DESIGN OF HYDROMETRIC NETWORKS USING HYDROLOGICAL MODELS

LEVERAGING HYDROLOGICAL MODELS IN CONJUNCTION WITH MULTI-OBJECTIVE OPTIMIZATION BASED METHODS TO DESIGN STREAMFLOW MONITORING NETWORKS

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TITLE: Leveraging Hydrological Models in Conjunction with Multi-Objective Optimization Based Methods to Design Streamflow Monitoring Networks

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Lay Abstract

Engineers in the field of water resources monitor hydrometric data to maintain a record of historical conditions that can be used to guide future designs and decisions. Hydrometric data are collected from monitoring networks that should be optimally designed to ensure measurements are gathered efficiently. One of the main applications of hydrometric data are to run and calibrate hydrological models. Therefore, hydrological models can be integrated into the network design process to design monitoring networks that enhance model performance while considering the intended model application. This research introduces a new model-based approach for designing streamflow monitoring networks and compares the relative effectiveness of the new technique to previously established methods. Results indicate the new process provides superior results but is also more computationally demanding. The newly proposed methodology is adaptable and can be used to facilitate user-directed designs of hydrometric monitoring networks for a wide variety of engineering applications.

Abstract

Hydrometric data provides forcing data inputs to run hydrological models and observed output time-series to facilitate the calibration and validation process. Hydrometric monitoring networks are often designed without considering the innate relationship between data collection, model set-up, and model application. This research compares the relative effectiveness of a previously established model-based network design strategy to a newly proposed method. The traditional design method identifies a set of Pareto-optimal networks using intermediate entropy-based design objectives, facilitated by the dual entropy multi-objective optimization (DEMO) tool, and then applies models as a post-processing mechanism. Streamflow time-series from networks initially identified by DEMO are used to calibrate two semi-distributed rainfall-runoff models. The calibration process enables a reassessment for non-dominance based on the primary network design objectives, which are maximizing model performance at manually defined flood sensitive catchment outlets and minimizing network size.

The newly proposed alternative method embeds the hydrological models and their calibration process into the optimization algorithm, resulting in direct optimization based on the primary design objectives. Both techniques were applied to design networks in two large western Canadian watersheds. Bubble maps are presented to illustrate variations in the spatial distribution of optimal solution sets, with respect to both model performance at flood sensitive catchments and individual station selection frequency, for all design scenarios. Results indicate the newly proposed method provides superior results regardless of network size and that trends in the spatial distribution of optimal networks are highly

case-specific. The proposed methodology can be readily adapted to address a wide variety of design applications by varying the models and model performance criteria used in the design process. The findings from this research can be used to guide future network design projects when the proposed network is intended to support one or more model-based applications.

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List of Abbreviations

Abbreviation	Description
CaPA	Canadian Precipitation Analysis
CRB	Churchill River Basin
CR-DEMO	Combined Regionalization Dual Entropy Multi-Objective Optimization
DDS	Dynamically Dimensioned Search
DEMO	Dual Entropy Multi-Objective Optimization
FSC	Flood Sensitive Catchments
FRB	Fraser River Basin
HBV	Hydrologiska Byrans Vattenbalansavdelning Model
HBV-NP	Hydrologiska Byrans Vattenbalansavdelning, Nitrogen and Phosphorus Model
Hydro-GFD	Hydrological Global Forcing Data
HYPE	Hydrological Predictions for the Environment Model
IDW	Inverse Distance Weighting
IDW-DAR	Inverse Distance Weighting - Drainage Area Ratio
KGE	Kling-Gupta Efficiency
MAC-HBV	McMaster University Hydrologiska Byrans Vattenbalansavdelning Model
MOEA	Multi-Objective Evolutionary Algorithm
NCRB	Nelson Churchill River Basin
NSE	Nash-Sutcliffe Efficiency
NSERC	National Sciences and Engineering Research Council
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
SAC-SMA	Sacramento Soil Moisture Accounting Model
SMHI	Swedish Meteorological and Hydrological Institute
WFDEI	WATCH, Forcing Data-ERA-Interim Method
WMO	World Meteorological Organization

List of Symbols

Symbol	Description
A_i	Drainage area of neighbouring stations facilitating IDW-DAR regionalization
A_u	Drainage area of station IDW-DAR regionalization is being performed for
$C(X)$	Total Correlation
h_i	Distance between monitoring stations
$H(X)$	Entropy (Marginal, Joint)
N	Number of NSGA-II decision variables
Q_i	Observed streamflow at neighbouring station facilitating IDW-DAR regionalization
Q_u	Regionalized streamflow
r	Pearson Correlation Coefficient
w_i	Weighting coefficient for IDW-DAR regionalization
x_r	Quantized streamflow observation
α	IDW-DAR fitting parameter
γ	Ratio of the standard deviation for the simulated times series to the standard deviation of the observed time series
β	The quotient of the mean of the simulated time series divided by the mean of the observed time series

Declaration of Academic Achievement

Thesis Structure

This thesis has been prepared as a sandwich thesis, per the stipulations outlined in the McMaster University School of Graduate Studies "Guide for the Preparation of Master's and Doctoral Theses." Enclosed within is the submitted paper listed below:

Chapter 2: Integration of Hydrological Models with Entropy and Multi-Objective Optimization Based Methods for Designing Specific Needs Streamflow Monitoring Networks

For Chapter 2, J. Ursulak collected all relevant data, set-up and calibrated all necessary models, designed the coding framework to implement both methods using Compute Canada systems, carried out the network design analysis, evaluated the results, drew conclusions, crafted figures presenting the results of the investigation, and drafted the initial manuscript. Dr. Paulin Coulibaly provided the initial research concept, supported the general research process, and edited the initial manuscript and figures before submission. The aforementioned research work was completed between September 2018 and June 2020.

Chapter 1. Introduction

1.1 Overview

Accurate and reliable data are the foundation for the successful completion of almost all scientific and engineering-based investigations or designs. Engineers routinely begin a study with the collection of background data to quantify baseline conditions. Similar data are then either modeled or continually collected throughout the design process, to enable a cost-benefit analysis of proposed design solutions for decision-making purposes. Furthermore, rapid advances in technology are contributing to the development of increasingly more substantial and sophisticated datasets, prompting a proliferation in the advancement of data-driven design methods capable of solving complex problems in many disciplines, including the natural sciences (Reichstein et al., 2019). These trends, in turn, raise a series of questions. How are we monitoring our data? How accurate and reliable are our monitoring efforts? And most importantly, for this research, how do we best design our monitoring and data collection systems to gather the information we need for specific design applications while accounting for practical constraints related to physical and financial barriers?

In the field of water resources, hydrometric data are collected to track the transfer and transformation of water through the water cycle over time. Typical hydrometric data collected by engineers and scientists include precipitation rates, streamflow discharge, soil moisture, groundwater levels, and evapotranspiration rates, to name just a few (World Meteorological Organization, 2008). Traditionally, hydrometric datasets were developed from in-situ observations measured using ground-based monitoring networks. Such networks obtain point source observations at discrete temporal intervals. Examples include using tipping buckets to measure precipitation rates or stream gauges to monitor water levels, which can be converted to discharge rates based on pre-defined stage-discharge rating curves.

Recent advances in remote sensing technologies and global climate models have led to an increasing number of robust areal datasets. These datasets often provide information at more detailed spatial and temporal resolutions than is economically feasible using traditional ground-based monitoring networks. However, in-situ measurements are still needed to test and validate the accuracy of remote sensing products (Swenson et al., 2006; Ragettli et al., 2015; Xiao et al., 2015). Furthermore, the continuation of well-established monitoring stations that predate available remote sensing datasets is needed to facilitate the long-term analysis of climatic and hydrologic conditions (Vaze et al., 2010; Francois et al., 2019).

While the continued collection of ground-based hydrometric data are required to support ongoing and future water resource projects, several studies have documented a decrease in the density of existing monitoring networks (Mishra and Coulibaly, 2009, 2010). Both globally and within Canada, the decline in network densities can be attributed to existing infrastructure breaking due to age or merely becoming too costly to continue to operate and maintain. The capital costs required to implement new stations also continues to increase, while the operating budgets for regulatory agencies in many parts of the world stagnate or some cases even recede (Ruhi et al., 2018). Overcoming these financial barriers requires better network design strategies to identify the optimal spatial distribution of monitoring stations and assess the cost-benefit relationship associated with increasing network density in relation to specific engineering applications. Fundamentally, network designers must first determine what data are needed, identify what applications the data are being used for, and then evaluate how that data can be collected as efficiently as possible.

1.2 Literature Review

General strategies historically applied in the design of hydrometric monitoring networks are well-reviewed by the World Meteorological Organization (1972) and The Netherlands Organization for Applied Scientific Research (1986). Numerous design strategies exist, each with their unique advantages and limitations. The approach selected for a given design application will depend in part on what type of data are being monitored. For example, is the network intended to monitor streamflow, precipitation, or groundwater? This research focuses specifically on the design of streamflow monitoring networks. Modern design strategies related to the design of such networks are comprehensively reviewed by Mishra and Coulibaly (2009) and Chacon-Hurtado et al. (2017).

Streamflow monitoring networks serve a wide variety of functions. Kurdin (1972) describes the fundamental types of streamflow monitoring networks as consisting of the basic network and the special/temporary networks. The basic network monitors spatial-temporal variations in the general hydrological regime of the monitored area using stations with long-standing observational records. Stations in the basic network are intended to be permanent and are expected to be maintained in perpetuity. Special & temporary networks are sets of complementary stations installed to enhance the information content provided from the basic network to address specific design problems. These stations are intended for short-term installation and are removed once the necessary information required to solve the problem at hand is obtained. Alternatively, if budgetary constraints allow it, stations from special and temporary networks can be absorbed into the permanent basic network.

Stations in the basic network are further subcategorized as regime stations, forecast stations, and water-management stations. Regime stations monitor general variations in the hydrological regime, whereas the data collected at forecast and water-management stations is intended to support specific applications. Forecasting stations provide accurate long-term data records at fine temporal intervals, which is needed to support hydrological forecasting. Water-management stations collect data required for the operation of major infrastructure, for instance, reservoir operations. Basic networks can be designed, considering all three types of stations separately or concurrently, and one station can serve multiple purposes. This investigation focuses on the design of basic networks, composed primarily of regime stations, to support general streamflow modeling applications. Ultimately regardless of what type of streamflow network is being designed, robust design strategies are required to ensure monitoring needs are satisfied.

