
	1	**2**	**3**	**4**	**5**	**6**
J	12.39	4.13	28.73	28.73	28.73	9.55
F	29.75	4.79	23.00	23.00	23.00	10.84
M	26.23	15.01	37.53	37.53	37.53	18.54
A	7.09	39.39	48.98	48.98	48.98	32.27
M	9.80	-4.72	1.58	1.58	1.58	3.31
J	-16.43	-62.44	-62.00	-62.00	-62.00	-50.91
J	-33.26	-32.20	-38.68	-38.68	-38.68	-37.67
A	-14.28	-19.55	-21.96	-21.96	-21.96	-22.12
S	-4.95	-7.08	15.67	15.67	15.67	2.32
O	-0.93	-18.49	-25.11	-25.11	-25.11	-17.09
N	-21.15	-17.16	-37.23	-37.23	-37.23	-23.89
D	4.15	-0.86	5.97	5.97	5.97	-5.03



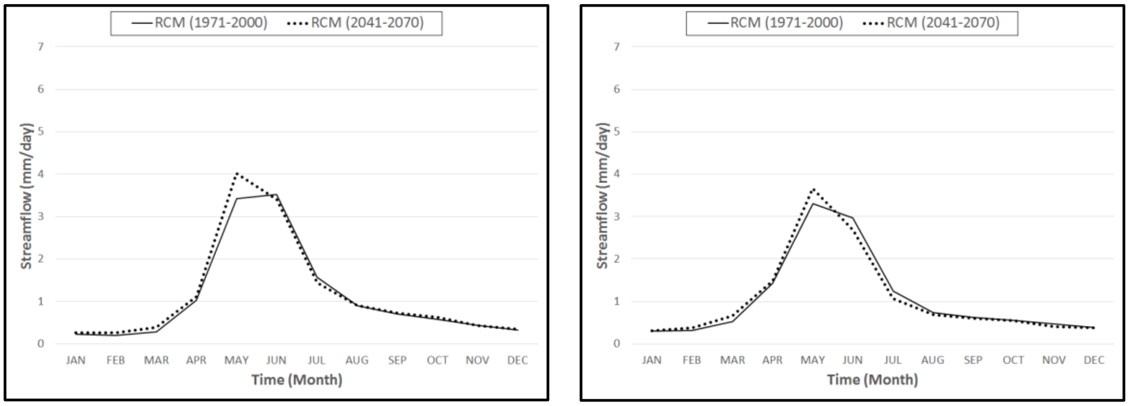
a) Sub-Watershed 1

b) Sub-Watershed 2



c) Sub-Watershed 3

d) Sub-Watershed 4



e) Sub-Watershed 5

f) Sub-Watershed 6

Figure 5-20. Comparison of average streamflow of historical (1971-2000) and future (2041-2070) period for all six sub-watersheds using the RCM3 (cooler/wetter) regional climate projection, driven by CGCM3 global climate model.

