Uncertainty in Streamflow Simulation of the Upper Assiniboine River Basin

By

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ABSTRACT

There is an increasing interest in assessing uncertainty and quantifying its impact on hydrological modeling. Four major sources of uncertainty are recognized in hydrologic modeling: (1) input uncertainty mainly due to error in model forcing data, such as error in precipitation measurement; (2) model structure uncertainty arising because models are only an approximation of reality; (3) parameter uncertainty originating because not all the parameters can be measured; and (4) output uncertainty given measurement error in streamflow data against which hydrologic models are calibrated. Despite significant development in computational science, the issue of reducing uncertainty remains a challenge especially its consideration in operational use is often ignored.

This research lies in the context of the Natural Sciences and Engineering Research Council (NSERC) funded FloodNET project that aims at developing advanced knowledge, tools, and technologies that will allow Canada to better face the reality of floods. The key of the FloodNet is the collaboration between academic experts, government scientists, and end-users i.e. operational flood forecasters which will ensure that the new knowledge and technology developed will meet the users' needs. Thus research has been carried in close collaboration with the Manitoba Hydrologic Forecasting Center (HFC) and the procedures put in place are studied.

With the overall FloodNet objective and the challenges faced by the Manitoba HFC, this research constructed a modified form of Soil Water Assessment Tool (SWAT) hydrologic model to better suit Prairie landscape characteristics to minimize and address uncertainty arising from the dynamics of contributing and non-contributing area. The modified model, together with its standard version, was applied to the Upper Assiniboine River Basin (UARB) at Kamsack. Significant improvement was observed in the case of the modified model as compared to the

original SWAT model. The modified model was then utilized to assess long-term uncertainty due to coupled impacts of climate and land use change (Prairie pothole removal) on downstream hydrology. Land use change scenarios were combined with future climate change scenarios to assess the importance of pothole wetlands in flood proofing and future water availability. Results suggest that while pothole wetlands are important, climate is the main driver in the future hydrologic regime of the study watershed.

Lastly, this study evaluated the performance of the modified model together with a Manitoba HFC operational model to help quantify uncertainty in streamflow forecasting within the UARB. Ensemble Streamflow Prediction (ESP) was investigated using a multi-model approach and post-processing tools developed to improve ensemble decision-making capacity for the HFC.

Uncertainty has been recognized as an essential component in both research and for operations, which provides added value in water resources related decision making. In fact, informed prediction uncertainty can increase confidence in forecasts, which are most certainly imperfect. Through this research, an attempt to address PPR relevant aspects of uncertainty have been demonstrated to increase confidence in streamflow forecast and to enhance decision-making capacity of the forecasting centres across Prairies.

ACKNOWLEDGMENTS

Many people and institutions have helped make this research possible. Firstly, I want to thank my late supervisor Dr. Peter Rasmussen, who is a key part to the journey of this research. His memory will be with me always. I will be ever grateful for his assistance and am sorry that he has not lived to see me graduate.

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CONTRIBUTIONS OF CO-AUTHORS

The thesis benefited from the contributions of multiple co-authors most notably from the manuscripts presented below. All authors contributed in providing critical feedback and helped shape the manuscripts. However, the overall analysis, results, discussion, and summary are chiefly of my own work.

Chapter 3

Impact of Model Structure on the Accuracy of Hydrological Modeling of a Canadian Prairie Watershed

(Muhammad, A., Evenson, G.R., Stadnyk, T., Boluwade, A., Jha, S., Coulibaly, P.)

Dr. Grey Evenson, assisted in model calibration and parameter optimization. Drs. Alaba Boluwade, and Sanjeev Kumar assisted with the study design. In addition to the manuscript editing, Dr. Tricia Stadnyk provided discussion and aided with the interpretation of the model results. Dr. Paulin Coulibaly helped in editing the manuscript. All the co-authors reviewed the manuscript before and during the submission process to the Journal of Hydrology: Regional studies.

Chapter 4

Assessing the importance of potholes in the Canadian Prairie Region under future climate change scenario **(Muhammad, A., Evenson, G.R., Stadnyk, T., Boluwade, A., Jha, S., Coulibaly, P.)**

This research has greatly benefited from the computational resources made available by the US-EPA through the help of Dr. Evenson, who not only provided insights on model calibration but helped execute model runs. Dr. Stadnyk contributed to the design of the climate change study methodology, provided edits, and interpretation of the model results. Bias correction code was made available in Matlab from Michael Viera of Manitoba Hydro, who developed the code during the times of his MSc study under the supervision of Dr. Stadnyk. Drs. Boluwade, and Jha provided critical feedback on framing research findings. Dr. Coulibaly aided in the review and editing of the manuscript.

Chapter 5

Multi-model approaches for improving seasonal ensemble streamflow prediction scheme with various statistical post-processing techniques in the Canadian Prairie Region **(Muhammad, A., Stadnyk, T., Unduche, F., Coulibaly, P.)**

Dr. Tricia Stadnyk provided valuable insights on overall improvement to the representation of this manuscript. Dr. Fisaha Unduche provided access to the HFC operational models. Dr. Paulin Coulibaly help in connecting with HFC and editing the manuscript. All the co-authors review the manuscript before and during the submission process to the Water-MDPI.

ACRONYMS

AAFC	Agriculture and Agri-food Canada
CaPA	Canadian Precipitation Analysis
CNHRI	Canada's National Hydrology Research Institute
DEM	Digital Elevation Model
DHI	Danish Hydraulic Institute
ECCC	Environment and Climate Change Canada
GIW	Geographically Isolated Wetland
JRC	Joint Research Centre
LU-UK	Lancaster University, United Kingdom
PPR	Prairie Pothole Region
RRB	Red River Basin
SMHI	Swedish Meteorological and Hydrological Institute
SWAT-PDLD	SWAT- Probability Distributed Landscape Depression
UARB	Upper Assiniboine River Basin
UoS	University of Saskatchewan
US- EPA	United States- Environmental Protection Agency
USDA-ARS	United States Department of Agriculture-
USGS	United States Geological Survey
WSC	Water Survey of Canada

1 INTRODUCTION

1.1 Project Background and Motivation

Floods are recognized as the most costly and frequently occurring natural disaster claiming approximately, 20,000 lives and affecting 20 million people every year worldwide (Kellens et al., 2013). The Canadian disasters database (Public Safety Canada, 2015) reported 298 flooding events during the period 1900 - 2014, almost five times as many as the second most common disaster. Many studies, including one by the Natural Resources Canada, predict that flooding is likely to get worse as the atmosphere heats up and increases its capacity to retain moisture. The occurrence of severe flooding events is a reality. In Canada, storms that used to come along only every 40 years are now occurring every six years in some regions (Insurance Bureau of Canada, 2012; McDonald and Alexander, 2014).

A large number of floods in Canada are due to increasing streamflow during the spring freshet. Streamflow in spring rises abruptly due to the melting of snow that has accumulated during the winter months. The Canadian Prairie region (CPR), which includes the provinces of Manitoba, Saskatchewan, and Alberta, in recent years, has experienced several major floods that have had a severe impact on people and infrastructure. The 1997 Red River flood is considered to be the worst flood in recent Canadian history and was therefore labeled as the flood of the century (Boluwade and Rasmussen, 2015). Literature based studies (Stadnyk et al., 2016; Warkentin, 1999; Wazney and Clark, 2016) indicate that soil moisture at freeze-up, total winter precipitation, rate of snow-melt, amount of spring rain and timing factors are the main variables that determine the severity of floods in the Canadian Prairies.

Floods cannot be eliminated, but with proper mitigating measures, the risk of damages can often be reduced. Effective mitigating measures require not only sound understanding of flood frequency and the ability to forecast flood events with high accuracy but must also have sufficient lead time to be of practical use. Unlike Europe and the US, Canada does not have a Flood Early Warning System (FEWS) as flood management is largely carried out at the provincial level (Faulkner et al., 2016). Furthermore, there is no national guideline that helps in improving the quality and consistency of flood information across the country. Consequently, the Natural Sciences and Engineering Research Council of Canada funded the FloodNet project to target gaps and uncertainties in current flood forecasting practices employed by provinces and other practitioners across the country (Coulibaly, 2014).

FloodNet is a nationwide project initiated by twelve Canadian universities in collaboration with government and industry. The project aims at developing advanced knowledge, tools, and technologies that will allow Canada to better face the reality of floods. The ultimate goal of this five-year research project is to enhance flood forecasting and management capacity in Canada. The key of the FloodNet is the collaboration between academic experts, government scientists, and end-users, i.e. operational flood forecasters who will ensure that the new knowledge and technologies developed will meet the users' needs. One of the projects under FloodNet is to review the current practices implemented by Hydrologic Forecasting Centres (HFCs) across Canada and evaluate their performance in meeting their intended purpose. The rationale for this research lies in the context of FloodNet, with a research interest in evaluating current operating practices and suggest improvements in forecasting tools and methodologies. This research specifically targeted improvements for the Canadian Prairie Pothole Region (CPPR).

The Prairie Pothole Region (PPR) of North America covers an area of ~ 750,000 km^2 (Millett et al., 2009) which spans across Alberta, Saskatchewan, and Manitoba in Canada and extends into North Dakota, South Dakota, Iowa, Minnesota, and Montana in the United States (Figure 1-1).

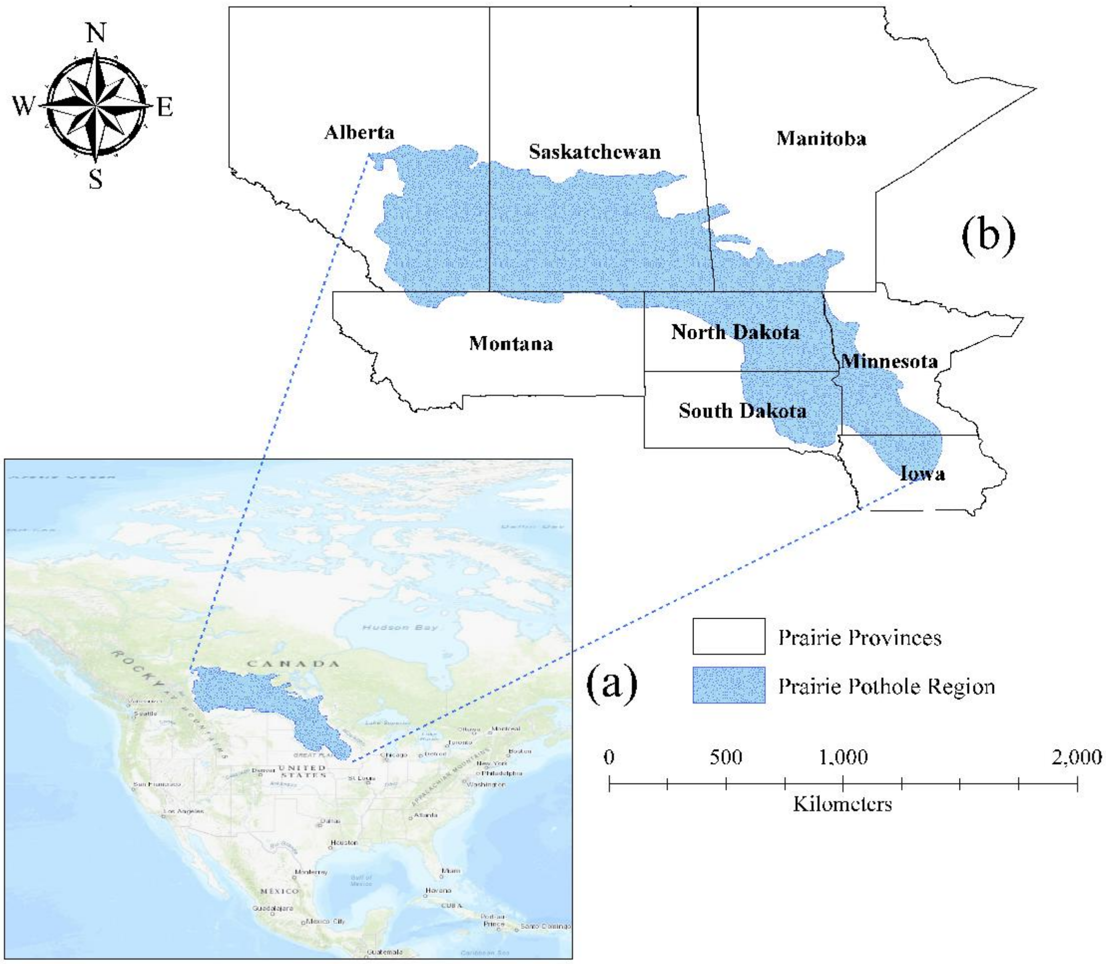

Figure 1-1: The Prairie Pothole Region (PPR) of North America

The PPR is home to 5 to 8 million of isolated wetlands (i.e., pothole wetlands) left behind by continental glaciers as recently as 10,000 years ago (Batzer and Baldwin, 2012). Pothole wetlands in their natural state provide a range of ecosystem goods and services such as flood attenuation, groundwater recharge, water purification, sediment control, biogeochemical processing, and regional diversity (Ando and Mallory, 2012; Conly et al., 2001; Gleason et al., 2011; Niemuth et al., 2010; Vanderhoof et al., 2016; Werner et al., 2013). Despite their numerous benefits, nearly 70% of the wetlands have been lost in the PPR with 84% of this loss attributed to agricultural development (Conly et al., 2001; Rashford et al., 2016).

The Prairie region is characterized by relatively low precipitation and high potential evapotranspiration (Burn et al., 2008). Annual precipitation in the region ranges between 300-400 mm (Mcginn, 2010) with one third of the precipitation falling as snow during winter. However, the snowmelt accounts for over 80% of annual streamflow (Dumanski et al., 2015), which when joined by rain, often causes flooding in the region. Prairie hydrology has been studied for many decades, so it is well established that surface runoff in the Prairies often drains into depressions, forming wetlands or potholes. These depressions are closed basins which retain water for longer periods (Hayashi et al., 2003) and do not contribute flow to the stream under normal conditions (Shook, 2012). During times of high runoff, the storage capacity of many depressions can be exceeded, causing a fill-and-spill process to occur (van der Kamp and Hayashi, 2009). Once the depressions are filled, the overflow water connects them and starts to flow to the stream. Consequently, temporary streams can form, resulting in a dynamic increase in the contributing area for runoff (Dumanski et al., 2015; Shaw et al., 2012). At some point, the movement of water stops, causing a break in the interconnection of wetlands, and consequently reducing the contributing area of runoff to a watersheds outlet. The uncertainty due to fill-and-spill processes and the dynamic nature of contributing and non-contributing area makes hydrological processes of the Prairie region difficult to model and quantify. Relatively few studies have examined the impact of potholes on the hydrology of a watershed.

The HFC of Manitoba, a partner of FloodNet, has employed and tested a combination of hydrologic models to better depict the dynamic presence of potholes and the fill-and-spill nature of the PPR. However, in most cases, either a lumped concept of these wetlands was adopted, or the fill-and-spill dynamics of pothole-driven runoff were missing. Furthermore, the HFC does not have any quantifiable measure of the uncertainty that arises from the presence and abundance of the pothole wetlands, their fill-and-spill processes, or long-term climate and land use induced changes in their distribution. This is partially as a result of not having suitable tools that would integrate modeling uncertainty into operational flood forecasts.

1.2 Research Objectives

The overall objective of this research is to develop a framework to address the complexity in calibrating and applying hydrological models for streamflow prediction in the PPR. The specific objectives are as follows:

1. Quantify the complexity associated with calibrating hydrological models and determining the impact of model structure on the accuracy of streamflow prediction in the PPR;

2. Assess uncertainty in PPR streamflow projections due to long-term climate and land use changes on Prairie hydrology, and the implications for future water availability; and

3. Develop an ensemble prediction system coupled with a statistical post-processing framework to help the decision-making process of the HFC for long-term reservoir inflow forecasting.

1.3 Scope of the Thesis

The study is designed to improve streamflow simulation in the Upper Assiniboine River Basin at Kamsack, which is a pothole wetland dominated catchment in the CPR. The scope of the thesis is the scope of one of the NSERC-FloodNet projects that aim at evaluating current flood forecasting procedures in place at HFC, identify gaps and suggest improvements.

1.4 Content of the Thesis

The thesis is comprised of six chapters consisting of an introduction, literature review, research compiled in three manuscripts, and a conclusion chapter.

Chapter 1 provides an overview of the thesis topic with overall and specific objectives. Chapter 2 summarizes the theory and current state of modeling pertaining Prairie Pothole Region (PPR) especially the presence of numerous number of pothole wetlands and model limitation to depict these pothole wetlands.

Chapter 3 investigates ways to incorporate pothole wetlands in hydrologic models and the complexity associated in calibrating such models. In chapter 3, a modified SWAT model is developed and evaluated together with its standard version to identify streamflow prediction accuracy with different structural arrangement of the model. Furthermore, resource cost such as computational and data requirement associated with each representation is explored. Chapter 3 targets the first objective and is published in Journal of Hydrology: Regional Studies.

Muhammad, A., Evenson, G.R., Stadnyk, T.A., Boluwade, A., Jha, S.K., Coulibaly, P., 2019. *Impact of model structure on the accuracy of hydrological modeling of a Canadian Prairie watershed*. J. Hydrol. Reg. Stud. 21, 40–56. doi:10.1016/J.EJRH.2018.11.005

Chapter 4 (second manuscript) assesses long-term uncertainty due to climate and land use changes on the hydrology of the PPR. The modified SWAT model, developed as a result of the first objective, was utilized to quantify the couple effect of climate and land use change on the downstream hydrograph. This work addresses objective 2. The manuscript has been published in Water- Multidisciplinary Digital Publishing Institute (MDPI), which is an open access journal.

Muhammad, A., Evenson, G.R., Stadnyk, T.A., Boluwade, A., Jha, S.K., Coulibaly, P., 2018. *Assessing the importance of potholes in the Canadian Prairie Region under future climate change scenarios*. Water (Switzerland) 10. doi:10.3390/w10111657

The third manuscript (Chapter 5) addresses the third objective that is to design a framework that would optimally combine the output of different hydrologic models. The focus of the study is to evaluate the performance of the HFC operationally used hydrological model together with the newly research-based hydrologic model, developed as a result of objectives 1, and 2, in predicting seasonal streamflow. A combination of various multi-model Ensemble Streamflow Prediction (ESP) scheme were investigated, and some post-processing tool were employed to get the best possible forecast. The goal is to help identify the uncertainty in the Manitoba Hydrologic Forecast Centres (HFC) seasonal streamflow forecast and to improve its ensemble decision-making capacity. The manuscript has been published in Water- Multidisciplinary Digital Publishing Institute (MDPI), which is an open access journal.

Muhammad, A., Stadnyk, T.A., Unduche, F., Coulibaly, P., 2018. Multi-Model Approaches for Improving Seasonal Ensemble Streamflow Prediction Scheme with Various Statistical Post-Processing Techniques in the Canadian Prairie Region. Water 10, 1604. doi:10.3390/w10111604

Chapter 6, which is the final chapter of the thesis, summarizes the findings of this research through the development of an enhanced pothole wetlands representative model, and outline recommendations for future work.

Overall this thesis makes a significant contribution to understanding the aggregate effects that pothole wetlands have in predicting the hydrology of the PPR identified as a critical gap in Theme 3-1 report under the Canadian NSERC FloodNet project. Furthermore, this research addressed some of the key modeling challenges such as pothole representation in the hydrologic model, long-term climate, and land use change uncertainty, and enhancing the decision-making capability of the HFCs through the development of various post-processing tool development.

2 BACKGROUND AND RELEVANT LITERATURE

This chapter reviews relevant theory and provides background literature regarding the hydrology of the Prairie region, different modeling approaches, uncertainty in hydrologic assessment, and streamflow forecast challenges in the Upper Assiniboine River Basin. Furthermore, description about model selection and details on the selected model are presented.

2.1 Prairie Pothole Hydrology

The Prairie PPR spans Alberta, Saskatchewan, and Manitoba in Canada and extends into North Dakota, South Dakota, Iowa, Minnesota, and Montana in the United States (US). Before the European settlement, the Prairie region was home to millions of wetlands, but with the passage of time, 70% of these wetlands have been lost, and 84% of this loss is attributed to agricultural development (Schindler and Donahue, 2006).

The loss of wetlands has resulted in deteriorating water quality, an increase in runoff-contributing areas, and increasing peak runoff (Ducks Unlimited, 2008). Wetlands play an important role in watershed health and can be seen as an integral component of much of the Canadian Prairie landscape. Prairie hydrology has been studied for many decades, so it is well established that surface runoff in Prairie regions often drains into depressions, forming wetlands or potholes. These depressions are closed basins that retain water for longer periods and do not necessarily directly contribute flow to streams under normal conditions. During times of high runoff, the storage capacity of many depressions can be exceeded, causing a fill-and-spill process to occur (Shook et al., 2013). Once all the depressions are filled, the overflows connect them and form a direct drainage pathway to the stream. Consequently, temporary streams can form, resulting in a dynamic increase in the contributing area (Shaw et al., 2012). When these depressions are empty, the drainage pathways are severed, which consequently reduces the contributing area (Mekonnen et al., 2014; Pomeroy et al., 2014; Shook and Pomeroy, 2011). The uncertainty due to dynamic fill-and-spill processes makes the hydrology of the Prairie region complex to model and difficult to quantify.

2.2 Climate change

There is significant variation in the climate of the Prairie Pothole Region (PPR) with a strong west-to-east precipitation gradient and north-to-south temperature gradient (Renton et al., 2015). The west receives mean annual precipitation of 300 mm while east receives 900 mm. Regions in the north are colder than the southern, lower-latitudes. Furthermore, the PPR experiences significant seasonal variation with temperatures below -40°C in the winter and above 40°C in the summer, which not only affect wetlands but the biotic community of the wetlands (Euliss et al., 1999; Stewart and Kantrud, 1971).

Global Circulation Models (GCMs) have been considered useful tools to explore the physical processes of earth's surface atmospheric system and are widely utilized to gain information regarding historical, current, and future climate (Zhang et al., 2016). Based on estimates of future populations levels, economic activity, and technological innovation (IPCC, 2013; Morita et al., 2001; Moss et al., 2010), future climate change scenarios are derived that can be used to assess future vulnerability in land surface processes associated with changing climate (Carter et al., 2001). On a global scale, climate change is projected to have far more impact on snow-dominated basins in mid-to-higher latitudes (Barnett et al., 2005).

The PPR is home to 5 to 8 million glacially formed wetlands, which have significant environmental, economic, and social values (Thompson and Young, 1992). Wetlands, however, due to their shallow nature, are highly susceptible to changes in precipitation and temperature (Johnson et al., 2005, 2004; Johnson and Poiani, 2016; Larson, 1995; Millett et al., 2009). The Intergovernmental Panel on Climate Change (IPCC) in its fifth assessment report, projected a 2°C to 5°C rise in the surface temperature (Collins et al., 2013; IPCC, 2013). As a result, it is very likely that extreme precipitation events will become more intense and frequent, altering the hydrologic cycle and water availability of many regions (Field and Barros, 2014; Trenberth, 2008) including that of the PPR. Thus, it is essential to explore long-term uncertainty imposed due to climatic change on water availability in the PPR.

2.3 Hydrologic Models

Hydrological processes of a catchment that transform precipitation into streamflow are highly complex and strongly nonlinear due to strong interactions and feedbacks among climate, vegetation, soil, and groundwater. This complexity is often handled through the use of hydrological models, which are combinations of mathematical Equations that simplify the representation of hydrological processes in a catchment (Xu, 2002). A wide range of hydrological models are available with different levels of complexity and data requirements (World Meteorological Organization, 2011). Therefore, it is important to categorize hydrological models into different types to appreciate their characteristics, computational capabilities, limitations and the theory behind (Jajarmizadeh et al., 2012). Classification in this way will help in selecting the model best suited for the study site under investigation.

2.3.1 Model Classification

Hydrological models have been classified in numerous ways in the literature (Chappell, 2006; Clarke, 1973; Jajarmizadeh et al., 2012; Pechlivanidis and Jackson, 2011; Shaw, 1994; Singh and Woolhiser, 2002). In general, models are broadly placed into two groups: deterministic and stochastic, which can be further sub-divided into different types. A detailed classification based on the World Meteorological Organization (WMO) is presented in Figure 2-1 and are discussed in sections below.

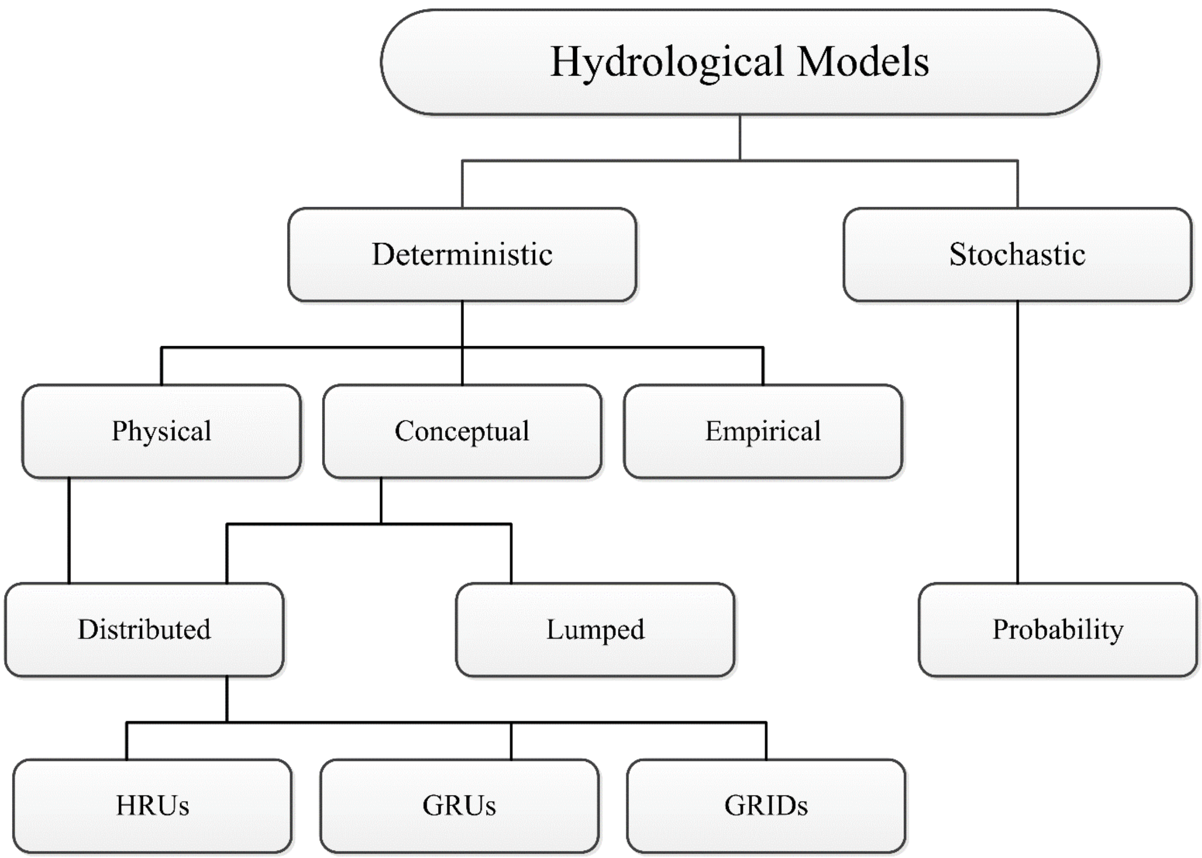

Figure 2-1: Hydrologic model classification as adopted from World Meteorological Organization

2.3.1.1 Deterministic models

A deterministic model assumes certainty in all aspects. That is if the input to the model is condition A and condition B, the result, after model execution, will always be condition C. In operational hydrology, deterministic models are being used for the design, planning, and management of water resources; which ignores model uncertainty associated with simulated responses (Farmer and Vogel, 2016). However, due to increasing non-stationarity in natural environments (Milly et al., 2008), as well as simplified representations of real systems, widespread attention has been given to uncertainty analysis in hydrologic modeling (Honti et al., 2014; Liu and Gupta, 2007; Wagener and Gupta, 2005). In fact, without consideration of uncertainty, the value of hydrologic prediction to water resource decision making is limited (Georgakakos et al., 2004). Deterministic models are further split into physical, conceptual, and empirical classifications, which are discussed below.

Empirical models

Empirical models are primarily based on input and output linkages, without detailed consideration of the physical processes of the system. These models are also termed black-box models (Nor et al., 2007), where statistically-based regression approaches are used to find functional relationships between inputs and outputs (Devia et al., 2015). Unit hydrograph, artificial neural network (ANN), and data-driven models are all examples.

Conceptual lumped or semi-distributed models

Conceptual models represent, to the extent possible, physical mechanisms that govern the processes within the system via the existence of a number of interconnected reservoirs each representing a physical element of the catchment (Devia et al., 2015). These types of models are median between physical and empirical models (Jajarmizadeh et al., 2012). Conceptual models can either be lumped or distributed. Lumped models treat the catchment as a uniform unit with all the variables represented as averages over the catchment area (Mockler et al., 2016). For example, the Canadian UBC (Quick and Pipes, 1976), the Swedish HBV (Bergstrom and Forsman, 1973), and the Danish NAM (Nielsen and Hansen, 1973) are some of the lumped conceptual type of models. Distributed hydrological models, on the other hand, are designed in such a way that enables the model to incorporate the spatial heterogeneity of the catchment by providing data to each distributed unit. Each unit can be considered as lumped with its own sets of parameters and variables (Beven, 1989; Beven and Binley, 1992), thus leading to an overall increase of two to three-fold of the number of parameters and variables as compared to lumped models (Refsgaard, 1997). The TOPMODEL may be characterized as a conceptual distributed (or semi-distributed) model (Refsgaard, 1997).

Physically-based distributed models

Physically-based distributed models utilize parameters that are directly related to the physical characteristics and spatial variability of the catchment (Sahoo et al., 2006)**.** Physically distributed model are considered mathematically idealized representations of real phenomenon which overcome many defects of the empirical and conceptual models (Devia et al., 2015). Such type of model, however, requires a large amount of data for parameterization (Arnold et al., 1998). In addition, these types of model are time-consuming and require considerable computational resources. However, the governing physical processes are modeled in detail, and if properly applied, they can provide the highest degree of accuracy (Cunderlik, 2003). The MIKE-SHE (Abbott et al., 1986), the IHDM (Beven et al., 1987), and the THALES (Grayson et al., 1992) can be regarded as the physically-based distributed models.

Depending on the computational unit, physically distributed models can be further split into three categories: Hydrologic Response Units (HRUs), Grouped Response Units (GRUs), and the finite element (GRIDs). HRUs are small computation units, formed using information from DEM, soil type, and land use data of the area. Each HRU is a computational unit and is hydrologically homogenous (Leavesley and Stannard, 1990). The SWAT model (Arnold et al., 1998) is based on the HRUs concept. The GRUs on the other hand, are formed using information from the land cover of the area. GRUs formation is based on the assumption that similar land covers exist in regions of similar soil types and topographic conditions (Kite and Kouwen, 1992). The WATFLOOD hydrological and routing model (Kouwen, 2017; Stadnyk et al., 2013) is based on the GRU concept. A grid-based model performs analysis at each grid node and thus requires a high-quality input dataset for good model performance. The CASC2D is a fully –unsteady, physically-based, distributed parameter, raster (square-grid) based hydrological model that can be used to simulate either single events, or long periods of record at users' discretion (Julien and Saghafian, 1991).

2.3.1.2 Stochastic models

Stochastic models incorporate one or more probabilistic elements into the model, which means the final output of the model will typically be some kind of confidence interval. Every time a stochastic model is run, the output will differ than the earlier run while using the same input for every run (Dalen, 2016; Jajarmizadeh et al., 2012). Stochastic hydrological models are important water resource management tools that help generate many representative synthetic streamflow sequences that are possible realizations of what could occur in the future (Farmer and Vogel, 2016; Matalas, 1967; Vogel, 2017). Numerous stochastic streamflow modeling packages including HEC-4 (USACE, 1971), SPIGOT (Grygier and Stedinger, 1988), SAMS (Salas et al., 2006), and

CASTALIA (Efstratiadis et al., 2014) among others, have been developed to assist in water resource planning and design.

Among the different types, physically-based distributed models are thought to be sophisticated and relatively reliable. Results of such models are considered good but often at the expense of a large amount of necessary input data (Stadnyk-Falcone, 2008). Furthermore, physically-based models are capable of verifying and examining internal process dynamics. On the other hand, studies suggest that lumped models can work equally well if provided with sufficient data for calibration. Beven and Binley (1992) and Grayson et al. (1992) concluded that physically-based distributed models often provide only slightly better, if not equal or even worse simulated flows. Reed and Gilbert (2004) reported that lumped models outperformed distributed models in more cases than distributed models outperformed the lumped models. A major drawback of the lumped models is that the parameters for lumped conceptual models are watershed-specific, while the parameters for physically-based models are based on the land cover or soil information, which, with little or no modification, can theoretically be transferred to another watershed in a similar geographic location. Therefore, physically-based models are considered to be superior for cases when there are insufficient data or in cases where changes in the basin (deforestation, urbanization, etc.) are observed.

2.4 Flood forecasting in Manitoba

The Hydrologic Forecasting Centre (HFC) of Manitoba is responsible for forecasting flow in Manitoban Rivers and provides reports on flood conditions, forecasts, and warnings to enable effective coordination of flood response. The Centre currently uses two hydrological models and one statistical model for managing and predicting river flow and reservoir inflows. Currently employed practices for predicting, over longer time horizons, the reservoir inflows resulting from the UARB include: the HEC-HMS (Hydrologic Modelling System of Hydrologic Engineering Centre) semi-distributed model, the WATFLOOD fully distributed model, and the Manitoba Antecedent Precipitation Index (MANAPI) regression based model, discussed in detail below.