All network design strategies attempt to identify a network configuration that will provide the optimal amount of information for a specific application, in the most efficient manner. Network design is defined by the network density, the spatial distribution of stations, the temporal intervals at which observations are measured, and the effectiveness with which information is transferred or interpolated between gauged locations (Dawdy et al., 1972).

Examples of traditional hydrometric network design techniques include applications of statistical sampling, joint mapping, regionalization and multi-regionalization, systematic and economic analysis, and general practical network design strategies based on study area characteristics (World Meteorological Organization, 1972).

Karasseff (1972) presents an early application of statistical sampling in the field of network design. A statistical methodology is introduced, defining a gradient and correlation criterion, which represents the lower and upper limits, respectively, for which the area gauged by a single station in an optimal network should be bound. This method was applied to assess the optimality of existing streamflow monitoring networks in the former Soviet Union. Tasker and Moss (1979) applied the Network Analysis for Regional Information technique, which is a different statistical design method introduced initially by Moss and Karlinger (1974), for an evaluation of similar monitoring networks in the United States. By using the true standard error of regional regression models to evaluate information content, and network size as a proxy for cost, information cost relationships were developed for streamflow monitoring networks in northwest Arizona. These cost-benefit relationships can provide network designers with a simple but effective means to assess the impact of budgetary cuts or increases on network performance.

An early example of the importance of regionalization on the design of streamflow monitoring networks is provided by Benson (1972). Multiple-regression analysis was used to establish relationships between streamflow characteristics and various hydrologic variables such as drainage area or basin length. The proposed methodology allows for the development of linear relationships that evaluate the adequacy with which information in an existing network can be transferred from station to station based on standard error estimates. Decision-makers can then decide using user-defined accuracy requirements, whether existing networks should either reduced, maintained, or augmented. The author also acknowledged effective network designs should consider the intended use of collected data during the design phase. Periodic re-designs of existing networks are also suggested to account for non-stationary trends in climatic and hydrological conditions.

Moreover, the multiple-regression analysis presented provides a suitable method for the generation of synthetic streamflow records at ungauged locations. The generation of synthetic streamflow records is a standard requirement in network augmentation designs that evaluate the optimal location for new stations to be added when attempting to enhance a pre-existing network. Recent studies on the regionalization of streamflow in the context of hydrometric network design include those presented by Samuel et al. (2013), Leach et al. (2015), and Werstuck and Coulibaly (2017).

Additional network design strategies focus on the transfer of information within a network, by designing networks that minimize the error associated with interpolating information from gauged to ungauged locations. This design strategy can be applied in both a univariate and multivariate sense because hydrological processes are interconnected and interdependent. For instance, streamflow and precipitation networks can be designed in tandem by acknowledging the inherent relationship between precipitation and runoff. Solomon (1972) describes joint mapping strategies, using both isoline maps and square gridded maps, that evaluate the transfer of information from precipitation monitoring networks to streamflow networks. Iterative applications of the proposed methodology enable decision-makers to measure how increasing network density minimizes the standard error of interpolation.

Unfortunately, inherent assumptions of normality and linearity limit many of the previously described methods. To alleviate these restrictions, Husain and Caselton (1980) introduced a universal basis for the design and evaluation of a hydrometric network by integrating the concepts of Information Theory originally presented by Shannon (1948). Shannon entropy provides dimensionless network performance criteria. Husain and Caselton initially used entropy-based design objectives to identify optimal station locations for a potential rainfall monitoring network and found that using Shannon's bivariate information criterion to design networks reduced estimation error when compared to other previously researched statistical methods. Later, Husain (1989) performed a network reduction and augmentation design in Vermont by using entropy theory to assess the transfer of information between neighboring monitoring stations.

Yang and Burn (1994) applied non-parametric estimation to approximate the multivariate probability density functions that are required for calculations involving Shannon entropy, thereby further reducing the error associated with making a priori assumptions about the distribution of monitored datasets. By calculating the directional information transfer between pairs of gauging stations, Yang and Burn were able to evaluate the value of individual stations within an existing monitoring network for a study area in southern Manitoba using extreme flow data records. A similar study conducted by Markus et al. (2003), built on the finding of Yang and Burn, introducing a different entropy-based method for evaluating existing networks. By calculating the net information transfer of individual stations in a network, Markus et al. were able to rank stations based on their relative importance and compare the results of their evaluation method to the generalized least square technique developed by the United States Geological Survey.

The network design strategies addressed so far can facilitate network reduction and augmentation designs based on non-competing design objectives. To enable a more robust network design adept at addressing the trade-offs associated with satisfying multiple conflicting design criteria simultaneously, Alfonso et al. (2010) introduced a multi-objective optimization procedure to evaluate the optimal spatial distribution of water level monitoring gauges in polder systems. Entropy-based design objectives were used to facilitate the multi-objective optimization. Joint entropy was maximized to optimize network information content, while network total correlation was minimized to limit monitoring redundancies. The result is a Pareto-front of non-dominated optimal networks. The selection of one Pareto-optimal network over another represents an improvement in one design objective at the expense of a different objective. While having many optimal solutions to chose from may be attractive to some decision-makers, in some instances, it may be preferred to select a strategy that determines a single optimal network. Li et al. (2012) address this issue by weighting the design objectives in their multi-objective optimization problem.

Samuel et al. (2013) applied a similar research methodology to the one introduced by Alfonso et al. (2010) to facilitate network augmentations for two streamflow networks in eastern Canada. The method is referred to as the combined regionalization and dual entropy multi-objective optimization (DEMO) procedure for hydrometric network design. DEMO first uses a regionalization technique, or an alternative strategy, to generate synthetic streamflow records for potential station locations. The synthetic streamflow records, coupled with observed measurements from an existing baseline network, provide the input data needed for the optimization procedure. A multi-objective evolutionary algorithm (MOEA) then identifies a set of Pareto-optimal networks by maximizing network joint entropy and minimizing total correlation. Additional research has integrated other design objectives into the DEMO design framework, demonstrating the adaptability of the methodology. Leach et al. (2015) found that including hydrologic signatures and indicators of hydrologic alteration as additional design objectives improved the spatial coverage/variability of Pareto-optimal networks. Furthermore, Keum and Coulibaly (2017) incorporated the principles of conditional entropy into the design process to facilitate an integrated design of precipitation and streamflow networks simultaneously.

While network design strategies using statistical and entropy-based methods are well suited to the design of robust general-purpose networks, these methods are often limited in their ability to design monitoring networks for specific design applications. Recently, a model-based approach has been introduced for the measurement-based evaluation of hydrometric networks. In this type of procedure, a hydrological model is employed to quantify the change in model error associated with varying sets of observed data, resulting from different spatial configurations of potential monitoring networks (Chacon-Hurtado et al., 2017). The selection of which model and model performance criteria to use can be varied depending on the intended design application, enabling user-directed designs. Previous research using a model-based approach for network design (Dong et al., 2005; Xu et al.;

2013, Xu et al.; 2015, Keum et al.; 2018; Zeng et al., 2018) employed models as part of a post-processing procedure. Intermediate or secondary design objectives/methods are used to identify an initial set of candidate networks. That set of networks is then filtered or further evaluated using hydrological models to measure how effectively the observational dataset from each network reduces model error, as measured by a manually defined set of model performance criteria.

The process of applying hydrological models as a post-processing mechanism does not represent a direct, cohesive, and fully continuous evaluation of the relationship between data collection, model calibration/validation, and model performance. For complex problems where the number of potential candidate networks to assess is significant, and an optimization algorithm is needed to search the solution space, networks that are optimal based on the primary model performance-based objectives may be unidentified during the initial design process facilitated by the secondary objectives. To search the solution space according to primary objectives directly, hydrological models, and if necessary, the model calibration process should be embedded directly into the selected optimization algorithms. This research compares the relative effectiveness of identifying networks most suitable for streamflow modeling in two large Canadian watersheds using two distinct methods. First, applying DEMO followed by post-processing with hydrological models and second identification of optimal networks through multi-objective optimization with hydrological models embedded into the optimization process.

1.3 Research Objectives

The objectives of the research presented herein are as follows:

1. Utilize the DEMO method to evaluate an initial set of Pareto-optimal networks for two large river basins in western Canada.
2. Employ hydrological models to post-process the initial set of networks identified by DEMO, recognizing a subset of networks most suitable for streamflow modeling. Observations from candidate networks identified by DEMO are then used to calibrate semi-distributed SAC-SMA and MAC-HBV models, allowing for networks to be further evaluated based on the primary design objectives: minimizing network size and maximizing model performance at user-defined flood sensitive catchments. The combination of steps 1 and 2 is referred to as design Method 1.
3. Apply a second design method where hydrological models and their calibration process are embedded into the MOEA, thereby enabling direct optimization according to the primary design objectives.
4. Compare the relative effectiveness of the designing networks with both proposed methods. Means of comparison include the number of optimal networks identified, their performance statistics, and variations in the spatial distribution of selected stations and model performance at flood sensitive catchment outlets.
5. Compare and comment on the impact of selecting between MAC-HBV and SAC-SMA models on the design of optimal monitoring networks for streamflow modeling.

This section concludes the first chapter of this thesis, intended to introduce the research topic, the research objectives, and provide a brief literature review of advancements in the field of hydrometric network design with an emphasis on entropy, multi-objective optimization, and model-based methods. The second chapter presents a full study, carried out for two large river basins in western Canada, in which both proposed design methodologies were applied to design monitoring networks for general streamflow modeling applications. Method to method and model to model comparisons are presented and discussed. The third chapter delineates the major research findings/conclusions and provides recommendations for further research.