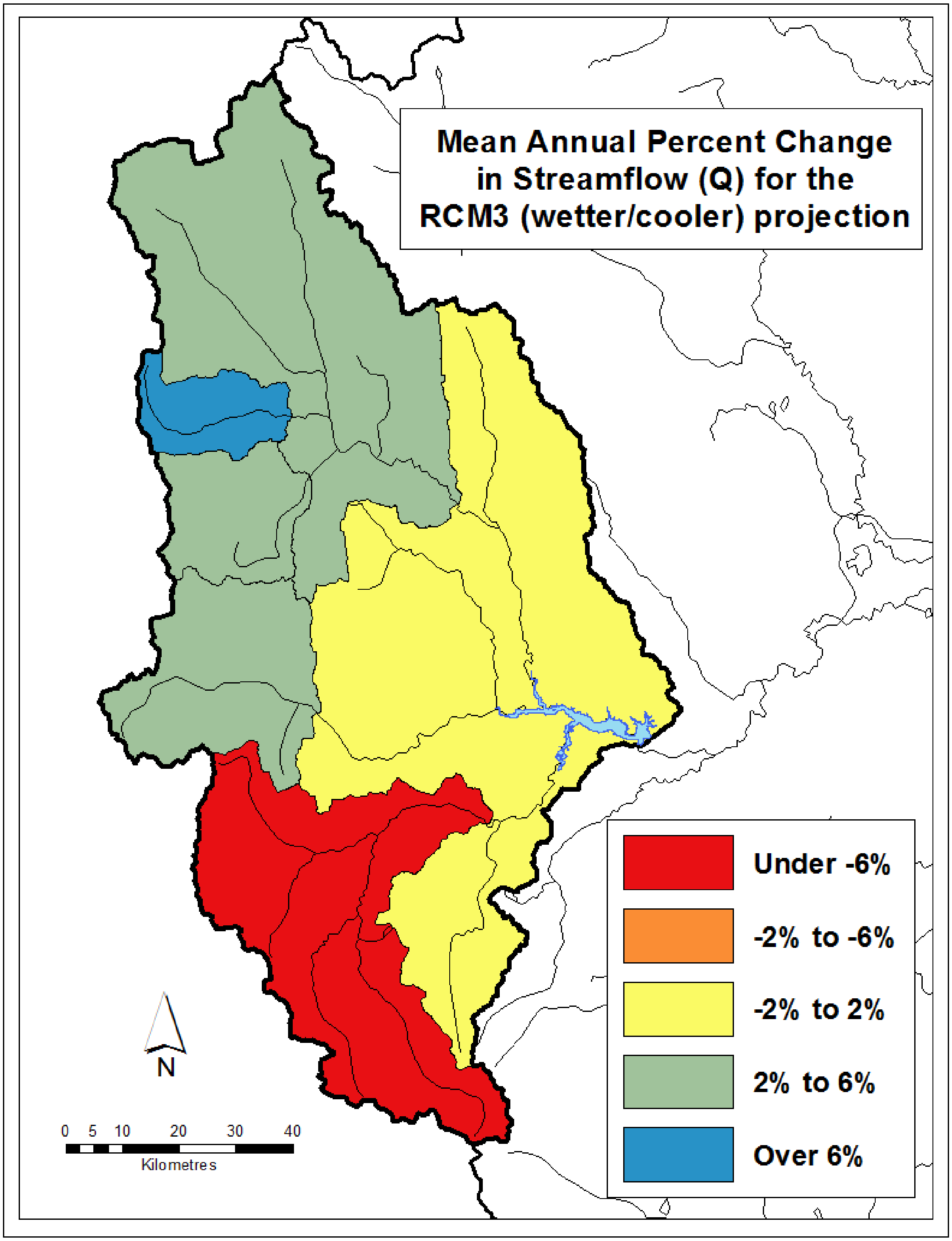
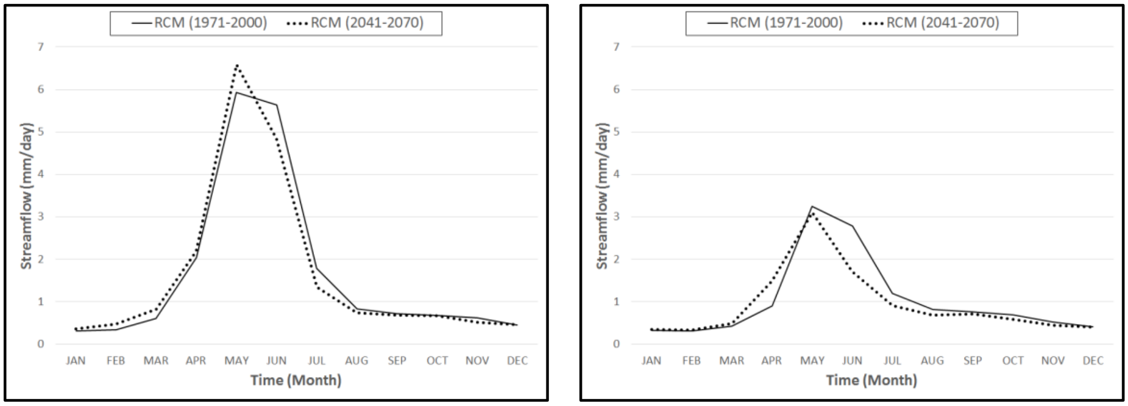
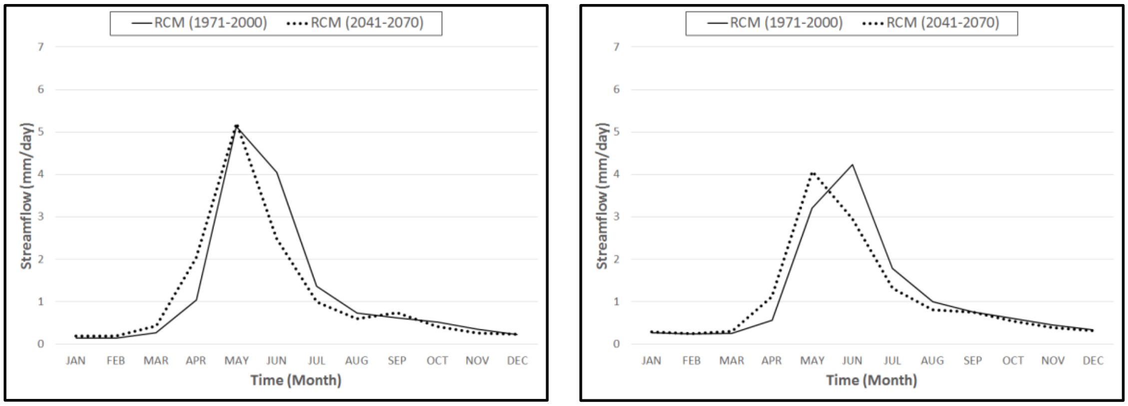


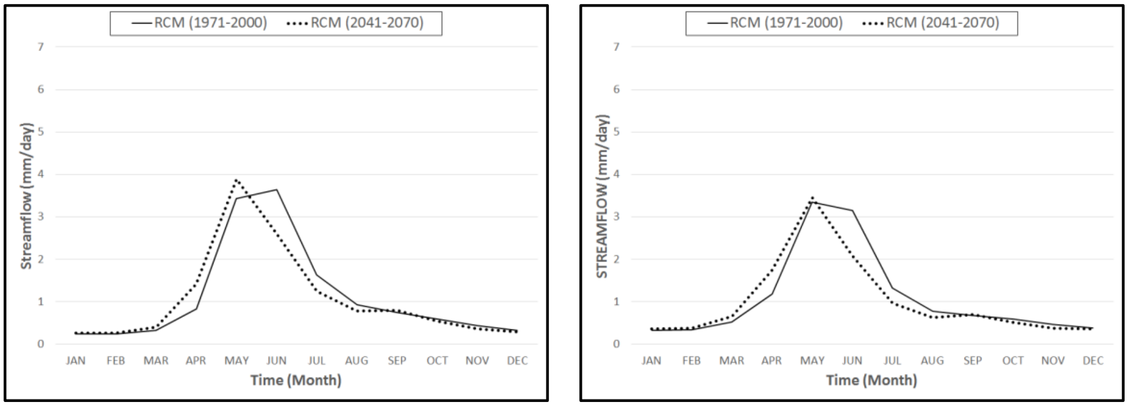
Figure 5-21. Mean annual percent change in streamflow (mm/day) of RCM3 (cooler/wetter) climate projection for the Oldman Reservoir Watershed



a) Sub-Watershed 1 b) Sub-Watershed 2



c) Sub-Watershed 3 d) Sub-Watershed 4



e) Sub-Watershed 5 f) Sub-Watershed 6

Figure 5-22. Comparison of average streamflow of historical (1971-2000) and future (2041-2070) period for all six sub-watersheds using the HRM3 (warmer/drier) regional climate projection, driven by GFDL global climate model