2.4.1 Hydrological Engineering Centre Hydrological Modelling System (HEC-HMS)

The HEC-HMS model developed by the US Army Corps of Engineer (Scharffenberg and Fleming, 2006) is designed to simulate the rainfall-runoff processes of a basin by representing the basin with interconnected hydrologic and hydraulic components. In HEC-HMS, the basin model consists of three components: the loss, the transform, and the base flow. Each element of the rainfall-runoff process within a portion of the basin, or sub-basin, is represented by a separate model. These separate models combine basin and meteorological models with a control specification for producing an outflow hydrograph at the basin outlet.

Surface runoff in HEC-HMS of the HFC-MI version is simulated using the soil conservation services (SCS-CN) curve number approach. Among the seven options for estimating basin losses, the SMA (soil moisture accounting), which is a lumped bucket-type model, is currently used at HFC-MI. The sub-basin in SMA is represented by well-linked storage layers/buckets accounting for canopy interception, surface depression storage, infiltration, and evapotranspiration as well as soil water and groundwater percolation. Any of the six techniques (lag, kinematic wave, modified pulse, Muskingum, Muskingum-Cunge standard section, and Muskingum-Cunge 8 point section) can be used for river routing. The HFC uses HEC-HMS primarily for simulating flow in the Upper Assiniboine River basin.

2.4.2 WATFLOOD

WATFLOOD is a partially physically-based and fully distributed hydrological model that can be used for forecasting floods. The model uses conceptualization of some physical processes in order to maintain high computational efficiencies (Kouwen, 2017; Stadnyk-Falcone, 2008). The model is made of two parts, WATFLOOD and SPL. WATFLOOD is the data management system that includes a number of data pre-processing programs, and SPL is the hydrological simulation module. The model operates on a grouped response unit (GRU), which represents the basic hydrologic computational unit that responds similarly to meteorological conditions (Kouwen, 2017). Groups are formed based on hydrological similarity, generally defined by the land cover and soil types. WATFLOOD relies on the assumption that similar land covers exist in regions of similar soil types and topographic conditions. Responses in each GRU for a grid are summed to give a total hydrologic response for the grid. Grids are connected by the drainage network to form the watershed, with upstream gridded responses being routed to downstream grids.

Runoff in WATFLOOD is a combination of three fluxes: overland, interflow, and base flow, which is computed using either the Philip, (1954) or the Green and Ampt, (1911) formula. Interflow is simulated through the use of variable-depth, while base flow is generated from deep, lower zone storage fed by the upper zone soil storage reservoir. WATFLOOD also has wetland and lake routing, lake evaporation, snow-melt and tracer routines in its framework. The model uses gridded data, and it is calibrated for both major river basins (Assiniboine and Red River) in Manitoba for flow forecasting.

2.4.3 Manitoba Antecedent Precipitation Index (MANAPI)

Hydrological models are both data-intensive and time-consuming to run. Hence, there is a need for simple techniques that can produce good results with limited input. Knowledge of soil moisture before a rainfall event is important to evaluate watershed's hydrological response correctly. Because it is very difficult to monitor soil moisture across entire watersheds continuously, the Antecedent Precipitation Index (API) plays an important role.

MANAPI (Manitoba Antecedent Precipitation Index model) is a lumped index model developed in the early seventies. In its current state, MANAPI is a snow-melt model that uses soil moisture, effective precipitation, winter precipitation, and snow-melt rate along with multiple regression and unit hydrograph theory for producing snowmelt-based flood hydrographs (Figure 2-2). Winter precipitation is a portion of the accumulated precipitation from October to March, which is obtained by applying a scaling coefficient to the total precipitation in each month. The method is based on the principle of establishing a statistical relationship between API and observed streamflow of past years.

MANAPI is considered to be the most reliable model at the HFC. The outlook before spring issued by the centre is based on MANAPI.

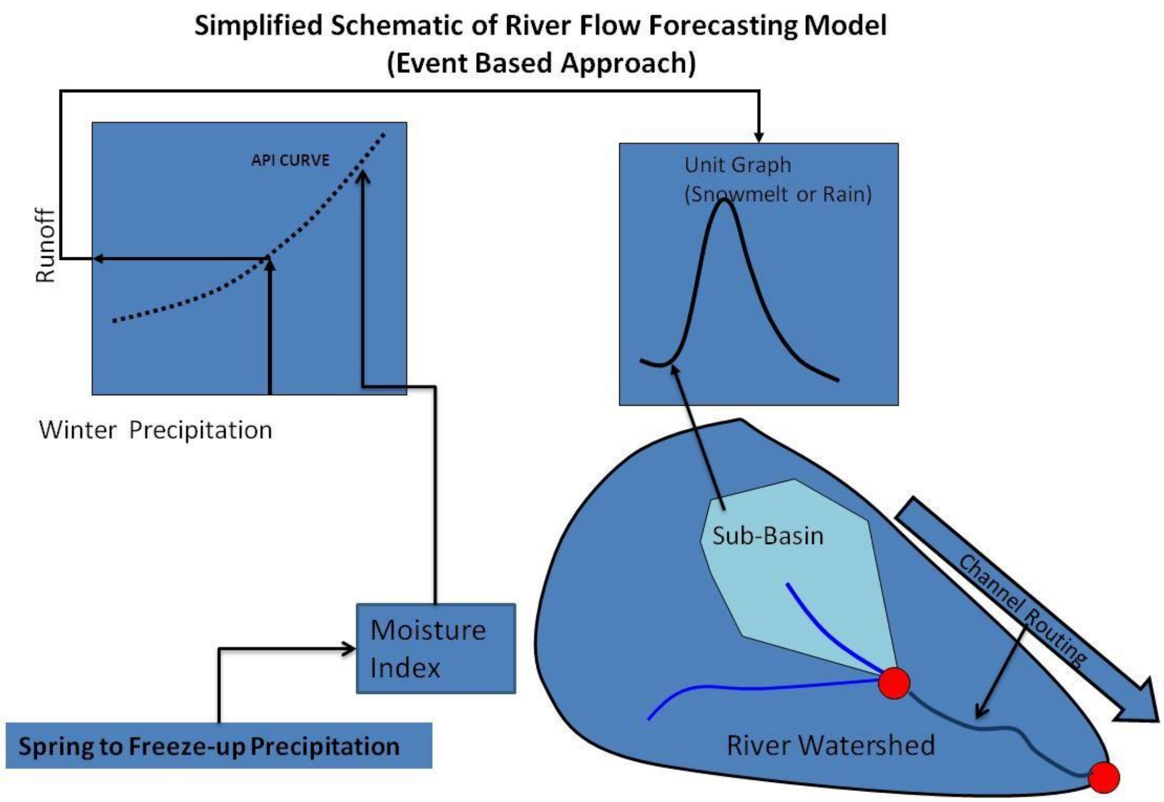

Figure 2-2: Schematic of the Manitoba Antecedent Precipitation Index (MANAPI). Source (HFC-MI)

2.4.4 Identified gaps in the currently used modeling practices

Hydrological models are designed to describe various water-related processes in a catchment. In practice, it is impossible to measure everything contributing to catchment hydrology. After an extensive literature review and personal discussion with the technical personnel at the Manitoba HFC (Zahmatkesh et al., in press), it was noted that several areas in their current practice could be improved. WATFLOOD is a hydrologic model built on kinematic wave theory that works best in areas with larger topographic variation. Elevation in the UARB ranges from 445 - 685 meters above sea level (masl) across the basin with a gentle average slope of 0.001 m. HEC-HMS is a semi-distributed conceptually based model. The model is built in a simple way, by eliminating or lumping some of the components usually used to predict runoff (percolation, storage, and movement of water through the soil layers). The lumping of HEC-HMS at subbasin scale diminishes the representation of heterogeneity at finer scale (Plesca et al., 2012). The largest floods in Manitoba are often due to the result of rainfall on top of, or shortly after, the snow-melt event, and since the Manitoba antecedent precipitation index is a snowmelt-based model, it is unable to produce reliable runoff forecasts (Infrastructure and Transportation, 2013).

To summarize, the current practices do not explicitly account for a) pothole surface depressions, b) dynamic contributing and non-contributing areas, c) soil moisture distributions, d) land use and cover characterization, e) and frozen soils and infiltration simultaneously, which often result in significant uncertainty when predicting streamflow on a seasonal basis. There is a need to explore other alternatives that can be adapted to improve current practices.

Despite significant developments in computational power and representation of hydrologic processes in models, current practice tends either to ignore the all modeling uncertainty or assume only specific contributions are essential (Liu and Gupta, 2007; Petrie, 2008). This is mainly due to a lack of guidelines and tools that would assist with quantifying uncertainty in complex forecasting systems where uncertainty can arise from multiple sources (Boelee et al., 2017; Zappa et al., 2010).

Several approaches have been developed to assess uncertainty in hydrological modeling (Kasiviswanathan and Sudheer, 2017; Liu and Gupta, 2007; Liu et al., 2017; Moradkhani et al., 2005; Wang et al., 2016; Westerberg et al., 2016). Among others, the ensemble streamflow prediction (ESP) (Day, 1985) approach has gained growing attention leading towards the development of Hydrological Ensemble Prediction System (HEPS) (Cloke et al., 2013; Cloke and

Pappenberger, 2009) which allows estimation of uncertainty in weather forecasting as well as the most likely outcome (WMO, 2012).

With the aim of describing part of the uncertainty embedded in their forecasts, the HFC-MI uses an ensemble streamflow prediction (ESP) technique that leverages historical climate data as input to river forecast models to generate long-term flow conditions at forecast sites across Manitoba. ESP without verification, however, is considered of low value (Alfieri et al., 2013; Randrianasolo et al., 2010). Assessing ESP performance is crucial for improving error diagnostics and for planning and development work required to improve system accuracy and extend forecast lead times (Alfieri et al., 2014). Furthermore, post-processing techniques can be developed to help improve ESP, which includes meteorological and hydrological postprocessors (Demargne et al., 2014; Jha et al., 2017; Mendoza et al., 2015; Schaake et al., 2007) to improve the ability of forecast. Statistical techniques such as linear regression (LR), quantile model averaging (QMA), and Bayesian model averaging (BMA) are also available to optimally combine ESP from hydrological models to enhance decision-making capacity, but have yet to be implemented operationally in Canada.

2.5 Sources of Uncertainty

Consideration of uncertainty has been recognized as an essential component in both research and operation modeling (Georgakakos et al., 2004) and provides added value in water resource related decision making. Four major sources of uncertainty have been identified: input, parameter, model structure and uncertainty due to output data. While the thesis does not aim to quantify all sources of uncertainty that can be introduced into forecasting, it does aim to highlight what sources of uncertainty exist. Details of the major uncertainty sources are provided in the section below.

2.5.1 Input Uncertainty

In traditional watershed modeling, uncertainty in the hydrologic modeling has often been attributed solely to model parameters and model structure, which effectively neglects errors in forcing data, assuming the forcing data is a true (exact) representation of reality (Vrugt et al., 2008). Hydrologic models, if forced with inaccurate precipitation data, will have significant erroneous results when predicting streamflow (Beven, 2012; Andréassian et al., 2001; Kavetski et al., 2006, 2003; Singh, 1997). Consequently, a variety of methods have been developed to characterize and control model forcing uncertainty. For example, see the work by McMillan et al., 2011; Thyer et al., 2009; and Vrugt et al., 2009 for more detail on addressing the rainfall uncertainty. Since the HFC-MI utilizes an ESP-based approach that leverages an ensemble of historical input data, this source of uncertainty was not further explored in this thesis.

2.5.2 Model Structure uncertainty

Hydrologic models are simplifications of reality and thus do not have the capacity to fully represent the complexity of natural hydrologic processes and interactions within watersheds. The incompleteness of the model structure and the mismatch between the actual structure of the system results in some degree of model prediction uncertainty (Refsgaard et al., 2006). Besides advancement in developing more physically distributed models, techniques such as multi-model averaging (Butts et al., 2004; Duan et al., 2007; Georgakakos et al., 2004; Shamseldin et al., 1997) help in reducing or quantifying model structure uncertainty. The HFC-MI was interested in better understanding the model structure uncertainty introduced by neglecting, or including in different forms, numerical representations of pothole wetlands.

2.5.3 Parameter Uncertainty

Often, there are parameters in a hydrologic model, which cannot be measured directly but are obtained through model calibration (Vrugt et al., 2003). Uncertainties arise during parameter estimation particularly as a result of converging on local optimal solutions, rather than a global best solution. The degree of parameter uncertainty is mostly affected by the experience and expertise of the modelers' who set up and calibrate the computational models. Parametrization of a hydrological model is an important step, and a variety of automatic model calibration techniques and interfaces have been developed to ensure consistency between model simulation and actual system behavior (Moradkhani et al., 2005). The Generalized Likelihood Uncertainty Estimation (GLUE) developed by Beven and Binley, (1992), the Metropolis-Hastings (MH) algorithm, which is a Markov Chain Monte Carlo (MCMC) methodology (Hitchcock, 2003), and the Sequential Uncertainty Fitting (Abbaspour, 2007) are some of the techniques those help reducing parameter uncertainty. Most recently, work on Pareto archived dynamically dimensioned search by Asadzadeh and Tolson, (2013), hybrid discrete dynamically dimensioned search by (Tolson et al., 2009), and model calibration using computationally efficient dynamically dimensioned search by Tolson and Shoemaker, (2007) has further advanced the knowledge regarding parameter space estimation through system optimization. Parameter uncertainty should be accounted for when performing ensemble-based forecasting.

2.5.4 Output Uncertainty

Observed data that models are calibrated to also contain uncertainty and often consist of discrepancies due to equipment, environmental, or reporting errors. Streamflow observation involves the monitoring of stage (water depth), which is then converted to streamflow (i.e., volume per unit time) with an established stage-discharge relationship on a pre-surveyed channel with the known cross-sectional area (Brakensiek and Osborn, 1979; Carter and Davidian, 1968). From equipment calibration to correlating changes in stage versus discharge, uncertainty in observed data can also be introduced (Harmel et al., 2006; SCHMIDT, 2002). Since we compare simulated conditions against observed discharge, bias can be introduced into our simulated results. HFC-MI and Water Survey of Canada provide hydrometric measurements for the Province of Manitoba that are generally considered to be within ±5% accuracy for ice-off conditions.

2.6 Model Selection and Selected Model Descriptions

Singh and Woolhiser, (2002) in their model selection criteria outlined that a catchment-scale hydrologic model should: be representative of the entire catchment, sufficiently representative of relevant hydrologic processes, be applicable to different types of catchment problems, and be able to integrate with GIS and remote sensing products. A traditional model selection approach is based on modeler personal interest, experience, and available inputs. Common input data, usually interpolated to the model grid from station data, are then used to force model simulations. Models may then be evaluated based on specified and appropriate performance metrics and ranked by performance, or model results may be assessed as an ensemble that represents the model structural uncertainty. This process may be repeated for different watersheds in various climatic regions of the world for comprehensive model assessment (Cunderlik, 2003; World Meteorological Organization, 2011). Selecting a model in this way can be cumbersome and time-consuming, which is why this approach is often not used to select a single best model (based on performance), but rather to evaluate model structural uncertainty. Traditionally, model selection is based on user expertise and available input data relative to model requirements. While there are a large number of both research and operational hydrologic models available, the focus of our research is the Canadian Prairie region. Thus the choice of models will consequently focus on those applicable to, and interest of Manitoba Infrastructure.

This study utilized a four-step procedure for selecting the most appropriate hydrological model to meet its intended purpose: (1) developing model selection criteria, (2) listing a gallery of models, (3) model evaluation based on established criteria, and (4) model selection.

2.6.1 Criteria for model selection

Following the World Meteorological Organization, (2011) guidelines and research interests for this study, the following points were set forth as criteria for model selection.

- Agriculture-dominated study area where pothole wetland removal has been occurring, therefore, the model should have the capability of testing dynamic land cover changes;
- User-friendly with expert guidelines;
- Ability to investigate the long-term climate and land use change impacts on water quantity;
- Routine for wetlands, potholes (surface depressions), and ponds as these are unique features of the study area landscape;
- Be of research interest for the Hydrologic Forecasting Centre (HFC) of Manitoba Infrastructure (MI);
- Computationally efficient with minimum data requirements for potential operational forecasting applications;

- Free to users with open source code so required modifications can be made to improve catchment processes;

2.6.2 List of candidate models

A number of meetings were held with the technical group of HFC-MI to discuss the model selection. Table 2-1 list all the models that were proposed during the initial stage with legends in section below. The models that are currently in operational use by HFC-MI are not listed in the table. Thus, the list of candidate models for this study was largely constrained by the research-based interest of the Hydrologic Forecasting Centre of Manitoba Infrastructure (HFC-MI).

Table 2-1: Listing of Candidate Hydrological Models

Models	***Source***	***Type***	***Input***	***Concept***	***Effort***	***Access***
NAM	DHI	1	2	2	1	2
MESH	ECCC	3	3	3	3	2
LISFLOOD	JRC	3	4	3	3	2
HYPE	SMHI	2	3	2	3	1
SLURP	CNHRI	2	3	2	3	2
SWAT	USDA-ARS	2	3	3	2	1
CRHM	UoS	3	4	3	3	2
MIKE-SHE	DHI	3	4	3	3	3
HSPF	US- EPA	2	4	2	3	2
TOPMODEL	LU-UK	2	3	2	2	1
PRMS	USGS	3	3	3	3	1

Legends for Table 2-1

Type	Data Requirement	Concept
1 Lumped	1 Rainfall	1 Empirical
2 Semi distributed	2 Rainfall +Some data	2 Conceptual
3 Fully distributed	3 Rainfall, Meteo data, DEM, Land use	3 Physical
	4 Rainfall, Meteo data, DEM, Land use, Snow data	

Operational Effort	Access
1 Low	1 Free
2 Intermediate	2 Limited version
3 High	3 Purchase

2.6.3 Models selection

From the Table 2-1, the source code for HSPF (Bicknell et al., 1996), MESH (Pietroniro et al., 2007), LISFLOOD (van der Knijff and De Roo, 2008), SLURP (Kite and Pietroniro, 1996), CRHM (Pomeroy et al., 2007), MIKE-SHE (Abbott et al., 1986) are not freely available. Furthermore the operational effort to set up models such as HSPF, MIKE-SHE, CRHM, LISFLOOD, SLURP, and MESH is high, with significant data requirements, so these model fails on the basic model selection criteria. CRHM and MESH have been applied in the Canadian Prairie Region (Cordeiro et al., 2017; Fang et al., 2007; Mahmood et al., 2017). However, CRHM has a high computational cost and data requirement and therefore was also considered not suitable for this study. HSPF did not have any graphical user interface (GUI), thus making the model less user-friendly, and has been tested in areas with wetlands where the results were found unsatisfactory (Pike, 1995).

The HYPE (Lindström et al., 2010), SWAT (Neitsch et al., 2011), TOPMODEL (Beven, 1997), and PRMS (Markstrom et al., 2015) are freely available with open access to their source code. HYPE, however, does not have a GUI thus making it less friendly. A primary disadvantage of TOPMODEL is that it comes in many forms, thus there is no standard version available (Pike, 1995). SWAT on the other, due to its open access, GUI, routine for wetlands, and world-wide application including for the PPR appear to be the most suitable model for this study. The HFC-MI technical staff also recommended the SWAT model and expressed a desire to assess it's suitability for long-term reservoir and seasonal inflow prediction across the UARB, which is located upstream of the Shellmouth reservoir.

2.7 Soil Water Assessment Tool (SWAT) hydrologic model

The Soil Water Assessment Tool (SWAT) model is receiving increasing attention in the research community due to its open source code, geographical user interface, routine for lakes, wetlands, ponds, and potholes, and its wide application to a range of watershed-related issues (Arnold et al., 2012; Gassman et al., 2010). The model has been widely tested around the globe for water resources assessment (Arnold et al., 1998; Jayakrishnan et al., 2005; Krysanova and White, 2015; Srinivasan et al., 1998), climate and land use changes (Abbaspour et al., 2009; Jha et al., 2006; Li et al., 2009; Mango et al., 2011; Narsimlu et al., 2013), water quality, pollutants and nutrients loading (Abbaspour et al., 2007; Jha et al., 2007; Santhi et al., 2001; Srinivasan and Arnold, 1994), and watershed management practices (Betrie et al., 2011; Singh et al., 2005; Tripathi et al., 2003).

SWAT is a physically-based and computationally efficient model capable of continuous simulation over long periods of time using a daily time step. Analysis of watersheds in SWAT is done through the formation of Hydrologic Response Units (HRUs). HRU are groups that consist of homogeneous land use, management, and soil characteristics. A hydrological balance for each HRU is simulated that includes: partitioning of precipitation, snow-melt water, redistribution of water within the soil profile, evapotranspiration, and return flow. Flow is summed from HRUs to the subwatershed level and then routed using either the variable rate storage(Williams, 1969) or the Muskingum method (Neitsch et al., 2011).

SWAT has a routine for modeling wetlands, ponds, potholes, and reservoirs explicitly. SWAT, while forming HRUs, uses Soil type, land cover and slope of the area thus representing the physical characteristic of the catchment more realistically.

2.7.1 Wetland routine of SWAT model

SWAT has routine for modeling wetlands. There are, however, three ways of representing wetlands in SWAT: wetland, pond, and pothole. Wetland in SWAT has no control flow regulation whereas pond is represented as a water-body with controlled release function. Potholes, on the other hand, mean a closed depressional area or isolated wetland, such as those so common in the Prairie region. In SWAT, wetlands and ponds are simulated at sub-basin scale while pothole is simulated at HRU level. The daily water balance for a pothole is given by Equation (1)

$$V_{pothole} = V_{pcp} + V_{flowin} + V_{storage} - V_{flowout} - V_{evap} - V_{seep} \qquad (1)$$

where V is the reservoir storage (m^3) at the end of the day; $V_{storage}$ is the reservoir storage (m^3) on the previous day; V_{flowin} is the surface and subsurface reservoir inflow (m^3) during the day; $V_{flowout}$ is the reservoir outflow (spillage) (m^3) during the day; V_{pcp} is direct precipitation (m^3) entering the reservoir during the day; V_{evap} is evapotranspiration (m^3) leaving the reservoir during the day; and V_{seep} is seepage (m^3) leaving the reservoir and entering the HRU soil profile during the day. The volume of precipitation that falls on the pothole during a given day is expressed as Equation (2)

$$V_{pcp} = 10 \times R_{day} \times SA \qquad (2)$$

Where SA is the surface area of the water body (ha) which is computed using either Equation (3) or Equation (4)

$$SA = \frac{\pi}{4} \times \left(\frac{3 \times V}{\pi \times slp}\right)^{2/3} \text{ if } \frac{\pi}{4} \times \left(\frac{3 \times V}{\pi \times slp}\right)^{2/3} \leq A_{hru} \tag{3}$$

$$SA = A_{hru} \text{ if } \frac{\pi}{4} \times \left(\frac{3 \times V}{\pi \times slp}\right)^{2/3} > A_{hru} \tag{4}$$

Here *slp* is the slope of HRU (m/m). The V_{flowin} is computed via Equation (5)

$$V_{flowin} = fr_{pot,hru} \times A_{hru} \times 10 \times \left(Q_{surf,hru} + Q_{gw,hru} + Q_{lat,hru}\right) \tag{5}$$

where $fr_{pot,hru}$ is the fraction of the HRU that drains to the pothole reservoir as specified by the model-user; A_{hru} is the area (ha) of the HRU; $Q_{surf,hru}$ is the surface runoff from the HRU for the day (mm), $Q_{lat,hru}$ is the lateral subsurface (soil profile) flow from the HRU for the day (mm), and $Q_{gw,hru}$ is the groundwater (shallow aquifer) flow from the HRU for the day (mm). The outflow from the pothole $V_{flowout}$ can be estimated by Equation (6)

$$V_{flowout} = V - V_{pot,max} \text{ if V} > V_{pot,max} \tag{6}$$

where $V_{pot,max}$ is the maximum storage (m^3) of the reservoir as specified by the model-user. The parameter V_{evap} can be computed with Equation (7)

$$V_{evap} = 5 \times \left(1 - \frac{LAI}{LAI_{evap}}\right) \times E_o \times SA \tag{7}$$

where LAI is the leaf area index of plants growing within the pothole as simulated as a function of observed plant-specific maximum leaf area index and accumulated heat units for the simulated day; LAI_{evap} is the leaf area index at which no evaporation occurs from the water surface; and E_o

is the potential evaporation (mm) during the day. The parameter V_{seep} can be calculated either of Equation (8)

$$V_{seep} = \begin{cases} 240 \times SA \times K_{sat} \text{ if } \mathrm{SW} < 0.5 \times \mathrm{FC} \\ 240 \times SA \times K_{sat} \times \left(1 - \frac{SW}{FC}\right) \text{ if } 0.5 \times \mathrm{FC} \leq \mathrm{SW} < \mathrm{FC} \\ 0 \text{ if } \mathrm{SW} > \mathrm{FC} \end{cases} \quad (8)$$

Where SW is the soil water content in the HRU soil profile for the day (mm); FC is the field capacity soil water content for the HRU (mm); and K_{sat} is the saturated hydraulic conductivity of the topsoil horizon in the HRU soil profile (mm/h).

2.7.2 Applications of SWAT model in the Prairie Pothole Region (PPR)

As per the SWAT literature database, around 2900 SWAT peer-reviewed journal publications are reported over the period 1984-2018. Several more recent studies evaluated the use of SWAT model over the North American PPR. For example, Shrestha et al., (2012) utilized the SWAT model for studying climate-induced changes in hydrology and nutrient fluxes of the UARB. The study revealed that future hydrologic scenarios consistently show earlier onset of spring snowmelt and discharge peaks and higher total runoff. Zhang et al., (2011) and Zhang and Huang, (2013) examined uncertainty in hydrological responses due to climate change in the Assiniboia watershed of Saskatchewan, Canada using the SWAT model. Results of the study advised the use ensembles of climate models to generate a more comprehensive vision of the future climate. Miller et al., (2009) used the SWAT model for investigating spatial distribution of historical wetlands classes on the Des Moines Lobe, in Iowa using soil characteristics as a basis. Their study highlighted that differences in wetland distributions among the zones probably derive from differences in initial topography and post-glacial processes such as erosion-deposition processes and stream-network formation. Schilling et al., (2008) utilized SWAT model to assess impact of land use and land cover change (LULC) on the annual and seasonal water balance of the Raccoon River watershed in west-central Iowa. Study results indicate that future LULC change will affect the water balance of the watershed, with consequences largely dependent on the future LULC trajectory.

A number of modeling studies have modified the source code of the SWAT model to better suit the model for evaluating the critical role that wetlands play in the hydrology of PPR. For example, Wang et al., (2008) modified the SWAT model at subbasin scale to better represent wetlands. In their work, Hydrological Equivalent Wetlands (HEW), which describe the aggregate functional attributes of wetlands, were designed and tested in the Otter Trail River watershed in Minnesota. It was concluded that compared to SWAT with no wetlands, the modified model had significant impact on decreasing the probability of exceedance of peak flow. In another study, SWAT was applied to investigate the effect of isolated wetlands 'closed-basin depressions' on the hydrologic flows and sediment yields in the Willow River watershed in Wisconsin (Almendinger et al., 2014). The pond and wetland features of SWAT were utilized to capture runoff from the watershed. Significant reduction in sediment yield were observed at the outlet as most of the sediment was trapped by the potholes and did not reach the outlet. Mekonnen et al (2017) used the SWAT model in conjunction with the probability distributed landscape depression model (PDLD) to better depict Prairie landscape depressions in hydrological modeling (Mekonnen et al., 2016a; Mekonnen et al., 2016b) and found improved results in comparison to the lumped, single storage SWAT approach to pothole representation. Evenson et al., (2015) modified SWAT model at the HRU scale to simulate the effect of GIWs on streamflow and sediment loading in Minnesota and North Carolina, USA. Building on their previous study, Evenson et al., (2016) further modified the SWAT to not only account for depressional storage but also to represent the fill-and-spill of these closed-basin depressions.

SWAT is not currently in use at HFC-MI, though they have expressed interest in the model. This is mainly because SWAT is a long-term continuous simulation model, but is not designed to simulate single, extreme events. On the one hand, the models currently in operation at the Manitoba HFC are useful for river forecasting, however, none can currently simulate pothole wetland dynamics. The modified version of SWAT developed in this research can, however, depict pothole dynamics in response to climate and land use change, which could perhaps more accurately simulate lone-term changes to reservoir inflow. Given the importance of pothole wetlands in the study watershed, the hypothesis set forth is that combining the two types of models in an ensemble fashion will capture or retain the best aspects of each model.

The goal of the thesis is to test this hypothesis by (1) modifying the SWAT model and testing it based on historic data across the PPR; (2) evaluating the ability of SWAT to make future predictions under land use and climate change in the PPR; and to (3) combine the existing HFC-MI river forecast model with the modified SWAT model to assess any potential improvements in seasonal forecast accuracy and/or uncertainty.

3 IMPACT OF MODEL STRUCTURE ON THE ACCURACY OF HYDROLOGICAL MODELING OF A CANADIAN PRAIRIE WATERSHED

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3.1 Abstract

The Prairie region spans across approximately 870,000 km^2 of the Great Plains region of Canada (80%) and the United States (20%). The presence of a large number of depressional wetlands (potholes) results in dynamic surface-water and stream connectivity during wet and dry year necessitating an improved understanding of watershed-scale interactions of the prairie potholes. The Soil Water Assessment Tool (SWAT) hydrological model with three structural variants is utilized to assess the degree of accuracy associated with increasing model complexity and its impact on the model calibration of the Upper Assiniboine River Basin at Kamsack. The SWAT model was calibrated and verified with three different structural arrangements in 1) lumped pothole, 2) semi-discretized pothole, 3) and fully-discretized pothole represenation. The fully-discretized pothole version of the SWAT model reflected streamflow best (KGE of 0.78) but with greater uncertainty, larger data and computational resource requirements. The fully-discretized pothole model, however, was able to capture the high flow and the fill-and-spill processes, which is a defining characteristic of the Prairie Pothole Region (PPR). Significant improvements to the predictive ability of SWAT in the case of the fully-discretized pothole model was observed, thus allowing an enhanced understanding of the aggregate effect of potholes in this watershed.

3.2 Introduction

The North American Prairie Pothole Region (PPR) is characterized by a large number of prairie pothole (PP) wetlands. Studies suggest that the number of PP fluctuates between 5 - 8 million such wetlands (Millett et al., 2009). Prairie pothole wetlands are traditionally smaller depressional wetlands developed following the last glacial recession (Winter and Rosenberry, 1995). Numerous studies have indicated these wetlands, hereafter simply “pothole wetlands” significantly influence the hydrology of watersheds in the PPR, affecting peak streamflow and flood characteristics (Bengtson and Padmanabhan, 1999; Phillips et al., 2011; Shaw et al., 2013; Vining, 2002), baseflow contributions (Euliss et al., 2014), and biogeochemical processing (Rains et al., 2016).

Wetlands play a major role in watershed health and are an integral component of much of the Canadian Prairie landscape. Nearly 70% of the wetlands have been lost in the PPR: despite the numerous benefits to flood mitigation, they are still considered a hindrance to agricultural production with 84% of this loss attributed to agricultural development (Conly et al., 2001). Prairie hydrology has been studied for many decades, so it is well established that surface runoff in the prairie region often drains into depressions, forming wetlands or potholes. These depressions are closed basins that retain water for prolonged periods of time and do not necessarily contribute flow to the stream under normal or below normal runoff conditions. During times of high runoff, the storage capacity of these depressions can be exceeded, causing a fill-and-spill process to be initiated (Shook et al., 2013). Once all the depressions are filled, overland flow serves to connect such depressions, inducing much larger runoff. Consequently, temporary streams can form that result in dynamic increases in the contributing area of the watershed (Shaw et al., 2012). When these depressions become empty the movement of water stops causing a break in their interconnections, and consequently reduce the contributing area (Shook et al., 2013). The dynamic nature of these isolated wetlands makes the hydrology of the Prairie region difficult to model and quantify.

Watershed-scale hydrologic models can be valuable tools that enhance our understanding of complex natural processes, and aid in examining the potential impacts of land-use change and best management practices (BMPs). Hydrologic models constructed to study PPR watersheds need to consider the vital role that pothole wetlands play in the PPR hydrologic cycle. A number of modeling studies have evaluated how these wetlands should be assessed in watershed-scale models. The Cold Region Hydrological Model (CRHM) in conjunction with the Prairie Hydrological Model (PHM) were used to establish pothole volume-area-depth relationships (Pomeroy et al., 2010) to better estimate pothole storage volume. CRHM (Pomeroy et al., 2014) was further utilized with the DEM based ponding model (Shook et al., 2013) for assessing streamflow fluctuation while changing pothole coverage. A significant increase (55%) in streamflow was observed when all the potholes within the DEM ponding model were removed.

The Soil Water Assessment Tool (SWAT), a widely utilized model (Arnold et al., 2012; Gassman et al., 2014; Neitsch et al., 2011), has been applied to assess the impact of depressions on hydrologic processes at the catchment scale. Wang et al., (2008), for example, used the SWAT model by constructing Hydrological Equivalent Wetlands (HEW), which describes the aggregate functional attributes of wetlands, at subbasin scale. Results suggested that, when compared to SWAT with no wetlands, the model with HEW had a significant impact on decreasing the probability of exceedance of peak flow. Almendinger et al. (2014) utilized SWAT to investigate the effect of isolated wetlands on the hydrologic flows and sediment yields in the Willow River watershed, Wisconsin. Significant reductions in sediment yield were observed at the outlet as most of the sediment was trapped by the potholes and did not reach the outlet. Evenson et al., (2015) modified SWAT model at the HRU scale to simulate the effect of Geographically Isolated Wetlands (GIWs) on streamflow and sediment loading in North Carolina, USA. Following a series of change scenarios in GIWs coverage, Evenson et al., (2015) found that change in GIW coverage has a significant influence on the downstream streamflow hydrograph. In an additional study, Evenson et al., (2016) further modified the SWAT model to account for depressional storage and to incorporate the fill-and-spill process of potholes, but on a more local scale that overlooks regional scale connectivity.