Chapter 2. Integration of Hydrological Models with Entropy and Multi-Objective Optimization Based Methods for Designing Specific Needs Streamflow Monitoring Networks

Summary of Paper 1: Ursulak, J., and Coulibaly, P. (2020) Integration of Hydrological Models with Multi-Objective Evolutionary Algorithms and Entropy-Based Optimization Objectives to Facilitate the Design of Streamflow Monitoring Networks, *Journal of Hydrology*, Under Review.

In this research, two model-based network design strategies were applied. The first method identifies a set of Pareto-optimal networks using the dual entropy multi-objective optimization (DEMO) tool. DEMO results are then post-processed using hydrological models. The second method embeds models into a multi-objective evolutionary algorithm, facilitating direct optimization according to the model performance-based objectives. Variations in the relative effectiveness of both methods and the spatial distribution of associated optimal solution sets are compared to determine which method is most suitable for the design of monitoring networks that support general streamflow modeling.

The most important results of this research include:

- Model-based network design with embedded models produces better results than model-based designs where models are applied as a post-processing mechanism
- Spatial trends in optimal networks identified by model-based designs strategies are highly case-specific and depend on which model facilitates the design

2.1 Abstract

Water resource managers depend on the collection of accurate hydrometric data for various modeling and planning projects. An essential use of hydrometric data includes hydrologic modeling and forecasting to support decision making in water resources planning and management. It is, therefore, essential to design hydrometric monitoring networks while considering the relationship between data collection and model application. A new model-based network design strategy is proposed that embeds hydrological models into a multi-objective evolutionary algorithm, facilitating direct optimization according to the model-based design objectives. This method is compared to the traditional model-based approach used to design hydrometric monitoring networks. The traditional approach is to first conduct optimization using secondary design objectives, that are not model based, to identify a set of optimal networks. Hydrological models are then applied as a post-processing mechanism to identify which of the optimal networks best satisfy the model orientated design objectives or users' needs. In this investigation the well-established dual-entropy multi-objective optimization (DEMO) approach was employed to conduct the initial network design based on the principles of information theory, followed by post-processing with rainfall-runoff models. Two case studies are evaluated, a monitoring network reduction in the Fraser River basin and a network augmentation in an upstream subsection of the Churchill River basin. Results show that embedding models in the optimization algorithm consistently yields better network configurations compared to those identified using the traditional method. It is shown that a smaller size optimal network that outperforms larger size networks, can be identified directly by the proposed method. The

models and model performance criteria used in the design process can be readily adapted, allowing for a user-directed design capable of addressing problem-specific objectives on a case by case basis.

2.2 Introduction

Professionals in the field of water resources depend on hydrometric data to provide forcing data inputs, as well as observed output time-series for the calibration and validation of hydrological and hydraulic models (Silberstein, 2006; Schumann et al., 2009; Yi et al., 2018). Such models are employed to simulate the response of natural, anthropogenic, and mixed systems to both historical and forecasted meteorological conditions (Beven, 2001). Effective modeling is essential to the successful planning and completion of numerous engineering endeavors including flood forecasting (Han and Coulibaly, 2019; Leach and Coulibaly, 2019; Wijayarathne and Coulibaly, 2020), drought assessment (Corzo Perez et al., 2011; Mishra & Singh, 2011; Trambauer et al., 2013) reservoir operation (Mateo et al., 2014; Awol et al., 2019) and the design of municipal infrastructure (Singh Bisht et al., 2016; Macro et al., 2019). Given the natural progression from data collection to model calibration and ultimately model application, it is logical to develop a process for the design of hydrometric monitoring networks that considers the implications of network design on model performance and utility.

A hydrometric network is a collection of two or more stations that provide point-source monitoring of the quality or quantity of various hydrological processes at discrete temporal intervals (World Meteorological Organization, 2008). Such networks are leveraged to collect water level or discharge rates along natural channel corridors (Halverson and Fleming, 2015; Stosic et al., 2017), monitor the quality of groundwater reservoirs (Mogheir and Singh, 2002; Kollat et al., 2011), and assess the spatial distribution of precipitation across a watershed (Krstanovic and Singh, 1992; Wang et al., 2019). Point-source measurements from traditional monitoring networks do not typically provide the fine spatial and temporal resolution of areal datasets developed with remote sensing technologies. However, continued in-situ data collection is still required to enable the validation of remote sensing products and prolong the historical record of well-established monitoring stations (Swenson et al., 2006; Ragettli et al., 2015; Xiao et al., 2015).

Climate change is continually contributing to deviations from the historical record, in terms of both the magnitude and frequency of extreme hydrological events, thereby limiting hydrologists and engineers in their ability to rely on assumptions of stationarity when leveraging hydrometric data for design and decision-making purposes (Vaze et al., 2010; Francois et al., 2019). The successful adaptation of modeling and design strategies to account for non-stationarity in both meteorological trends and land use characteristics is dependent on the continued collection of accurate hydrometric data, preferably at increasingly finer spatial and temporal resolutions. However, in many countries around the world, including Canada, the number of operational hydrometric monitoring stations is decreasing (Mishra and Coulibaly, 2009, 2010). The reduction in the global density of many monitoring networks can be attributed to a combination of aging infrastructure, increasing capital costs associated with the establishment of new monitoring stations, and stagnating or diminishing operational budgets for the maintenance of existing networks

(Ruhi et al., 2018). Therefore, the optimal design of hydrometric monitoring networks is needed to facilitate the continued capture of fundamental hydrologic data while accounting for practical design constraints imposed by financial and physical limitations.

Optimal network design requires the spatial distribution of stations in a network to result in a non-dominated system when considering the chosen design criteria. Typical network design objectives include: minimizing network size or cost (Tasker and Moss, 1979; Luo et al., 2016), maximizing the amount of information collected by the network (Alfonso et al., 2010; Samuel et al., 2013), and minimizing the collection of redundant information (Werstuck and Coulibaly, 2018). Employing multiple objectives in the design process typically produces a Pareto-front of non-dominated solutions. The comparison between Pareto-optimal solutions represents a trade-off such that the selection of one solution over another results in an improvement of one design objective to the detriment of a different objective. Applying weights to objective functions provides decision-makers with a means to determine a single optimal network when considering multiple design criteria (Li et al., 2012). Ultimately, the number of candidate networks selected and their respective spatial distributions varies depending on which technique or methodology is employed in the network design process.

Mishra & Coulibaly (2009) provide an extensive review of the techniques commonly employed in the design of surface water networks for the monitoring of precipitation and streamflow. Some of the primary design methodologies reviewed include: statistical analysis (Rodriguez-Iturbe and Mejia, 1974; Burn and Goulter, 1991), spatial interpolation techniques (Karnieli, 1990; Weisse and Bois, 2002), entropy-based methods (Husain 1989;

Joo et al., 2019), various optimization procedures (Kollat et al., 2008; Reed and Kollat, 2011), network design based on physiographic characteristics (Laize, 2004; Nour et al., 2006), and several hybrid approaches (Pardo-Iguzquiza, 1998; Markus et al., 2003). While all network design methods have their distinct merits and shortcomings, recent studies have shown that the design of hydrometric networks using multi-objective optimization with entropy-based optimization objectives is well suited to the design of robust multipurpose monitoring networks (Samuel et al., 2013; Keum et al., 2017).

The dual-entropy multi-objective optimization (DEMO) approach (Samuel et al., 2013) designs general-purpose hydrometric networks by employing a multi-objective evolutionary algorithm (MOEA) to assess candidate monitoring networks based on multiple design objectives related to information theory. Traditionally, DEMO identifies candidate networks by seeking to maximize the joint entropy of a network while simultaneously minimizing total correlation. DEMO is adaptable and capable of addressing problem-specific design characteristics by incorporating additional design objectives (Leach et al., 2015, 2016; Keum and Coulibaly, 2017a). Recently, Keum et al. (2018) added conceptual hydrological models as post-processors to the network design process to further evaluate candidate networks according to model performance statistics. This type of evaluation creates opportunities for user-directed designs that consider the impact of data collection on specific modeling applications. For instance, when designing a network for flood forecasting purposes, networks that promote the collection of hydrometric data leading to the effective modeling of peak flows may be favored.

Previously studies that utilize hydrological models as part of the network design process (Xu et al., 2013, 2015; Keum et al., 2018; Zeng et al., 2018) typically do so by using selected models as part of a post-processing procedure. Firstly, intermediate design objectives, such as those traditionally applied by DEMO, guide the network design process generating a set of non-dominated candidate networks. Hydrological models are then used to further evaluate and filter the original solution set according to the primary design objectives, which are, at least in part, some combination of model performance criteria. Applying models as a post-processing mechanism does not enable a unified review and assessment of the relationship between data collection, model calibration, and model application as part of a single continuous design process. Networks that are optimal according to the primary design objectives, derived from model performance statistics, can be unidentified if dominated during the optimization process facilitated by the intermediate objectives. Embedding hydrological models, and when necessary, the model calibration procedure into existing MOEAs addresses this issue by enabling MOEAs to explore the solution space according to the primary design objectives directly.

This research compares a newly proposed model-based network design technique, which embeds hydrological models into MOEAs, to the traditional approach of applying models as a post-processing mechanism. Semi-distributed models are applied to facilitate the design of streamflow monitoring networks in two large Canadian watersheds. Both methods generate a set of Pareto-optimal networks that assess the trade-off between maximizing model performance at select flood sensitive catchments (FSC) and minimizing network size. Maps visually summarizing the spatial distribution of station selection frequency and model performance at FSC are presented for all design scenarios. Thereafter conclusions and observations regarding the differences between the two investigated model-based design strategies are discussed.

2.3 Study Areas and Data

2.3.1 Fraser River Basin Upstream of the Town of Hope

Discharging directly to the Pacific Ocean, the Fraser River basin (FRB) provides drainage for approximately 25% of British Columbia (Canada). Headwaters originate in the northeastern extents of the watershed in the Rocky Mountains. The river generally flows southward merging with the Nechako River, the Chilcotin River, and other major tributaries before passing through the Strait of Georgia and discharging into the Salish Sea southwest of Vancouver (Benke and Cushing, 2005). The terrain in the basin is classified mainly as mountainous with a 3950 m elevation differential between the high point and the basin outlet. More than 90% of the watershed is undeveloped. The only major urban centers, excluding the area immediately surrounding the outlet, are Prince George and Kamloops. Nevertheless, many small towns and semi-isolated settlements line the major drainage corridors. The FRB is culturally significant to many First Nations communities and is considered one of the most ecologically important riverine habitats for salmon in the world (Northcote and Larkin, 1989).