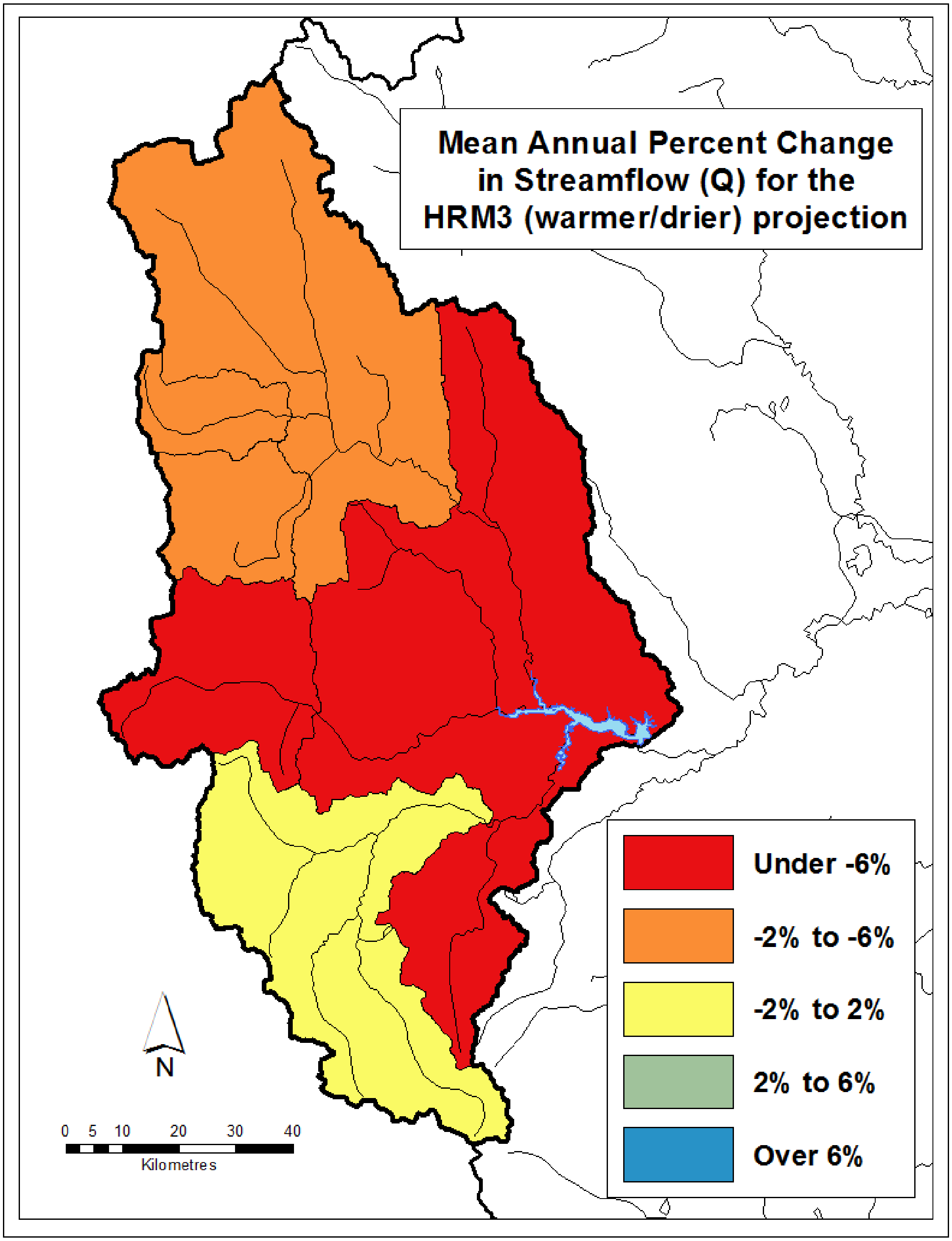


Figure 5-23. Mean annual percent change in streamflow (mm/day) of HRM3 (warmer/drier) climate projection for the Oldman Reservoir Watershed

5.4 Discussion

Based on the findings found in this study, the discussion of model evaluation and projected changes in temperature, precipitation and streamflow for the Oldman Reservoir Watershed is covered in this section.

5.4.1 Hydrological Model Validation

The evaluation of distributed models is more complicated and difficult in comparison to lumped conceptual rainfall-runoff models (Xu & Singh, 2004). The application of a rigorous testing scheme for the Oldman Reservoir Watershed highlighted the need to validate current hydrological models for climate change studies (Andreassian et al., 2009; Bathurst et al., 2004; Coron et al., 2014; Coron et al., 2012; Ewen et al., 1996; Henriksen et al., 2003; Kirchner et al., 1996; Leavesley, 1994; Parkin et al., 1996; Refsgaard & Knudsen, 1996; Tsioptsias et al., 2016; Xu & Singh, 2004). In this study, the ACRU model went through validation using four tests. The statistics for calibration usually performed better than the validation (Moriasi et al., 2007). When compared with previous study within the Oldman River Basin, the available performance statistics for both the temperature and streamflow verification for the Oldman Reservoir Watershed were comprehensive during the calibration and validation phases of the ACRU model (see Table 5-26 and Table 5-27). As with other previous model evaluation tests, the performance ratings for each test decreased at each level of testing. This is consistent with Patil et al. (2015) findings and Moriasi et al. (2007) review of benchmark ratings. In addition, Klemeš (1986) testing scheme showed that the parameter transferability that involves both changing the spatial and climatic conditions performed the least ideal. Again, this is consistent with findings in other climate change studies that utilized differential split-sampling test (Andreassian et al., 2009; Coron et al., 2014; Gharari et al., 2013). However, it is important to note that extremely high average precipitation (1974-1976) period was selected for the calibration of the ACRU model. For simulating dry climate scenario, the low peak flows were adversely affected, although overall model performance was still satisfactory. Essentially, the ability of the ACRU model to reasonably simulate middle and high peak flows during wet and dry climate conditions were validated for the Oldman Reservoir Watershed.