Table 3-1: Summary of studies that focus on modeling the hydrology of the Upper Assiniboine River basin at Kamsack (WSC ID: 05MD004)

Source	Watershed	Model	Scale (km^2)	Application/Description
Shrestha et al., 2012a	UARB at Kamsack	SWAT	13,000	Impact of climate change on hydrology and nutrient loading.
Shrestha et al., 2012b	UARB at Kamsack	SWAT	13,000	Climate induced hydrological changes with respect to a baseline period
	Morris in the RRB		0.0043	
Mekonnen et al., 2014	UARB at Sturgis	MESH modeling system	1,939	To improve surface and subsurface runoff generation within PPR via the development of a probability based runoff
Mekonnen et al., 2016a	UARB at Kamsack	SWAT-PDLD	13,000	To incorporate heterogeneity of landscape depressions storage into the SWAT model using a probability distribution approach
	Moose Jaw River watershed, in the RRB		9,230	
Mekonnen et al., 2016b	UARB at Kamsack	SWAT-PDLD	13,000	Applicability of SWAT-PDLD to simulate sediment export a depression dominated watershed
	Moose Jaw River watershed, in the RRB		9,230	
Mekonnen et al., 2017	UARB at Kamsack	SWAT-PDLD	13,000	To study soil erodibility for Nutrient export and to assess impacts of agricultural practices on nutrient export in the study watershed

Several studies (Table 3-1) have evaluated the critical role that pothole wetlands play in the hydrology of the Upper Assiniboine River Basin (UARB). For example, Shrestha et al., (2012a, 2012b) used the SWAT model to assess climate-induced hydrological changes and the impact on nutrient loading in the basin. The study, however, utilized the standard representation of SWAT pothole wetlands representation, that is, the fill-and-spill functionality of pothole wetlands was not explicitly represented. Mekonnen et al. (2017) used the SWAT model in conjunction with the probability distributed landscape depression model (PDLD) to better depict Prairie landscape depressions in hydrological modeling (Mekonnen et al., 2016a; Mekonnen et al., 2016b) and found improved results in comparison to the lumped, single storage SWAT approach to pothole representation. Mekonnen et al., (2016a)'s approach, however, did not simulate fill-and-spill hydrology between pothole wetlands, that is, hydrologic flow was not routed between depressional wetlands (pothole wetlands); it simply spilled to the subbasin reach once a pothole wetland is filled to capacity.

Advances in our understanding of how pothole wetlands impact watershed hydrology have been made, with the aforementioned studies providing valuable insights into evaluating pothole wetlands at the watershed-scale using hydrologic models. Added complexity in hydrological models, however, typically results in complex model calibration problems, and therefore often limits them in operational use. Previous studies have mostly focused on multi-model performance comparison. The selection of model with an appropriate complexity is as crucial as the ability of model performance to replicate hydrologic processes (Beckers et al., 2009), which is often defined based on required data, resources, and time to parameterized and calibrate the model. Thus, there is a need to investigate the degree of accuracy associated with increasing model complexity and its impact on model calibration in the Canadian Prairie Pothole Region (CPPR).

The objective of this study is not to identify a singular "best" method for evaluating pothole wetland complexes within the PPR; instead, we aim to evaluate alternative structural (i.e. mechanistic) avenues of pothole wetland representation and to highlight their impact on model calibration (i.e., parameter uncertainty), which is known to compensate for model structural limitations in complex hydrologic landscapes (Evenson et al., 2016; Mekonnen et al., 2015).

We use the SWAT, a watershed-scale process-based hydrologic model tailored to simulate rural and agriculturally dominated watersheds (Gassman et al., 2007; Neitsch et al., 2011). SWAT was selected for this study due to a series of recent studies proposing alternative methods of pothole wetland simulation within PPR (see Evenson et al., 2016, 2015, Mekonnen et al., 2016a, 2016b; Mekonnen et al., 2017). We focus on how the changing model structure impacts the accuracy of streamflow simulation, and the computational resource implications for each model structure.

3.3 Material and methods

3.3.1 Study area

The Upper Assiniboine River Basin (UARB) at Kamsack is located in the PPR and spans across Saskatchewan and Manitoba in Canada (Figure 3-1a, b). The watershed is of critical importance as flow generated in the basin enters the Lake of the Prairies (Shellmouth Reservoir), which was constructed for flood mitigation purposes and is situated approximately 45 km downstream of the watershed outlet. The UARB at Kamsack drains about 13,000 km^2, and is monitored by five streamflow gauging stations (see Figure 3-1c also detailed in Table 3-2). Except the gauge located at the UARB outlet, gauging stations inside the basin are seasonal with records available from March to October only. The UARB is dominated by agriculture (72%) followed by forest (14%) (Figure 3-1d), with a significant portion of the watershed labeled as “non-contributing", meaning these regions do not contribute to streamflow under normal conditions resulting from a large number of prairie potholes disconnecting large portions of the basin drainage area (Figure 3-1e). Using Geographic Information System (GIS), the density of potholes, which is the number of pothole wetlands identified divided by total area of the watershed, is estimated at 3.5 per km^2 covering around 140 km^2 of the watershed area. The presence of such a large number of potholes and the dynamics of contributing and non-contributing basin area are complex, and, therefore, the UARB has been given the nickname *"the graveyard of hydrological models"* (Shook, 2012).

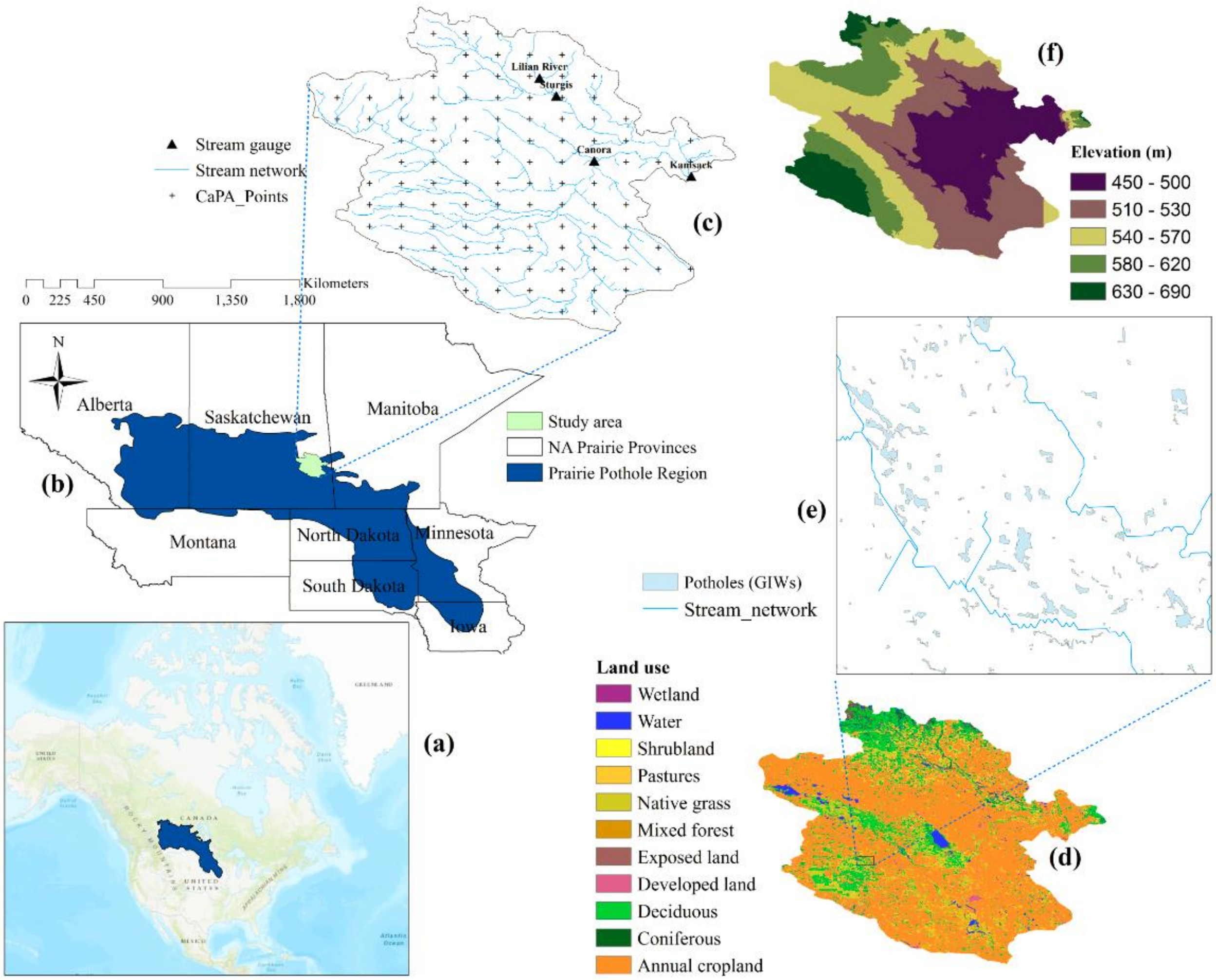

Figure 3-1: Geospatial information of the UARB at Kamsack showing (a) PPR of North America, (b) Study watershed with respect to PPR, (c) WSC streamflow gauges and the CaPA grid point, (d) AAFC land-use map, (e) GIWs, and (f) DEM of the study area

Black Chernozemic soils overlay almost 70% of the basin, which are high in organic matter and have generally developed under native grassland (Saskatchewan Water Security Agency, 2000; Shrestha et al., 2012). The watershed is flat with elevation ranging from 450 to 690 meters above sea level (masl) and an average slope of 0.002 m/m (Figure 3-1f). The climate of the UARB is continental sub-humid characterized by long, cold winter and short summer where the mean annual temperature and potential evapotranspiration is about 1°C and 850 mm, respectively (Saskatchewan Water Security Agency, 2000). Average annual precipitation is 450 mm, with approximately 26% of the precipitation falling as snow (Shrestha et al., 2012). Spring freshet occurs from April to June, accounting for 82%, on average, of total mean annual streamflow (Shrestha et al., 2012) .

Table 3-2: Selected Water Survey of Canada hydrometric stations in the Upper Assiniboine River basin until Kamsack

Serial no	Station ID	Station name	Start year	End year	Drainage area (km^2)	Remarks
1	05MC003	Lilian River near Lady lake	1965	2015	229	Seasonal[a]
2	05MC001	Assiniboine River at Sturgis	1944	2015	1930	Seasonal
3	05MB003	Whitesand River near Canora	1943	2015	8740	Seasonal
4	05MD004	Assiniboine River at Kamsack	1944	2015	13,000	Continuous
5	05MB001	Yorkton Creek near Ebenezer	1941	2015	2320	Seasonal

[a] Stations for which streamflow records were available from March -October for a given year

3.3.2 Data sources and description

Precipitation, maximum and minimum temperature, land use, soil type and a digital elevation model (DEM) are used to construct the SWAT model for a watershed. Streamflow data is required to calibrate and validate the model (Table 3-3).

Table 3-3: Input data used to set up the SWAT model for the Upper Assiniboine River Basin at Kamsack (UARB)

Description	Reference	Application	Source
DEM	NRC, 2007	Watershed delineation	http://geogratis.gc.ca/
land use data	Olthof et al., 2009	Land use properties	http://geogratis.gc.ca/
Soil type	AAFC	Soil properties	http://www.globalsoilmap.net/
Daily climate data	Lespinas et al., 2015	Precipitation and temperature	https://weather.gc.ca/
NARR climate data	Mesinger et al., 2006	Wind speed, relative humidity, and solar radiation	ftp://nomads.ncdc.noaa.gov/NARR/
Observed streamflow	WSC	model calibration- validation	*https://wateroffice.ec.gc.ca/*

The Canadian Precipitation Analysis (CaPA) (Lespinas et al., 2015) was used as precipitation forcing from 2002 to 2011, supplied at a daily time step and 10 km grid resolution (Figure 3-1c). The CaPA product combines different sources of information on precipitation from radar, satellite, atmospheric model and surface network (see Carrera and Fortin, 2008). Land-use data at a spatial resolution of 30 m (Olthof et al., 2009) and the 20 m spatial resolution digital elevation model (DEM) (NRC, 2007) data were obtained from the Canadian GeoGratis Data Portal (http://geogratis.gc.ca/). Detailed soil data were obtained from the Agriculture and Agri-Food Canada (Manitoba regional office), which were collected under a global soil mapping project (http://www.globalsoilmap.net/) at a spatial resolution of 30 m for up to 6 layers of soil depth at 5, 15, 30, 60, 100 and 200 cm. Temperature, solar radiation, and wind speed data were obtained from the North America Regional Reanalysis (NARR) (Mesinger et al., 2006). The NARR project is an extension of the National Centers for Environmental Prediction (NCEP) global reanalysis which is run over the North American Region (see further detail in Mesinger et al., 2006). The NARR product is available at 32 km grid resolution, however, in this study those data were interpolated to CaPA grid point. These data have been tested and found suitable for hydrological modeling across the Canadian Prairie (Choi et al., 2009; Shrestha et al., 2012). Observed streamflow data for gauges in the catchment were obtained from the Hydrometric Database (HYDAT) of the Water Survey of Canada.

3.3.3 Hydrological Model

SWAT was used to assess the impact of model structure on the accuracy of streamflow simulation. SWAT is a physically based and computationally efficient model capable of continuous simulation at a daily time step. Analysis of a water balance in SWAT is done using hydrologic response units (HRUs), which are the most elementary spatial unit of the model, making it a semi-distributed model. HRUs are groups consisting of homogenous land-use management and soil characteristics. To form SWAT HRUs, soil type, land cover and slope of the area representing the physical characteristics of the catchment are used (Douglas-Mankin et al., 2010). A daily hydrological balance for each HRU is simulated that includes partitioning of precipitation, snowmelt water, redistribution of water within the soil profile, evapotranspiration and return flow (Neitsch et al., 2011; Setegn et al., 2008; Singh et al., 2005a; White et al., 2011). Streamflow in SWAT is simulated as the combined runoff from all HRUs in the subwatershed routed through the stream network. SWAT also has an internal routine for modeling wetlands, ponds, potholes, and reservoirs explicitly (Evenson et al., 2016, 2015). The freely available, open source SWAT code, graphical user interface, and previous application in the PPR were among the selection criteria for working with the SWAT model.

3.3.4 Experimental Setup

To examine the impact of model structure on streamflow simulation, we evaluated multiple methods of pothole wetland representation and spatial discretization within a singular watershed-scale hydrologic model. Three versions of SWAT were constructed; lumped, semi-distributed, fully distributed. In this study, the definition of lumped and distributed model is strictly based on the pothole wetland representation in the hydrological model (landcover discretization), and does not refer to the underlying model spatial discretization. When pothole wetlands in a sub-basin are represented as a single storage entity, the model is termed as lumped, however, when pothole wetlands are spatially discretized are appreciated, the model is termed as distributed. We describe the differences between these models below.

3.3.4.1 Model-1: Lumped pothole version of SWAT model

In the lumped modeling system, the UARB was portioned into five subbasins, where each subbasin drained to one of the five streamflow gauges. SWAT was allowed to use all the combination of land use, soil type, and slope while constructing its HRUs, resulting in 271 HRUs. Modeling pothole wetlands in a lumped fashion within a catchment represents all parameters and variables of wetlands as spatially averaged values over the watershed area, and thus ignores the spatial structure and heterogeneity of the basin and input data. Model-1 does not represent pothole fill-and-spill processes; all pothole wetlands within a subbasin are represented as a single lumped depression. Flow directed towards pothole wetlands is stored in this lumped depression, and when the depression is filled to its capacity, it is spilled to the subbasin reach.

3.3.4.2 Model-2: Semi discretized pothole version of SWAT.

In comparison to Model 1, a more discretized version of the SWAT model was used to account for spatial heterogeneity in landcover and physiographic characteristics across the landscape, and of various forcing data. In this version of the SWAT model, the watershed was delineated by creating 45 subbasins, with no threshold for HRUs defined. Instead, the model setup used all combinations of land use, soil type, and slope, resulting in 971 HRUs representing landscape variability. This model version, however, did not have any specific representation of pothole fill-and-spill processes (Evenson et al., 2016; Mekonnen et al., 2016). Instead, it uses the internal SWAT wetland module (Neitsch et al., 2011) to represent prairie potholes. For this representation, the physical and functional attributes of all wetlands within a subbasin are aggregated to depict a single "lumped" wetland within each subbasin. The hydrologic effects of each subbasin's "lumped" wetland are then proportionally distributed across all HRUs within the subbasin. Importantly, the model's "lumped" wetland representation does not facilitate representation of "fill-spill" routing among pothole wetlands, as is the case for Model-1.

3.3.4.3 Model-3: Fully discretized pothole version of SWAT

Given the complexity of the PPR landscape, SWATs representation of pothole wetlands was modified to capture the dynamics of contributing and non-contributing areas; in theory, representing the pothole fill-and-spill routing processes among pothole wetlands within a subbasin more realistically. A procedure similar to that of Evenson et al., (2016) was selected for this model to examine potential improvements in streamflow simulation by adding pothole wetland representation and fill-and-spill processes to the model structure. This study, however, was conducted on a regional scale (13,000 km^2) with the goal of assessing the tradeoff made between model physical accuracy and calibration complexity. Furthermore, the spatial discretization of pothole wetlands and how this impacts streamflow simulation were examined on a regional scale. The research interests of Evenson et al., (2016) were to investigate GIW hydrologic behavior on local-scale water balance (i.e., < 2000 km^2), which does not examine the regional connectivity of fill-and-spill processes under varying climatic conditions.

We first identify potholes, hereafter called as the GIWs, following the procedure by Lane et al., (2012). Using the 30 m thematic map from Agriculture and Agri-Food Canada (Circa2000), a 10 m buffer (20 m total buffer cross width) from the natural stream network obtained from the Hydrologic Forecasting Centre (HFC) of Manitoba was used to identify all wetland areas not crossed by the 20-m buffer as GIWs. Out of 4353 wetlands, 4012 were identified as GIWs, comprising an area of 142 km^2. The storage capacity of the identified GIWs was computed using Equation (9), which is based on experimental studies conducted by Ducks Unlimited Canada and Water Security Agency of Saskatchewan (Wiens, 2001).

$$V_{GIW} = \begin{cases} 2.85 \times A^{1.22} & \text{if A } \leq 70 \\ (7.1 \times A) + 9.97 & \text{if A } > 70 \end{cases} \tag{9}$$

Where A is the surface area of the GIW in hectares, and V is the volume of GIW in cubic decameter (dam^3) that will be converted to cubic meter.

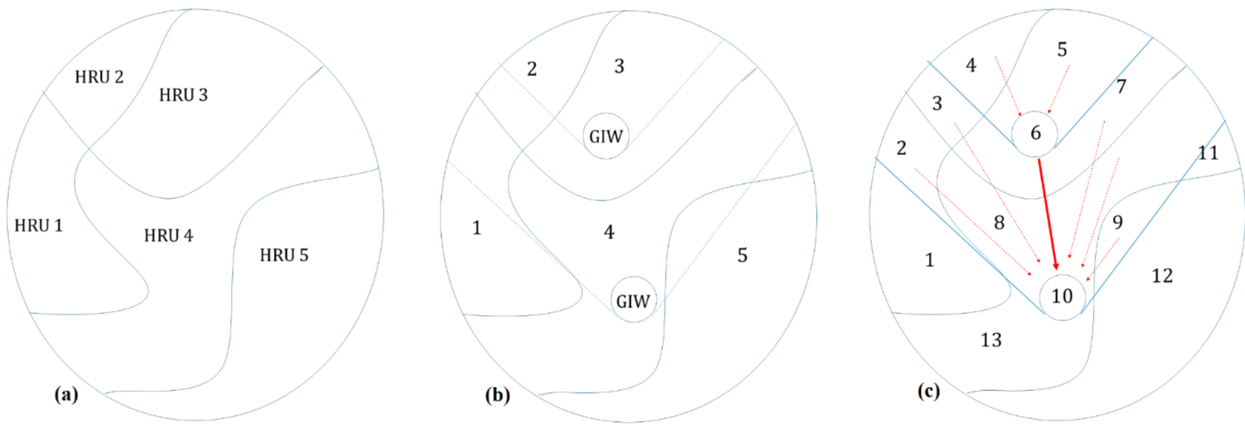

Figure 3-2: Modification to SWAT HRUs, showing (a) standard SWAT sub-basin and HRU, (b) GIWs and up-gradient catchment areas overlaid atop HRU boundaries, and (c) modified HRUs based on GIWs and catchment area boundaries. The arrows indicate flow direction. The figure is reproduced from Evenson et al., (2016)

The standard representation of potholes at the HRU level was redefined in SWAT (Figure 3-2). In the standard SWAT version, HRUs are formed using soil information, land-use, and topography data and are non-spatial unit. In the modified version, the identified GIW map was added as a fourth attribute that serves as an indicator of the HRUs spatial and hydrological connectivity to identified GIWs. HRUs that fall within an identified GIW were merged into a single GIW-HRU. A pothole equivalent to the storage capacity of the identified GIW was placed in the GIW-HRU. A set of new text input files were constructed to facilitate GIWs fill-and-spill processes. All HRUs positioned within a GIW drainage area were channelized to drain to the immediately downgradient GIW- HRU. In other words, GIW-HRU act as subbasins;- flow from all upgradient HRUs that falls within the catchment area of a GIW-HRU is routed to the GIW-HRU. Modifications alter the original routing scheme and drainge order as flow from HRUs are routed to (and through) the GIW-HRU, instead of directly to the outlet of the subbasin In this way, GIW-HRUs do preserve some spatial discretization within the subbasin in the form of a routing or drainage order. Once filled, outflow (spillage) from GIW-HRU is routed to the GIW-HRU located immediate downgradient. Therefore, in Figure 2, the redefinition creates GIW HRUs (HRUs 6 and 10). Outflow from HRUs 4 and 5, which are non-GIWs HRU, is routed to GIW HRU 6 as HRU 4 and 5 falls inside the catchment area of GIW HRU 6. Outflow (spillage) from GIW HRUs (e.g., HRU 6) is routed to the GIW HRU located immediately downstream (e.g., GIW HRU 10). In case there is no GIW HRU or non-GIW HRU present immediately downstream, the flow is routed to the stream. Constructing SWATs HRUs in this manner results in a 1500 % increase in the number of HRUs, totaling 15,235 for the UARB.

3.3.5 Model Setup

The three SWAT models with various structural arrangements were constructed using meteorological forcing from CaPA (precipitation) and NARR (temperature, solar radiation, wind speed, and relative humidity) for the 2002-2011 period. SWAT considers each grid point as a station within a particular subbasin, using the grid point nearest to the subbasin centroid for meteorological forcing.

The models' were developed using Arc SWAT interface of SWAT2012 revision 627 (Neitsch et al., 2011). To ensure a consistent comparison among the three models, the technique employed for calibration and validation of the model were kept the same. The predefined streams network, obtained from the HFC of Manitoba, are added to the DEM while delineating the catchment boundary and the sub-watershed draining to the catchment outlet at Kamsack. Potential evapotranspiration (ET) is computed following Penman-Monteith (Monteith, 1965). The degree-day method was chosen for estimating snowmelt runoff, the Soil Conservation Service (SCS) method estimating rainfall-runoff, and the variable storage (Williams, 1969) for routing the generated runoff.

3.3.6 Model calibration, validation, and uncertainty analysis

Once all three models were constructed, they were calibrated and verified at a daily time step against the observed streamflow records at each gauge location (see Figure 3-1c). The period from 2002-2004 was used for model spin-up, 2005-2008 for model calibration, and 2009-2011 for model verification. To ensure robust modeling practice, both the calibration and validation period were chosen with approximately matching mean precipitation and temperature statistics (e.g., consisting of both wet and dry periods). The year 2011 in the validation period was an extreme high flow year that has resulted in a slight increase in mean flow across the validation period (see Table 3-4).

Table 3-4: Statistics for model input variables for both the calibration (2005-2008) and validation (2009-2011) periods averaged across the entire UARB unless otherwise specified

Variables statistics average across the basin: calibration (validation)				
Serial No	**Variable**	**Max**	**Min**	**Mean**
1	Precipitation (mm/day)	37.9 (33.3)	0.0 (0.0)	1.3 (1.3)
2	Max temperature (ºC)	37.0 (32.2)	-28.6 (-24.8)	7.9 (7.0)
3	Min temperature (ºC)	22.3 (22.0)	-36.9 (-36.3)	-0.8 (-1.2)
4	Streamflow at Kamsack (05MD004) in (m^3/day)	252.0 (369.0)	0.12 (0.2)	12.8 (28.8)

The Sequential Uncertainty Fitting version 2 (SUFI-2) in the SWAT-Calibration and Uncertainty Program (CUP) was employed to explore the feasible parameter space and investigate parameter sensitivity and its associated uncertainty. SWAT-CUP is a module developed to automate calibration (Abbaspour, 2007). The program provides an interface that links uncertainty techniques such as SUFI-2, parameter solution (ParaSol), Generalized Likelihood Uncertainty Estimation (GLUE), Particle swarm optimization (PSO), and Markov chain Monte Carlo (MCMC). This thesis used SUFI-2, and thus the discussion is limited to the used of this uncertainty algorithm only. SUFI-2 is an uncertainty analysis tool, and not a calibration tool; however, the tool has been extensively used to find a feasible parameter space that sufficiently replicates watershed hydrologic processes. The feasible parameter space is achieved by performing several iterations, usually at most 5 (Abbaspour et al., 2004). Each iteration results in a smaller parameter space, highlighting the region that produces better results compared to the previous iterations. As each iteration narrows the parameter space obtained by the pervious iteration, a better or "best" solution based on the defined objective function is found (Abbaspour et al., 2007). In SUFI-2 parameter uncertainty is described by a multivariate uniform distribution, which is expressed in ranges, while output uncertainty is described by the 95% prediction uncertainty band (95PPU). The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution function (CDF) for the output variables (Abbaspour et al., 2004; 2007). Latin hypercube sampling is used to draw independent parameter sets (Abbaspour et al., 2007). SUFI-2 is considered computationally efficient where good results can be achieved with smaller number of model runs (Abbaspour et al., 2017; Abbaspour et al., 2007; Yang et al., 2008), which is an important aspect concerning the scope of work of this thesis. The goodness-of-fit during calibration, and prediction uncertainty are evaluated based on the closeness of the p-factor to 100% (i.e., all observations fall within the 95PPU) and the r-factor to 0 (i.e., the width of the 95PPU). Abbaspour *et al.*, (2015) suggested that p-factor values above 0.7 and r-factor values below 1.5 are satisfactory.

Parameters in SWAT are process-based and therefore must be defined within a realistic range. Obtaining a single set of acceptable parameters, however, can be problematic when parameter equifinality is considered. Equifinality is defined as different combinations of parameters that result in equal likelihood of a model outcome (Beven, 2009, 1989; Beven and Binley, 1992; Beven and Freer, 2001; Kelleher et al., 2016). To reduce the issue of equifinality, model calibration was constrained with regional signatures, local observations, and published literature. The current study benefits from the published literature in terms of selecting calibration parameters (Almendinger et al., 2014; Evenson et al., 2016, 2015; Mekonnen et al., 2016; Wang et al., 2008).

A total of 27 parameters were identified (Table 3-5) that may potentially affect the streamflow through a combination of global and trial-and-error sensitivity analyses and were included within the calibration process.

The auto-calibration interface (SWAT-CUP) was run in a set of four iterations each with 500 simulations, for a total of 2000 model simulation calls to get the best possible range for the parameters considered.

Table 3-5: Calibrated hydrological parameters used in the lumped pothole (Model-1), semi discretized pothole (Model-2), and fully discretized pothole representation (Model-3) in SWAT[1]

Parameter	Initial range[b]		Calibrated Values			Description (units, if applicable)
			Model-1	Model-2[c]	Model-3[d]	
	Min	Max	Fitted value	Fitted value	Fitted value	
ALPHA_BF	0.01	0.50	0.08	0.24	0.26	Baseflow alpha factor (days)
GW_DELAY	0.00	500	276	282	169	Groundwater delays (days)
GW_REVAP	0.02	0.20	0.22	0.19	0.17	Groundwater revap coefficient
GWQMN	0.00	5000	1649	3074	2366	Threshold depth of water in the shallow aquifer (mm)
RCHRG_DP	0.00	1.00	0.01	0.04	0.06	Deep aquifer percolation faction
REVAPMN	0.00	500	291.04	443	394	Threshold depth of water in the shallow aquifer (mm)
CH_K1	0.00	150	49.66	114	15.98	Effective hydraulic conductivity in tributary (mmh-1)
CH_K2	0.00	150	75.85	121	147	Effective hydraulic conductivity in main (mmh-1)
CH_N1	0.01	0.30	0.51	0.27	0.18	Manning's N value for the tributary channel
CH_N2	0.01	0.30	0.31	0.20	0.22	Manning's N value for the main channel
CN2[a]	-0.25	0.25	0.38	-0.12	-0.09	SCS runoff curve number
SOL_AWC[a]	-0.25	0.25	0.32	0.00	0.00	Available water capacity (mm H_2O mm-1)
EPCO	0.00	1.00	0.40	0.67	0.26	Plant uptake compensation factor
ESCO	0.00	1.00	0.15	0.26	0.72	Soil evaporation compensation factor
TIMP	0.01	1.00	0.73	0.01	0.76	Snow pack temperature lag factor
SFTMP	-3.00	3.00	-2.68	1.14	-1.78	Snowfall temperature
SMTMP	-3.00	3.00	4.82	0.50	2.19	Snowmelt base temperature
SMFMN	0.00	10.00	1.96	3.93	0.24	Melt factor for snow on winter solstice (mm c-1day-1)
SNOCOVMX	5.00	500	292	47.89	235	SWE that corresponds to 100% snow cover (mm)
SNO50COV	0.05	0.50	0.22	0.04	0.33	SWE that corresponds to 50% snow cover (%)
SMFMX	0.00	10.00	5.48	4.24	6.29	Snow meltrate on summer solstice (mm c-1day-1)
WET_K	0.00	3.60	0.95	1.23	3.34	Hydraulic conductivity of bottom of wetland (mmh-1)
OV_N[a]	-0.25	0.25	-0.09	0.13	-0.14	Manning's N value for overland flow
CH_L1[a]	-1.00	1.00	-0.03	-0.18	-0.07	Longest tributary channel length in subbasin
CH_W1[a]	-1.00	1.00	0.61	-0.99	0.03	Average width of tributary channels (m)
CH_L2[a]	-1.00	1.00	-0.01	0.08	0.35	Length of main channel m)
CH_W2[a]	-1.00	1.00	0.80	-0.28	0.00	Average width of main channel (m)

[a] Parameter handled with a relative change
[b] Parameter absolute range was set based on previous literature and SWAT user manual
[c] Calibrated values for the distributed model with no modification to potholes
[d] Calibrated values for the distributed model with modification to potholes representation

[1] Initial range for considered parameters was based on SWAT absolute values. During calibration ranges for some of the sensitive parameters were change based on the hydrograph and objective function following Abbaspour et al., (2015)

3.3.7 Performance metrics

To guide parameters selection and define the parameter space, the Kling-Gupta Efficiency criterion (Gupta et al., 2009), or KGE (Equation 10), was used as the objective function to evaluate model performance. KGE allows for a multi-objective perspective by focusing on correlation error, variability error, and bias (volume) error (Pechlivanidis and Arheimer, 2015). That is, KGE is the decomposition of the means squared error (MSE) and NSE performance criteria (Gupta et al., 2009) and was developed to help reduce model calibration problems when NSE is used. A KGE > 0.5 is set as the threshold value for selecting any simulation run while running the auto calibration program.

$$KGE = 1 - \sqrt{(r-1)^2 + (\propto -1)^2 + (\beta - 1)^2} \tag{10}$$

Where

$\alpha = \frac{\sigma_s}{\sigma_m}$, $\beta = \frac{\mu_s}{\mu_m}$,

σ_s and σ_m stand for the standard deviation of simulated and measured data; μ_s and μ_m are the means for simulated and measured data, and r is the linear regression coefficient between measured and simulated data.

Other performance statistics such as the Nash-Sutcliffe Efficiency (NSE), which is a normalized statistic used for comparing the residual variance to measured data variance (Nash and Sutcliffe, 1970), percent bias (PBIAS), which computes the average tendency of the simulated variable to be larger or smaller than the observed variable, and the coefficient of determination

(R^2), which is an index that measures the degree of linear relationship between observed and simulated variable were also considered, to provide further perspective on model performance.

The NSE ranges between -∞ and 1, where values between 0.5 and 1 are generally considered as an acceptable range (Moriasi et al., 2007) although Motovilov et al., (1999) suggested a value between 0.36 – 0.75 as satisfactory. The optimum value for PBIAS is 0 however, values between ±25 are considered satisfactory (Singh *et al.*, 2005; Moriasi *et al.*, 2007). The R^2 ranges between -1 and 1, with 1 being perfectly positive and -1 as the perfectly negative relationship. The $R^2 > 0.5$, is considered satisfactory (Moriasi et al., 2007).

3.4 Results

3.5.1 Comparison of model parameters

Model parameters (Table 3-5), initial, and calibrated values were analyzed with a focus on how the parameters change in the evolution from simple to more complex representation, and how these changes affect hydrological processes within the watershed.

Wet_K increased as model complexity increased, changing from 0.95 (Model-1) to 1.23 (Model-2) and 3.34 (Model-3). This leads to higher water loss into the ground, which increased (as expected) percolation and groundwater recharge from Model-1 to Model-3, respectively. This same effect is seen in the RECHRG_DP and ALPHA_BF parameters, which represent groundwater recharge and baseflow, as both parameter have a higher coefficient of contribution due to more groundwater availability. To further validate, CN2, which governs the behavior of surface runoff, decreases for the most complex model (Model-3), which therefore results in a reduced capacity to generate surface runoff in Model-3.

3.5.2 Model comparison based on daily and seasonal streamflow

To investigate the impact of model structure on the accuracy of streamflow, we first performed a visual inspection of the simulated to observed daily streamflow hydrograph for each model at the five gauge locations (Figure 3-1c). Here, we present results for the catchment outlet (05MD004 – Assiniboine River at Kamsack) only.