The climatic profile of the FRB is spatially diverse, with notable variations in climate and vegetative cover between the coastal, mountainous, and plateau regions. Annual precipitation rates average 400-800 mm in the interior plateaus but can exceed 3000 mm/year in the coastal and mountainous portions of the river basin. The mean annual air temperature drops from 7.5 °C in the south to 0.5°C in the northwest as the elevation increases (Benke and Cushing, 2005). The semi-distributed hydrological models leveraged in this study utilize daily temperature and precipitation as forcing inputs. The gridded daily Canadian Precipitation Analysis (CaPA) dataset provides precipitation data for this study area. Thiessen polygon analysis facilitated spatial interpolation of daily temperature observations, taken from 134 meteorological stations, to generate daily temperature data representative of specific catchments.

The FRB upstream of the town of Hope is one of two study areas. This portion of the watershed has a drainage area of 217,000 square kilometers or 90% of the total FRB. The study area has 106 streamflow monitoring stations to consider during the network design process. The World Meteorological Organization (WMO) guidelines recommend a network density of one station per 1,000 km^2, 1,875 km^2, and 2,750 km^2 for mountainous, hilly/undulating, and coastal regions, respectively. The FRB is a mixture of all three regions; therefore, an average network density of one station per 1,875 km^2 is the recommended network density. These guidelines suggest a network of 116 stations, only 10 stations more than currently existing in the FRB.

Given that the FRB is relatively well gauged by WMO guidelines, a network reduction design was facilitated instead of a more traditional network augmentation. By performing a network reduction in the FRB, only observed time series associated with existing stations are considered during the design process, thereby allowing for a proof of concept scenario that is not dependent on the assumptions and uncertainty associated with the generation of synthetic time-series for potential station locations. Network design applications require some stations to be defined as existing or fixed unless the objective is to design the entire monitoring network from scratch. For the FRB, the 43 non-first order gauged catchment outlets were considered as existing stations. These stations are included as part of each candidate network identified during the design process. Consequently, the remaining 63 first-order catchments outlets were treated as pseudo-potential stations. Essentially, variations in the spatial distribution of the most upstream monitoring stations characterize the differences between the optimal networks identified for this study area.

Keum and Coulibaly (2017b) suggest utilizing at least 10-years of continuous daily data when designing hydrometric networks using DEMO. Based on this recommendation, 10 years of daily streamflow data from 2003-2012 were obtained for the 106 stations included for use in this study. Missing streamflow values were infilled using inverse distance weighting - drainage area ratio (IDW-DAR) regionalization. Several studies have identified IDW-DAR as one of the most effective regionalization techniques for infilling missing streamflow measurements in Canadian watersheds (Samuel et al., 2013; Werstuck et al., 2017).

The network design process carried out in this study aims to maximize model performance at FSC while limiting network size. Land use maps (Government of Canada, 2010) were used in conjunction with data from the 2016 Canadian Census to identify the flood sensitive catchments (FSC) in the FRB. Figure 2-1 provides maps visualizing the spatial distribution of stations, land use, and FSC in the FRB. Table 2-1 summarizes the primary study area statistics pertaining to the network design process.

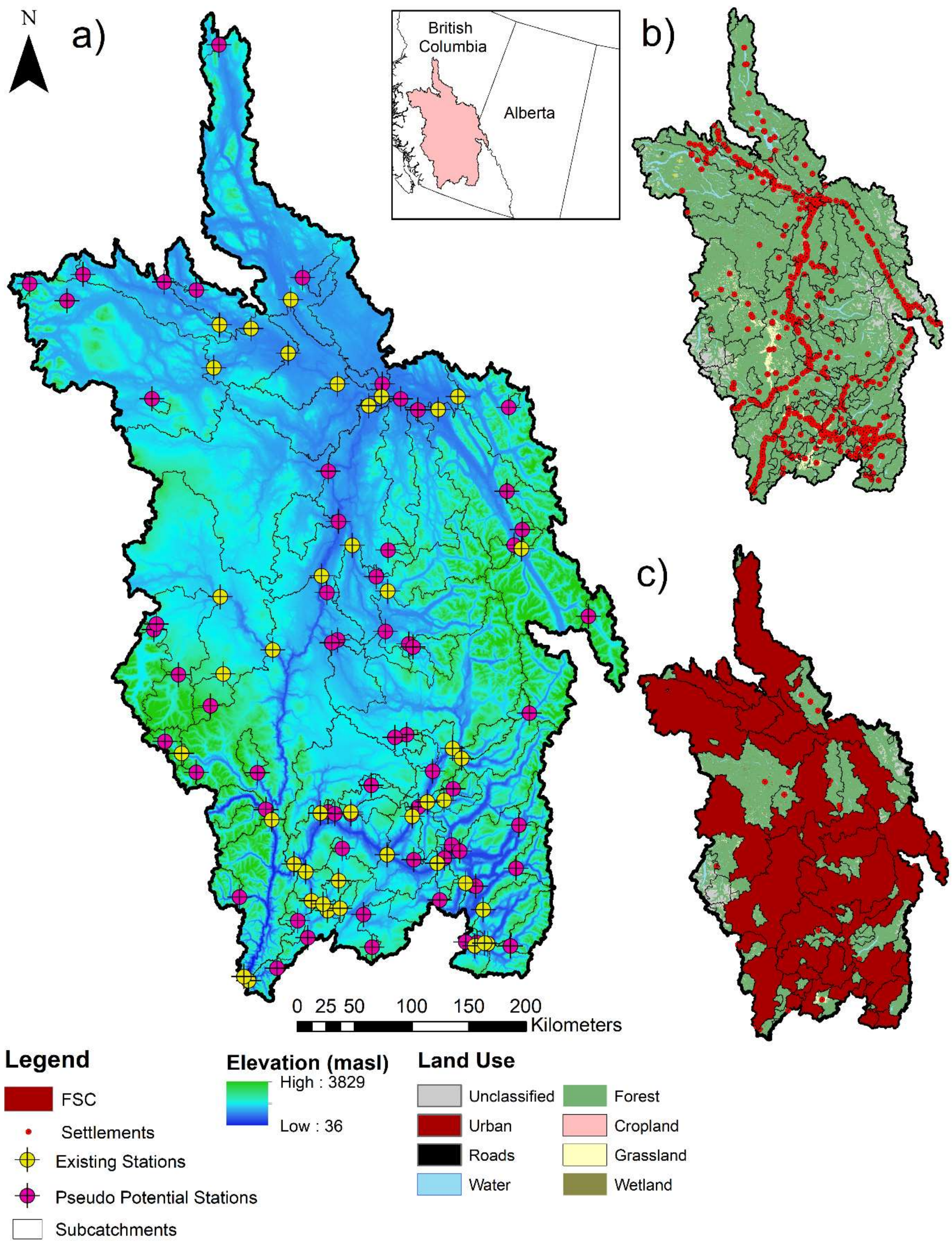


Figure 2-1: a): Study area topography with the spatial distribution of existing and pseudo-potential stations overlain for the Fraser River basin. **b)**: Land use map. **c)**: Delineation of FSC.

2.3.2 Churchill River Basin Upstream of the Otter Rapids

Headwaters for the Churchill River originate in northeastern Alberta at Beaver Lake and northern Saskatchewan around the Wollaston Lake area. The river runs eastward, passing through the provinces of Alberta, Saskatchewan, and Manitoba before discharging into Hudson Bay (Benke and Cushing, 2005). Approximately 75% of the flow through the Churchill River is diverted to the south, into the more extensive Nelson River system at Southern Indian Lake in north-central Manitoba. Partial diversion of the Churchill River into the Nelson Valley system was conducted to enhance hydropower development in the downstream extents of the Nelson River valley (Newbury et al., 1984). The cold and dry climate of the Churchill River Basin (CRB) is characteristic of subarctic regions (Lane & Sykes, 1982). The frost-free period ranges from 60-120 days annually. Mean daily air temperatures range from as low as -27.5°C in January to as high as 17.5°C in July. The rain shadow effect of the Rocky Mountains to the west limits annual precipitation to 400-600 mm/year on average. Concerning land use, the CRB is mostly undeveloped. The landscape is generally dominated by forest and wetlands (Zubrycki et al., 2016), except for limited agricultural and urban development predominately located along the southern boundary of the watershed.

The portion of the CRB upstream of Otter Rapids acts as the second study area for this research investigation. This region represents a total drainage area of 119,000 square kilometers. The entire study area is upstream of the major river diversion. Based on WMO guidelines, a watershed of that size with an interior plains physiographic classification should have a network density of one streamflow monitoring station per 1,875 km^2 (World

Meteorological Organization, 2008), translating to a recommended network density of 64 stations. The existing monitoring network is comprised of only 13 stations, therefore the CRB can be considered poorly gauged by WMO minimum network density guidelines.

A network augmentation design was performed by applying the proposed research methodology. HYPE model results for the Nelson-Churchill River Basin (NCRB) (Stadnyk & Bajracharya, 2019) provide time-series for potential station locations. In some instances, the sub-catchment configurations utilized in the HYPE model set-up were aggregated to reduce the number of potential stations and, by extension, the computational cost. Aggregation of sub-catchments was only performed in unpopulated and undeveloped areas, as the emphasis of the study was to identify monitoring network configurations that optimize model performance at flood sensitive, or highly developed, catchments. A total of 13 existing stations and 78 potential stations were considered in the network design process. Gaps in observed time-series for existing stations were infilled using HYPE model output. The Hydro-GFD reanalysis dataset provides daily temperature and precipitation time-series representative of individual catchments (Berg et al., 2018). A ten-year daily times-series record from 2001-2010 was applied to conduct the network augmentation, representing the most recent ten-year period suitable for analysis based on the availability of HYPE model results.

As with the FRB, land use maps (Government of Canada, 2010) were used in conjunction with data from the 2016 Canadian Census to identify the FSC in the CRB. Figure 2-2 provides maps visualizing the spatial distribution of stations, land use, and FSC in the CRB. Table 2-1 provides the study area statistics related to the network design process.