Table 5-26. Comparison of Temperature validation daily performance results between Oldman Reservoir Watershed and Castle River Watershed (Anderson, 2014)

	Oldman Reservoir Watershed	Castle River Watershed
Sample Size	47343	13323
Observed Mean	5.57	-
Simulated Mean	5.37	-
% Difference	3.59	-
Observed Variance	77.76	-
Simulated Variance	80.92	-
% Difference	-4.06	7.88
Observed Standard Deviation	8.82	-
Simulated Standard Deviation	9.00	-
% Difference	-2.04	-
Slope	0.99	0.92
Coefficient of Determination (r^2)	0.94	0.921
Pearson Correlation Coefficient (r)	0.97	-
Root mean square error (RMSE)	0.01	-

Table 5-27. Comparison of Streamflow validation daily performance results between Oldman Reservoir Watershed and Castle River Watershed for calibration (1971-1980) period and validation (1981-1990) period (Anderson, 2014).

	Oldman Reservoir Watershed Calibration	Castle River Watershed Calibration	Oldman Reservoir Watershed Validation	Castle River Watershed Validation
Sample Size	3653	3653	3652	3562
Observed Mean	1.601	-	1.413	-
Simulated Mean	1.609	-	1.454	-
Observed Q	5849.670	-	5159.280	-
Simulated Q	5877.230	-	5308.280	-
Observed Variance	7.888	-	3.867	-
Simulated Variance	6.617	-	4.539	-
% Difference of Variance	16.111	-37.4	-17.398	-75.61
Observed Standard Deviation	2.809	-	1.966	-
Simulated Standard Deviation	2.572	-	2.131	-
% Difference of STD	8.409	-	-8.351	-
Slope	0.822	0.76	1.015	0.66
Y-Intercept	0.292	0.44	0.020	0.36
Coefficient of Determination R^2	0.806	0.802	0.877	-
Correlation Coefficient, R	0.898	-	0.937	-
Root mean square error, RMSE	1.238	-	0.749	-
RMSE-observed standard ratio, RSR	**0.441**	**-**	**0.381**	**-**
Percent Bias, PBIAS	**-0.471**	**3.46**	**-2.888**	**-9.14**
Nash Sutcliffe Efficiency Index, NSE	**0.806**	**0.80**	**0.855**	**0.75**
Modified NSE	0.726	-	0.713	-
Index of Agreement, D	0.944	-	0.966	-
Modified D	0.861	-	0.859	-

5.4.2 Projected Changes in Temperature, Precipitation and Streamflow

The climate scenario approach for modelling regional hydrological impacts under a changing climate was applied in Oldman Reservoir Watershed. The approach applied in this study is consistent with other studies that focus on modelling hydrological impacts using regional climate data (Chiew, 2010; Graham, Andréasson, et al., 2007; Graham, Hagemann, et al., 2007; Peel & Blöschl, 2011). After carefully spatially matching the resolution to the observed 10 km climate grid time series, the overall seasonality and magnitude of the 1971-2000 climate was replicated for the regional climate models. However, despite the careful downscaling methods, the selection of scenarios reflected the uncertainty in the future regional projections for the Oldman Reservoir Watershed. Only two scenarios were simulated for this study, the RCM3 (cooler/wetter) and HRM3 (warmer/drier) climate scenarios.

Based on the regional simulation of two climate scenarios, changes in higher mean summer temperature and seasonal shift in hydrology were projected for the Oldman Reservoir Watershed. Several key climate indicators of higher temperatures and decreasing volumes of snowpack, earlier snowmelt and decrease in summer soil moisture have been reported in North America (Barnett et al., 2005; Barnett et al., 2008; Gleick, 1987; Mortsch et al., 2015; Romero-Lankao & Ruiz, 2014; Sauchyn & Kulshreshtha, 2008). Streamflow declines have already reported in the northern regions of the Rocky Mountains (Rood et al., 2005), which means changes to the magnitude and the duration of peak spring flows for Alberta (Rood et al., 2008). In southern Alberta, declines in mean annual streamflows have been recently reported (Cohen et al., 2015; Forbes et al., 2011; Romero-Lankao & Ruiz, 2014; Shepherd et al., 2010). Interestingly, the Oldman River Basin, which encompasses the Oldman Reservoir Watershed, is a semi-arid region characterized with high spring melt, late spring heavy rains and low summer flows (Poirier et al., 2011). The findings of this study projected similar changes in temperature, precipitation and streamflow and are similar to the finding found in previous studies for the region (Anderson, 2014; Forbes et al., 2011). Decreasing precipitation and earlier spring floods could potentially impact the freshwater resources and the riparian and floodplain areas within the region (Rood et al., 2008; Rood et al., 2005).

Irrigation is an important livelihood in Alberta. It enables the highly intensive agricultural production despite the inherent moisture deficiencies within the region. The projected changes of climate will reduce soil moisture and water availability for the region (Kulshreshtha, 2011; Romero-Lankao & Ruiz, 2014). Reduced precipitation and heavier downpours could lead to lower crop yields and flooding (Kulshreshtha, 2011). Although, historical crop yields are attributed to increasing temperatures for Canada (Romero-Lankao & Ruiz, 2014), the quality and availability of water diverted to the Oldman Reservoir and for the Lethbridge Northern Irrigation District (LNID) will be impacted by the potential hydrological impacts of climate change where projections in this study predict significant higher winter flows, earlier spring melt and considerable reduction in summer flows. The average gross annual diversion may be further reduced than current water licence allocation for the regional irrigation districts. Thus, the potential hydrological impacts of climate change will continue to add pressure for irrigation and agriculture within Oldman River Basin in the future.