Figure 3-3 presents both the observed and simulated streamflow, along with 95% uncertainty bounds at the outlet of the catchment for all three models. A poor fit is seen in the case of Model-1 (lumped pothole version of SWAT) during the calibration period, especially for peak flows, which are highly underestimated. A further decrease in the performance of the model is seen during the validation period, in particular, during the fall 2010 and spring 2011 thus showing the models lack of robustness with respect to simulating peak flows. Significant improvement can be observed in the case for both the second (lumped pothole wetland version of SWAT with more spatial discretization of the system) and third (SWAT distributed pothole wetlands version) model. Both Model-2 and Model-3 were able to produce simulated hydrographs that are representative of the observed daily average flow during the calibration and validation periods. More importantly, both models (Figure 3-3) closely simulate the timing and duration of the peak streamflow. Model-2 in comparison to Model-3, tends to underpredict the larger peaks (e.g., the peaks during 2006, 2007, 2010, and 2011).

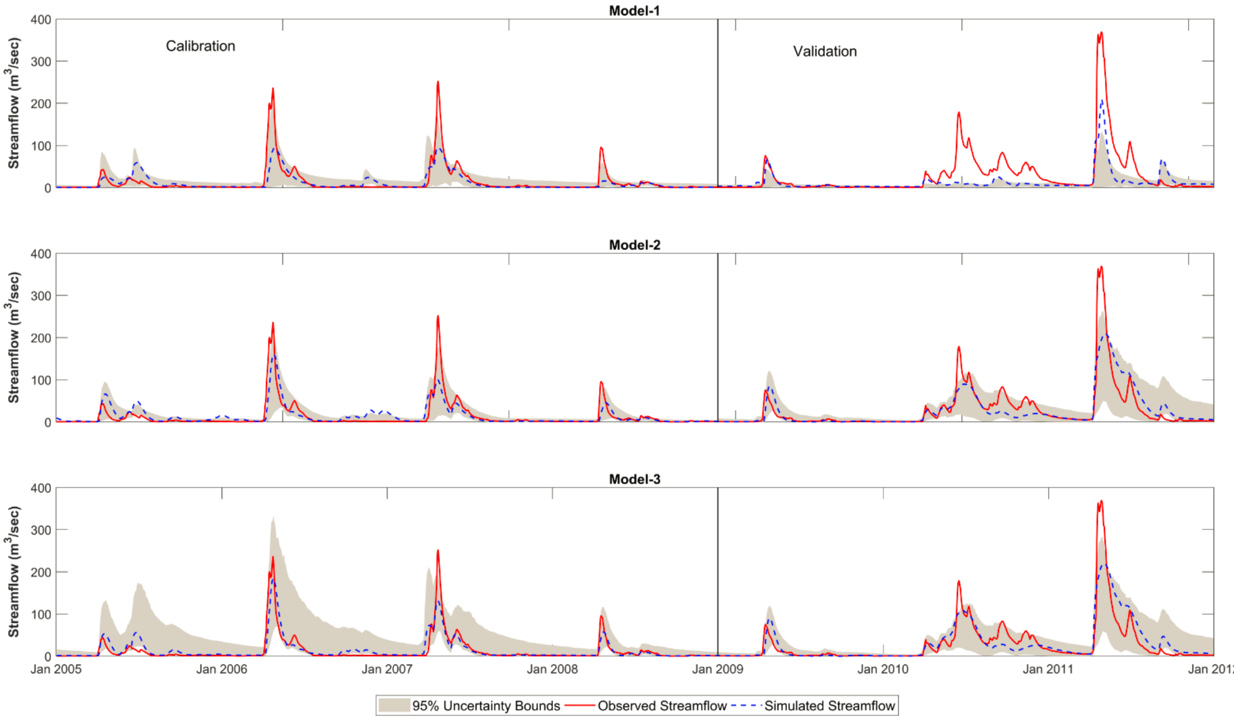

Figure 3-3: Streamflow hydrograph showing observed and simulated streamflow along with 95% prediction uncertainty bound of the UARB at Kamsack gauging station (WSC ID: 05MD004).

We further assess the performance of the models at a daily time step on the basis of multiple statistical metrics (Table 3-6). The rating of model performance was based on the guideline presented by Abbaspour et al., (2015); Moriasi et al., (2007); Singh et al., (2005). Based on the established criteria, Model-1 is categorized as satisfactory during the calibration period, however, unsatisfactory during the validation period. On the other hand, streamflow simulation capabilities of both Model-2 and Model-3 can be rated as good to very good for the calibration as well validation period due to improved performance metrics (KGE, NSE, and R^2). Model-3, however, has the most improved performance relative to both Model-2 and Model-1.

Table 3-6: Statistical measure of model performance at the catchment outlet (WSC ID: 05MD004) at the daily time step

	Model performance at daily time step: calibration (validation)					
Model	**P-factor**	**R-factor**	**KGE**	**NSE**	**PBIAS**	**R^2**
Model-1	0.85 (**0.58**)	0.77 (0.25)	0.50 (**0.21**)	0.58 (0.45)	17.50 (**55.30**)	0.63 (0.66)
Model-2	0.88 (0.91)	0.68 (0.86)	0.67 (0.74)	0.68 (0.72)	-5.70 (6.10)	0.69 (0.72)
Model-3	0.82 (0.92)	1.75 (0.89)	0.78 (0.80)	0.80 (0.76)	-6.60 (-3.20)	0.72 (0.76)

*Number in bold indicates non-satisfactory statistics

To further understand the changes in simulated flow processes, results were compared on a seasonal basis. The seasons were defined as per standard practice: Winter (WI) = December to February (DJF), Spring (SP) = March to May (MAM), Summer (SU) = June to August (JJA), and Fall (FA) = September to November (SON).

Since continuous streamflow records were available for the watershed outlet only, the analysis was restricted to the outlet of the catchment. Fall was chosen as the low-flow season (average daily flow ~ 23 m^3/sec) and spring as the high flow season (average daily flow ~ 43 m^3/sec). We present results for the high- and low-flow seasons (Figure 3-4 and Table 3-7) only.

Table 3-7: Seasonal statistical performance metrics for high (spring) and low (fall) streamflow at the catchment outlet (WSC ID: 05MD004)

	Model performance on seasonal basis: calibration (validation)		
High flow season (MAM[1])			
Model type	**KGE**	**NSE**	**R^2**
Model-1	**0.37 (0.32)**	0.50 (0.62)	0.79 (0.93)
Model-2	0.61 (0.68)	0.64 (0.75)	0.81 (0.88)
Model-3	0.75 (0.73)	0.78 (0.79)	0.89 (0.90)
Low flow season (SON[2])			
Model-1	0.53 (**-0.28**)	**0.09 (-0.48)**	0.50 (0.60)
Model-2	0.68 (0.74)	0.45 (0.54)	0.70 (0.78)
`Model-3	0.69 (0.71)	0.40 (0.61)	0.70 (0.84)

[1] Streamflow during March, April, and May (MAM), [2] Streamflow during September, October, and November (SON), [*]Number in bold indicates non-satisfactory statistics

Based on Table 3-7, all performance measures suggest that Model-3 performs better (higher KGE, NSE, and R^2), followed by Model-2. Model-1 does not seem to replicate both high and low seasonal flows well. The Nash-Sutcliffe coefficient of efficiency suggests that Model-2 and Model-3 are capable of predicting high seasonal flow. This can be visually observed in Figure 3-4 where Model-2 and Model-3 more closely follow the observed streamflow during the validation period.

One main interest in testing different model configurations was to evaluate how each model responds to peak flows, which we statistically represent as the 10% quantile of the peak streamflow over the 2005-2011 period (Figure 3-5). Following Moriasi et al., (2007), both Model-2 and Model-3 can be rated as good as satisfactory (Table 3-8) and has higher performance statistics overall (higher KGE and NSE).

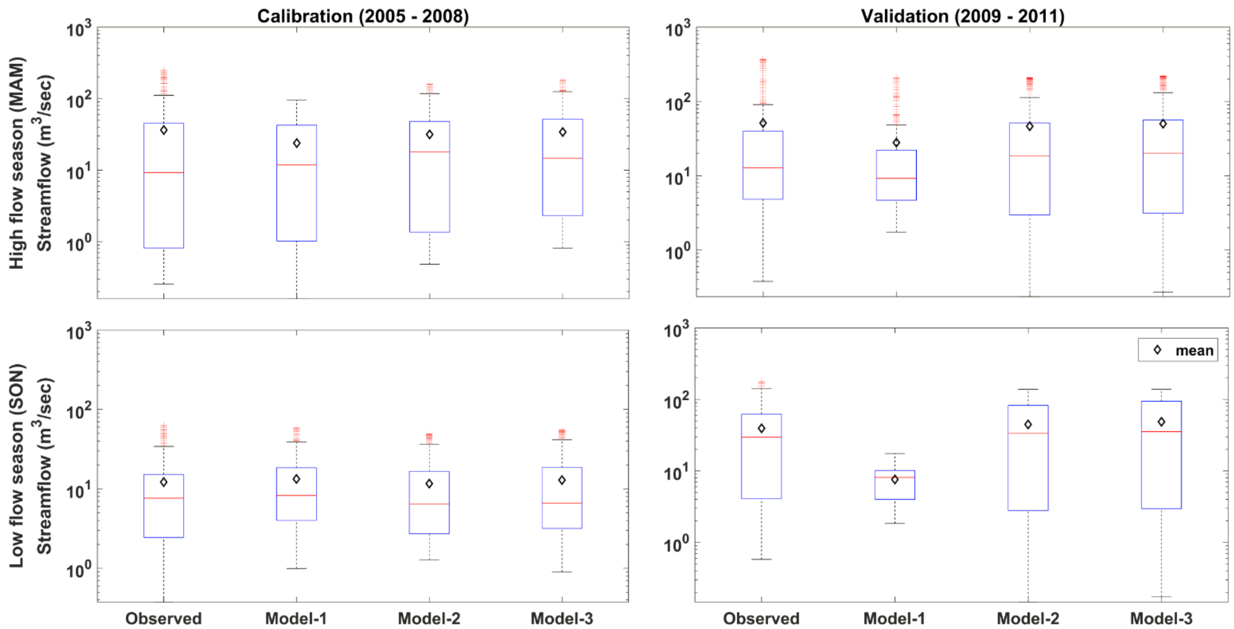

Figure 3-4: Box plots displaying observed and simulated streamflow for the three models for high (MAM) and low (SON) seasonal flow at the catchment outlet (WSC ID: 05MD004). The red horizontal line is the median. Whiskers are 1.5 times the interquartile range

Table 3-8: Peak flow statistical performance based on 10% quantile of daily streamflow records at the catchment outlet (WSC ID: 05MD004)

Model type	**KGE**	**NSE**	**R^2**
Model-1	**0.29**	**0.16**	0.98
Model-2	0.54	0.72	0.96
Model-3	0.57	0.77	0.96

*Number in bold indicates non-satisfactory statistics

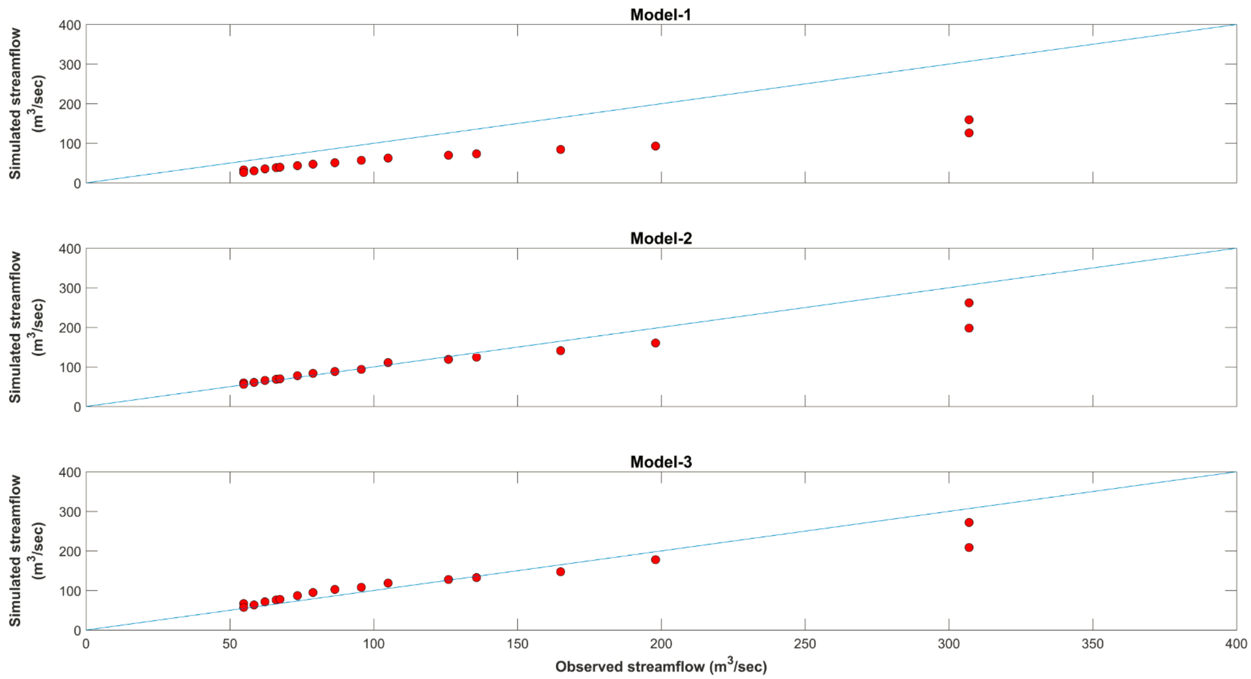

Figure 3-5: Q-Q plots for the upper 10% quantile of the peak flow, comparing observed vs simulated streamflow of the three models at the catchment outlet (05MD004).

A weakness of all the models was their inability to simulate the peak flow in 2011 (Figure 3-6). Furthermore, all models tend to overestimate the median flow. Why the model fails to adequately capture median flow is debatable. This could be due model structural limitations, that is, they are unable to account for all runoff-generating processes. Or it may be due to overestimation of or bias in the rainfall (Lespinas et al., 2015; Zhao, 2013). In general, Model-2 and Model-3 (in comparison to Model-1, which consistently underestimates high flow) perform well for high flows, except for the major peaks of 2010 and 2011. Also based on Figure 3-6, Model-2 and Model-3 better replicate low flows relative to Model-1, which suggests that these models may be better at representing the full range of flows rather than just the medians.

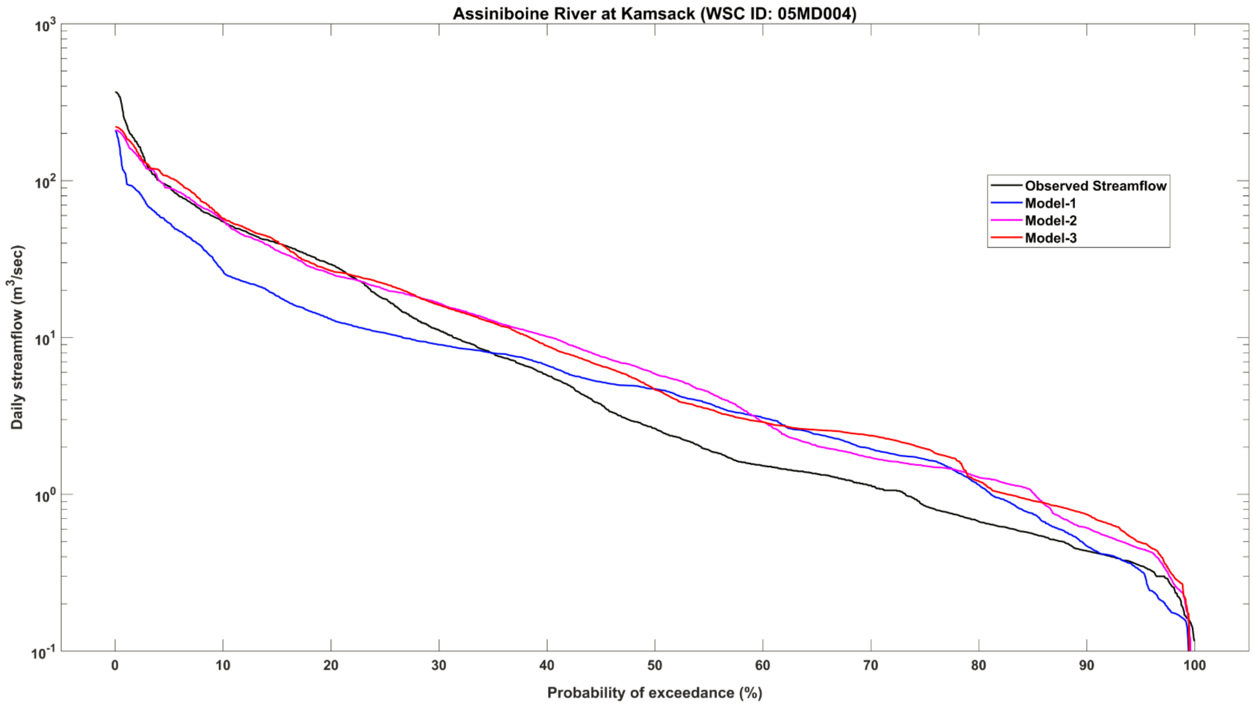

Figure 3-6: Flow duration curve for the calibration and validation periods comparing simulated output from the three models at the catchment outlet over 2005-2011

As an additional test, we assess the models' performance utilizing the coefficient of variation (CV), which is defined as the standard deviation divided by its mean. The seasonal mean, standard deviation, and coefficient of variation are summarized in Table 3-9 for the three models' along with the observed flow records. Based on the Table (Table 3-9), more than half of the total streamflow over the period 2005-2011 occurs during spring. The relatively low (1.15) value of the coefficient of variation in spring for the observed streamflow suggests lower inter-annual variability during the spring period. In general, Model-3 has similar statistics (i.e., mean, standard deviation, and coefficient of variation) compared to the other two models.

Table 3-9: The mean, standard deviation, and coefficient of variation in streamflow of the observed and the three models at catchment outlet (WSC ID: 05MD004)

Data type	Flow Statistics	Winter	Spring	Summer	Fall
Observed	Mean (Std. Dev)	2.87 (5.26)	42.62 (44.44)	23.85 (27.75)	9.07 (18.28)
	Coeff. Of Variations	1.78	1.15	1.26	2.00
Model-1	Mean (Std. Dev)	2.75 (2.54)	25.56 (23.49)	10.85 (9.15)	6.99 (8.78)
	Coeff. Of Variations	0.90	0.96	0.78	1.14
Model-2	Mean (Std. Dev)	5.93 (5.92)	37.78 (35.42)	25.73 (29.62)	7.69 (8.6)
	Coeff. Of Variations	1.00	1.10	1.18	1.09
Model-3	Mean (Std. Dev)	4.34 (5.88)	40.85 (38.29)	28.17 (31.65)	8.54 (9.07)
	Coeff. Of Variations	1.35	1.08	1.16	1.04

3.5.3 Water balance

To investigate how various hydrological processes (e.g., evaporation, runoff, etc.) respond to change in model structure, we analyzed each models water balance. In Table 3-10, the total precipitation falling over the watershed (PCP) is the primary source of inflow, whereas the evapotranspiration (ET) and water yield (WYLD) are the major outflows. In SWAT, WYILD is the summation of surface flow (Q_{surf}), the lateral flow (Q_{lat}), and the shallow aquifer flow termed as the groundwater flow (Q_{gw}), which at some point returns to the stream minus the transmission losses of tributary channels. ET is the dominant process during both the calibration and validation period accounting for 70-90 % of the water losses, which is consistent with the estimates reported by Saskatchewan Water Security Agency, (2000), in all three models.

Table 3-10: Dominant hydrological component of the annual water balance at the catchment outlet (Assiniboine river basin at Kamsack) over the 2005 – 2011 period. All values are in mm

	PCP	Q_{surf}	Q_{lat}	Q_{gw}	ET	WYLD	PERC	SW
Calibration								
2005	550.98[a]	56.21	1.32	0.00	395.32	30.03	92.77	110.99
	539.34[b]	67.41	1.04	47.32	395.49	119.13	74.99	113.01
	539.34[c]	68.95	0.88	49.34	384.88	125.12	79.65	120.96
2006	597.44	66.79	1.44	0.00	395.21	42.67	126.62	97.38
	586.43	88.37	0.99	71.22	379.40	165.17	89.40	95.44
	586.43	88.68	0.85	77.10	383.20	173.82	96.01	90.66
2007	489.97	64.80	0.99	0.00	445.58	40.31	65.38	34.52
	488.60	87.15	0.72	34.39	441.40	124.85	48.03	28.95
	488.60	85.28	0.61	31.39	436.55	121.72	44.75	32.48
2008	405.63	24.80	0.71	0.00	406.20	12.90	7.27	17.86
	405.08	48.06	0.52	2.63	373.64	51.79	5.81	22.63
	405.08	48.44	0.43	3.55	380.95	53.97	7.30	16.53
Validation								
2009	428.93	14.07	0.88	0.00	361.05	13.52	9.62	80.37
	429.79	39.84	0.66	2.84	355.53	43.62	4.88	71.43
	429.78	37.15	0.57	3.56	347.67	42.68	5.30	73.94
2010	614.47	24.62	1.58	0.00	347.53	19.32	127.16	159.95
	624.40	53.50	1.25	55.14	371.40	113.55	90.74	130.73
	624.40	53.57	1.06	60.12	363.59	121.37	95.65	133.16
2011	469.39	51.34	1.23	0.00	372.28	43.81	150.34	95.43
	462.53	121.91	0.84	71.45	369.73	198.87	88.81	82.50
	462.53	122.70	0.71	74.15	359.89	204.46	91.29	89.68

[a] Model-1 (each first row of the year contains water balance information of model-1)
[b] Model-2 (each second row of the year contains water balance information of model-2)
[c] Model-3 (each third row of the year contains water balance information of model-3)

During low to normal conditions, potholes are internally drained and are represented in reality as non-contributing areas. In 2007, a drier year, Model-2 reports more than 2% (2.18×10^{16} mm^3) increase in surface runoff volume compared to Model-3 (Table 3-10). Likewise, an approximate 3.65×10^{16} mm^3 increase in volume at the outlet can be observed. On the contrary, potholes connecting via fill-and-spill during periods of high flow result in increasing contributing area, and thus lead to higher flows. For example, in the year 2011, which is the wettest year considered in the study, Model-3 simulates ~7.65×10^{15} mm^3 higher surface runoff volume and more than 3% (~7.0×10^{18} mm^3) flow volume at the outlet.

3.6 Discussion

Calibrating a hydrological model is a difficult task due to the complex interaction and feedback between various hydrological processes. Complexity is further exacerbated in the prairie region because of the dynamic nature of isolated pothole wetlands and runoff generation mechanisms. Therefore, hydrologic models constructed to study PPR watersheds must account for the important role that pothole wetlands play in the PPR hydrologic cycle.

A few studies that have attempted to use SWAT to replicate streamflow in the PPR (see Chanasyk et al., 2003; Mekonnen et al., 2016) without explicitly considering landscape depression, and have reported poor modeling results. Consequently, we evaluate alternative structural (mechanistic) avenues of pothole wetland representation with the express intent of comparing model complexity, accuracy (based on performance metrics) and parameter uncertainty for each structural representation embedded within the SWAT model.

In the lumped pothole version of SWAT (Model-1), where various depressions are represented as a single lumped storage, it was seen that the model consistently under-estimated high flows during the calibration and validation period (Figure 3-3). The results are similar to those obtained by Wang et al., (2008) and Mekonnen et al., (2016) indicating that lumped representation of pothole depressions, which varies in storage capacity within the watershed, leads to the underestimation of peak flows, which is not optimal for inflow forecasting applications.

Furthermore, parameters in the lumped model are considered as averages across the UARB and thus ignore spatial variation within the catchment. For example, while the land use, soil properties as well as rainfall are spatially distributed, the calibration of Model-1 was lumped by using single factor for all parameters about these variables. On the one hand, lumped representations of parameters significantly decrease model's degree of freedom and computational cost during calibration, which thus results in a more robust calibration representing long-term average watershed conditions. On the other hand, the setup has resulted in a less physically realistic processes representation thus, limiting model performance and adequacy under climate-hydrologic feedback scenarios.

Improved performance is obtained in the semi and fully discretized pothole versions of the SWAT model, maximizing the NSE value (0.64 to 0.78 from Model-2 to Model-3). Such improvement can be attributed to the incorporation of spatial heterogeneity of various inputs as well as enhanced representation of potholes. The GIWs are a more realistic interpretation of the surface hydrology processes and water "distribution" for runoff generation leading to better performance statistics overall (Table 3-6; Table 3-7; Table 3-8). None of the models, however, were able to adequately replicate peak flow events, especially the extreme peak event of the year 2011, which was a 1:330-year event (Mortillaro, 2014). This could partially be due to the hydrometric station (WSC ID: 05MD004), which is listed as regulated under WSC, as there was no flow regulation introduced into our modeling effort. One other possible explanation for models' being unable to capture the 2011 year event could be watershed heterogeneity. For example, snow parameters were calibrated at the basin scale, meaning one value represents the entire watershed. For flat regions such as the Prairies, significant spatial variability in snow accumulation, and therefore snowmelt, can be observed based on land cover type (Lapen and Martz, 1996). The degree of variability can be especially pronounced in open areas as compared to canopy covered areas where snow tends to sit for an extended period (Latron and Lo, 2008). Improved modeling results may require adjusting snow parameters at finer spatial resolutions, preferably at the HRU level.

Model calibration is a complex task due to uncertainties arising from simplifying the different processes and because of processes that are not accounted for by the model, such as the fill-and-spill process or the effect of wetlands on the hydrology of a watershed in general. We, therefore, see larger uncertainty in the case of Model-3. Process-based uncertainty increases due to the added complexity of the model, specifically impacting how the wetlands store water - either allowing it to stay in the reservoirs and spill if a small value or seep out the bottom if a high value. Additionally, the modified concept of pothole representation in the case of Model-3 has resulted in a significant increase (over 1500%) in the number of HRUs. Since SWAT operates and performs water balance analysis at HRU level, the increasing computational units have resulted in a significant increase in the number of parameters to tune, thus providing a greater degree of freedom during model calibration. However, such modifications have led to a significant increase in model complexity, and therefore runtime. For example, for a computer with 8 Cores, 8 Gigabyte ram, and dual 2.70 GHz processing speed, to run an iteration of 500 simulations for UARB: it takes 4 hours for Model-1, 48 hours for Model-2, and 360 hours for Model-3 to complete the run. Model execution time can be of critical importance especially in forecasting applications where timely forecasts are required, or in the case of climate change studies where many scenarios are executed over longer time periods.

A unique feature of the PPR is the fill-spill process. Each of the three models utilize (1) a unique structural representation of the watershed's pothole wetlands; and (2) a unique combination of SWAT model parameters. While each of the models show satisfactory performance (in general) concerning streamflow (Table 3-6), the models produce distinct depictions of the system's internal water balance (Table 3-10). This indicates that significant equifinality impacts the models (i.e., distinct structural/mathematical representations of the system can replicate observed data approximately well). This is important for other modelers' looking at this system. If we assume that Model-3's water balance is closest to reality (because we know that fill-and-spill hydrology is important for the system), then we can say that a modeler that produces something approximate to Model-1 or Model-2 can get a reasonable streamflow simulation, but at the expense of the system's internal representation of water balance.

Furthermore, the modification provides additional avenues for evaluating the aggregate effects that pothole wetlands have on the regional hydrology of prairie watersheds. The modified GIW concept can be adapted to assist in quantifying the nutrient loading to Lake Winnipeg (i.e., the world's 10^{th} largest freshwater resource) and the role GIWs can play in reducing nitrification (Committee, 2005). Additionally, studies report decreasing future water availability in the Canadian Prairies for summer (Dibike et al., 2017, 2012), thus the modified concept can be utilized to evaluate the economics of water storage that pothole wetlands may provide when agricultural demands are highest.

A limitation of this particular study was the lack of high-resolution input data (e.g., LiDAR), which could assist with better representing the spatial distribution and characterization of the pothole terrain and internal drainage pathways within the catchment. Also, the computational intensity associated with increasing the number of HRUs from 271 (lumped) to 971 (distributed) to 15235 (modified distributed), which enhances structural physical accuracy but significantly increased the number of parameters to optimize, was challenging.

3.7 Conclusions

In this study, the SWAT model was calibrated and validated with three different structural arrangement for a Canadian Prairie watershed at a daily time step. The models were compared and evaluated to assess the impact of model structural complexity on the accuracy of streamflow at daily, seasonal and annual basis.

In general, the fully discretized pothole model that represent modified concept of PPR pothole wetlands (Model-3) performed better reporting a high-performance efficiency and better represent the regionally dominant GIW hydrological processes. Also, Model-3 was better able to capture the peak flows which suggests that it would be a better tool over the other models for flood forecasting. On the other hand, the added complexity significantly increased the number of parameters which makes the calibration process more complex and therefore, is an operational decision factor that would affect the choice of the model.

Given the complexities in calibrating the hydrological model for the prairie region, it is encouraging to see that the modified structure of Model-3 improves simulation of high and peak flows. On that positive note, the recommendation would be to use the concept of the modified calibrated model to quantify the flooding value of potholes, examination of climate and land use changes, and the importance of potholes in reducing nutrient loading in particular to the Lake Winnipeg. The technique and model developed as a result of this study could be of help to the water resources management authorities (i.e., HFCs, Water stewardship, Ducks Unlimited Canada, etc.) working across the Prairie region.

4 ASSESSING THE IMPORTANCE OF POTHOLES IN THE CANADIAN PRAIRIE REGION UNDER FUTURE CLIMATE CHANGE

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4.1 Abstract

The Prairie Pothole Region (PPR) of Canada contains millions of small isolated wetlands and is unique to North America. The goods and services of these isolated wetlands are highly sensitive to variations in precipitation and temperature. We evaluate the flood-proofing of isolated wetlands (potholes wetlands) under various climate change scenarios for the Upper Assiniboine River Basin (UARB) at Kamsack, a headwater catchment to the Lake of Prairies in the Canadian portion of Prairie Pothole Region (PPR). A modified version of the Soil Water Assessment Tool (SWAT) model is utilized to simulate projected streamflow under the potential impacts of climate change, along with changes to the distribution of pothole wetlands. Significant increases in winter streamflow (~200%) and decreasing (~11%) in summer flow, driven by changes in future climate are simulated. Simulated changes in streamflow resulting from pothole removal were between 55% for winter and 15% for summer, suggesting that climate is the primary driver in the future hydrologic regime of the study region. This research serves as an important guide to the various stakeholder organizations involved in quantifying the aggregate impacts of pothole wetlands in the hydrology of the Canadian Prairie region.

4.2 Introduction

The North American Prairie Pothole Region (PPR) spans across Alberta, Saskatchewan, and Manitoba in Canada and extends into North Dakota, South Dakota, Iowa, Minnesota, and Montana in the United States (US) (Figure 4-1). Details on the study area are provided in Chapter 3 section 3.3.1 and thus are not repeated here.

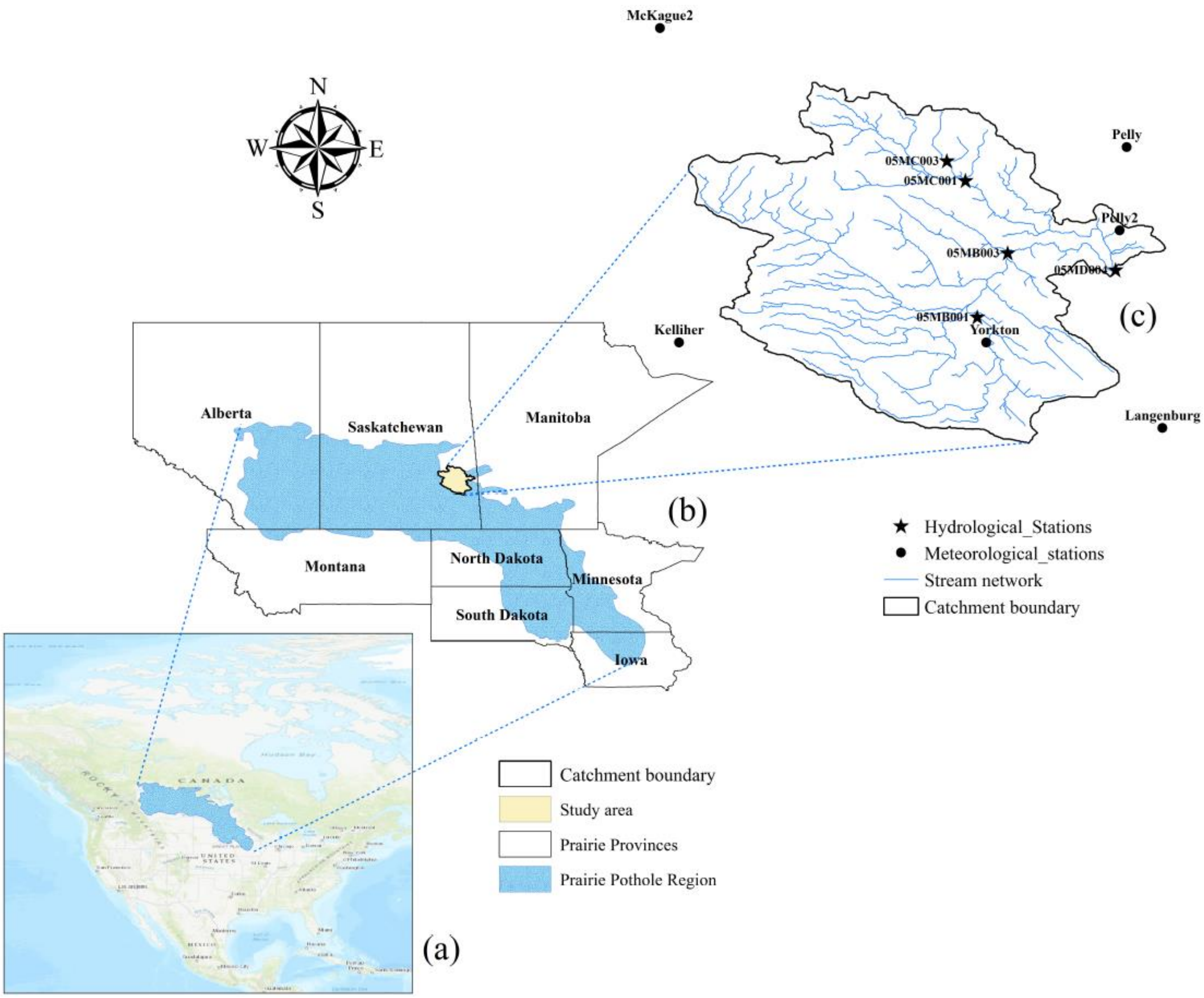

Figure 4-1: Location map of the UARB at Kamsack: (a) PPR of North America (USGS), (b) location of the Prairie provinces, and (c) study watershed along showing hydro-meteorological stations.