Table 2-1: Study Area Characteristics

Study Area	Number of Existing Stations	Number of Potential Stations	Drainage Area (km^2)	Number of FSC	Recommended Number of Stations based on WMO Guidelines
Churchill River Upstream of Otter Rapids	13	78	119,000	62	64
Fraser River Upstream of Town of Hope	43	63*	217,000	41	116

*Existing stations treated as pseudo-potential stations

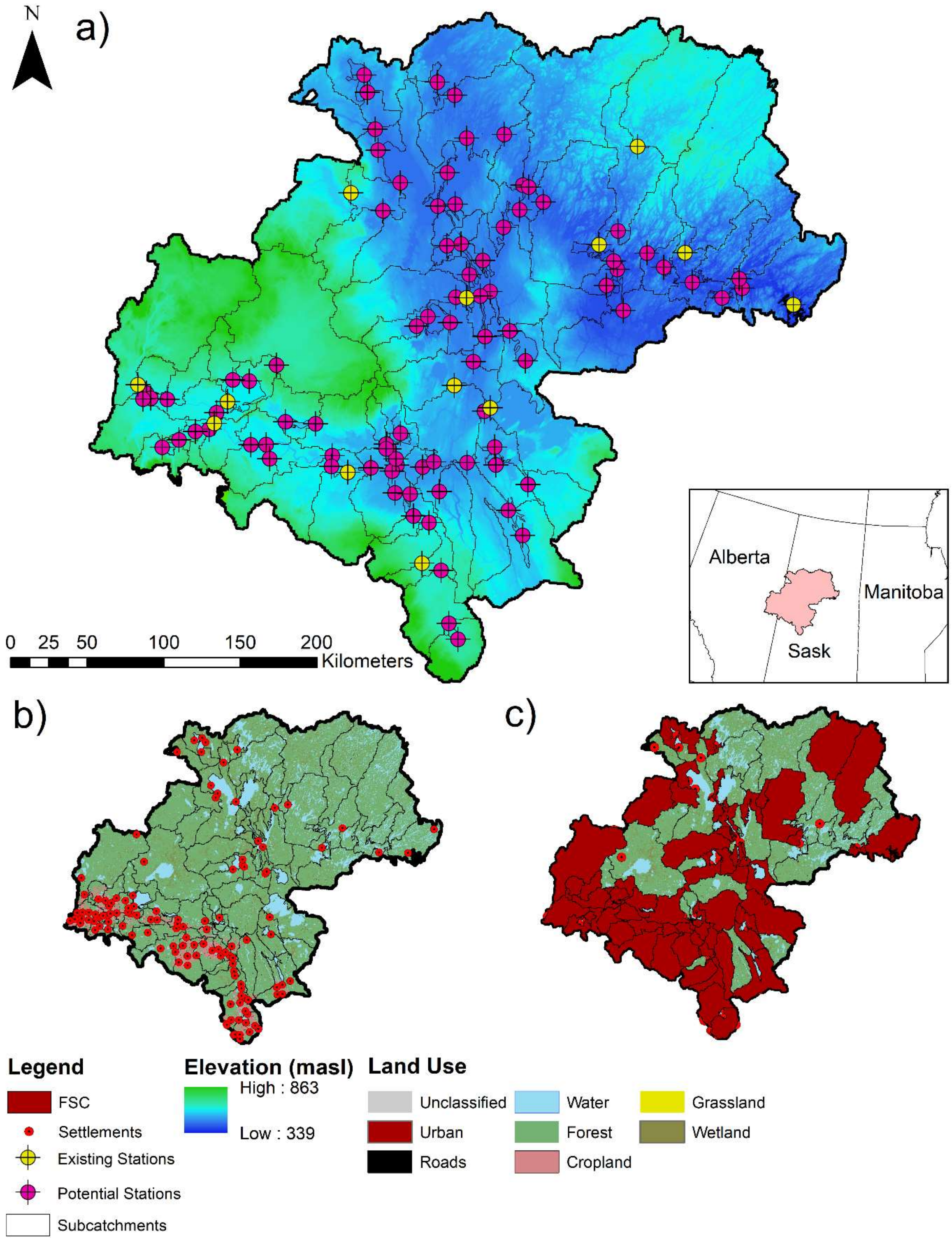


Figure 2-2: a): Study area topography with the spatial distribution of existing and potential stations overlain for the Churchill River basin. **b)**: Land use map. **c)**: Delineation of FSC.

2.4 Methodology

The primary objective of this investigation is to identify the hydrometric networks most suitable for streamflow modeling applications in two large Canadian watersheds. This objective is accomplished by leveraging semi-distributed hydrological models and multi-objective evolutionary algorithms to assess the tradeoff between maximizing model performance at FSC while simultaneously seeking to minimize network size. Two distinct research methods are applied. Figure 2-3 provides a flowchart delineating the steps and processes that comprise both methods. A more detailed description of both approaches follows thereafter.

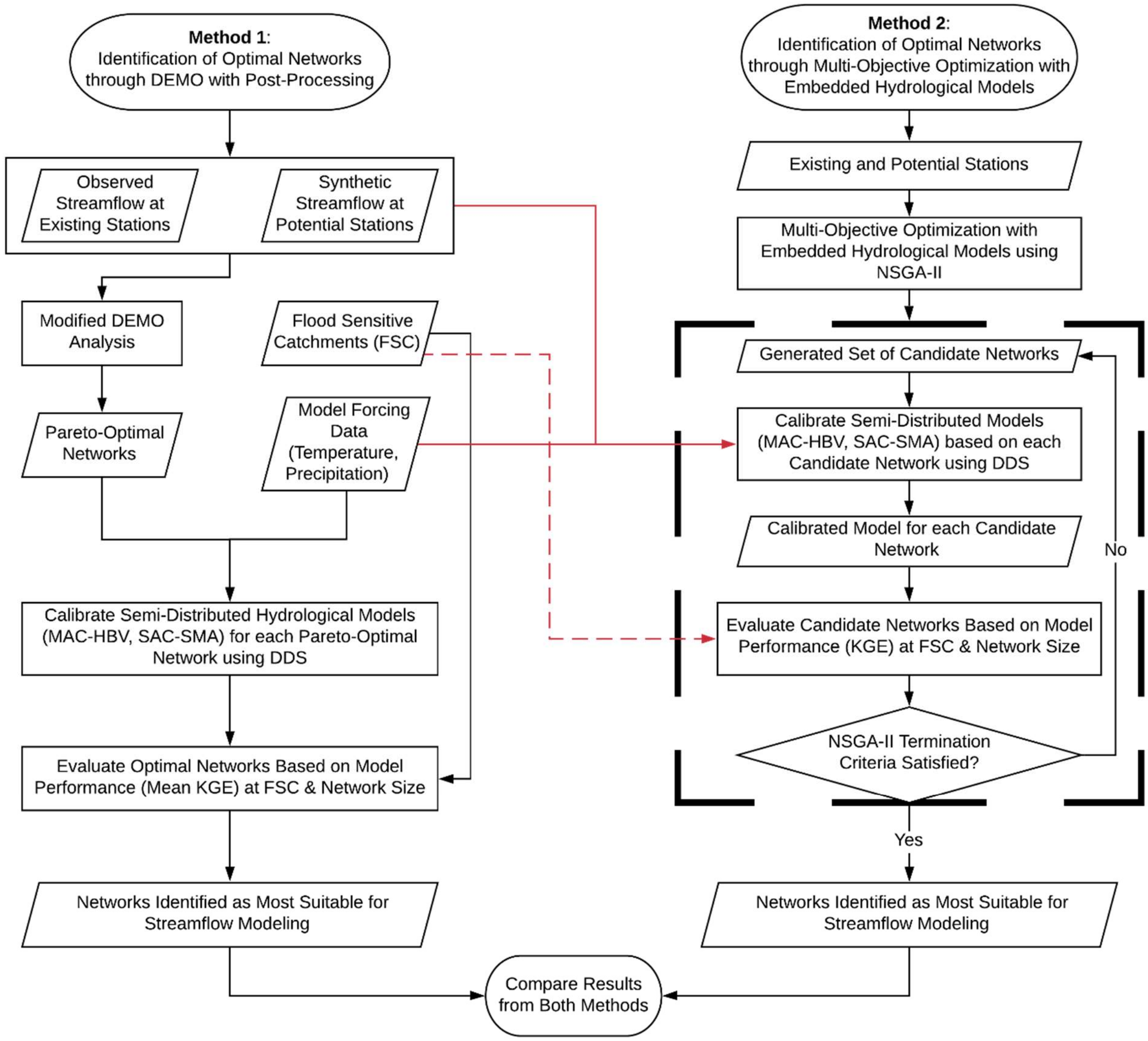


Figure 2-3: Flowchart delineating research methodology

Method 1 seeks to identify a set of optimal networks by initially applying a modified version of DEMO, followed by post-processing using hydrological models. When conducting network designs, a certain number of stations are typically designated as existing or fixed. Existing stations constitute a baseline network and are considered part of every candidate network analyzed throughout the design process. A set of potential stations are also identified. The purpose of the network design is to identify which combination of potential stations best complements the existing network with respect to desired design criteria. Therefore, time-series for both existing and potential stations represent the inputs to a typical network design process.

For this investigation, modified DEMO inputs were prepared by coupling observed streamflow time-series for existing monitoring stations with either synthetic streamflow time-series for potential stations in the case of the CRB, or more observed streamflow time-series for pseudo-potential stations in the case of the FRB. An MOEA is used to identify Pareto-optimal networks by seeking to maximize joint entropy, minimize total correlation, and maximize the number of gauged stations at FSC. FSC are manually identified using the land use maps provided with Figures 2-1 and 2-2. The third criterion, maximizing the number of gauged stations at FSC, was added to the objectives traditionally associated with DEMO because it is anticipated networks that heavily gauged FSC offer better average model performance at these locations.