5.4.3 Uncertainty in Hydrological Modelling

There are many sources of uncertainty in hydrological modelling. Despite the application of a rigorous modelling framework that involved extensive calibration of the ACRU model, many scholars argue about the considerable amount of uncertainty in hydrological modelling studies (Abebe et al., 2003; Athira et al., 2016; Bathurst et al., 2004; Benke et al., 2008; Beven, 1989, 2012; Beven et al., 2012; Bocchiola et al., 2013; Butts et al., 2004; Oni et al., 2014; Prudhomme et al., 2003; Refsgaard et al., 2006; Rochester, 2010; Sivapalan et al., 2003; Teutschbein et al., 2011; Uhlenbrook et al., 1999; Wagener et al., 2003). Sources of uncertainty come from parameter identification, estimation and objective approach used during model calibration, data sources that involved data observations and measurement errors, the selection of global climate models that drive regional climate scenarios, and model structure uncertainty with the bias-correction methods used in the downscaling techniques and the choice of hydrological models and the conceptual structure of the model chosen. However, due to the scope of this research, structure uncertainty of the ACRU model was not considered and therefore will not be discussed. The regional hydrological modelling ensemble chosen for this study is, nevertheless, inherent with uncertainty.

5.4.3.1 Parameter Identification and Estimation

One of the biggest sources of uncertainty is the model parameterization used in the study. One of the task of a modeller is to identify the parameters suitable for the watershed in question. Wagener, Wheater, et al. (2004) argued the importance of the parameter set that is characteristic of the watershed, data available and the modelling purpose. The parameters for the ORW were initially derived from a previous study of the Castle River Watershed. The donor watershed share similar geology, hydrology and climatology with Oldman Reservoir Watershed. The transfer of parameters from Castle River Watershed to the Oldman Reservoir Watershed was assumed to provide some certainty due to the excellent modelling results in the Castle River Watershed (Anderson, 2014). The parameter values for temperature lapse rates were used in the validation phase as well as in the model application using future regional climate projections. Nevertheless, the Castle River Watershed is not entirely representative of the entire Oldman Reservoir Watershed. The transfer of parameters added uncertainty to the model calibration and validation and has been discussed in literature (Athira et al., 2016; Bárdossy, 2007; Beven, 1996; Buytaert & Beven, 2009). However, further calibration of the parameters was undertaken for each gauged sub-watershed. The identification and estimation of parameters suitable to the watershed characteristics proved to be a difficult task due to the inherent heterogeneous characteristics of hydrological response units across the Oldman Reservoir Watershed. Likewise, the simulation of the ungauged watershed solely relied on the Klemeš (1986) proxy-basin test. Overall, more than 100 model runs were employed in the Oldman Reservoir Watershed. Although, it adequately validated the spatial transferability of two gauged watersheds in the ORW, caution must still be used when validating the ACRU model in other study areas. Thus, finding an optimal parameter set that is suitable for a particular study area may not be representative of other similar watersheds.

In addition, the selection and utilization of certain performance criteria impact the parameter identification and estimation of hydrological models during calibration runs. Although an extensive evaluation procedure was applied for the ACRU model using four-level model testing scheme, a multi-objective criteria was considered. Previous research on hydrological modelling exercises found biases with certain performance criteria and the uncertainty of errors was reduced by utilizing more than one criterion (Boyle et al., 2000; Gupta et al., 2006; Khakbaz et al., 2012; Lamb, 1999; McCuen, 1973; Vrugt et al., 2003; Wagener et al., 2003; Wagener et al., 2011; Yapo et al., 1998).

5.4.3.2 Data Sources

Most observed data are scarce, intermittent and prone to different measurement scales and errors to the exclusion of higher elevation locations, which makes modelling hydrological impacts a challenging task to undertake (Athira et al., 2016; Bárdossy, 2007; Beven, 2012; Blöschl, 2016; Hrachowitz et al., 2013; Merz et al., 2004; Peel & Blöschl, 2011; Sivapalan, 2003; Sivapalan et al., 2003; Wagener, Sivapalan, et al., 2004; Wagener, Wheater, et al., 2004; Winsemius et al., 2009). For instance, similar to previous research studies of ACRU model within the Oldman River Basin, no fieldwork was carried out in the study of the Oldman Reservoir Watershed. For this study, the daily 10k gridded dataset compiled by Hutchinson et al. (2009) was used as an observed input data. However, Kienzle and Mueller (2013) found that the precipitation estimates are a source of uncertainty due to the lack of high latitude climate stations. In addition, the lack of mid latitude and elevation climate stations was considered for solar radiation, sunshine hours, humidity and wind speed. Therefore, data corrections were utilised so that higher elevation can be considered in this study.

Moreover, the selection of regional climate model projections are considerable sources of uncertainty. One of the challenges is factoring uncertainty and whether certain approaches are deemed appropriate where a small set of climate scenarios or very large numbers should be used to characterize the potential hydrological impacts of climate change on water resource (Jiménez Cisneros et al., 2014). Although this is beyond the scope of this study, the chosen bias-correction technique and the assumption of stationary model errors attribute to the data uncertainty related to the regional climate model (Barrow & Yu, 2005; Bergström et al., 2001; Graham, Hagemann, et al., 2007; Jiménez Cisneros et al., 2014; Teutschbein, 2013; Teutschbein & Seibert, 2010, 2012; Teutschbein et al., 2013; Teutschbein et al., 2011). The RCM3 (driven by the CGCM3 Global Climate Model) and the HRM3 (driven by GFDL Global Climate Model) each used a different climate forcing of greenhouse gas emissions and boundary conditions. It is evident that even with the successful spatial downscaling of the bias-corrected RCM data, uncertainties are more pronounced in mountain regions like the upper watersheds in the Oldman Reservoir Watershed. Although the historical (1971-2000) time series closely matched the seasonality and magnitude of the 1971-2000 climate normal streamflow behaviour, the downscaling technique used in this study can be attributed to adding uncertainty. Therefore, even with better correction techniques, there is still considerable uncertainty that could be attributed to the regional climate data projections used in impact assessment of water resources.