Wetlands play a major role in watershed health (Bullock and Acreman, 2003; Hunter et al., 2017; Revenga and Tyrrell, 2016; Weller et al., 1996) and can be seen as an integral component of much of the prairie landscape. Wetlands help to mitigate the effects of climate change by reducing the effects of drought and inundation. During wetter periods they store large amount of water helping to reduce peak flood flows; and in dry periods, they retain water helping to recharge groundwater (Millett et al., 2009; Shaw et al., 2012; Shook et al., 2013). Wetlands, however, due to their shallow nature, are highly susceptible to changes in climate and land use (Dumanski et al., 2015; Rashford et al., 2016; Werner et al., 2013). The Intergovernmental Panel on Climate change (IPCC) in its fifth assessment report, projected a 2^{o}C to 5^{o}C rise in the surface temperature (Collins et al., 2013; IPCC, 2013). Consequently, it is very likely that extreme precipitation events will become more intense and frequent, altering the hydrologic cycle and water availability of many regions (Field and Barros, 2014; Trenberth, 2008).

Global Circulation Models (GCMs) have been considered effective tools to explore physical processes of earth's surface atmospheric system and are widely utilized to gain information regarding historical, current, and future climate (Zhang et al., 2016). Based on estimates of future populations levels, economic activity, and technological pattern (IPCC, 2013; Morita et al., 2001; Moss et al., 2010), the future climate change scenarios from GCM are used to assess future vulnerability attributed to climate change (Carter et al., 2001). Numerous studies suggest that climate change may have a far more significant impact on PPR of North America, where runoff is mainly driven by seasonal snowmelt (Betts et al., 2013; Herring et al., 2015; Johnson and Poiani, 2016; Qian et al., 2016; Shrestha et al., 2012). Most regions of the Canadian Prairie Pothole Region (CPPR) are projected to warm over the next 60 years (Actuaries, 2015), in particular central CPPR where warming is expected to be more pronounced (Gurrapu et al., 2014), thus potentially resulting in increased drought and excessive moisture risk (Olmstead, 2014). For example, snowfall in the CPPR accounts for about 30% of total annual precipitation and produces 80% or more of the total annual surface runoff (Fang and Pomeroy, 2007; Shook et al., 2015). Changes in the amount and seasonality of air temperatures and precipitation could significantly alter the volume, distribution, and timing of snowfall, which may affect the hydrology of the prairie.

While it is essential to consider the potential effect of climate change, several studies have also highlighted the significance of land use change and its vital role in the hydrology of CPPR (Conly et al., 2001; Dumanski et al., 2015; Fang et al., 2007; Mekonnen et al., 2017, 2015). Surface runoff in the prairie often drains into depressions, forming wetlands or pothole wetlands. Pothole wetlands are closed basin that retains water for a longer duration due to their higher storage capacity (Hayashi et al., 2003; Muhammad et al., 2016a; Shook, 2012; Shook et al., 2013), and do not contribute flow to stream under normal condition. However, during times of high runoff, pothole wetlands connect to each other and to the stream via a fill and spill process (van der Kamp and Hayashi, 2009), which results in a dynamic increase in contributing area for runoff to the streams (Dumanski et al., 2015; Shaw et al., 2012). Land use changes, in particular, the loss of pothole wetlands mainly due to agricultural development, greatly alter hydrological processes affecting both water quality and quantity. Thus, there is a pressing need to thoroughly investigate the coupled effect of climate and land use change on the hydrology of the CPPR.

Watershed-scale hydrologic models can be valuable tools that enhance our understanding of complex natural processes, and that aid in examining land-use change and best management practices (BMPs). Advances in computational resources have further enhanced modeling at finer-scale resolutions while discretizing the geospatial heterogeneity of a watershed. SWAT is a watershed–scale model which has been widely used for water resources assessment (Arnold et al., 1998; Jayakrishnan et al., 2005; Krysanova and White, 2015; Srinivasan et al., 1998), climate and land use changes (Abbaspour et al., 2009; Jha et al., 2006; Li et al., 2009; Mango et al., 2011; Narsimlu et al., 2013), water quality, pollutants and nutrients loading (Abbaspour et al., 2007; Jha et al., 2007; Santhi et al., 2001; Srinivasan and Arnold, 1994), and watershed management practices (Betrie et al., 2011; Singh et al., 2005; Tripathi et al., 2003). Hydrologic models constructed to study PPR watersheds must pay close attention to the important role that pothole wetlands play in the PPR hydrologic cycle. Shrestha et al., (2012) utilized the SWAT model for studying climate-induced changes in hydrology and nutrient fluxes of the Upper Assiniboine River Basin (UARB). The study, however, did not explore land use as a factor along with climate change affecting hydrology. Zhang et al., (2011) and Zhang and Huang, (2013) examined uncertainty in hydrological responses due to climate change in the Assiniboia watershed of Saskatchewan, Canada using SWAT model. A few other studies (Mekonnen et al., 2016, 2015; Yang et al., 2010) used SWAT model for investigating the impact of pothole wetlands on downstream hydrographs without considering the effect of climate change.

Given the importance of pothole wetlands to ecological goods and services, especially flood mitigation, there is a need for more research on the coupled impacts of climate and land use change. The primary focus of this research is to present an analysis of the compounding effect of climate and land use change on streamflow in the CPPR. Our method of land use change involves removal of pothole wetlands from the land surface. Our specific interests are to (1) examine the hydrological response at the outlet resulting from changes in both land use and climate change, and to (2), evaluate the effect of hydrograph sensitivity due to pothole wetland removal for extreme events. This research will provide quantitative information for water managers and stakeholders in the PPR regarding the importance and significance of pothole wetlands in controlling the future PPR runoff response.

4.3 Methods and materials

4.3.1 Study area

The presence of potholes that creates intermittent flow, the existence of numerous lakes, and the dynamics of the wetlands are defining characteristics of the Upper Assiniboine River Basin (UARB) at Kamsack. Spanning the provinces of Saskatchewan and Manitoba, the UARB has a total area of 13,000 km^2 and is monitored by five streamflow gauging stations (Figure 4-1c). The basin is of vital importance as flow generated in the basin enters the Lake of the Prairie (Shellmouth Reservoir), which was constructed for flood mitigation purposes and is situated approximately 45 km downstream of the watershed outlet.

The climate of the UARB is continental sub-humid characterized by long, cold winters and short summers where the mean annual temperature and potential evapotranspiration is about 1°C and 850 mm, respectively (Saskatchewan Water Security Agency, 2000). Average annual precipitation is 450 mm, with approximately 26% of the precipitation falling as snow (Shrestha et al., 2012). Spring freshet occurs from April to June, accounting for 82%, on average, of total mean annual streamflow (Shrestha et al., 2012; Figure 4-2).

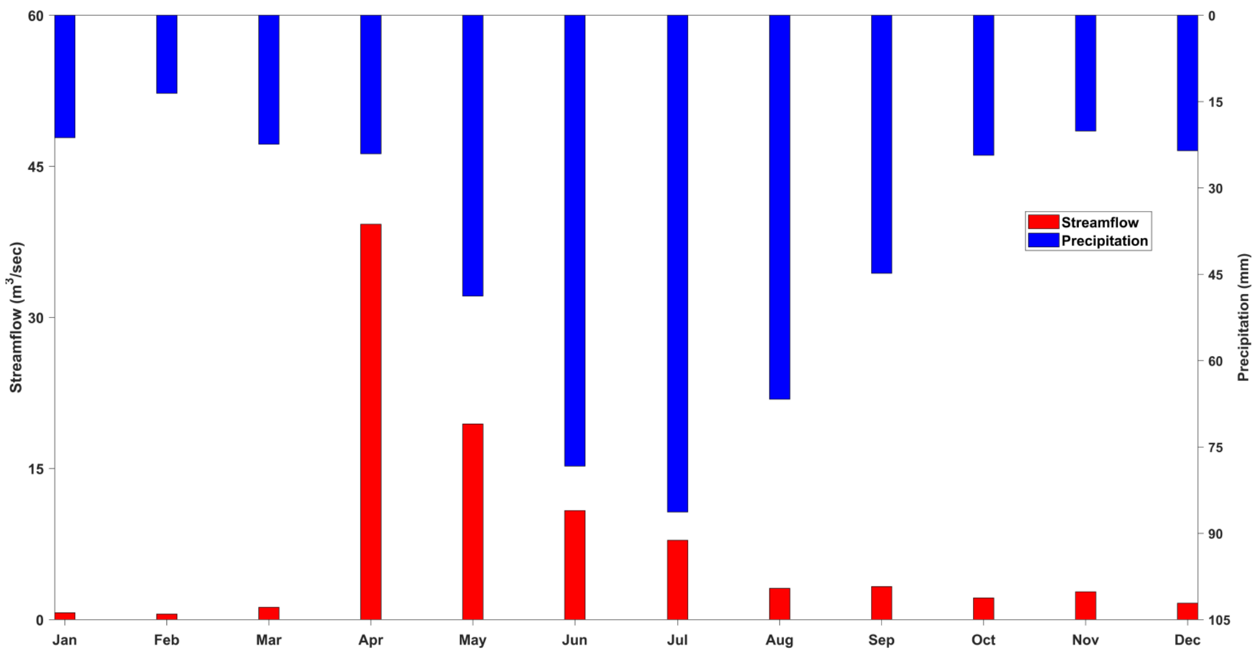

Figure 4-2: Mean monthly streamflow and precipitation (1981-2010) at Kamsack (WSC ID: 05MD004), outlet for the UARB.

4.3.2 Geospatial and hydro-climatic data

SWAT requires climate data, topography, land use, and soil type as inputs. Climate data at a daily time step for the period 1981-2015 were obtained from Environment and Climate Change Canada (ECCC). Six meteorological stations were considered, of which two resided within the basin, and four were nearby (Figure 4-1c). A digital elevation model (DEM) at 20 m spatial resolution (NRC, 2007) and the 30 m spatial resolution land use data (Olthof et al., 2009) were obtained from the GeoGratis Data Portal (http://geogratis.gc.ca/). Detailed soil data were obtained from the Agriculture and Agri-Food Canada's Manitoba regional office. These data are of 30 m spatial resolution with information for up to six layers of soil depth at 5, 15, 30, 60, 100 and 200 cm. The observed daily streamflow time series, which is required for model calibration and validation, was obtained from ECCC's Water Survey of Canada (WSC) hydrometric Database (HYDAT) (Table 4-1).

Table 4-1: Available hydrological stations in the UARB at Kamsack utilized during model calibration and validation.

Serial no	Station ID	Station name	Start year	End year	Drainage area (km^2)	Remarks
1	05MC003	Lilian River near Lady lake	1965	2015	229	Seasonal[a]
2	05MC001	Assiniboine River at Sturgis	1944	2015	1930	Seasonal[a]
3	05MB003	Whitesand River near Canora	1943	2015	8740	Seasonal[a]
4	05MD004	Assiniboine River at Kamsack	1944	2015	13,000	Continuous
5	05MB001	Yorkton creek near Ebenezer	1941	2015	2320	Seasonal[a]

4.3.3 Hydrological model

This study utilized the modified version of the SWAT model (see section 3.3.4.3). Potholes in SWAT are defined at HRU level. The standard version of SWAT does not recognize the hydrologic relationship of pothole wetlands to uplands and other up-gradient pothole wetlands. For instance, in the prairie region; the up-gradient drainage area of a pothole may stretch out past the limits of its particular HRU and would receive inflow from numerous up-gradient HRUs. SWAT does not mimic between pothole fill–and-spill connections in light of the fact that hydrologic transport between HRUs is unrealistic inside the model (Evenson et al., 2015). The modified version, which has enhanced representation of pothole wetlands, overcomes these issues and is able to better adapt to the physical processes that occur in our study watershed.

4.3.4 Calibration and validation

The Sequential Uncertainty Fitting (SUFI-2) tool was used as a means of calibrating and validating the model. Details on the SUFI-2 methodology are provided in Chapter 3 section 3.3.6.

In this study, the model was calibrated for the period 1981–2010 and verified from 2011-2015, considering all flow gauging stations. The Kling-Gupta (Gupta et al., 2009) efficiency (KGE) metric was used as a guide for selecting the most optimal parameter and to evaluating model performance (Equation 11).

$$KGE = 1 - \sqrt{(r-1)^2 + (\propto -1)^2 + (\beta - 1)^2} \quad (11)$$

Where $\alpha = \frac{\sigma_s}{\sigma_m}$, $\beta = \frac{\mu_s}{\mu_m}$,

σ_s and σ_m are the standard deviation of simulated and measured data; μ_s and μ_m are the means for simulated and measured data, respectively; and r is the linear regression coefficient between measured and simulated data. KGE allows for a multi-objective perspective by focusing on correlation error, variability error, and bias (volume) error (Pechlivanidis and Arheimer, 2015). A KGE > 0.5, recommended by Gupta et al. (2009), is set as the threshold value for selecting simulation runs while running the auto-calibration program. Other performance metrics such as Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970) and percent bias (PBIAS) (Gupta et al., 2009; Yapo et al., 1996) were also utilized to further assess model performance. In this paper, the model calibration effort should satisfy the following criteria for satisfactory performance:

1. KGE ≥ 0.5 as recommended by Gupta et al., (2009)
2. NSE ≥ 0.5 by Moriasi et al., (2007)
3. PBIAS $\leq \pm 0.25$ as recommended by Moriasi et al., (2007)

4. p-factor $\geq$ 0.7 and r-factor $\leq$ 1.5 as suggested by Abbaspour et al., (2015) for the 95% prediction uncertainty when using SUFI-2

4.3.5 Scenario formulation: Climate and land use change

The Canadian Regional Climate Model (CRCM) version 5 is used to extract future climate data. It is higher resolution than GCM data, and therefore the most up-to-date CRCM and has several improvements, such as an improved land surface scheme (Diaconescu et al., 2016; Martynov et al., 2013; Šeparović et al., 2013). We select RCP 4.5 and 8.5 and two future periods: near future (2030s: 2011-2040) and middle future (2050s: 2041-2070) in our study. RCP 4.5 represents a moderate population and economic growth with an average of 1.4ºC rise in temperature. RCP 8.5 portrays rapid population growth with modest technological changes, and relatively slow income growth, thus leading to an increased greenhouse gas emissions, consequently, resulting with an average of about 2.0 ºC rise in temperature (Collins et al., 2013; Vinet and Zhedanov, 2010).

Output from RCMs is, however, subject to systematic biases (Hagemann et al., 2011; Ines and Hansen, 2006; Piani et al., 2010; Teutschbein and Seibert, 2012) that may potentially affect hydrological simulations (Roosmalen et al., 2010). Thus we bias correct these data before using them to drive our hydrological model. Performance and effectiveness of bias correction techniques is very much dependent on the study location (Chen et al., 2013). We utilized a quantile-quantile (Q-Q) mapping approach (Mpelasoka and Chiew, 2009) to bias correct the RCM data used in our study based on recommendations from Vieira (2016). Figure 4-3 presents basin averaged RCM data before and after the application of our Q-Q mapping bias correction.

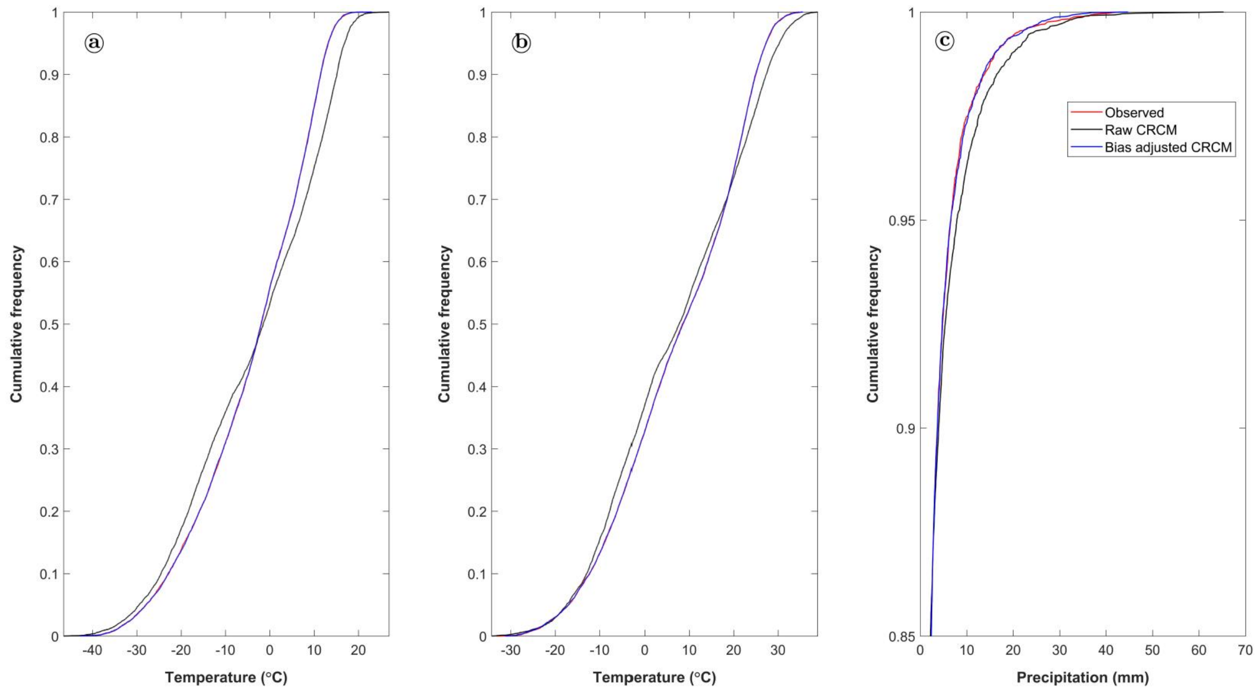

Figure 4-3: Cumulative distribution of observed, raw CRCM, and bias-adjusted CRCM data averaged across the basin for (a) minimum temperature, (b) maximum temperature, and (c) precipitation.

The land use scenarios were created by varying the percent of pothole wetland coverage in the watershed. We used five land use scenarios by randomly removing 0%, 25%, 50%, 75%, and 100% pothole wetlands from the land surface (Figure 4-4).

The calibrated model as a baseline model was used to run the combination of land use and climate change scenarios to assess the effect on the downstream hydrograph (WSC ID: 05MD004). Figure 4-5 shows a schematic diagram outlining scenario formulation. The combination of four climate and 5 land use change scenarios resulted in total 20 coupled land use and climate change scenarios.

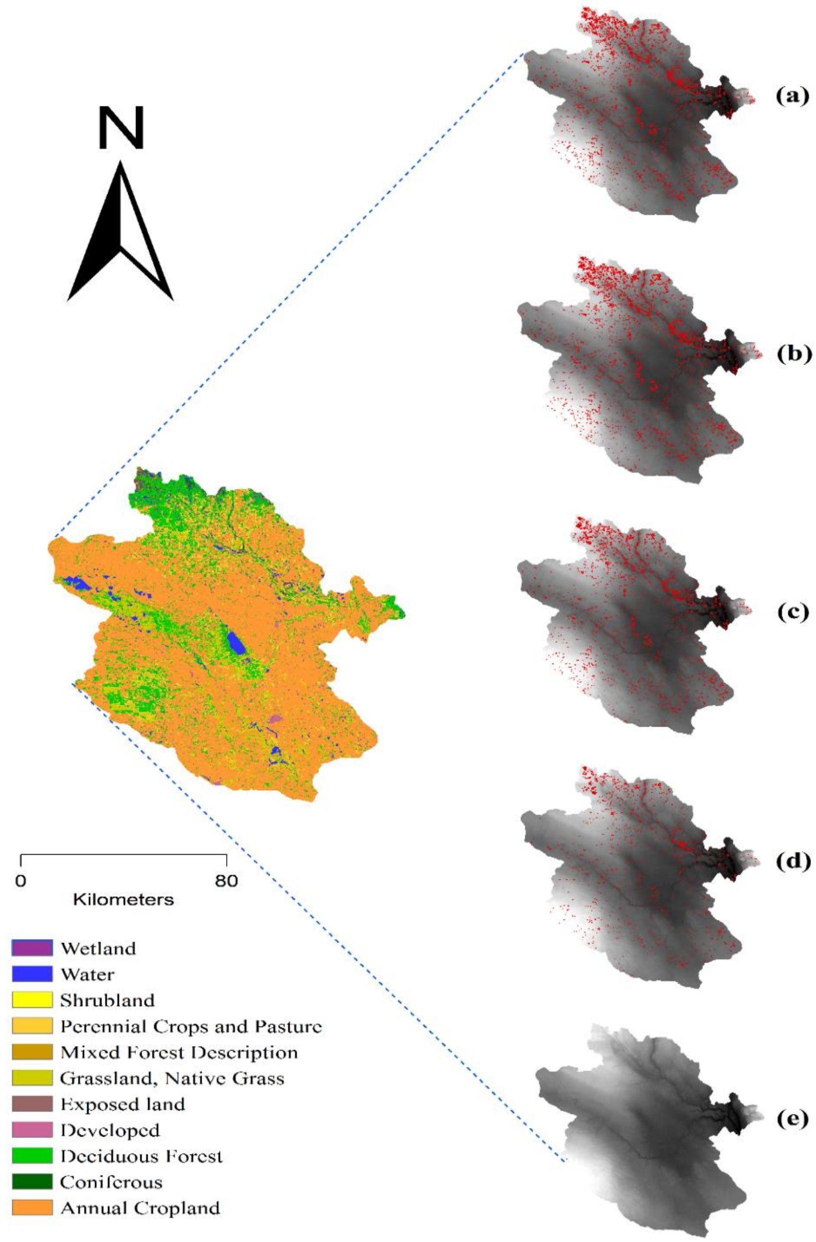

Figure 4-4: Land use scenarios for (a) no pothole wetlands removed, (b) 25% pothole wetland removal, (c) 50% pothole wetland removal, (d) 75% pothole wetland removal, and (e) all pothole wetlands removed.

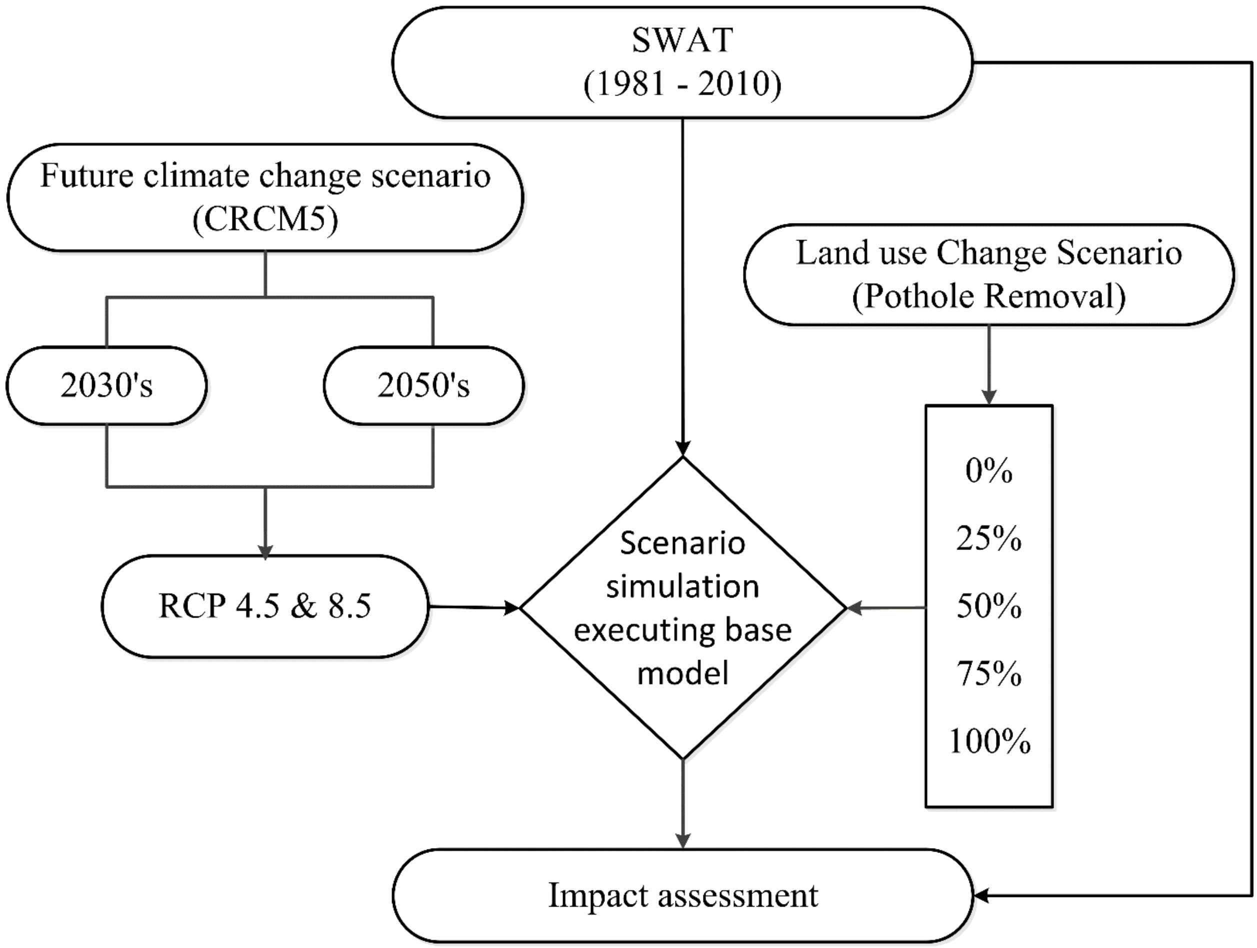

Figure 4-5: Schematic of climate and land use change scenario workflow.

4.4 Results

4.4.1 Model calibration and validation

For model calibration, key parameters that govern hydrologic processes of the study watershed were selected based on available literature (Mekonnen et al., 2017; Mekonnen et al., 2016, 2015b, 2014; Rahbeh et al., 2011; Shrestha et al., 2012; Yang et al., 2010; Zhang et al., 2011a, 2011b).

Table 4-2: SWAT parameters used for calibrating the modified SWAT model.

Parameter	Parameter range			Descriptions (units, if applicable)
	Min	Max	Fitted value	
ALPHA_BF	0.01	0.80	0.43	Base flow alpha factor (days)
GW_DELAY	0.00	500.00	208.78	Groundwater delays (days)
GW_REVAP	0.02	0.20	0.17	Groundwater revap coefficient
GWQMN	0.00	5000.00	4095.50	Threshold depth of water in the shallow aquifer (mm)
RCHRG_DP	0.00	1.00	0.05	Deep aquifer percolation faction
REVAPMN	0.00	500.00	69.00	Threshold depth of water in the shallow (mm)
CH_K1	0.00	150.00	104.60	Effective hydraulic conductivity in tributary channel alluvium (mm h^{-1})
CH_K2	0.00	150.00	86.58	Effective hydraulic conductivity in main channel alluvium (mmh^{-1})
CH_N1	0.01	0.30	0.09	Manning's N value for the tributary channel
CH_N2	0.01	0.30	0.22	Manning's N value for the main channel
CN2[a]	-0.25	0.25	0.02	SCS runoff curve number
SOL_AWC	-0.25	0.25	-0.10	Available water capacity (mm H2O mm^{-1})
EPCO	0.00	1.00	0.77	Plant uptake compensation factor
ESCO	0.00	1.00	0.49	Soil evaporation compensation factor
TIMP	0.01	1.00	0.04	Snow pack temperature lag factor
SFTMP	-3.00	3.00	-0.85	Snowfall temperature
SMTMP	-3.00	3.00	-0.12	Snowmelt base temperature
SMFMN	0.00	10.00	5.53	Melt factor for snow on winter solstice (mm c^{-1} day^{-1})
SNOCOVMX	5.00	500.00	44.33	Minimum snow water content corresponds to 100% snow cover (mm)
SNO50COV	0.05	0.80	0.12	Snow water equivalent that corresponds to 50% snow cover (%)
SMFMX	0.00	10.00	4.71	Maximum melt rate for snow on summer solstice (mm c^{-1} day^{-1})
OV_N	-0.20	0.20	-0.07	Hydraulic conductivity of bottom of wetland (mm h^{-1})
CH_L1	-1.00	1.00	0.01	Manning's N value for overland flow
CH_W1	-1.00	1.00	0.86	Longest tributary channel length in sub basin
CH_L2	-1.00	1.00	0.01	Average width of tributary channels (m)
CH_W2	-1.00	1.00	-0.03	Length of main channel m)
WET_K	0.00	3.60	0.57	Average width of main channel (m)

A total of 27 parameters were considered in the calibration process. The minimum, maximum and the fitted values (Table 4-2) and observed and simulated hydrographs with 95% prediction uncertainty for catchment outlet are presented (Figure 4-6).

In general, the model was able to capture the variability of streamflow, particularly the timing of the peak flow. The places, the model overestimates observed streamflow, such as during the years 1982-83,89 and in the spring of the year 2002, were dry years (relative to normal). During the validation period, low flows are overestimated and high flows underestimated. However, the model generally follows the seasonal patterning of streamflow. The p-factor and r-factor are within an acceptable range (Table 4-3), and KGE, NSE, and PBIAS indicate satisfactory modeling results. All gauging stations listed in Table 4-3 were parameterized and optimized simultaneously. This may lead to some outlets being more poorly simulated than others, for example, at Ebenezer (WSC ID: 05MB001). In this case, the gauge is located downstream of approximately ten unregulated reservoirs, collectively known as the Yorkton complex, which significantly impacts the SWAT model performance due to the poor parameterization of reservoir releases.

Table 4-3: Statistical measure of baseline model performance: Calibration (1981–2010) validation (2011–2015)

	Model performance at monthly time step: calibration (validation)				
Station name	**p-factor**	**r-factor**	**KGE**	**NSE**	**PBIAS**
Lilian River near Lady lake	0.8 (0.9)	1.3 (1.4)	0.7 (0.4)	0.5 (0.3)	-6.2 (-31.0)
Assiniboine River at Sturgis	0.6 (0.8)	1.3 (1.0)	0.5 (0.7)	0.4 (0.6)	-32.0 (-19.4)
Whitesand River near Canora	0.5 (0.6)	1.2 (0.6)	0.5 (0.5)	0.4 (0.6)	-12.0 (30.9)
Assiniboine River at Kamsack	0.8 (0.8)	1.1 (0.7)	0.6 (0.6)	0.5 (0.7)	-1.7 (9.1)
Assiniboine River at Ebenezer	0.9 (0.4)	1.1 (0.3)	0.5 (0.1)	0.2 (0.2)	2.1 (62.7)

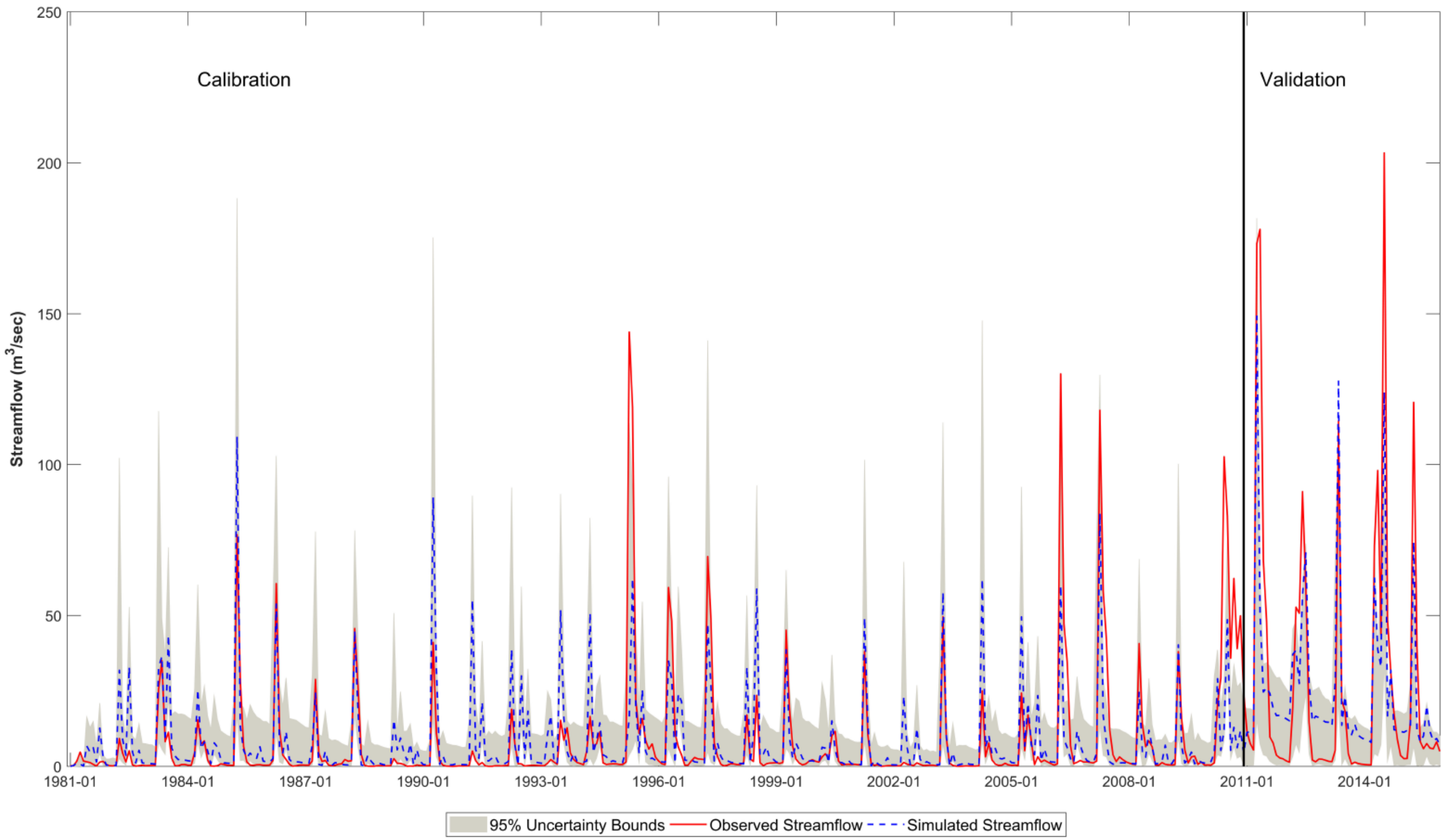

Figure 4-6: Calibration (1981-2010) and validation (2011-2015) of baseline SWAT model at the catchment outlet (WSC ID: 05MD004)

4.4.2 Future climate for period 2030s and 2050s under RCP 4.5 and RCP 8.5 scenarios

Figure 4-7 shows changes in the mean monthly (a) precipitation (mm), and (b) temperature (ºC) for RCP 4.5 and RCP 8.5 over two climatological periods centered around 2030 (2011-2040) and 2050 (2041-2070).