Each Pareto-optimal network identified by the modified DEMO analysis provides output observations for the multi-site calibration of semi-distributed SAC-SMA and MAC-HBV models. Dynamically dimensioned search (DDS) performs the model calibrations in this study. Forcing data are provided from a combination of CaPA and spatially interpolated ground-based measurements for the FRB and the Hydro-GFD reanalysis dataset for the CRB. Non-dominance is then reassessed based on the overarching network design objectives: maximizing average calibrated KGE at FSC and minimizing network size. This post-processing mechanism ultimately identifies a smaller subset of networks (when compared with the original set of networks identified by DEMO) that are most suitable for streamflow modeling.

In summary, the first method employs computationally efficient secondary design objectives to search the whole solution space, identify a set of Pareto-optimal networks based on those objectives, and then reassess for non-dominance based on the overarching or primary design criteria. In contrast, the second proposed method embeds hydrological models and their multi-site calibration process directly into the MOEA, allowing for direct optimization according to the primary design objectives. While substantially more computationally demanding, the second method is necessary to ensure that optimal networks (according to the primary design objectives) are not left unidentified if considered dominated during the modified DEMO analysis. Optimal networks, according to the primary design objectives may be dominated during the first method because secondary or intermediate objectives facilitate the optimization process associated with DEMO.

2.4.1 Information Theory-based Metrics

Introduced by Shannon (1948) as part of an investigation into the transmission of messages within communication systems, entropy in the context of information theory, can be used to quantify the uncertainty of a single event or subset of events occurring by considering the information provided in a larger inclusive set of observations. When applied discretely, Shannon entropy can quantify the information content of nonparametric datasets, without any assumptions about the data distribution. As a result, entropy-based metrics are well suited for the analysis of complex environmental systems. The role of Shannon entropy in the broader field of water resources is well-reviewed by Singh (1997). In terms of hydrometric network design, information theory-based metrics are routinely applied as objective design criteria (Alfonso et al., 2010; Samuel et al., 2013). The varied applications of information theory as part of the design of hydrometric monitoring networks are reviewed by Keum et al. (2017).

Marginal entropy is an information theory-based metric that can be used to quantify the amount of information associated with a given time-series observed at a single monitoring station. Marginal entropy is defined as follows (Shannon, 1948; Husain, 1989):

$$H(X) = \sum_{i=1}^{n} P(x_i) \log_2 P(x_i) \tag{1}$$

where $P(x_i)$ refers to the probability of observation x_i, after being binned accordingly, occurring within an observed time-series, n is the number of bins in the associated time-series histogram, and $H(X)$ is the marginal entropy of the dataset measured in bits.

The amount of information present within an entire monitoring network can be evaluated by calculating the joint entropy of the network. Joint entropy is formulated mathematically as follows (Shannon, 1948; Husain, 1989):

$$H(X_1, \dots, X_N) = -\sum_{i=1}^{n1} \sum_{j=1}^{n2} \dots \sum_{k=1}^{nN} P\left(x_{1,i}, x_{2,j}, \dots, x_{N,k}\right) \times \log_2 P\left(x_{1,i}, x_{2,j}, \dots, x_{N,k}\right) \tag{2}$$

where $\left(x_{1,i}, x_{2,j}, \dots, x_{N,k}\right)$ represents distinct observations belonging to time series $(X_1, \dots, X_N)$. $P\left(x_{1,i}, x_{2,j}, \dots, x_{N,k}\right)$ is the probability of these observations occurring at the same temporal interval once binned according to the related binning intervals $(n_1, n_2, \dots, n_N)$.

If there is no redundant information present in a monitoring network, then the joint entropy of the network is equal to the sum of the marginal entropies associated with each station. In instances where redundant information is present in a network or system, the amount of redundant information is referred to as the total correlation. Total correlation is equal to the difference between the sum of the marginal entropies for all stations and the joint entropy of the network, and is represented as follows (McGill, 1954; Watanabe, 1960):

$$C(X_1, \dots, X_N) = \left[\sum_{i=1}^{N} H(X_i)\right] - H(X_1, \dots, X_N) \tag{3}$$

2.4.2 Experiment Data Preparation & Processing

2.4.2.1 Delineation of Flood Sensitive Catchments

FSC were manually delineated using the land use maps provided with Figures 2-1 and 2-2. Firstly, the land use and distribution of settlements within each sub-catchment was reviewed individually. Non-first order catchments with any form of development (urban areas, cropland, dense road or infrastructure networks, etc.) were then designed as flood sensitive. Additionally, all catchments gauged by an existing monitoring stations in the CRB were also identified as FSC. This conservative approach was taken to identify all sub-catchments where flood events could potentially cause substantial damage. Depending on the purpose of the network design investigation, decision makers could apply stricter methods to identify sensitive or highly important catchments that should be prioritized during the network design process.

2.4.2.2 Data Quantization

Discrete entropy calculations require precisely measured data to be selectively binned into smaller coarser datasets. The configuration of optimal networks identified using entropy-based design strategies is sensitive to the selection of quantization techniques (Fahle et al., 2015). However, a universally preferred method has not yet been identified (Keum and Coulibaly, 2017a). For this research, observed and simulated discharge rates in units of cubic meters per second were converted to mm/day by dividing by catchment drainage areas. A bin width of 1 mm/day was then applied with values rounded up to the nearest integer. Previous investigations using DEMO have applied a similar technique (Samuel et al., 2013; Werstuck et al., 2017). The mathematical representation of this method is as follows:

$$x_r = \lceil x \rceil \tag{4}$$

where x_r is the quantized value, and x is the observed value to be binned.

2.4.2.3 Streamflow Regionalization

Streamflow time-series for the existing and pseudo-potential stations within the FRB required infilling to account for missing measurements. Data gaps in observed hydrometric time series can be a result of many factors, including equipment failure, seasonal inactivity, and deactivation of a station during the midst of the selected 10-year monitoring period.

Missing streamflow measurements were infilled using the inverse-distance weighting – drainage area ratio method. Studies have consistently shown through cross-validation that IDW-DAR is one of the best regionalization techniques for infilling streamflow data in Canadian watersheds (Samuel et al., 2013; Werstuck et al., 2017). IDW-DAR is calculated using the following equations:

$$Q_u = \sum_{i=1}^{n} w_i \left(\frac{A_u}{A_i}\right)^{\alpha} Q_i, \;\; w_i = \frac{(h_i^{-2})}{\sum_{i=1}^{n}(h_i^{-2})} \tag{5}$$

where Q_u is regionalized streamflow, A_u is the drainage area of the catchment of interest, A_i is a drainage area associated with a catchment whose times series is being used to facilitate the regionalization, α is a fitting parameter set equal to 1, w_i is a weighting coefficient and h_i is the distance between the centroid of the catchment, whose times series is being infilled, and the centroid of the neighboring catchment facilitating the regionalization.

2.4.2.4 Synthetic Streamflow Generation with HYPE Model

The Hydrological Predictions for the Environment (HYPE) model is a semi-distributed model developed by the Swedish Meteorological and Hydrological Institute (SMHI). Sub-catchments are first categorized as either land or lake and are then further spatially refined into classes, each of which represents a fraction of the total sub-catchment area. Classes are demarcated based on a combination of vegetation, soil, land use, and topographic characteristics. Developed based on the traditional HBV and HBV-NP models, HYPE is capable of simulating catchment discharge/runoff in addition to the transfer of nitrogen and phosphorus through the modeled area (Lindstrom et al., 2010). A HYPE model of the combined Nelson-Churchill River Basin was used to generate synthetic time-series for potential streamflow monitoring stations in the CRB. This variant of HYPE was developed at the University of Manitoba, based on the Hudson Bay Drainage Basin HYPE model, which is a subset of the Arctic-Hype model initially developed by SMHI. Alterations to predecessors were made to produce the NCRB HYPE model, including adding modeling routines, refining catchment characteristics, and adjusting calibration procedures to better account for frozen soils, prairie potholes, and localized flow regulation. Further information on the development of the NCRB HYPE model is provided in (Stadnyk and Bajracharya, 2019).

2.4.2.5 Canadian Precipitation Analysis – CaPA

The Canadian Precipitation Analysis or CaPA provides gridded accumulated precipitation for most of North America, including the entire FRB. Precipitation estimates are available daily at six-hour intervals for a gridded network with a 10 km spatial resolution. CaPA integrates short-term numerical weather predictions from the Regional Deterministic Prediction System (RDPS) developed by Environment Canada, with in-situ measurements from a variety of ground-based monitoring networks. A robust series of quality control measures are in place to mitigate the impact of erroneous data measurements on the quality of the final analysis. Studies have shown that precipitation estimates from CaPA are generally more accurate than estimates from raw RDPS (Lespinas et al., 2015). CaPA data were aggregated and averaged on a catchment by catchment basis, to generate forcing data for the semi-distributed rainfall-runoff models applied during the network design process in the FRB.

2.4.2.6 Hydrological Global Forcing Data – HydroGFD

The Hydrological Global Forcing Data (HydroGFD) reanalysis dataset provides global daily forcing data estimates at 0.5° spatial resolution. HydroGFD is a successor to the WATCH, Forcing Data-ERA-Interim (WFDEI) method (Weedon et al., 2011). Similar to CaPA, various reanalysis datasets are updated/corrected using observed in-situ measurements. Previous studies using the European and Arctic HYPE models have utilized HydroGFD to generate forcing inputs. A modified subset of the Arctic HYPE model was used to generate synthetic time-series for potential stations in the CRB. Data consistency was maintained by using the same precipitation, and temperature time-series to calibrate semi-distributed MAC-HBV and SAC-SMA models as part of the CRB network design.

2.4.3 Multi-Objective Evolutionary Algorithm

The non-dominated sorting genetic algorithm II (NSGA-II) developed by Deb et al. (2002) is one of the most widely applied MOEAs in the field of water resources (Kollat et al., 2008). NSGA-II improves on the original NSGA algorithm by addressing issues related to computationally inefficient non-dominated sorting, non-elitist selection, and the sensitivity of algorithm performance to the selection of a user-defined sharing parameter. NSGA-II applies elitism selection by assessing the non-dominance of the union of parent and child populations, thereby ensuring the best solutions generated during the optimization process are carried forward. A fast non-dominated sorting mechanism is employed to enhance computational efficiency, while diversity is maintained during elitism selection by implementing a parameterless crowded-comparison approach. NSGA-II was used to facilitate the multi-objective optimization associated with both proposed research methodologies. The NSGA-II algorithm parameters for both methods are summarized in Table 2-2. Smaller population sizes and few algorithm generations were applied for Method 2, to reduce the computational workload to feasible levels.