5.5 Summary

The evaluation of the ACRU model demonstrated the much-needed universal guideline for assessing hydrological models in climate change studies. The proposed combined methodology for a rigorous model evaluation highlighted key trends and important insights into the ability of the ACRU model to be representative of heterogeneous ungauged watershed in the Oldman Reservoir Watershed. The ACRU model was able to simulate temperature and streamflow in an ungauged watershed within the ORW based on the proxy-basin test. In addition, the ACRU model was able to simulate hydrological impact under changing climate conditions using the differential split-sample test. Although the performance of ACRU model was overall good, the proxy-basin differential split-sample test adequately highlighted the ACRU model's ability to simulate middle and high flows well under a future dry climate scenario compared to wet climate scenario. Projected increases in temperature coupled with decrease in precipitation as well as earlier spring melt were noted based on the two selected bias-corrected regional climate model projections for the Oldman Reservoir Watershed. Considerable uncertainty can be attributed to the many sources, most notably, the final parameter set used for each watershed, the selection of regional climate projections and their bias-correction methods for downscaling techniques, and the data observations available for the study area. Despite the inherent uncertainties in hydrological modeling of climate change impacts, this study has added more credibility to the ACRU model for modelling in an ungauged watershed, under changing climate conditions in southern Alberta.

CHAPTER 6

SUMMARY AND RECOMMENDATIONS

6.1 Summary

The ACRU agro-hydrological model was evaluated based on its ability to simulate hydrological responses of climate change within the Oldman Reservoir Watershed using a rigorous model-testing scheme. For this study, Klemeš (1986) four-level model testing scheme was applied for the entire Oldman Reservoir Watershed (ORW). Likewise, it was critical to overcome the modelling challenges that any distributed and physically-based hydrological models face. These challenges required the data management of large datasets consisting of bio-physical parameters and hydro-climatological time series and a more efficient data analysis as part of the ACRU modelling system. Overcoming these challenges through the development of various utility tools became the secondary objective of this study. This subsequently facilitated the operational use of the ACRU model efficiently in a distributed environment.

There are many challenges in utilizing a distributed physical-based hydrological model for climate change impact assessment. The utilization of the ACRU model using the hydrological response unit (HRU) approach required large data management, processing, and analysis. The increasing operational challenges in utilizing the ACRU model for regional climate modelling required the development of utility programs that resolved the current operational constraints. Overall, ten different programs were developed for the ACRU model. The utility tools developed for the ACRU model encompassed: (1) ACRU-Hydro-Climatological Data File Generator, HRU Delineation Tool, ACRU Correction Factors and RCM Downscaling Tool for the purposes of data processing; (2) ACRU MenuBuilder v2.0 and SubMenu program for the purposes of parameterization; and (3) The Canadian Climate Data Scraping Tool, ACRU-CCDST Temperature Verification Tool, ACRU-HYDAT Streamflow Verification Tool and ACRU –RCM Analysis Tool for comprehensive data analysis. With the adoptions of new utility programs, ACRU model users can utilize the model in increasingly efficient, consistent, and accurate manner.

The ORW was divided into 6 watersheds, based on the gauging station location that defined the outlet. However, at the outlet of ORW is the Oldman Reservoir, which was assumed to be ungauged. Each watershed was further divided into hydrological response units based on elevation, land cover, solar radiation, climate grids, and watershed boundary. This resulted in a total of 1706 HRUs, the largest number applied to the ACRU model in the Canadian context. Each HRU underwent parameterization in order to validate the ACRU model against two observed data sets: (1) daily air temperature from 10 climate stations, and (2) daily streamflow observations from 5 gauging stations. The model evaluation focused on certain performance criteria that use both statistical and graphical benchmarks. Simulation accuracy was noted on the final calibration and validation. The Klemeš (1986) four-level model testing scheme provided a framework to rigorously evaluate hydrological models using increasingly complicated tests: split-sampling test, the proxy-basin test, the differential split-sampling test and the proxy-basin differential split-sampling test. Due to the labour-intensive data processing and analysis, the automation and development of utility programs allowed for a more efficient and accurate model calibration and validation of the ACRU agro-hydrological model. Thus, the data and methods presented in this study effectively allowed the first careful and rigorous testing of the ACRU model of an ungauged watershed in a changing climate.

The evaluation of distributed models are typically complicated. In this study, the initialization, calibration and validation of the ACRU model required thousands of hydrological response units involving a 57 bio-physical parameters and 8 hydro-climatic variables alone. In addition, the heterogeneity of the climate data, parameter values, and differences between other measurement scales also contributed to the complexity and difficulty of model validation. Despite these complexities, the results of the present study showed that the ACRU model could be used with confidence to simulate temperature and streamflow in the snow-dominated watershed such as the Oldman Reservoir Watershed. Due to the scope of this study, the model evaluation method focused on comparison of predicted and observed temperature and streamflow data.