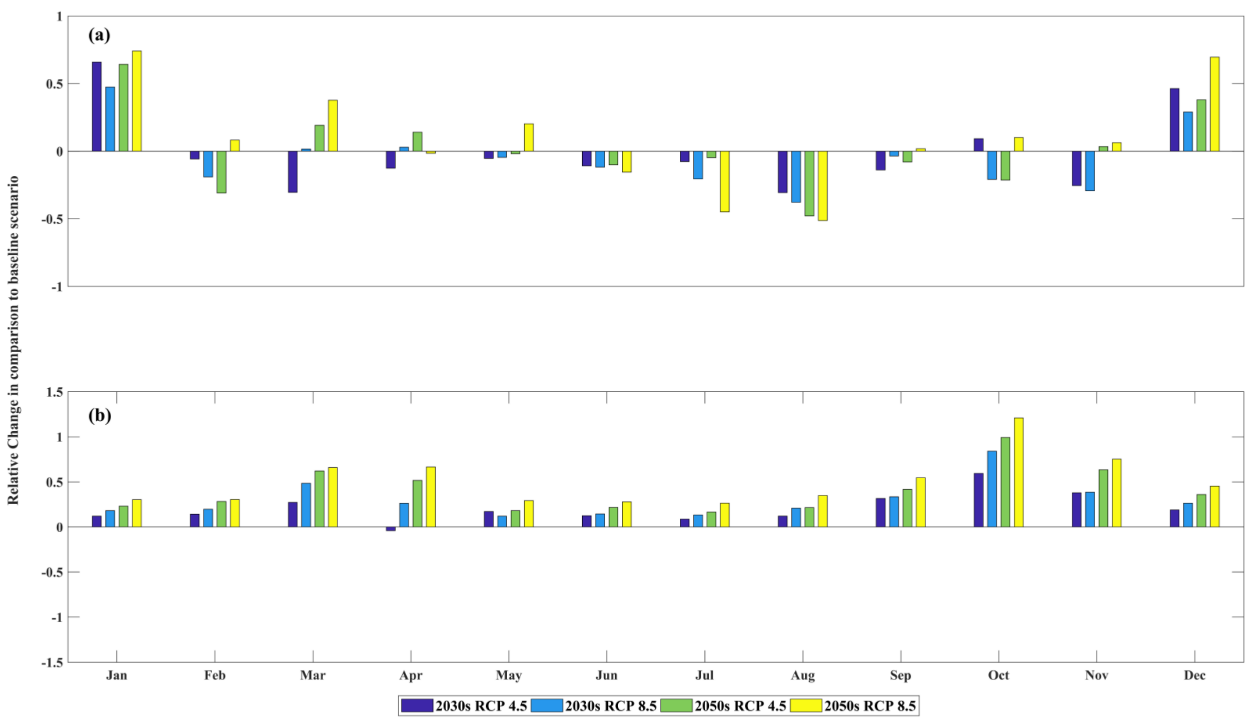

Figure 4-7: Projected relative change in comparison to the baseline period for (a) precipitation and (b) average temperature under RCP 4.5 and RCP 8.5 for near (2030) and middle (2050) futures, averaged across the basin.

We used seasonal averages for ease of inter-comparison. Our seasons are defined as winter (DJF), Spring (MAM), Summer (JJA), and Fall (SON). There is a notable increase in winter precipitation, especially in December and January, under all climate projections. Precipitation decreases during summer, as also noted in Mcginn, (2010) . The climate model indicates an increase in temperature across the year for the basin. Increasing temperature, averaged across the basin, is more pronounced under RCP 8.5 (3.5ºC) compared to RCP 4.5 (2.5ºC) for the 2030s but reverses by the 2050s (6ºC and 4.8ºC for RCP 4.5 and 8.5, respectively). Thus, it should not be assumed that the RCP 8.5 scenario represents the most extreme changes in climate for this region.

4.4.3 Variations in streamflow

We begin our evaluation by comparing future changes in the ensemble mean of all climate and land use change scenarios. Ensemble mean is used to reduce the uncertainty of future projections, primarily resulting from future climate. The mean monthly variation in streamflow response under climate and land use change for the two future time periods shows a significant increase in streamflow during winter (DJF), and decreases in spring peak discharge and summer streamflow across all scenarios (Figure 4-8). Such variations in streamflow are not unexpected for this region (Henderson and Sauchyn, 2008) and can be attributed to a shift toward wetter winters and drier summers. We, however, see relatively high spring streamflow during the period 2050s in comparison to the period 2030s. This can be attributed to higher precipitation in the 2050s period.

To further investigate the coupled impact of land use and climate change, seasonal analyses were carried out. Changes in winter and summer streamflow were most notable (Figure 4-9). Median streamflow for winter is likely to increase (based on all climate scenarios; Figure 4-9), perhaps due to increasing precipitation falling as rain. Interestingly, increases from RCP 4.5 are relatively higher compared to RCP 8.5 for the 2030s. This could be linked to the climate data, where increasing precipitation for RCP 4.5 is observed than RCP 8.5 (Figure 4-7a).

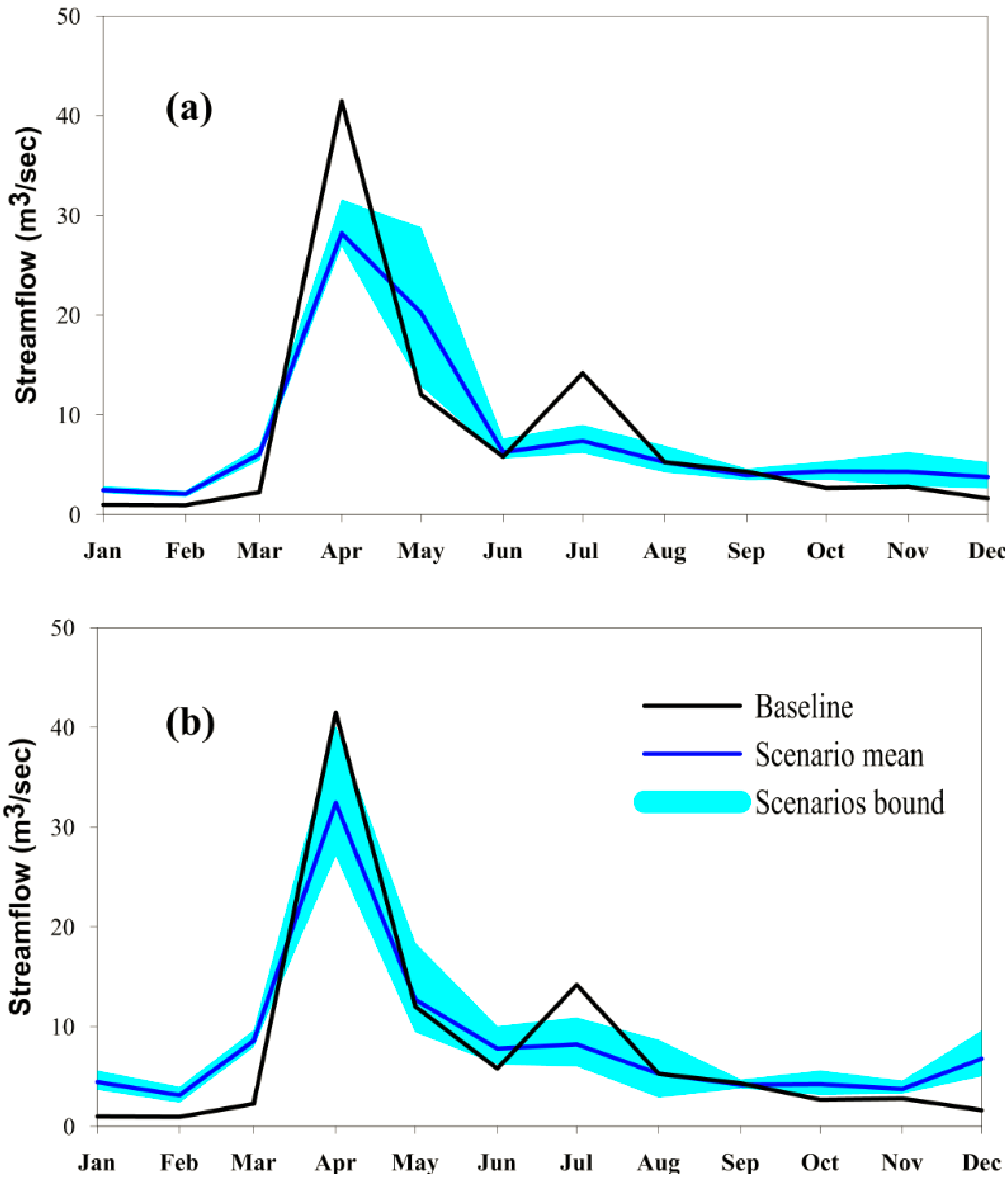

Figure 4-8: Mean monthly streamflow hydrographs for (a) 2030s and (b) 2050s under RCP 4.5 and RCP 8.5 for all climate and land use change scenarios at catchment outlet (WSC ID: 05MD004) relative to the baseline period (1981-2010).

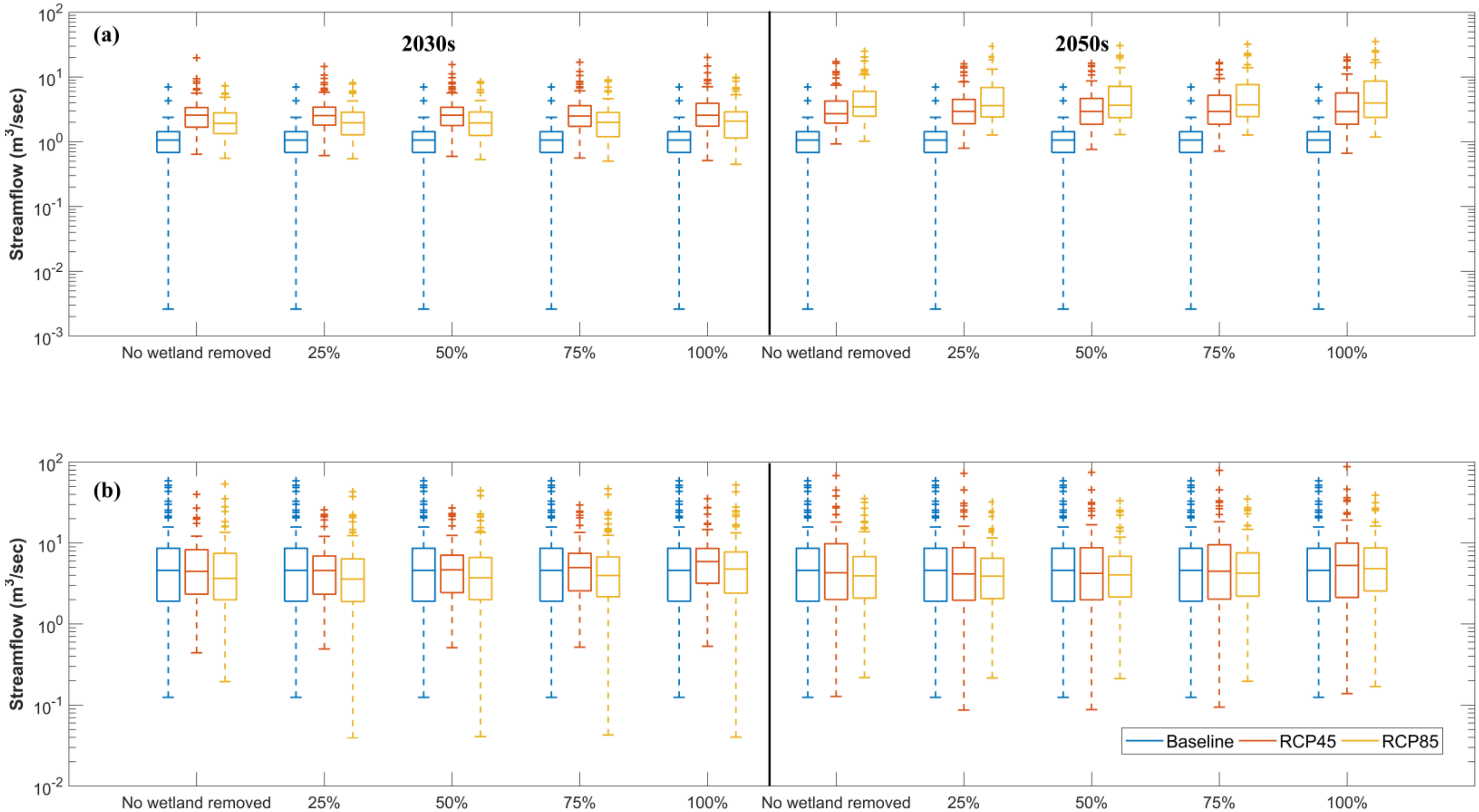

Figure 4-9:Seasonal streamflow boxplots for (a) winter (DJF), and (b) summer (JJA) under RCP 4.5 and 8.5 for all climate and land use change scenarios at the catchment outlet (WSC ID: 05MD004), relative to the baseline period.

Table 4-4: Seasonal changes (%) in streamflow relative to baseline, for various land use scenarios under a changing climate.

	Climate period 2030s: RCP4.5 (RCP8.5)			
Wetland Removed (%)	**Winter**	**Spring**	**Summer**	**Fall**
0	1.58 (0.91)	0.67 (0.55)	-0.16 (-0.19)	0.45 (0.07)
25	1.64 (1.0)	0.67 (0.54)	-0.17 (-0.23)	0.57 (0.06)
50	1.64 (0.99)	0.70 (0.58)	-0.14 (-0.20)	0.59 (0.08)
75	1.69 (0.98)	0.76 (0.65)	-0.08 (-0.16)	0.64 (0.13)
100	1.87 (1.04)	0.91 (0.81)	0.05 (-0.05)	0.77 (0.26)
	Climate period 2050s: RCP4.5 (RCP8.5)			
0	2.11 (3.10)	0.71 (0.8)	0.08 (-0.15)	0.09 (0.37)
25	2.33 (3.36)	0.76 (0.81)	0.01 (-0.20)	0.12 (0.38)
50	2.37 (3.46)	0.8 (0.86)	0.04 (-0.17)	0.13 (0.40)
75	2.46 (3.69)	0.88 (0.94)	0.09 (-0.13)	0.16 (0.46)
100	2.76 (4.25)	1.06 (1.15)	0.22 (-0.02)	0.25 (0.61)

The expansion of agriculturally-dominated regions through pothole wetland removal further increases streamflow, indicating the sensitivity of streamflow to land use changes. For example, in comparison to the zero removal scenario, a 30% increase in streamflow could be observed if all pothole wetlands are removed (Table 4-4) under RCP 4.5 period 2030s. The change under RCP 4.5 for the period 2050s could be up to a 65% increase in streamflow when all pothole wetlands are removed. A similar increasing pattern from the aforementioned future period is observed for RCP 8.5. For example, during the middle future, winter streamflow could nearly threefold with no land use change, up to a fourfold increase if all pothole wetlands are removed. Changes regarding percentage variation in summer streamflow are not as high in comparison to winter flows. For example, there is a 16% decrease in summer streamflow under RCP 4.5 with no wetland removal in comparison to a 160% increase in winter for the same period and scenario. Similarly, impact on streamflow variability between the two extreme land use scenarios during summer (~ 20%) is also lower in comparison to that during the winter season (~ 30%).

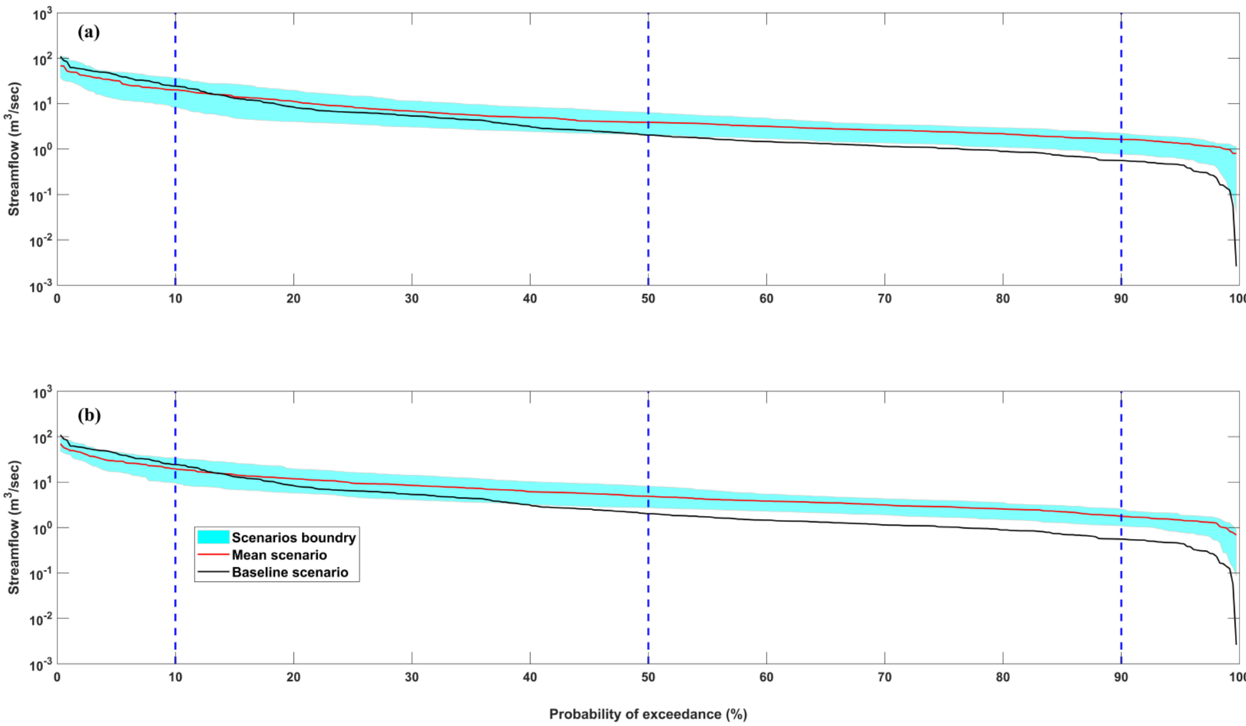

Figure 4-10: Flow duration curves for (a) 2030s and (b) 2050s indicating 10, 50, and 90% quantiles for observed (1980-2010), mean, and spread (minimum and maximum) of land use and climate change scenarios at the catchment outlet (WSC ID: 05MD004).

The flow duration curve for the baseline, extreme climate and land use change scenarios, and the ensemble mean of the future scenarios (Figure 4-10), along with quantiles for 10, 50, and 90% exceedance probabilities (Table 4-5) are presented. A $\log_{10}$-normal probability curve for the extreme (high and low) of the combined land use and climate change, mean of the scenario, and baseline scenario were used to allow the low and high quantiles to be more visible. In general, we see increasing flow in near and middle futures in comparison to the baseline period.

While the coupled impact of climate and land use change indicates overall increasing streamflow, there is a greater likelihood of lower high flows (relative to the baseline) based on the Q10 (10% exceedance). Mean low-flows in the future may increase by up to 106% based on the Q90, relative to the baseline period. Changes in the median quantile (i.e., Q50) suggest an increase of up to 180% over the baseline period (Table 4-5).

Table 4-5: Quantitative comparison (in %) of baseline scenario to mean, maximum, and minimum scenarios at Q10, Q50, and Q90 under near (2030s) and middle future (2050s).

Quantile	Baseline	Climate and land use change scenario: 2030s (2050s)		
		Max	Min	average
Q10	0.56	2.21 (2.56)	0.76 (1.09)	1.62 (1.77)
Q50	2.02	6.33 (8.07)	2.03 (2.73)	3.86 (4.86)
Q90	24.23	36.86 (34.10)	8.19 (9.60)	20.05 (19.48)

4.5 Discussion

Hydrology in the Canadian Prairie region is highly complex. Historically, only one-third of the precipitation occurs during winter in the form of snow. However, snowmelt contributes approximately 80% of spring discharge. Both the timing and duration of seasonality are essential aspects of the CPPR climate. For the CPPR, variability in climate means changes in the distribution of solid and liquid precipitation; for example, increased precipitation during winter (accumulated solid precipitation resulting in spring discharge) and decreased rainfall-runoff during summer. Increasing precipitation coupled with a potential increase in temperature will likely result in more precipitation falling as rain during the winter, or shoulder season, months, thus causing a shift toward earlier spring peak flow events (Figure 4-8). Consequently, this leads to less water availability during summer and autumn when evaporative potential and agriculture demand is the highest. Dibike et al. (2012, 2017) also showed increasing water supply variability in the CPPR and, more specifically, decreased summer flows, where extreme deficits in water availability during summer months were projected.

Though climate warming is not uniformly projected across the globe, results for the CPPR indicate that warming (~6ºC rise by 2070 across basin) may be more pronounced than the global average (~2-3ºC) for the same period. Previous studies (Barnett et al., 2005; Bonsal et al., 2017; Carter Johnson et al., 2016) highlighted that rising temperatures would act as a catalyst in enhancing evapotranspiration, which has the potential to cause more water stress in summer. The combined effects of water availability deficit, increasing temperatures, and increasing evapotranspiration suggest the potential for increasing frequency and severity of drought.

Our research has indicated that the disappearance of isolated pothole wetlands plays an equally critical role as climate in changing the hydrology of the CPPR. In our study, a 55% increase in winter streamflow was simulated for the 100% pothole removal scenario compared to our baseline scenario. Removing pothole wetlands could also potentially cause an increase in summer flow (~16%). Similar findings were observed by Pomeroy et al., (2014) and Yang et al., (2010b) when isolated wetlands were fully drained.

All climate and land use change scenarios suggest an increase in low and median streamflow, and a decrease in high flows (Figure 4-10), hence resulting in a more uniform streamflow behavior. The lack of variability in streamflow is often viewed negatively in the ecological community. For example, ecologist see changes in streamflow positively as it maintains channel structure through sediment transport and interaction between the river and its floodplain that drives nutrient exchange and breeding cycle.

4.6 Study limitations

We utilized future climate projections from the Canadian Regional Climate Model (CRCM) version 5. Our selection of climate model was based on past-performance (Pierce et al., 2009), where the model has been found skillful (Diro et al., 2017; Martynov et al., 2013) at simulating future climate because of various improvements, including the inclusion of the latest Canadian Land Surface Scheme (CLASS 3.5) (Yang Kam Wing et al., 2016). It is, however, important to recognize the effect on output due to uncertainties in future climate projection, the reader is referred to Latif, (2011) for detail. The use of an ensemble of climate models would provide the ability to add confidence bounds to our projections, but would not necessarily improve accuracy.

Our method of pothole wetlands definition was based on the work by Lane et al., (2012) using a 20 m DEM. Availability of high-resolution input data (e.g., LiDAR) could assist in better representing local drainage pathways and complex pothole terrain within the catchment, which may further improve the capability of our model to simulate the hydrology of this region.

Baseflow is an important component of hydrological balance. In our research, we did not directly assess how pothole wetland removal will affect base flow, therefore future studies should thoroughly investigate pothole wetland removal on watershed base flow contribution.

Moreover, the UARB at Kamsack has a sparse meteorological gauge network as indicated by the presence of only two active meteorological stations, concentrated toward the outlet of the basin (Figure 4-1c). We, therefore, make use of those stations, which surround the basin, within a radius of 100 km^2. While the overall performance of the model was satisfactory, some of the stations such as the Assiniboine River at Ebenezer did not replicate streamflow adequately. Availability of more rainfall-gauging network would have improved the performance and reliability of the results.

4.7 Conclusion

This study highlights the important role that pothole wetlands play under future climate in the hydrology of the Canadian Prairie Region (CPR). While the analysis suggests that both land use and climate change will intensify hydrological processes within the study region, changes in climate appear to play a more dominant role in altering streamflow in the watershed. In this study, we utilized the modified form of the SWAT model to assess changes in streamflow hydrograph at downstream of the UARB at Kamsack due to climate and land use change. We, however, foresee many other applications of the current model such as conducting policy and impact studies, flood forecasting, impact on reservoir operation (in particular, for Lake of Prairie) and water management, quantifying nitrogen loading from upstream to downstream and the overall export of nutrients to Lake Winnipeg.

5 MULTI-MODEL APPROACHES FOR IMPROVING SEASONAL ENSEMBLE STREAMFLOW PREDICTION SCHEME WITH VARIOUS STATISTICAL POST-PROCESSING TECHNIQUES IN THE CANADIAN PRAIRIE REGION

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5.1 Abstract

Hydrologic models are an approximation of reality, and thus, are not able to perfectly simulate observed streamflow because of various sources of uncertainty. On the other hand, skillful seasonal streamflow forecast are vital for long-term water resources planning and management purposes. Multi-model techniques can be used to help represent and quantify various uncertainties in forecasting. In this paper, we assess the performance of a Multi-model Seasonal Ensemble Streamflow Prediction (MSESP) scheme coupled with statistical post-processing techniques for the purposes of issuing operational hindcasts with three month lead time (April to July) in the Upper Assiniboine River Basin at Kamsack (UARB) for the Manitoba Hydrologic Forecasting Centre (HFC). The ESP from WATFLOOD and SWAT are used along with four statistical post-processing techniques: Linear regression (LR), Quantile mapping (QM), Quantile model averaging (QMA), and Bayesian model averaging (BMA). While multi-model ESPs coupled with post-processing techniques improve predictability (in general), results suggest that additional avenues for improving the skill and value of seasonal streamflow prediction. Next steps towards an operational ESP system include adding more operationally used models, improve models calibration methods to reduce model bias, increasing ESP sample size, and testing ESP schemes at multiple lead times.

5.2 Introduction

The science of hydrological forecasting has greatly improved with the introduction of numerous distributed models, numerical weather models (NWMs), and data assimilation techniques (Pagano et al., 2016). A large number of hydrological forecasting models are in operation around the globe and several of these are used in Canada (Bourdin et al., 2012). However, no single model is suitable for all drainage systems due to the varying characteristics and complexities of watersheds, local-scale heterogeneity, and different climate zones (Clark et al., 2015c, 2015b, 2015a). The model used by a forecasting unit is dependent upon the data available, hydrologic expertise, type of watershed, and the specific nature of the problem. Distributed and physically-based hydrologic models are data intensive but are considered to provide improve streamflow forecasting mainly because they are capable of leveraging a variety of spatially distributed data (Beven, 1989; Beven and Binley, 1992; Carpenter and Georgakakos, 2006; Chen et al., 2016; Paniconi and Putti, 2015). In operational forecasting, however, there are trade-offs between the complexity of the model, the inclusion and accuracy of catchment-scale processes affecting runoff generation, and the model speed. The goal is always, and always must be, the highest accuracy forecast for reliable, operational flood management and warning (Butts et al., 2004; Crochemore et al., 2016).

Flood forecasting is not only required to be sufficiently accurate within a defined time horizon but must also provide information on the forecasting uncertainty to facilitate effective decision-making and the timely issuing of forecasts (Petrie, 2008). Consideration of uncertainty has been recognized as an essential component in for both research and operations (Georgakakos et al., 2004; Liu and Gupta, 2007), and provides added value in water resources related decision making. Informed uncertainty prediction can increase confidence in forecasts, which are most certainly imperfect (Dietrich et al., 2009). Four major sources of uncertainty have been identified: input, parameter, model structure and uncertainty due to observations, or output uncertainty (Kauffeldt et al., 2016; Liu and Gupta, 2007; Renard et al., 2010; Yen et al., 2014). A lack of practical tools for Canadian flood forecasting centres (FFC) has resulted in the use of primarily deterministic forecasts, or the prediction of a single flood level or event-based flow (Zahmatkesh et al., 2018; submitted). Ensemble forecasts have led to operational difficulty when communicating flood risk with emergency responders (Maxey et al., 2012). Several approaches have been developed to assess uncertainty in hydrological modeling (Kasiviswanathan and Sudheer, 2017; Liu and Gupta, 2007; Liu et al., 2017; Moradkhani et al., 2005; Wang et al., 2016; Westerberg et al., 2016). Among others, the ensemble streamflow prediction (ESP) approach (Day, 1985) has lead to the development of Hydrological Ensemble Prediction Systems (HEPS) (Cloke et al., 2013; Cloke and Pappenberger, 2009), which allow us to estimate uncertainty in weather forecasts, as well as predict the most likely outcomes (WMO, 2012).

In ESP, hydrologic models are forced with a historical sequence of climate data such as precipitation, temperature and/or potential evapotranspiration during the time of forecast, providing a plausible range of future streamflow states (Harrigan et al., 2017). The method assumes that the forcing data and model are perfect (i.e. there are no errors in the initial hydrological conditions (IHCs); Mendoza et al., 2017). In operational practice, the skill attributed to IHCs has been ranked high in comparison to the skills attributed to the climate forecast (Lucatero et al., 2017; Wood et al., 2016; Wood and Lettenmaier, 2008), with both being the two major contributing factors to successfully predicting streamflow dynamics.

Whether or not forecasts are generated using deterministic or ensemble methods, raw forecasts should not be used directly for operational decision-making due to their bias (Li et al., 2017). Consequently, a number of hydrological post-processing statistical techniques (Demargne et al., 2014; Jha et al., 2017; Mendoza et al., 2015; Schaake et al., 2007) have been developed to improve the ability of a forecast, which accounts for uncertainty in the hydrological output. This has led to the development of schemes that seek to obtain consensus from a combination of multiple model predictions to compensate for errors in one model by the others.

This study is designed to develop a new post-processing tool to help identify the uncertainty in seasonal streamflow forecasts for the Manitoba Hydrologic Forecast Centres (HFC) using their operational hydrologic model (WATFLOOD), and one newly developed research-based model (SWAT). Our goal is to improve ensemble decision-making capacity for the Manitoba HFC by 1) developing a framework to evaluate the forecast skill of an ensemble of hydrologic models, and 2) developing a tool to explore the use of four post-processing approaches for ensemble forecasting: Linear Regression (LR), Quantile mapping (QM), Quantile Model Averaging (QMA), and Bayesian Model Averaging (BMA). We, in particular, seek an answer to the questions: what ensemble-generating mechanism results in a better forecast? Moreover, how can post-processing schemes be used to improve the reliability and accuracy of forecasts? This study falls under Theme 3 of the Canadian Natural Science Engineering Research Centre (NSERC) funded FloodNet project that aims to enhance flood forecasting system across Canada (Coulibaly, 2014; Zahmatkesh et al., 2018; submitted).

5.3 Material and methods

5.3.1 Study area

The presence of potholes that creates intermittent flow, the existence of numerous lakes, and the dynamics of the wetlands are defining characteristics of the Upper Assiniboine River Basin (UARB) at Kamsack (Figure 5-1). A detailed description of the study area is covered in Chapter 3 section 3.3.1.

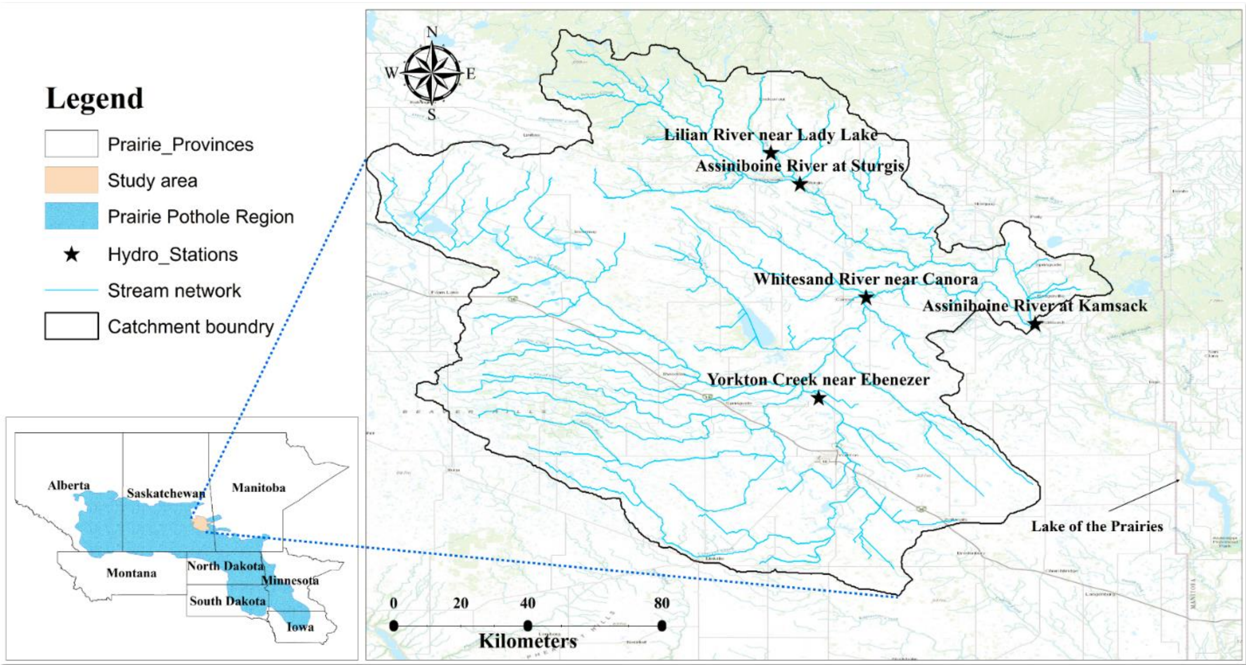

Figure 5-1: Geographical location of the Upper Assiniboine River Basin (UARB) with respect to Prairie Pothole Region (PPR).