Table 2-2: Summary of Model Parameters: Non-Dominated Sorting Genetic Algorithm II (NSGA-II)

Model Parameters	Method 1 - Parameter Value	Method 2 - Parameter Value
Population Size	5000	1000
Number of Decision Variables	# of Potential Stations (N)	# of Potential Stations (N)
Maximum Generations	2*N	N
Crossover Operator	Single Point Crossover	Single Point Crossover
Crossover Probability	1.0	1.0
Mutation Operator	Bit String Mutation	Bit String Mutation
Mutation Probability	2/N	2/N
Variable Type	Binary	Binary

2.4.4 Streamflow Modeling

Two hydrological models were incorporated into the network design process to evaluate the hydrometric networks best suited to support streamflow modeling within the selected study areas. The two models chosen were the McMaster University-Hydrologiska Byrans-Vattenbalansavdelning (MAC-HBV) model and the Sacramento Soil Moisture Accounting Model (SAC-SMA). Both models are lumped conceptual rainfall-runoffs models that were configured in a semi-distributed fashion. Channel routing between sub-catchments was facilitated using the Muskingum routing method.

2.4.4.1 MAC-HBV

MAC-HBV is an adaptation of the original HBV model developed by Bergstrom (1976). MAC-HBV has been applied to conduct studies related to a wide variety of hydrological modeling applications (Han and Coulibaly 2019; Wijayarathne and Coulibaly, 2020), including previous network design research (Keum et al., 2018). Snowpack storage volume is determined using a snow routine. Upper and lower threshold temperatures determine whether precipitation is classified as rainfall or snowfall. Changes in snowpack volume are based on the application of a simple degree-day concept to calculate meltwater volume and a snowfall correction factor to determine snowpack accumulation. Soil moisture storage is dependent on the difference between the rate of infilling, which is a function of rainfall and snowmelt, and the rate of evapotranspiration, calculated using a simplified Thornthwaite equation. A nonlinear function considering the relationship between soil moisture storage and maximum storage capacity is used to evaluate the rate of recharge from soil moisture into the upper soil reservoir. Water then either leaves the upper reservoir as runoff or percolates to a lower storage reservoir that maintains a relatively slow outflow rate. Internal channel routing of the combined outflow from the upper and lower reservoirs is assessed using a triangular weighting function. Further background on the structure of the MAC-HBV model is provided in Samuel et al. (2011, 2012).

2.4.4.2 SAC-SMA

SAC-SMA is one of the most widely applied conceptual models for streamflow forecasting (Vrugt et al., 2006). As with MAC-HBV, upper and lower threshold temperatures are applied to classify precipitation as rainfall, snowfall, or mixed. The degree-day method is used to evaluate changes in snowpack storage. SAC-SMA divides the basin into pervious and impervious areas and two soil zones: upper and lower. Five model states track the accumulation of water in the two zones. Storage in each zone is further subdivided into various sub-storage regimes depending on if the water is considered free or under tension. Only water under tension is available for evapotranspiration. This model configuration allows for direct surface runoff from previous and impervious areas, interflow runoff from the upper storage zones, and baseflow contributions from the lower storage zones. Internal channel routing is applied using the Nash-Cascade method. Further details on the SAC-SMA model are provided by (Burnash et al., 1973; Vrugt et al., 2006). Both SAC-SMA and MAC-HBV require daily time-series for precipitation and temperature as inputs. Ten years of observed streamflow data were used for model calibration allowing for a one-year spin-up period and a nine-year calibration period. For the FRB daily time-series from 2003-2012 were employed, the timeframe for the CRB was 2001-2010.

2.4.4.3 Model Performance Criteria

Model performance criteria such as Nash-Sutcliffe Efficiency (NSE) and Kling-Gupta Efficiency (KGE) quantitatively assess how accurately a simulated model output compares to the corresponding historical observations (Nash and Sutcliffe, 1970; Gupta et al., 1998). KGE was selected as the calibration function objective and was also used to assess model performance for the calibration period. An optimal KGE score is 1.0, which occurs when the two times-series being compared to one another are identical. KGE is defined mathematically as (Gupta et al., 1998):

$$KGE = 1 - \sqrt{(r-1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \tag{6}$$

where r is the Pearson correlation coefficient between the simulated and observed time series. α is the ratio of the standard deviation for the simulated times series to the standard deviation of the observed time series, which quantifies the relative variability of the two datasets. β is the quotient of the mean of the simulated time series divided by the mean of the observed time series; this ratio measures the bias present in the two datasets.

2.4.4.4 Model Calibration Algorithm

The Dynamically dimensioned search (DDS) algorithm, developed by Tolson and Shoemaker (2007), was used to calibrate the model parameters for both the MAC-HBV and SAC-SMA models. DDS is a stochastic optimization process that is capable of efficiently locating a near-global optimal solution for problems with high-dimensionality. DDS has two main parameters, the number of algorithm iterations and the search coefficient. For this study, the standard search coefficient 0.2, as recommended for general applications by Tolson and Shoemaker (2007), was applied. Embedding the model calibration process, which is itself an optimization procedure, into an MOEA is computationally expensive and requires the use of supercomputing resources and parallel computing architecture to process results in a reasonable timeframe. In this study 1,000 DDS iterations were applied for model calibration, allowing for identification of near-optimal model parameter sets, while limiting computational workload to manageable levels.

2.5 Results and Discussion

2.5.1 Method 1: Identification of Optimal Networks through DEMO Solutions Post-Processing Using Hydrologic Models

The modified DEMO analysis, employed as the initial phase in Method 1, identified 699 Pareto-optimal networks for the FRB and 4,599 Pareto-optimal networks for the CRB. During the optimization process, network size was allowed to vary from the size of the existing network to a fully gauged network where all potential station locations are selected. The range in joint entropy amongst the Pareto-optimal solutions set was 9.79 - 11.04 bits and 6.65 - 9.98 bits for the FRB and CRB, respectively. The decision variables applied in network design are binary, since a station is either included or else excluded from each potential network. For a system with binary decision variables, the saturated or maximum joint entropy is equal to the binary logarithm of the number of temporal intervals assessed. In this investigation, 10 years of daily data or 3652-time steps were evaluated, equating to a saturated entropy of 11.83 bits. The range in joint entropy values identified using the modified DEMO analysis for both study areas are reasonable as they approach but do not exceed the saturated entropy. Networks with saturated entropy may indicate inappropriate data quantization, where data was binned too finely, resulting in unique time-series.

While DEMO maximizes joint entropy to maximize network information content, total correlation is also minimized to limit redundancies. Network total correlation ranged from 52.02-125.73 for the FRB compared to a range of 5.12-89.27 for the CRB. When compared with the CRB, the FRB has more existing stations. Furthermore, many of the FRB stations are clustered together in the downstream extents of the watershed. In comparison, the existing CRB monitoring network is very sparsely gauged and not highly clustered geospatially. Therefore, there is more informational redundancy present in the existing FRB network, which is reflected in the differences between the minimum total correlations for networks identified by DEMO for the two study areas.

Assessing networks entirely on the principles of information theory does not allow for a user-directed design that promotes the modeling of streamflow at FSC specifically. It was expected that networks which heavily gauge FSC would contribute to better-calibrated models for simulating streamflow at these manually identified locations. Thus, a third optimization objective maximizing the number of FSC gauged was added to the traditional DEMO objectives to account for this expectation. The FSC are densely gauged by the existing FRB network resulting in minimal variability for that design objective when compared to the CRB, where the majority of FSC are ungauged. A summary of the modified DEMO results for both study areas is provided as part of Table 2-3.

Table 2-3: Summary of Method 1 and Method 2 Results

Study Area	Method 1					Method 2	
	Joint Entropy Range (bits)	Total Correlation Range (bits)	# of Gauged FSC Range	KGE Range*	Range in Network Size*	KGE Range**	Range in Network Size**
FRB	9.79 - 11.04	52.02 - 125.73	38 - 41	0.45 - 0.68	44 - 67	0.61-0.75	44 - 70
CRB	6.65 - 9.98	5.12 - 89.27	18 - 62	-0.01 - 0.67	18 - 87	-0.02-0.72	14 - 68

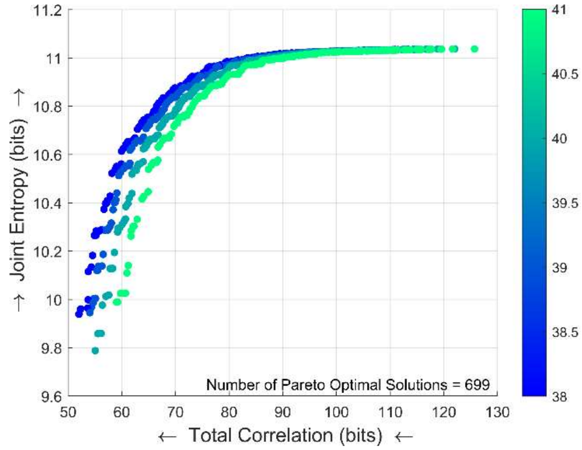
*Based on combined model results for Pareto-optimal solutions identified after post processing

**Based on combined model results

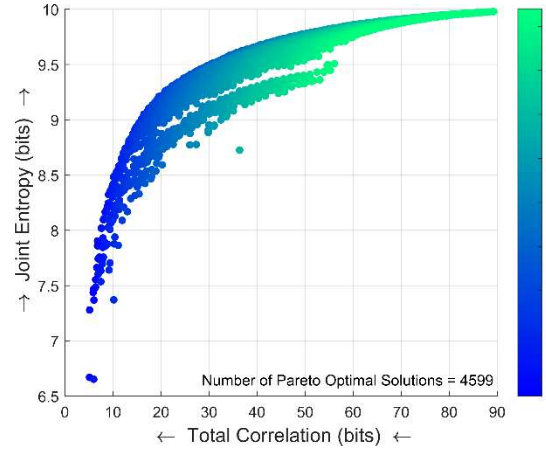
Each optimal solution generated by the modified DEMO analysis is non-dominated when compared to the rest of the corresponding solution set. Figure 2-4 a) and b) are three-variable Pareto-fronts illustrating the tradeoffs between selecting different optimal solutions for both study areas. The Pareto-front for the FRB shows an apparent plateau after a joint entropy of 11 bits is reached. The maximum network size amongst optimal networks identified was also only 80 stations, compared to a potential maximum of 106 stations if all potential stations were gauged. The choice to perform a network reduction design in the FRB is consequently further justified, as network analysis based on entropy theory shows adding additional stations does not significantly improve the information content of candidate networks. In contrast, the Pareto-front for the CRB does not exhibit a plateau effect, and the maximum network size amongst optimal networks is 89 stations, which is just two short of a fully gauged network. Increasing network size up to near the prescribed upper limit continues to improve network information content, thereby justifying the choice to perform a network augmentation in the CRB.