This research has highlighted the importance of rigorously testing a hydrological model for climate change studies. Klemeš (1986) four-level model testing scheme was applied in this study. Klemeš (1986) described the model-testing scheme as modest and urges its use outside the field of hydrology. The implementation of a rigorous model-testing scheme has been lacking, with much emphasis placed on utilizing the split-sample test as the standard test used in evaluating hydrological models for climate change studies (Andreassian et al., 2009; Bathurst et al., 2004; Coron et al., 2014; Coron et al., 2012; Ewen & Parkin, 1996;

Henriksen et al., 2003; Kirchner et al., 1996; Leavesley, 1994; Parkin et al., 1996; Refsgaard & Knudsen, 1996; Tsioptsias et al., 2016; Xu & Singh, 2004). However, the simple-sample test is an inadequate assessment test of model credibility. The multiple-performance criteria used in this study allowed a comprehensive look at the ACRU model's performance. Thus, the confidence in the ACRU model's ability to simulate under stationary conditions is quite excellent but was not adequate for the purposes of climate change studies.

The challenge of evaluating the ACRU model for ungauged watershed was recently considered. By adding more rigorous validation methods, the ability of the ACRU model can be carefully tested. The spatial transferability is discussed in many studies regarding predictions of ungauged basins (PUB) (Blöschl, 2016; Hrachowitz et al., 2013; Klemeš, 1986; Leavesley, 1994; Sivapalan, 2003, 2006; Sivapalan et al., 2003; Wagener, Sivapalan, et al., 2004; Wagener et al., 2010; Xu & Singh, 2004) but rarely utilized in validation of hydrological models. The challenge of predicting on ungauged basins has been widely recognized as one of the most difficult challenges in hydrologic studies (Sivapalan, 2003; Sivapalan et al., 2003; Xu & Singh, 2004). The proxy-basin test was one of the approaches that could be used for ungauged studies along with other regionalization techniques used for ungauged watersheds. The results highlighted the ability of the ACRU model to simulate streamflow in an ungauged watershed (Leavesley, 1994; Xu & Singh, 2004).

On the other hand, the importance of climatic transferability for hydrological models used in climate change studies is widely discussed (Kirchner, 2006; Patil & Stieglitz, 2015; Peel & Blöschl, 2011; Seibert, 2003; Thirel et al., 2015). Klemeš (1986) proposed the differential split-sample test, which aims to narrow this gap. The test was applied to the ACRU model and showed its adequate predictive ability to simulate low, middle and high peak flows for the Oldman Reservoir Watershed. Ultimately, the ACRU model can be utilized under changing climate.

The last and more rigorous of all four tests, the proxy-basin differential split-sample test focused on the climatic transferability from gauged to ungauged watersheds. Similar to the findings of Patil and Stieglitz (2015), the parameter transferability that involves both changing spatial and climatic condition performed the least ideal. The low peak flows were adversely affected, although the model performance was still satisfactory. Essentially, this test showed the ability of the ACRU model to reasonably simulate high peak flows during wet and dry climate conditions.

Overall, the application of the hierarchical testing scheme to the ACRU model highlighted several key findings. Indeed, the performance of the ACRU model decreased as it underwent each level of testing. This is consistent with Patil and Stieglitz (2015) findings where the parameter transferability schemes under temporal conditions performed superior compared to the spatial and spatiotemporal parameter schemes. Based on the findings of this study, the ACRU model could be used with confidence to simulate temperature and streamflow in the ORW. However, it is clear that the performance of the calibrated ACRU model is significantly reduced when simulated against different spatial and climate conditions (Andreassian et al., 2009; Coron et al., 2014; Gharari et al., 2013). By considering the spatial and climatic transferability of the ACRU model, the hierarchical model testing can be seen as further adding credibility to the ACRU model in snow-dominated watersheds like the Oldman Reservoir Watershed.

The regional hydrological impacts under a changing climate were considered in Oldman Reservoir Watershed. Future climate projections were downscaled to spatially match the observed values using a delta change method, where the differences between baseline present and future climate were considered. After spatially matching the resolution of the observed data, the projected changes in temperature and precipitation were analysed. This study found similar projected higher summer temperatures, increasing winter flow, decreasing summer flows as well as earlier spring flows expected in North America (Barnett et al., 2005; Barnett et al., 2008; Gleick, 1987; Mortsch et al., 2015; Romero-Lankao & Ruiz, 2014; Sauchyn & Kulshreshtha, 2008). Based on the ACRU model simulation of two regional climate scenarios, similar potential future changes in temperature, precipitation and streamflow for the Oldman Reservoir Watershed. The findings of this study also follow the findings in previous studies within the Oldman River Basin (Anderson, 2014).

The methodology for a rigorous model evaluation highlighted key trends and important insights regarding the ACRU model. The model has the ability to be representative of a heterogeneous, ungauged watershed in the Oldman Reservoir Watershed using the HRU approach to predicting streamflow behaviour. The ACRU model was able to simulate temperature, precipitation and streamflow in an ungauged watershed. Nevertheless, the performance of ACRU model under the proxy-basin differential split-sample test adequately highlighted its ability to simulate middle and high flows better under a future dry climate scenario. However, considerable uncertainty can be attributed to the final parameter estimation used for each watershed, the selection of regional climate projections and their bias-correction methods for downscaling techniques, as well as the available data observations for the study area.

Many scholars argue about the considerable amount of uncertainty in hydrological modelling studies (Abebe & Price, 2003; Athira et al., 2016; Bathurst et al., 2004; Benke et al., 2008; Beven, 1989, 2012; Beven & Alcock, 2012; Bocchiola et al., 2013; Butts et al., 2004; Oni et al., 2014; Prudhomme et al., 2003; Refsgaard et al., 2006; Rochester, 2010; Sivapalan et al., 2003; Teutschbein et al., 2011; Uhlenbrook et al., 1999; Wagener et al., 2003). The sources of uncertainty are extensive. These uncertainties are identified as the model uncertainty, model parameter estimation and data sources uncertainty. Emphasis on uncertainty was directed at the model parameter estimation and data sources, which involved the selection of global climate models that drive regional climate scenarios. The regional hydrological modelling ensemble approach chosen for this study is, nevertheless, inherent with uncertainty.