5.3.2 Hydrological model

This study utilized two hydrological models to generate ensemble streamflow predictions (ESP). The WATFLOOD model, a semi-physically-based distributed model; and SWAT, a physically-based, semi-distributed hydrologic model. WATFLOOD is currently used as an operational tool for reservoir inflow forecasting at the Manitoba HFC, while SWAT has been developed as a research tool in cooperation with the Manitoba HFC (see Chapter 3). To provide accurate feedback to the HFC on the current state of their operational models, we purposely did not re-calibrate the operationally used model (WATFLOOD), utilizing in-house model setup and calibration.

5.3.3 Statistical post-processing

A straightforward method of statistical post-processing of model output is the arithmetic mean, also known as simple model averaging (SMA). It is based on the assumption that all ensemble members have equal likelihood of occurrence, and that ensemble size is irrelevant. That is, the multi-model hydrologic predictions are formed by merging the individual runoff forecasts with equal weighting (Qu et al., 2017). Although, the method has been shown to be more reliable than deterministic model predictions in some cases (Georgakakos et al., 2004; Hagedorn et al., 2005; Hsu et al., 2009; Raftery et al., 2005; Zhang et al., 2009), studies suggest that SMA does not make full use of all the information available to the ensemble members (Tian et al., 2012). This is mainly because the SMA treats the good and bad simulations equally, thus yielding an intermediate solution. Consequently, the SMA does not guarantee an improved estimate, and in some cases, estimates may even be worse than individual model simulations. Techniques such as Linear Regression (LR) (Wood and Schaake, 2008), Bayesian Model Averaging (BMA) (Raftery et al., 2005), and Quantile Model Averaging (QMA) (Schepen and Wang, 2015) are developed to overcome the limitations of SMA.

We present a brief overview of the statistical post-processing techniques used in this study; the reader is referred to Wood et al., (2018) for further detail. The LR method developed by Wood and Schaake, (2008), uses the mean of ESP with observations to generate conditional forecast mean and spread to improve upon the traditional ESP forecast. The method, however, may not be of great help during extreme events, such as flood warnings, as parameters are trained using the mean rather extreme due to the rarity of the extreme events. The QM method adjusts the cumulative distribution function (CDF) of the forecast according to the CDF of the observations, thus mapping the forecast value to the corresponding quantile in the observation CDF (Hashino et al., 2007; Wood and Schaake, 2008). A noted weakness of the method is that it does not preserve the connection between each pair of forecast and observation value, leading to unsatisfactory results (Li et al., 2017). Furthermore, the LR and QM are mostly applied in cases when ESP is generated using single hydrological models. Consequently, post-processing techniques such as BMA and QMA are developed to overcome this limitation and to merge ESPs from multiple hydrologic models, while appreciating individual model performance. The BMA method (Raftery et al., 2005) is one of the most popular multi-model post-processing methods where each member of the ensemble forecast is associated with a conditional probability distribution function (PDF). A weight for each member of the ensemble forecast is computed based on the performance of the model during the training period, such that all weights sum to one. QMA on the other hand is the weighted average of forecast quantiles from all the models (Schepen and Wang, 2015). A noted difference between BMA and QMA is that BMA produces bimodal outputs, while QMA produces smooth and unimodal distributions (Schepen and Wang, 2015). All mentioned post-processing techniques have been extensively used to reduced uncertainty in hydrologic predictions that arise from different sources, including atmospheric forcing and prediction, model initial states, model parameters, model structure and assumptions, among others (Demargne et al., 2014; Gupta et al., 2005; Jiang et al., 2017; Madadgar and Moradkhani, 2014; Mendoza et al., 2017; Najafi and Moradkhani, 2016).

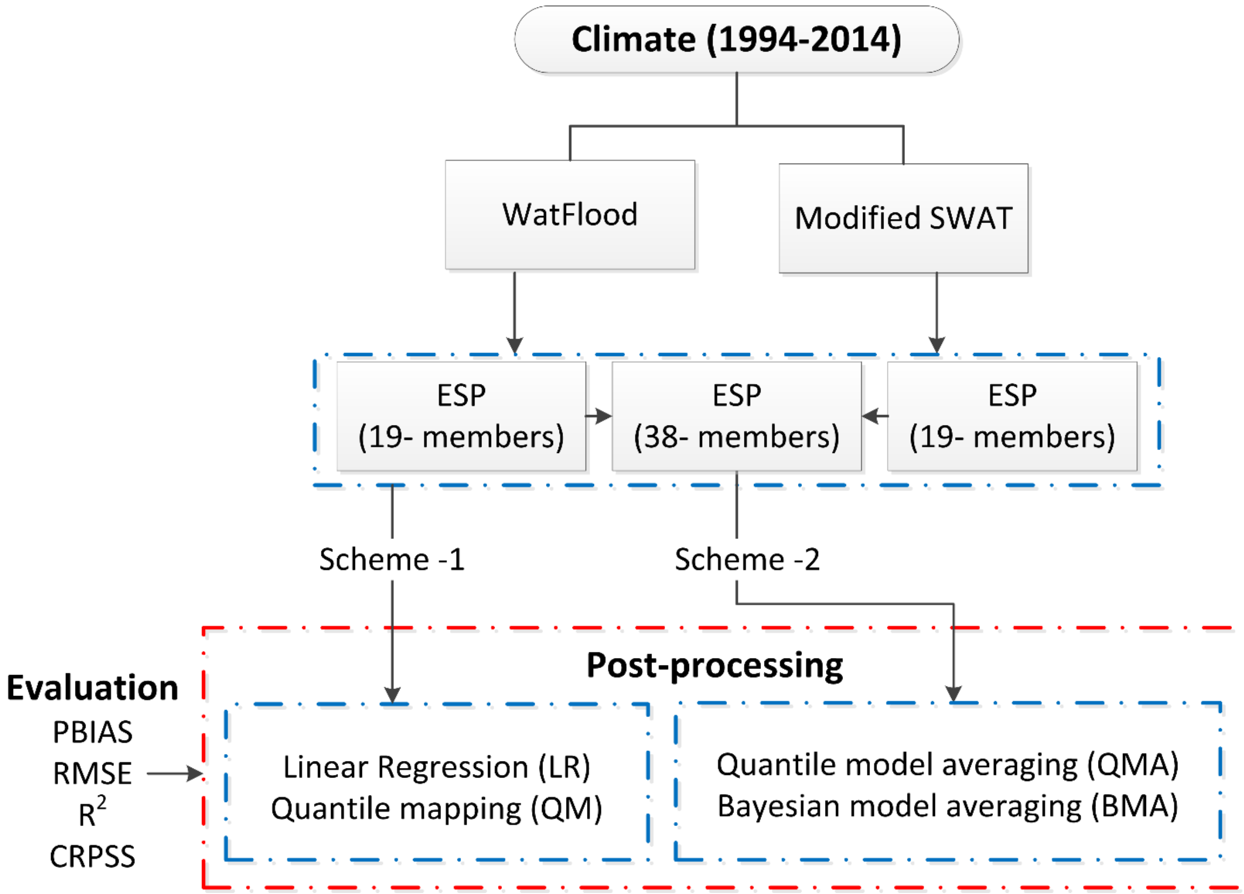

Figure 5-2: Schematic of ensemble forecast generation and the application of post-processing technique

5.3.4 Forecast generation

We utilized historical observations from 1994-2014 to generate long-term probabilistic (ensemble) streamflow hindcasts, using 1994 as a spin-up period. Each model was forced with observed meteorological input up until the time of the hindcast initialization, repeatedly, leading to a sample size of 20 (i.e., one hydrologic sequence per year, for 20 years, based on previous meteorological conditions). Following the Manitoba HFCs methodology, the year of interest (i.e., hindcast year) is withdrawn during ESP generation. Thus, the total number of ensemble members generated for the ESP (per hydrologic model) is 19. In Manitoba, streamflow forecast outlooks are issued at the start of March, with conditions monitored up until August. The most critical water supply period for the UARB is April to July, which generates more than 80% of annual streamflow (Shrestha et al., 2012a). A schematic outlining the procedure we used to generate the ensembles is presented in Figure 5-2. Scheme-1 results in 19 ensembles per model, while Scheme-2 combines all ensemble members (regardless of the model used to generate it), resulting in 38 members. Hindcasts for each scheme are issued and are then post-processed using the LR, QM, BMA, and QMA techniques.

5.3.5 Performance metrics

To evaluate the quality of the hindcasts, we evaluated the ensembles using percent bias (PBIAS), Root Mean Square Error (RMSE), coefficient of determination (R^2), and the Continuous Ranked Probability Skill Score (CRPSS). Percent bias computes the average tendency of the simulated variable to be larger or smaller than the observed variable and can be expressed using Equation (12).

$$PBIAS = 100 \times \frac{\sum_1^n (Q_o - Q_s)_i}{\sum_1^n Q_o} \tag{12}$$

Where Q is a variable (e.g., discharge), o and s stand for the observed and simulated variable. The optimum value is 0 however, values between ±25 are considered satisfactory (Singh *et al.*, 2005; Moriasi *et al.*, 2007). Values above zero mean the models are under-predicting, while PBIAS below 0 indicates the models are over-predicting.

Root Mean Square Error (RMSE) measures the difference between observed and simulated values. Individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power. The RMSE is expressed in Equation (13).

$$RMSE = \sqrt{\frac{\sum_1^n (Q_o - \ Q_s)^2{}_i}{n}} \tag{13}$$

The threshold for RMSE is difficult to establish, however, RMSE > 0.5 is often related to a model with decreasing predictive power (Veerasamy et al., 2011).

The coefficient of determination (R^2) is an index that measures the degree of linear relationship between observed and simulated values and can be computed using Equation (14):

$$R^2 = \frac{\sum_1^n \left[\left(Q_o - \ \overline{Q}_o\right) \times \left(Q_s - \ \overline{Q}_s\right)\right]^2}{\sum_1^n \left(Q_o - \ \overline{Q}_0\right)^2 \times \left(Q_s - \ \overline{Q}_s\right)^2} \tag{14}$$

Where the bar represents average variables over a given time period. R^2 ranges between -1 and 1, with 1 being perfectly positive and -1 as the perfectly negative relationship. When R^2 is 0, it implies that there is no connection between observed and simulated variable.

The CRPSS (Equation 15) is a widely utilized performance metric that assesses the overall quality of the probabilistic forecast (or hindcast) in reference to the climatology-based ensemble, which in most cases, is the reference forecast (or hindcast) (Alfieri et al., 2014; Hersbach, 2000).

$$CRPSS = 1 - \frac{\overline{CRPS}}{\overline{CRPS}_{ref}} \tag{15}$$

Where

$$CRPS = \int_{-\infty}^{\infty} [F(y) - F_0(y)]^2 dy$$

and

$$F_0(y) = \begin{cases} 0, y < Observed\ value \\ 1, y \geq Observed\ value \end{cases}$$

F(y) is the stepwise cumulative distribution function (CDF) of the ESP for each considered forecast (hindcast). CRPSS ranges from $-\infty$ to 1, where 1 indicates a perfect forecast (hindcast), and positive values indicating high skill over the reference period.

5.4 Results and discussion

5.4.1 Hydrologic model evaluation

Daily average annual hydrographs using two hydrologic models (WATFLOOD and SWAT) were hindcast from 1994 to 2004 and compared to observed streamflow (Figure 5-3). In general, both hydrologic models followed the trend of observed streamflow and were able to capture the timing of the spring runoff, however, there are inconsistencies in capturing the correct magnitude of runoff for both models. This could be a result of the model's individual calibrations, but can also, in part, be explained by the development philosophy behind each model. For example, SWAT is an agricultural model, which is developed to most accurately predict the impacts of best management practices (BMPs) on water, sediments, and nutrient loading across large spatial scales and over long periods of time. This results in SWAT being able to provide reasonable simulations of long-term, average to low-flow conditions for the watershed (Figure 5-3). Whereas WATFLOOD was developed for operational flood forecasting in an agriculturally-dominated landscape (Kouwen, 1988), where physically-based routing assists the model in predicting peak flows more accurately.

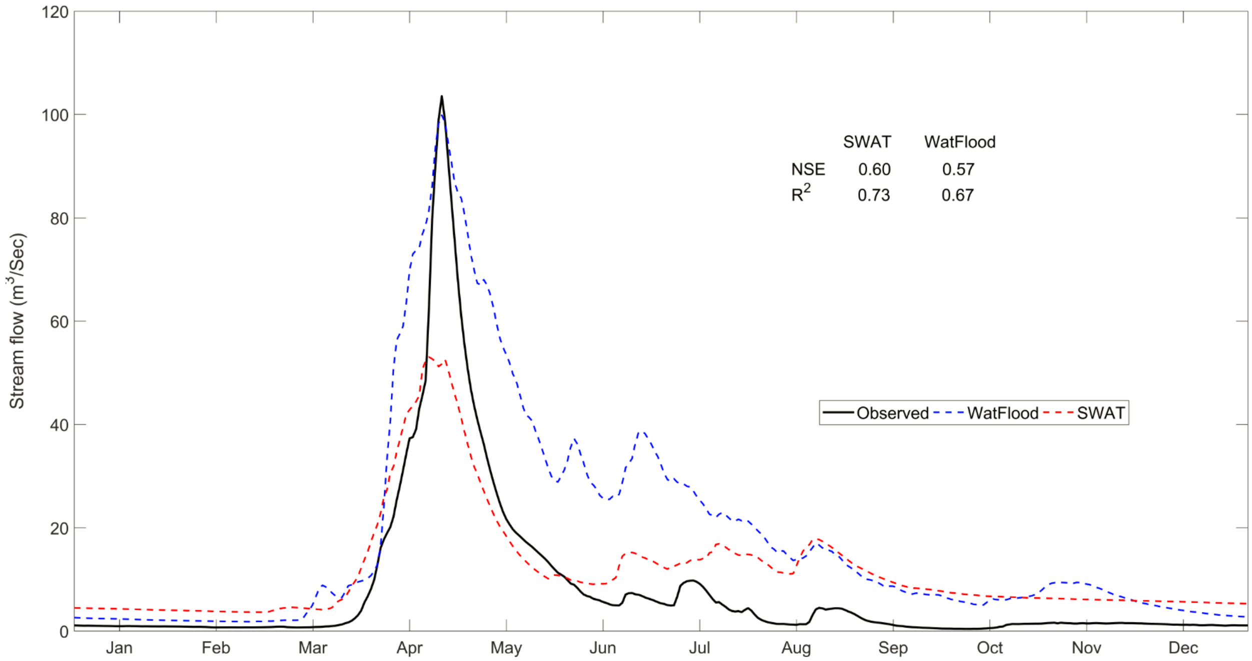

Figure 5-3: Daily average annual streamflow hydrograph from 1994-2004 at the catchment outlet (WSC ID: 05MD004) using two hydrologic models. NSE and R^2 are computed using daily observed-simulated data over the entire period.

Furthermore, wetlands play an important role in correctly attenuating streamflow in the UARB, as do the dynamic contributing areas, which are internally drained and only contribute to streamflow after reaching their maximum storage capacity (Shook et al., 2013). Structurally, the two models differ substantially in how they simulate these crucial hydrological storages and dynamic connectivity within the channel network. The version of SWAT used in this study (Muhammad et al., submitted) has an enhanced spatial representation of the Prairie pothole wetlands that is dynamic and modifies the wetland-channel routing network. In WATFLOOD, wetland area is defined using a (constant) threshold value that splits wetlands into coupled wetland-channel regions (i.e., riparian areas) and uncoupled (disconnected from the channel) regions. While uncoupled wetland area does not contribute to channel flow, the coupled wetlands have a dynamic interaction with the channel based on the Dupis-Forecheimer formulation

(Kouwen, 2018). This wetland routing scheme is robust and computationally efficient, however, it does not recognize the dynamic spatial relationship between isolated wetlands and the channel that is determined by annual antecedent conditions. Results are similar to those found in Unduche et al., (2018) where models are criticized for their inconsistency in correctly capturing the magnitude of runoff in the UARB due to their structural differences. We further assessed the performance of the models using the Nash-Sutcliffe (NS) and Coefficient of determination (R^2) metrics for WATFLOOD (0.57, 0.67) and SWAT (0.60, 0.73), respectively. As per Moriasi et al., (2007); Motovilov et al., (1999); Krause and Boyle, (2005), both models performed satisfactorily in this study based on NSE values > 0.5 and $R^2 > 0.5$ alone.

5.4.2 Deterministic evaluation of the benchmark and post-processed ESPs

The two schemes proposed for assessing the various post-processing approaches (Figure 5-2) were compared to the observed April to July runoff period using mean volume at the outlet of the UARB (WSC ID: 045MD004). The flow generated in the UARB at Kamsack enters Lake of the Prairies (Shellmouth reservoir), which is solely constructed to regulate flow and mitigate floods. Thus, it is of critical importance to determine the volume of inflow generated in the upstream basin for reservoir optimization and flood forecasting operations. The LR and QM post-processing techniques are applicable when ensembles are generated from a single model. Both techniques can also be applied when a multi-model ensemble is placed together to increase ensemble size (i.e., considering the ensembles of the two hydrologic models as a single forecast product), whereas QMA and BMA techniques are applicable when weights are used for each model based on their relative performance. In our experiment, Scheme-1 represents the application of LR and QM post-processing techniques on the ensemble of each of hydrological model (Figure 5-4), while in Scheme-2, all post-processing techniques are applied to the multi-model ensemble (Figure 5-5).

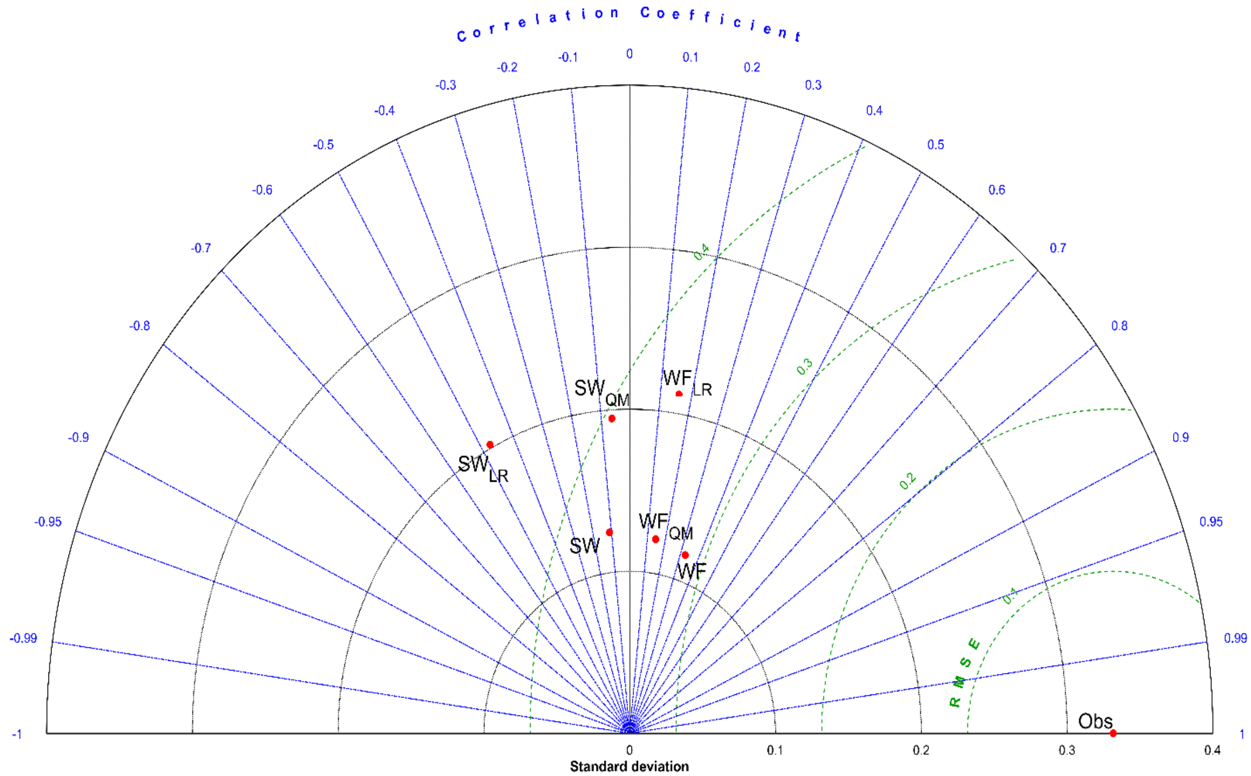

Figure 5-4: Taylor diagram of observed streamflow volume relative to the mean of benchmark (raw) ESP performance (1994-2004) for two hydrologic models and various post-processing techniques. WF stands for WATFLOOD, and SW for SWAT; subscripts LR and QM stand for linear regression and quantile mapping post-processing techniques.

WATFLOOD indicated better correlation (R^2 closer to 1) and lower RMSE relative to the observed streamflow in comparison to SWAT. SWAT, however, reflects a lower standard deviation (dispersion), indicating it more often captured the mean simulation. Post-processing the ensembles in Scheme-1 does not appear to improve the predictability of observed streamflow for either hydrologic model, and it appears that the benchmark ensemble (raw ESPs) in fact provide the best hindcast (Figure 5-4). Scheme-2 combines the two hydrologic models and evaluates the LR, QM, BMA, and QMA post-processing techniques (Figure 5-5).

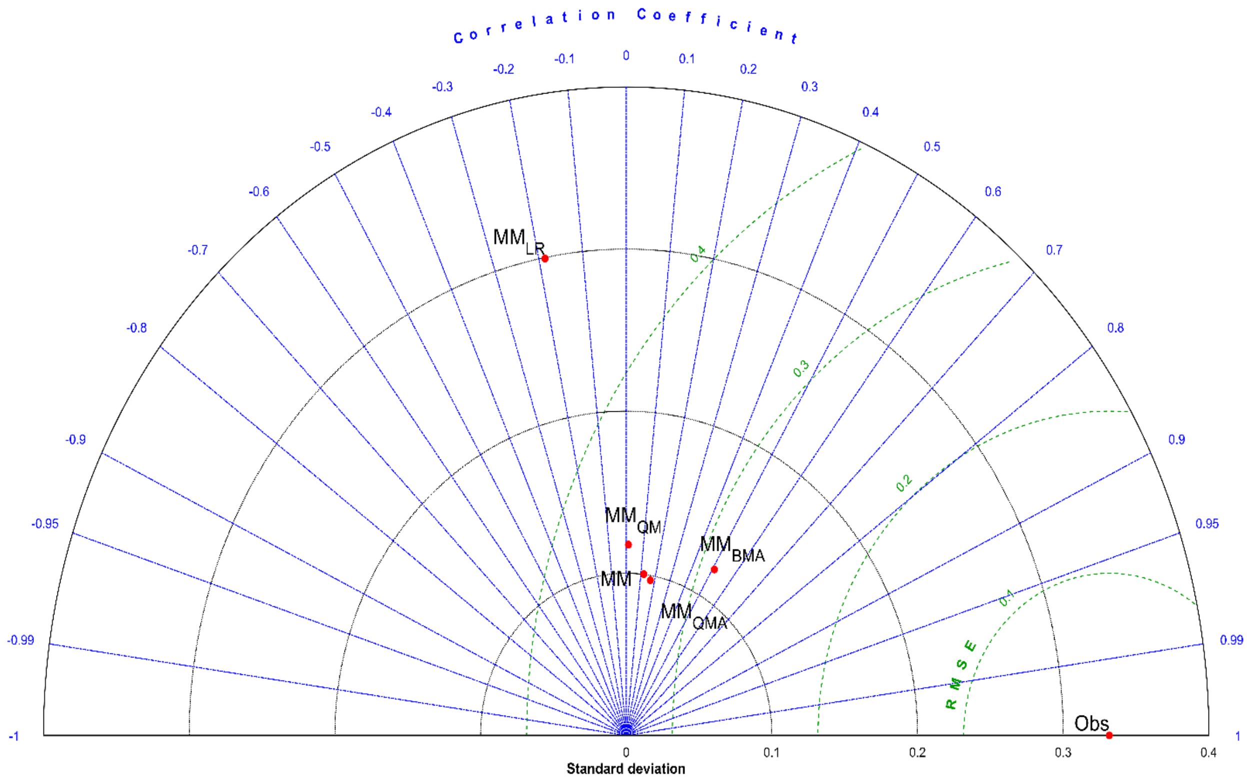

Figure 5-5: Taylor diagram of observed streamflow volume relative to the mean of multi-model benchmark ESP performance (1994-2004) for two hydrologic models (combined in linear fashion) and all post-processing techniques. MM indicates the benchmark ESP formed using both WATFLOOD and SWAT models; subscript LR stands for linear regression, QM for quantile mapping, BMA for Bayesian model averaging, and QMA for Quantile model averaging.

Both BMA and QMA improved the predictability of observed streamflow volume the most, given their improved correlation (positive R^2) and lower RMSE in comparison to the benchmark multi-model ensemble (MM). Linear regression (LR) and quantile mapping (QM) techniques have lower correlation and higher RMSE, which is expected as both LR and QM are recommended to be utilized in cases where forecast are generated using single hydrological models.

There are a number of reasons why the application of various post-processing techniques did not more significantly improve the predictability of seasonal runoff volume. For seasonal lead times (as opposed to hourly or daily), the accurate determination of IHCs is of critical importance and would exert a dominant influence on the hydrologic forecast (Greuell et al., 2016; Wood et al., 2016; Wood and Lettenmaier, 2008). The Prairie pothole region is a hydrologically diverse and complex landscape that makes accurately defining the IHCs prior to the time of hindcast difficult, at best. Post-processing would be expected to have a more pronounced impact (on improving predictability) if IHCs during the time of the hindcast were sufficiently represented (Wood et al., 2018).

Furthermore, the suitability of post-processing techniques is very much dependent on the sufficiency of a hindcast time series, and consistency of retrospective model runs, used to train the post-processing methods (Mendoza et al., 2017; Najafi and Moradkhani, 2015). In a study by Lucatero et al., (2018) a sample size of 23 ESP members are used to train the model. However, another recent study by Wood et al., (2018) outlined that three-years of daily short-range forecasts would provide a nominal sample size of over 1000 records for training the post-processing method parameters to account for different hydrologic regimes. A 30-year hindcast for seasonal prediction offers a sample size of 30 members, thus making it difficult to estimate the optimum parameter value in a statistical post-processing model. It is likely that the low impact of the various post-processing approaches tested on the seasonal runoff hindcast resulted from the limited sample size used in this study.

The benchmark ESP for both the WATFLOOD and SWAT hydrologic models are presented in Figure 5-6. The benchmark ESP for WATFLOOD appears to better capture peak flow events in comparison to the benchmark ESP from SWAT. Although all hydrological models are built to approximate physical processes that occur across catchment scales, the two models differ in structure, and likely, therefore, accuracy in simulating the UARB hydrological landscape (as was discussed in Section 5.1). For example, the WATFLOOD ESP was able to capture the extreme runoff volumes observed in 1995, 2011 and 2014 (Figure 5-6a), while the SWAT ESP failed to do so (Figure 5-6b) as SWAT is not designed to simulate single, extreme flood events (Neitsch et al., 2011). This is why SWAT is not often recommended for flood forecasting applications (Borah et al., 2004; Yaduvanshi et al., 2018), and why the Manitoba HFC is considering does not use it as a river forecasting model. The SWAT ensemble, however, is better able to replicate low-flow years with lower uncertainty (Figure 5-6b), and had slightly better skill (CRPSS of 0.22) in comparison to WATFLOOD (CRPSS of 0.20). Given the higher frequency of lower runoff (as opposed to peak runoff), this results in the SWAT model having more skill in simulating "average" hydrologic conditions, or low-flow events. Given the enhanced dynamic contributing area module embedded in this version of SWAT, this points to the strength of this version of the SWAT model for simulating the low-runoff threshold where effective drainage areas are less than actually reported drainage area (Shook and Pomeroy, 2011).

5.4.3 Probabilistic evaluation of the benchmark and post-processed ESPs

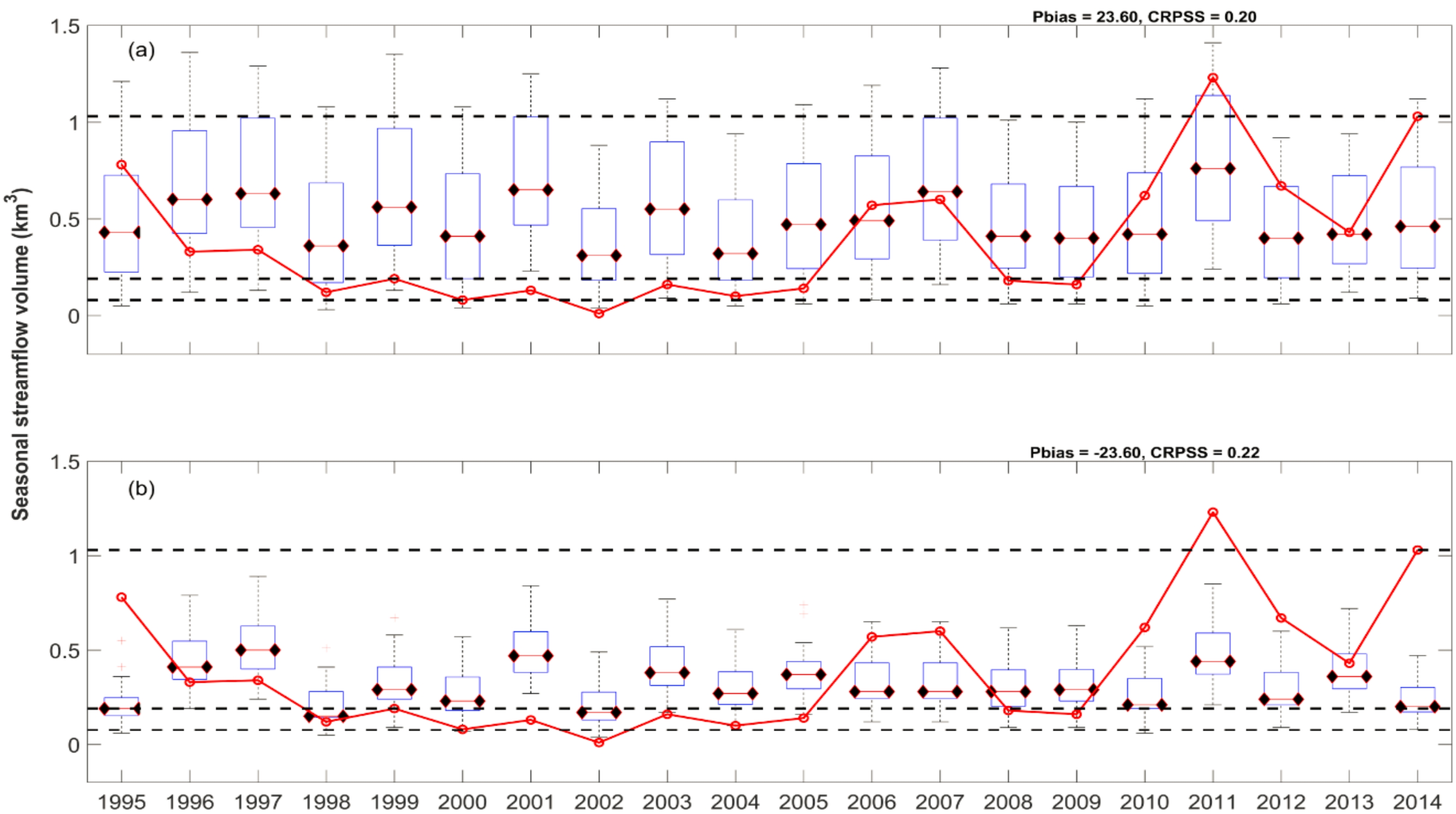

Figure 5-6: Time series of seasonal streamflow volume for the benchmark ESP from (a) WATFLOOD, (b) SWAT. Black dashed lines represent 10, 50, and 90% flows from the observed climatology, and the boxplot shows the spread in ensembles. The red line represents the observed volume of discharge

Percent bias (PBIAS) and continuous rank probability skill score (CRPSS) for Scheme-1 using LR are shown on Figure 5-7. Results of the post-processed ensembles for WATFLOOD and SWAT model are displayed on Figures 5-7a and Figure 5-7b, respectively. Post-processing did not improve WATFLOOD's skill, while a near 20% increase in the SWAT CRPSS was observed. The LR post-processing technique operates on the ensemble mean and generates adjusted mean and spread statistics (Wood and Schaake, 2008). Since SWAT is more capable of predicting low to median flow, it is very likely that the model benefited more from post-processing, resulting in higher overall skill. Though it should be noted, given the importance of peak flow prediction in operational forecasting, that post-processing reduced the skill of SWAT in predicting the 2011 peak runoff event (Figure 5-7b). In general, the post-processed multi-model ensemble (Figure 5-7c) showed improved skill (CRPSS 0.23) in comparison to the predictive skill of individual hydrologic models (0.20, 0.22). The results also highlight how multi-model approaches compensate for the individual error among the models. As noted above, the post-processed WATFLOOD ESP over predicted low- flow events (Figure 5-7a), while the SWAT ESP under-predicted peak runoff events (Figure 5-7b). When post-processing is applied to the multi-model ensemble, however, we see improved skill and lower bias. These results agree with those from other researchers who found that the forecast errors from individual models can "cancel out" (Duan et al., 2007; Georgakakos et al., 2004; Shamseldin et al., 1997), and offers hope for future applications of ESP for improving operational forecasting. This is why multi-model ensemble means are often regarded as more skillful predictions than the results from individual models (Bohn et al., 2010).

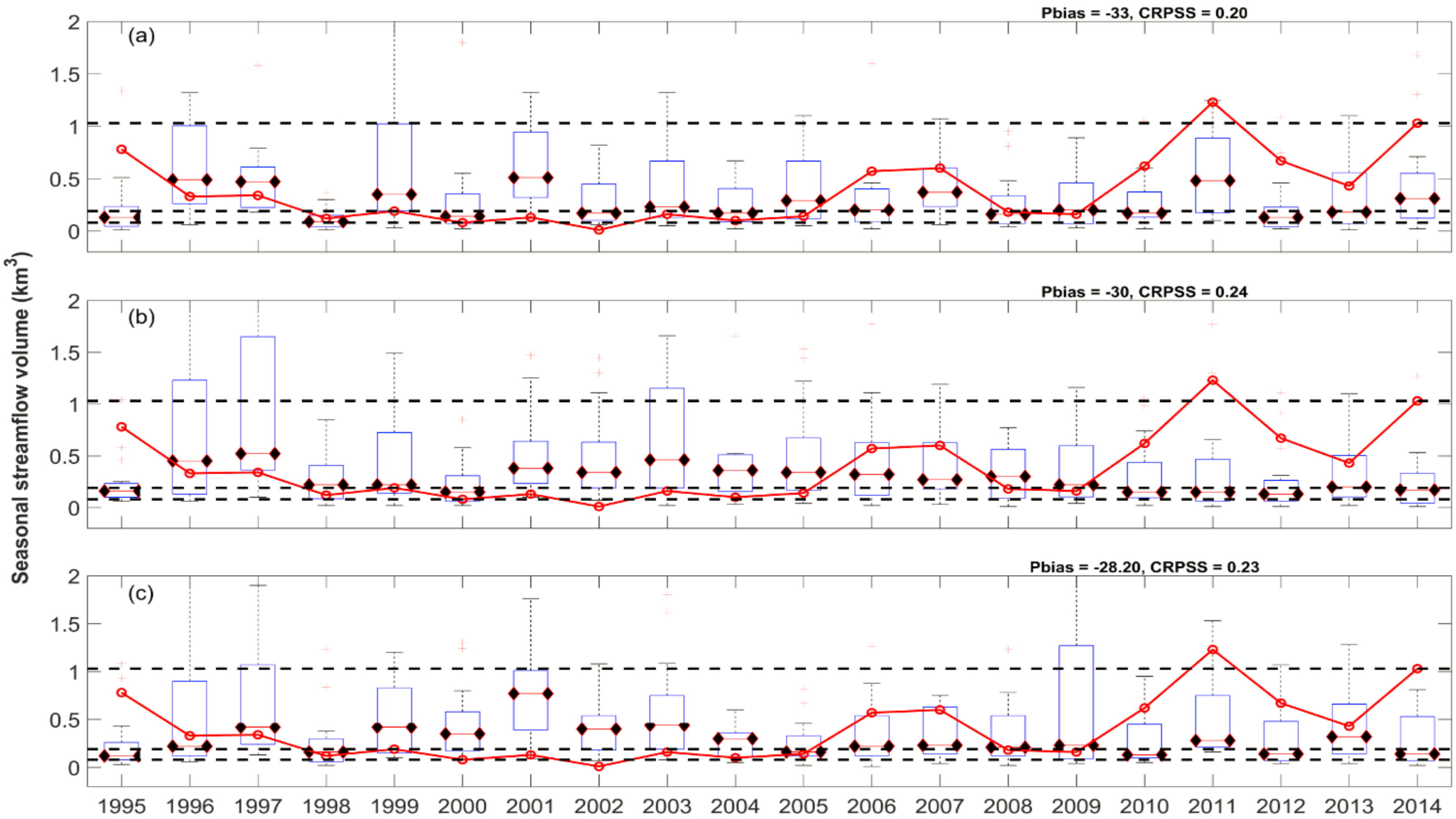

Figure 5-7: Time series of seasonal streamflow volume for the post-processed ESPs from (a) WATFLOOD, (b) SWAT, and the (c) Multi-model ESP using LR. Black dashed lines represent 10, 50, and 90% flows from the observed climatology, and the boxplot shows the spread in ensembles. The red line represents the observed flow volume.

Figure 5-8 represents the post-processed ESPs for WATFLOOD and SWAT using QM. The QM post-processing technique does not improve the predictability of WATFLOOD runoff volume (Figure 5-8a), however, a modest improvement was observed for SWAT (Figure 5-8b), with the CRPSS improving from 0.20 to 0.24. QM similarly does not produce a noticeable improvement in the forecast accuracy for the multi-model ensemble (Figure 5-8c). The QM approach is simple: the CDF of the forecast is adjusted to make the observed CDF. QM does not preserve the connection between each pair of forecast and observed values, thus, QM may sometimes adjust the raw forecast in the wrong direction, producing less satisfactory results (Madadgar and Moradkhani, 2014; Zhao et al., 2017). This is why more advanced post-processing techniques may be preferable.

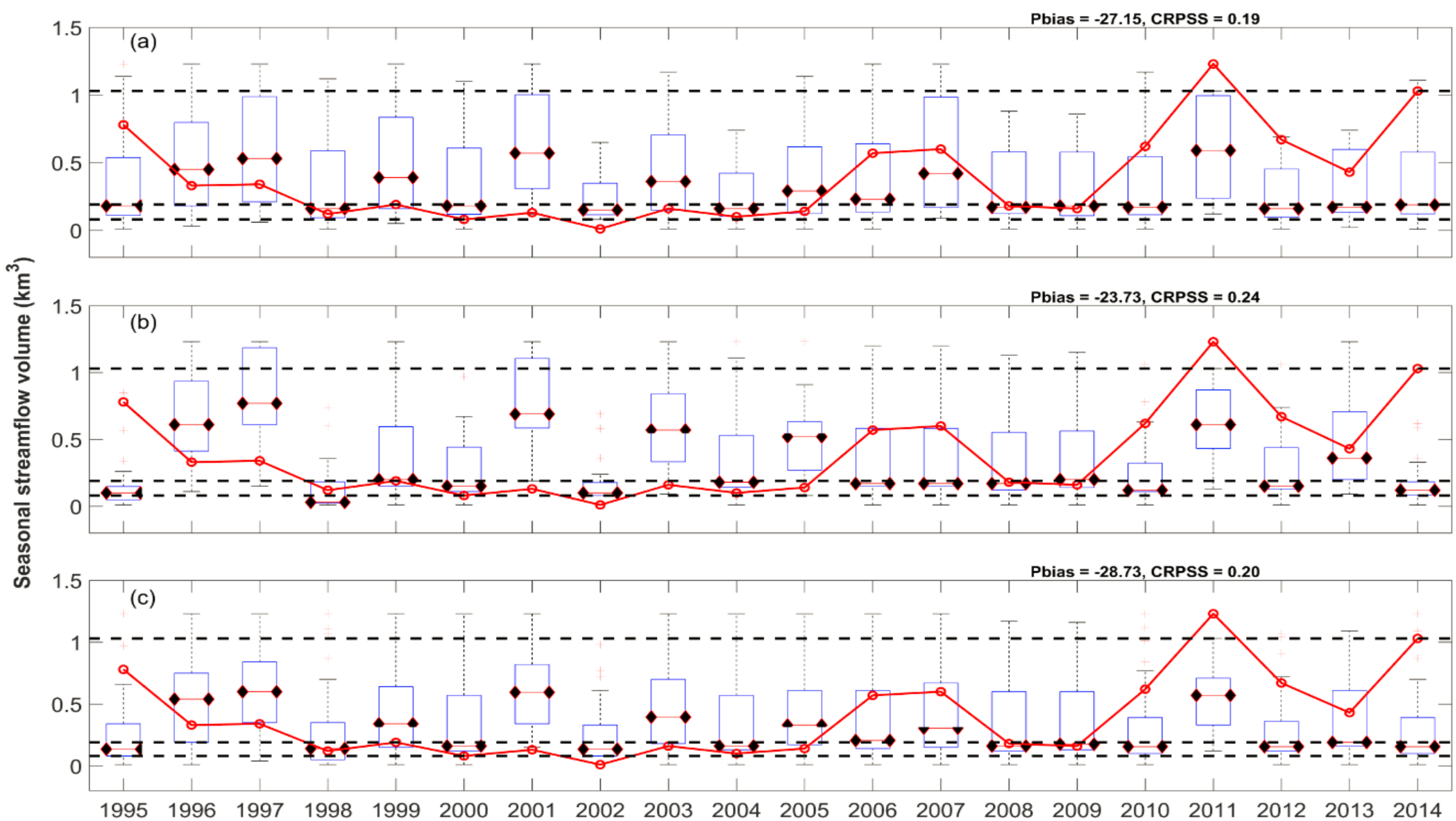

Figure 5-8: Time series of seasonal streamflow volume for the post-processed ESPs from (a) WATFLOOD, (b) SWAT, and the (c) Multi-model ESP using QM. Black dashed lines represent 10, 50, and 90% flows from the observed climatology, and the boxplot shows the spread in ensembles. The red line represents the observed flow volume.

5.4.4 Evaluation of weighted multi-model ESPs

In Scheme-1, we presented results when post-processing techniques (LR and QM only) are applied on individual model ESPs, as well as a multi-model ESP when ensembles are combined in a linear fashion (i.e., without assigning weight to models based on their performance). Merging multi-model ensembles without considering the performance of individual models, however, is considered to be of less value (Krysanova et al., 2018); hence why there are a number of schemes developed to appreciate individual model performance (Li et al., 2017; Mendoza et al., 2017; Wood et al., 2018).

Scheme-2 represents the application of the BMA and QMA post-processing techniques to the merged ensemble formed from the two hydrological models, or the multi-model ESP. Initial weights for the two models were computed using Root Mean Squared Error (RMSE) to appreciate the individual model performance. Based on the simulation performance, SWAT receives 0.53 while WATFLOOD 0.47. The benchmark multi-model ESP (Figure 5-9a) appears to have captured most observed events, however, there are instances - particularly peak flow events (i.e. 1995, 2011, 2014) where the benchmark ensemble did not perform as well. The post-processed multi-model ESP using BMA (Figure 5-9b) appears to improve the predictability of those peak events that were missed by the benchmark ensemble, however the overall PBIAS and CRPSS did not improve. Various studies suggest that the performance of BMA can be further improved if climatology is used as one of the candidate models (Grantz et al., 2005; Mendoza et al., 2015; Rajagopalan and Lall, 2001; Wood et al., 2018). In fact, the use of climatology would help in reducing the overconfidence of individual model forecasts (Weigel et al., 2008).

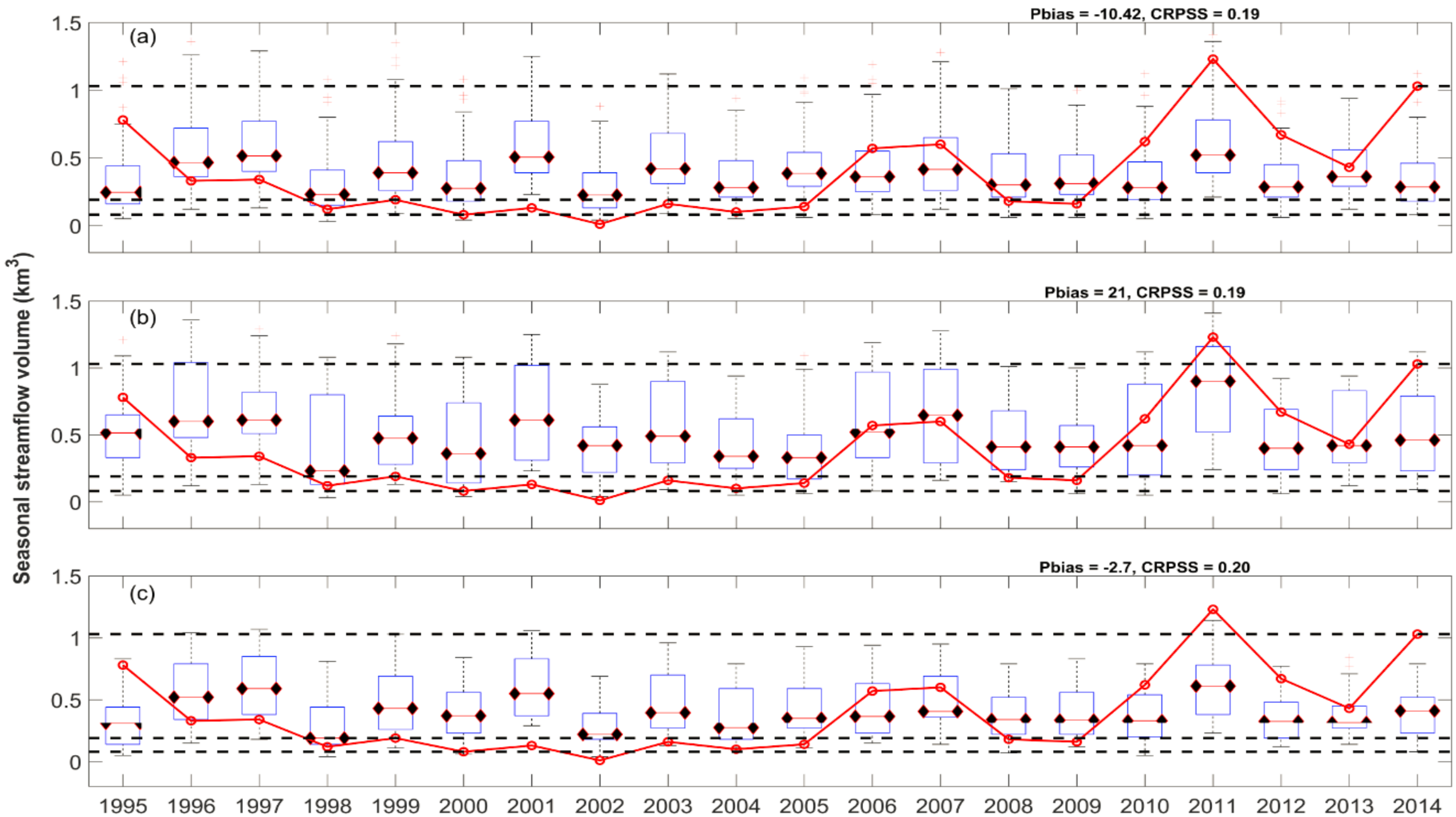

Figure 5-9: Time series of seasonal streamflow volume for (a) multi-model benchmark ESP (WATFLOOD and SWAT combined in a linear fashion), and the post-processed multi-model ESP using (b) BMA and (c) QMA. Black dashed lines represent 10, 50, and 90% flows from the observed climatology, and the boxplot shows the spread in ensembles. The red line represent the observed flow volume.

QMA post-processing (Figure 5-9c) showed a slightly improved overall hindcast, with better skill (0.20) and lower bias (-2.7). The QMA hindcast is a weighted average of quantiles from all models (Schepen and Wang, 2015), which not only corrects the CDF of the forecast with respect to observations, but place weights on the hydrological model output based on their performance. In their recent experiment Schepen and Wang, (2015) found that nearly identical skill can be obtained using BMA and QMA, which is a confirmation of results in our experiment using the two techniques. The slight improvement (lower bias) in QMA could be due to the CDF correction, which is an added step as compared to BMA.

5.4.5 Post-Processing Effectiveness for Operational Prediction

In general, we find the post-processing techniques in many cases have improved the streamflow hindcast, however, the improvement is not as significant as expected. There could be many reasons for this result. Probabilistic forecasts were verified against observations in this study (to evaluate CRPSS and PBIAS). As models are only abstracts of the reality, and given the complex and highly non-linear response of UARB hydrology, there will be bias introduced into hindcasting due to the models' not fully replicating reality. Comparing model ESP to post-processed ESPs statistically would result in improved skill scores for the post-processing techniques. For example, in Figures 5-4 and 5-5, the benchmark ESPs are centrally located between post-processed ESPs, thus the skill of post-processed ESPs would be much stronger relative to the benchmarks (as compared to the observations). Results are similar to those obtained by Verkade et al., (2013) where the application of various post-processing techniques did not necessarily improve predictability.

Another possible explanation could be that our study focused on hindcast verification at a single, seasonal time step using three months lead-time. It is possible that the forecast skill, and the application of various statistical post-processing techniques, would be more notable at multiple, and shorter lead-times. For example, Mendoza et al. (2017) evaluated post-processing techniques for seasonal flow volume for a singular hydrologic model. In their work, improvement in forecast accuracy at three-month lead time is low to nil. Though many studies have reported the benefit of using multi-model ESP approaches, it is often far from a trivial challenge to select a suite of models and a method for combining their output. Mendoza et al. (2014) found that the impact of design choice on the performance of multi-model forecast configurations; which included decisions about forecast quality attributes, weighting methods, and the number of models to include; had a significant impact on the identification of an optimal approach. Other studies also highlight the importance of design choices, including the number of hydrological models to be used (Bormann et al., 2007; Hagedorn et al., 2005; Krishnamurti et al., 1999; Velázquez et al., 2010). Most of the above studies recommended using at least five hydrologic models. Moreover, post-processing of any type of hydrological forecast is based on the assumption of stationarity in climate, weather patterns, and hydrologic response (Li et al., 2017; Mendoza et al., 2017;). That means that the statistical correlation between observations and forecasts during the training and verification period should remain constant, which is not always valid in hydrology, and arguably may not have been the case over this study period for the UARB with two >130 year return period floods (i.e., 2011, 2014, Blais et al., 2016a, 2016b). Such assumptions can introduce errors in the post-processed forecast, leading to greater uncertainty than is expected (Wood et al., 2018).

As the CRPSS scores of all the post-processing techniques are quite similar, the two-sample Kolmogorov-Smirnov (KS test) test was used to test the significance of the change to the simulated distributions after post-processing was conducted.

Table 5-1: Two-sample Kolmogorov-Smirnov (KS) test for resulting significance of the post-processing techniques relative to the raw ensembles.

	WATFLOOD (CRPSS)	Stat. Sig: H(p)	SWAT (CRPSS)	Stat. Sig: H(p)	Multi-model (CRPSS)	Stat. Sig: H(p)
Scheme 1						
LR	0.20	1 (0.0232)	0.24	1 (0.0082)	0.23	0 (0.4973)
QM	0.19	1 (0.0026)	0.24	0 (0.4973)	0.20	0 (0.0591)
Scheme 2						
BMA					0.19	1 (0.0232)
QMA					0.20	0 (0.7710)

The KS-test results return a decision for the null hypothesis that the data of the two samples are from the same continuous distribution. The alternative hypothesis is that the two samples are from different, continuous distributions. H is 1 if the test rejects the null hypothesis at the 5% significance level, and 0 otherwise. The p-value indicates the significance of the test result (Table 5-1). Here, the null hypothesis is rejected in the case of WATFLOOD under Scheme-1, indicating there is no significant change to the distribution of simulated flows after post-processing. Both the SWAT and multi-model ESP, however, indicate weak but statistically significant changes in simulated distributions (p-value close to critical rejection threshold) with the application of QM. This result is perhaps not surprising given QM explicitly targets distribution quantiles and adjusts them to be closer to the desired distribution of values. Given WATFLOOD reasonably replicated peak volumes before post-processing, it is likely that, given the small sample of the ESP, post-processing had less of an impact. The multi-model ESP under Scheme-1 showed weak but significant changes in the distribution of flow volume. For Scheme-2, the BMA shows a significant impact on the simulated distribution of simulated flows produced from the multi-model ensemble, however, QMA failed to alter the distribution of peak runoff with any significance.

5.5 Conclusion

ESP is a key component of operational, long-lead streamflow prediction, which is currently utilized by HFCs in the US, UK, Australia, and other countries. In Canada, its application to-date has been limited. In this study, we evaluated the value of ESP to operational forecasting and compared four statistical post-processing techniques for their ability to improve seasonal flow (volume) prediction. We found that using an ensemble over a deterministic forecast would likely enhance operational decision-making capacity as it reduced uncertainty while providing an envelope of realistic, possible future scenarios. Furthermore, the use of the multi-model ESP helped to compensate for errors interjected into the forecast by selection of any one hydrological model, likely due to structural differences impacting predictive capacity for high and low flow volume differently, and error trade-off. For example, the enhanced representation of pothole wetlands in SWAT compensated for the structural deficiency in WATFLOOD in this regard in the multi-model ensemble, and preserved the capability of WATFLOOD to better predict peak flood events, which SWAT is not designed to do. So the combination of the two models, is in fact, very symbiotic and shows the advantage of leveraging multi-model ESPs.

In most cases, statistical post-processing slightly improved forecast accuracy, however, there were instances where the benchmark ensembles better represented the observed streamflow. Both simpler (i.e., LR and QM) and more complex (BMA and QMA) methods were tested to evaluate the incremental benefits of more complex (parameter-intensive) techniques. While the QMA approach appears to be promising, this study cannot yet confidently recommend any one particular post-processing technique due to limitations imposed by the number of models used, the ensemble sample size, basin complexity, and the time period used for analysis. Based on this analysis, we can recommend that testing the performance of the statistical post-processing techniques in the future should be conducted across multiple (smaller) basins, lead times, using more hydrological models, and larger sample sizes. Care should be taken to select a relatively stationary hydrologic period, without multiple extreme events so as not to violate the stationarity assumption required for model training.

6 MAJOR RESEARCH FINDINGS, RESEARCH SIGNIFICANCE, AND RECOMMENDED FUTURE RESEARCH

6.1 Summary of research findings

The primary interest of this thesis work was to develop a hydrologic modeling framework that would better suit Prairies hydrology, and to understand, identify, and address different sources of uncertainty in simulating streamflow for the Upper Assiniboine River Basin (UARB) at Kamsack. The UARB is best known for its hydrologically complex landscape terrain and is thus labeled as the graveyard of hydrologic models (Shook, 2012). As a result of this research, improved modeling techniques were developed that can facilitate enhanced decision-making capacity for the management of prairie water resources, while better representing hydrologic processes at the river basin scale.

In Chapter 2, a detailed overview of various sources of uncertainty, modeling challenges, operationally used techniques, and the current gaps among various techniques in operation by the Manitoba Hydrologic Forecasting Centre (HFC) was provided. As a result of an extensive literature review and consultation with FloodNet partners, and the Manitoba HFC, the Soil Water Assessment Tool (SWAT) hydrologic model was selected as the primary research tool to address some of the modeling challenges within the UARB. SWAT has been widely used for a variety of simulation purposes, including in Canada for both water quantity and quality, and specifically due to the existence of pothole wetlands module. As UARB lies within PPR, which is dominated by pothole wetlands, therefore SWAT was the most desirable hydrological model for this study.

Major research findings as a result of this thesis work have been documented in three compiled papers. The first paper (Chapter 3) highlighted the complexity in calibrating hydrological models with the different structural arrangements for representing Prairie potholes in the SWAT model. The UARB contains millions of Geographically Isolated Wetlands (GIWs), also called Pothole Wetlands in this thesis, which is a unique and hydrologically complex feature of the Prairie Pothole Region (PPR). Consequently, a modified SWAT model was developed to better represent pothole wetlands and to improve simulation of peak flows by capturing fill and spill processes. The capability of the modified model was evaluated relative to the lumped pothole models with the express intent of evaluating process-based representations of each model and calibration cost trade-offs. The study indicated that the modified SWAT model better represented the prairie spill and fill processes, improving hydrologic simulation as compared to the other two versions of SWAT, however, with higher computational resources and time costs.

The second paper (Chapter 4) assessed the role of pothole wetlands under changing climate in the UARB. The modified SWAT model with the enhanced representation of the Prairie pothole landscape (Chapter 3) was utilized to address the issue of long-term climate and land use change uncertainty, and to assess the coupled effect of climate and land use change on the hydrology of the UARB. The term land use change in this study referred to the percent removal of pothole wetlands from the land surface of the UARB. The study confirmed an increase in winter streamflow and decrease in summer flow due to the aggregated effect of simultaneous climate and land use changes. While the analysis suggested that both land use and climate change could intensify hydrological processes within the study region, changes in climate appeared to play a more dominant role in altering streamflow in the watershed.

The third paper (Chapter 5) focused on developing a multi-model framework to improve seasonal runoff prediction using Ensemble Streamflow Prediction (ESP) coupled with various post-processing techniques. The modified SWAT model together with WatFlood (used operationally by the Manitoba HFC) were utilized to generate a multi-model ensemble for hindcasting during the 1994-2014 historical period. The linear regression (LR), quantile mapping (QM), quantile model averaging (QMA), and Bayesian model averaging (BMA) statistical post-processing techniques were analyzed to combine multi-model ESPs optimally, thus reducing model input and structural uncertainty. Results suggest that ensemble from both models, when combined, was better able to capture the observed seasonal flow. While, the multi-model ensemble, when coupled with the quantile base statistical post-processing approaches, show improvement in the predictability of the observed streamflow forecast. The research, however, highlighted the importance of further research needed to confidently recommend a particular post-processing technique that would enhance decision-making capacity of the Hydrologic Forecast Centre (HFCs) in the prairie region.

6.2 Research significance

Uncertainty due to fill and spill processes that incorporate the dynamic contributing area in response to climate is a common challenge in the Prairie Pothole Region (PPR) that makes the hydrology of the PPR difficult to model, and therefore quantify. This study developed an improved modeling framework where site-specific processes are conceptualized first, followed by modifications to the existing modeling framework to improve suitability to the conditions of the area of interest. Furthermore, this study is first of its kind to investigate model calibration complexity with changing model structure to represent PPR fill-and-spill processes, and the resulting impact on parameter uncertainty, which is a significant contribution to FloodNet based on the complexity of this region and need to further study (NSERC-FloodNet, 2018).

Further, this study assessed the importance of pothole wetlands under future climate uncertainty. Much of the earlier research explored the impacts of either climate or land use change on the hydrology, whereas this study investigated the combined and individual effects of climate and land use change. While the analysis suggests that both land use and climate change will intensify hydrological processes within the study region, changes in climate appear to play a more dominant role in altering streamflow in the watershed.

Another contribution of this research is the development of a Seasonal Multi-model Post-processing Ensemble Streamflow Prediction (SMPESP) framework that enhances the decision-making capacity of the Hydrologic Forecasting Centres (HFC) across Canada. The post-processing framework can be used with any hydrologic model or a combination of hydrologic models. In the current study, the newly developed SWAT model, which has the enhanced representation of prairie pothole wetlands, together with the WatFlood flood forecasting model, were utilized to generate a hindcast ensemble of seasonal streamflow. The ESPs of each model were then combined and evaluated using various post-processing techniques to assess fore(hind)cast skill. Results suggest that multi-model ESP is an effective way of reducing structural uncertainty, and a means to improve prediction accuracy. The framework evaluated at the long lead time would be of great help for decision making in managing water resources, forecasting reservoir inflows, hydropower and reservoir operations.

6.3 Research limitation and future direction

The studies main interest was to understand, identify, and address various sources of uncertainty in simulating streamflow in the PPR as part of the FloodNet group of projects. Although this research makes significant contributions towards improving the modeling capabilities of this hydrologically complex landscape, some gaps remain which are highlighted as future research that can advance the methods, tools, and outcomes presented.

- This study utilized the Circa 2000 land cover map to identify pothole wetlands in the study watershed. High-resolution data such as LiDAR would greatly improve the representation of pothole wetlands spatial distribution and characterization including internal drainage pathways within the catchment. This would reduce model uncertainty.

- Added complexity in the case of the modified SWAT model, designed to better depict pothole wetlands, significantly increased the numbers of HRUs resulting in a large number of parameters to be optimized. Increasing complexity means increased uncertainty and higher computational demand, thus limiting model effectiveness across longer periods (i.e., robustness). As high-performance computing resources are made available, a recommendation would be to recalibrate and test the newly developed technique at various temporal and spatial scales.

- The Canadian Regional Climate Model (CRCM) version 5, which is the most up to date RCM with the Canadian Land Surface Scheme (CLASS 3.5) (Yang Kam Wing et al., 2016), was used to assess long-term climate change uncertainty. It is, however, important to recognize that climate models are run with different realizations of climate-based processes and different perturbations in initial and boundary conditions, and thus result in different future climates. Therefore, the use of an ensemble of climate models would provide the ability to fully assess uncertainty due to future climate projections, and would provide the opportunity to add confidence bounds to quantify the propagation of uncertainty into streamflow projections.

- Base flow is an important component of the hydrologic balance. Removal of pothole wetlands may increase infiltration and since infiltrating flow from HRUs are no more going to GIWs, it may result in increasing baseflow contribution. However, the study did not assess impact of pothole wetlands removal on baseflow contribution. Therefore, it is suggested to investigate impact of pothole wetlands removal on baseflow.

- There is a potential contradiction between the prescence of GIWs in reality within subbasins, which act to retain small runoff events, and connect to form larger more direct routing connections, increasing runoff during large events. Removal of pothole wetlands may increase runoff given there is no obstacle (no GIWs) to retain water. On the other hand, the presence of GIWs in SWAT (based on the new routing scheme) may provide shorter, more direct path to the basin outlet, which may also contribute to increasing streamflow. In this research, we did not fully explore the impact of GIWs on runoff/streamflow and thus we strongly recommend that this should be further studied.

- This study employed various post-processing techniques to merge multi-model ensembles. It is, however, recommended to explore the impacts of both, pre- and post-processing techniques while predicting seasonal runoff.

- As models differ in structure, different models will have strengths (weaknesses) in capturing different hydrologic processes dominating in different seasons, and process interactions. Consequently, in the post-processing experiment, two operational hydrologic models were used to account for model structure uncertainty pertaining to low- (i.e., pothole landscape dominated) and peak-flow (i.e., event-based) conditions. It is, however, advised to use an ensemble approach based on more models to fully exploit model structure uncertainty, and to further improve prediction accuracy.

- In the multmodel ESP post-processing experiment (Chapter 5), ESPs comprised of 19 members were used. This made it difficult to estimate optimum parameter values for the statistical post-processing models, therefore a larger sample size (> 30) is recommended for future applications.
- In this thesis work, SUFI-2 is used to obtain optimized parameter values, while in reality SUFI-2 is an uncertainty analysis tool.. There are other algorithms such as Particle Swarm Optimization (PSO) within SWAT-CUP that are meant specifically for model calibration. It is therefore suggested, that these most feasible parameter space should be used as an input to PSO, which may effectively minimize simulations runtime and may further improve model performance.

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Title:	Impact of model structure on the accuracy of hydrological modeling of a Canadian Prairie watershed
Author:	Ameer Muhammad,Grey R. Evenson,Tricia A. Stadnyk,Alaba Boluwade,Sanjeev Kumar Jha,Paulin Coulibaly
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Appendix C: Publications, Presentations, and Other works

Peer reviewed research articles published in Journals

1. **Muhammad, A.,** Evenson, G.R., Stadnyk, T.A., Boluwade, A., Jha, S.K., Coulibaly, P., 2019. Impact of model structure on the accuracy of hydrological modeling of a Canadian Prairie watershed. J. Hydrol. Reg. Stud. 21, 40–56. doi:10.1016/J.EJRH.2018.11.005
2. **Muhammad, A.,** Evenson, G.R., Stadnyk, T.A., Boluwade, A., Jha, S.K., Coulibaly, P., 2018. Assessing the importance of potholes in the Canadian Prairie Region under future climate change scenarios. Water (Switzerland) 10. doi:10.3390/w10111657
3. **Muhammad, A.,** Stadnyk, T.A., Unduche, F., Coulibaly, P., 2018. Multi-Model Approaches for Improving Seasonal Ensemble Streamflow Prediction Scheme with Various Statistical Post-Processing Techniques in the Canadian Prairie Region. Water 10, 1604. doi:10.3390/w10111604
4. **Muhammad, A.,** Jha, S.K., Rasmussen, P.F., 2017. Drought characterization for a snow-dominated region of Afghanistan. J. Hydrol. Eng. 22. doi:10.1061/(ASCE)HE.1943-5584.0001543

Selected conference presentation

1. **Muhammad, A.,** Evenson, G. R., Boluwade, A., Jha, S. K., & Rasmussen, P. F., 2016. Quantifying the Impact of geographically isolated wetlands on the downstream hydrology of a Canadian Prairie watershed. In AGU Fall Meeting Abstracts.
2. **Muhammad, A.,** Rasmussen, P., Boluwade, A., & Jha, S., 2016. Quantifying uncertainty in the hydrologic simulation of a catchment with potholes using spatial calibration

approach through the Soil Water Assessment tool. In EGU General Assembly Conference Abstracts (Vol. 18, p. 4865).

3. **Muhammad, A.,** Stadnyk, T.A., Coulibaly, P., 2018. Flood proofing of Prairie potholes under future climate using the modified version of Soil Water Assessment Tool (SWAT). Canadian Water Resources Association National Conference, Victoria, British Columbia, Canada
4. **Muhammad, A.,** Rasmussen, P. F., 2015. Drought characterization and application of ERA40 and Remote sensing data. Canadian Water Resources Association National Conference, Winnipeg, Manitoba, Canada

Other selected research presentation

1. **Muhammad, A.,** Stadnyk, T.A., Coulibaly, P., 2018. A multimodel framework coupled with various statistical post-processing techniques for improving seasonal ensemble streamflow prediction in the Canadian Prairie Region. Progress and developmnet presentation at Annual General Meeting (AGM) on theme 3.1 of the Canadian FloodNet project. Quebec city, Quebec, Canada.
2. **Muhammad, A.,** Stadnyk, T.A., 2018. Importance of Prairie pothole wetlands: issues and options for improvement. Invited presentation to the technical team of the Ducks Unlimited Canada (DUC). Stonewall, Manitoba, Canada
3. **Muhammad, A.,** Stadnyk, T.A., Coulibaly, P., 2017. A modified Soil Water Assessment tool (SWAT) to capture the fill-and-spill processes of the prairie pothole region. Natural Sciences and Engineering Research Council of Canada FloodNet project Annual General Meeting (AGM). Montreal, Quebec, Canada.

4. **Muhammad, A.,** Rasmussen. P.F., 2016. Aggregate Effect of Prairie Potholes on Downstream Hydrology: Case Study of the Upper Assiniboine River Basin at Kamsack. Natural Sciences and Engineering Research Council of Canada FloodNet project Annual General Meeting (AGM). Toronto, Ontario, Canada.