Notwithstanding the inherent uncertainties in hydrological modeling, the present study has added credibility to the ACRU model for simulating potential hydrological impacts of climate change for both gauged and ungauged watersheds in southern Alberta, where the potential hydrological impact of climate change could have adverse effects on the future of irrigation and agriculture. Consequently, by overcoming the operational challenges inherent with model upgrades, the rigorous model testing of the ACRU model for assessing the hydrological impacts of climate change became possible as it has not been applied to previously studied watersheds in Canada. Therefore, allowing a more accurate and efficient data management, processing and analysis for the ACRU model in Canada.

6.2 Recommendations

Future research opportunities can further enhance our understanding of the ability of the ACRU model in snow-dominated regions. The ACRU model was evaluated based on its ability to simulate only the temperature and streamflow data on a daily and monthly time scale in the Oldman Reservoir Watershed. Due to the scope of this research, evapotranspiration, soil moisture and snow-water equivalent data were not considered in the model validation of the ACRU model. In addition, glacier melt contributions were not compared against available data. The snowmelt routine, which is newest module added on to the ACRU model, could not be fully tested. Therefore, additional extensive validation using multiple climatic variables would further improve credibility in the ACRU model predictions in the region.

Given the operational challenges of the ACRU model, better parameterization could optimise model calibration and validation. This will assist in further understanding key sensitivity of parameters for the ACRU model. Typically, the automatic calibration scheme employs single-objective criteria whereas the manual calibration is more laborious and subjective. Nonetheless, most hydrological studies considered the manual calibration to be superior compared to automatic calibration. A hybrid approach to calibration will efficiently and accurately analyse predicted values against observed data in both gauged and ungauged watershed. This will ensure that multi-objective performance criteria can be used with the automatic model simulations for the ACRU model. Essentially, expert hydrologists can still exercise analysis of the visual techniques that show how low, middle and high flows are simulated properly.

Lastly, the selection of regional climate models for this research did not cover the full spectrum of future climate scenarios for the region. Dr. David Sauchyn provided the available regional climate models that have undergone bias-correction procedures. The selection of regional climate models were based on the model evaluation strategy employed for this study. More importantly, only two regional scenarios and one future period (2041-2070) were considered in this study. It may be useful to assess a remaining climate scenarios and a range of future time periods for the Oldman Reservoir Watershed based on the present available regional climate scenarios for southern Alberta.

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APPENDIX I

ACRU MODEL UTILITY REPOSITORIES

This appendix briefly lists the repository that contains all the code for each utility tool for this study. An online repository lets the developer organize all files and folders that pertains to a single project. Anytime a project goes through a change, a commit can be done in order to capture version of the project at a specific point in time (GitHub, 2016). Check out GitHub (2013) for more information on understanding GitHub flows,

1) ACRU-Hydro-Climatological Data File Generator

   This program consists of the data file generator programs used to create a 7 variable input file for the ACRU model.

   The online repository can be found here:
   https://github.com/charmainebonifacio/acru_compf7

2) HRU Delineation Tool

   This program allowed for the automated delineation of 5 different layers within ArcGIS environment. There is an option to work within the ArcGis environment or use as a standalone project.

   The online repositories can be found here:
   ArcGis Environment: https://github.com/charmainebonifacio/acru_hru
   Standalone : https://github.com/charmainebonifacio/acru_hru_sa

3) ACRU Correction Factors

   This program allows the automatic calculation of correction factors for precipitation, solar radiation, sunshine hours, relative humidity and wind speed as the differences tend be larger in the mountainous regions.

   The online repository can be found here:
   https://github.com/charmainebonifacio/acru_corfac

4) RCM Downscaling Tool

   This program takes care of calculations for downscaling the RCM data into 10K scale.

   The online repositories can be found here:
   Step 1: https://github.com/charmainebonifacio/rcm_average
   Step 2: https://github.com/charmainebonifacio/rcm_ratio
   Step 3: https://github.com/charmainebonifacio/rcm_compf7

5) ACRU MenuBuilder v2.0

This program consists of the initialization and calibration phases of menu building exercise for the ACRU Model.

The online repositories can be found here:
https://github.com/charmainebonifacio/acru_menu_macro
https://github.com/charmainebonifacio/acru_menu_init
(for initializing menu with initial parameter values)
https://github.com/charmainebonifacio/acru_menu
(for calibrating parameters)

6) ACRU SubMenuBuilder

This program allows the creation of a sub menu file for a sub-watershed study using the ACRU Model.

The online repository can be found here:
https://github.com/charmainebonifacio/acru_menu_range

7) The Canadian Climate Data Scraping Tool

The Canadian Climate Data Scraping Tool (CCDST) has been published by the Computers & Geosciences Journal.

The online repository can be found here:
https://github.com/charmainebonifacio/cageo

8) ACRU-CCDST Temperature Verification Tool

This program is used with the CCDST to verify simulated data against observed data. It calculates comparative statistics for minimum, maximum and mean temperatures, creates scatter plots and line graphs to compare seasonality.

The online repository can be found here:
https://github.com/charmainebonifacio/acru_ver_temp

9) ACRU-HYDAT Streamflow Verification Tool

This program is used during the process of model calibration/validation for ACRU output file. It calculated comparative statistics between observed and simulated streamflow data, calculate Nash-Sutcliffe Efficiency Index, create annual hydrographs, mean monthly scatterplots and flow duration curves.

The online repository can be found here:
https://github.com/charmainebonifacio/acru_ver_strmfl

10) ACRU-RCM Analysis Tool

This programs allows the analysis of the RCM data after it has been simulated in the ACRU model.

GUI: https://github.com/charmainebonifacio/acru_rcm