DEMO generates many non-dominated solutions. Semi-distributed MAC-HBV and SAC-SMA models post-processed the DEMO output to reduce the number of networks decision-makers need to consider for implementation and to determine which of the optimal networks are most suitable for streamflow modeling applications. The model-based design objectives applied during the post-processing procedure were to maximize KGE at FSC and minimize network size. This process is visually represented as a series of scatter plots in Figure 2-4 c) - f). All the networks generated from DEMO are re-plotted according to the post-processing results, with non-dominated solutions based on the primary design objectives shown as bolded markers. The post-processing procedure significantly reduces the number of optimal solutions from 699 to 7-8 for the FRB and from 4,599 to 40-41 for the CRB.

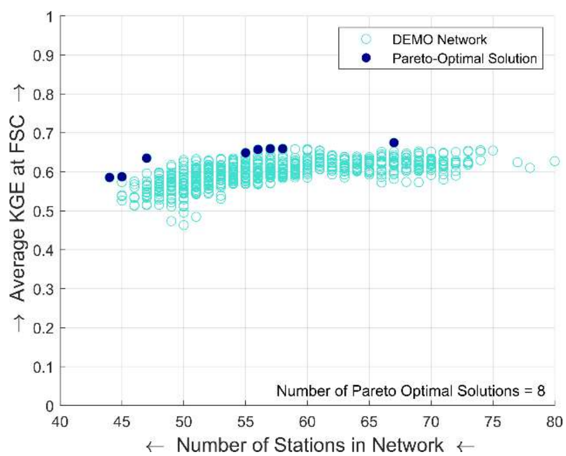
The FRB has a well-established existing network with 43 stations, many of which gauge FSC. From Figure 2-4 c) and e) it is evident that when evaluating the merits of adding additional stations to FRB, the benefit obtained from gauging additional headwater catchments on improving model calibration is limited for both models after the first five stations are added and non-existent once a network size of 67 stations is exceeded. Conversely, for the sparsely gauged CRB, method one results establish a consistent and generally linear trend between increasing network size and improving calibrated model performance, as seen in Figure 2-4 d) and f). In terms of model-model comparisons, the semi-distributed SAC-SMA and MAC-HBV models offer similar levels of performance in both study areas.



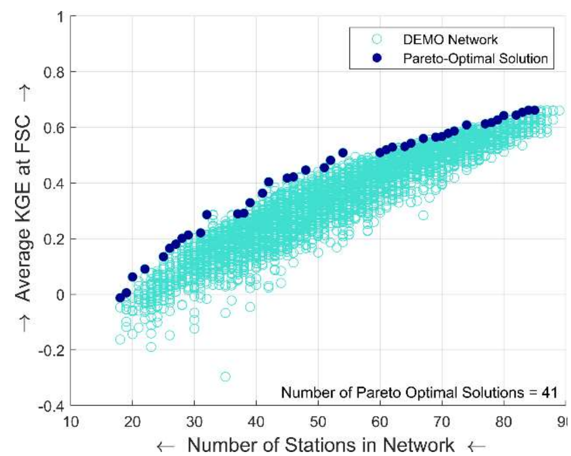
a) FRB DEMO Results



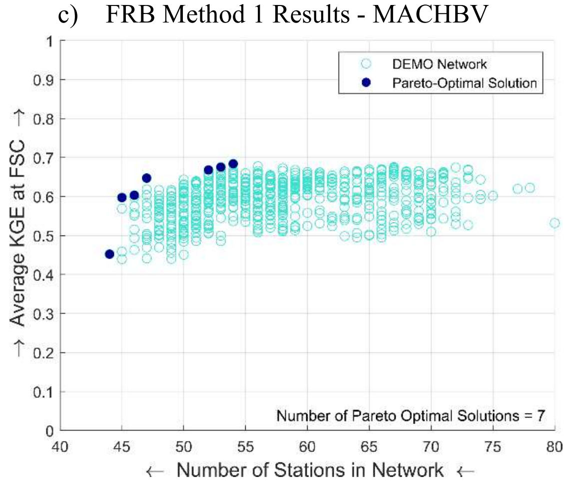
b) CRB DEMO Results



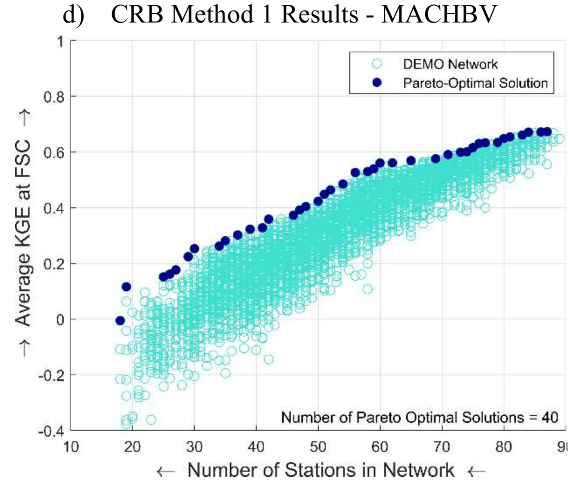
c) FRB Method 1 Results - MACHBV



d) CRB Method 1 Results - MACHBV



e) FRB Method 1 Results - SACSMA



f) CRB Method 1 Results - SACSMA

Figure 2-4: Pareto-fronts and scatter plots illustrating non-dominated solutions based on modified DEMO analysis [**a)-b)**] and post-processing of modified DEMO outputs with hydrological models [**c)-f)**].

2.5.2 Method 2: Identification of Optimal Networks through Multi-Objective Optimization with Embedded Hydrological Models

Method two embeds hydrological models and their calibration process into NSGA-II to allow for the optimization algorithm to search the solution space according to the primary optimization objectives directly. Comparative Pareto-fronts for the non-dominated solutions determined by both methods using each model are provided in Figure 2-5 for the FRB and Figure 2-6 for the CRB. Both figures also illustrate the baseline model performance obtained using the existing network to calibrate the SAC-SMA model, in addition to the model performance associated with calibration using a fully-gauged network. As with method one, the overall performance of MAC-HBV and SAC-SMA for method two is nearly equivalent. More important to note is that embedding hydrological models into the MOEA, while significantly more computationally demanding, consistently identifies networks that provide superior model performance for any given network size when compared to the networks identified using hydrologic models as a post-processing mechanism. The range in model performance and network size identified by both methods is summarized as part of Table 2-3.

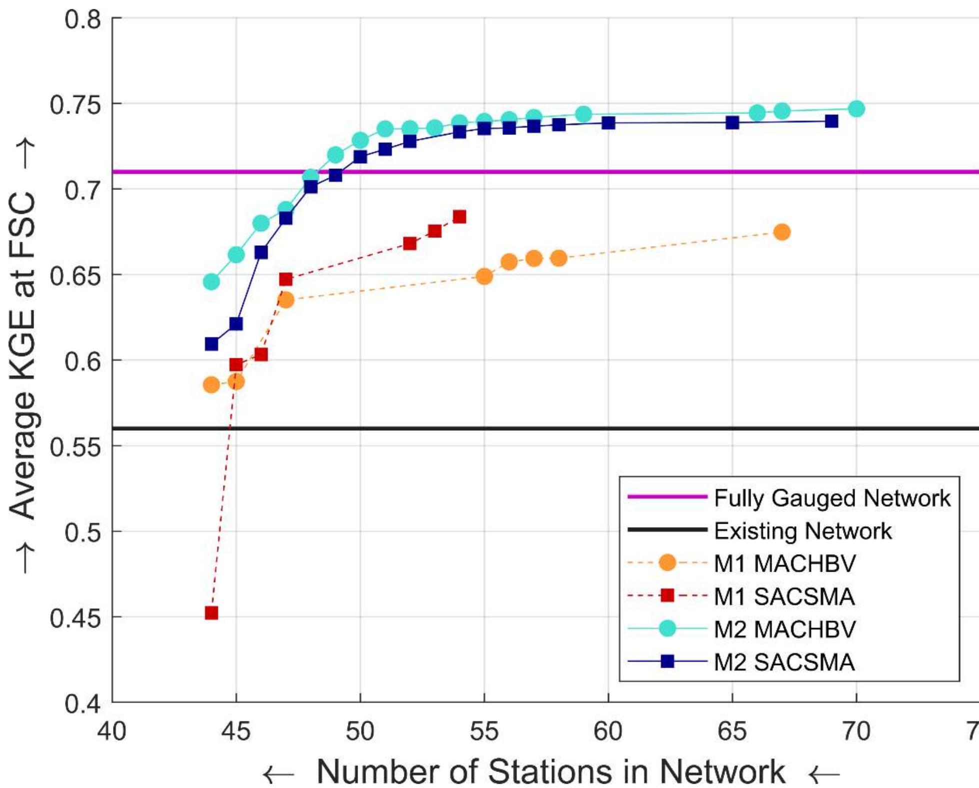


Figure 2-5: Comparative Pareto-fronts for Method 1 and Method 2 results in the Fraser River basin. Performance of the existing monitoring network and a fully gauged network, based on the calibration of the SAC-SMA model, provided as frames of reference.

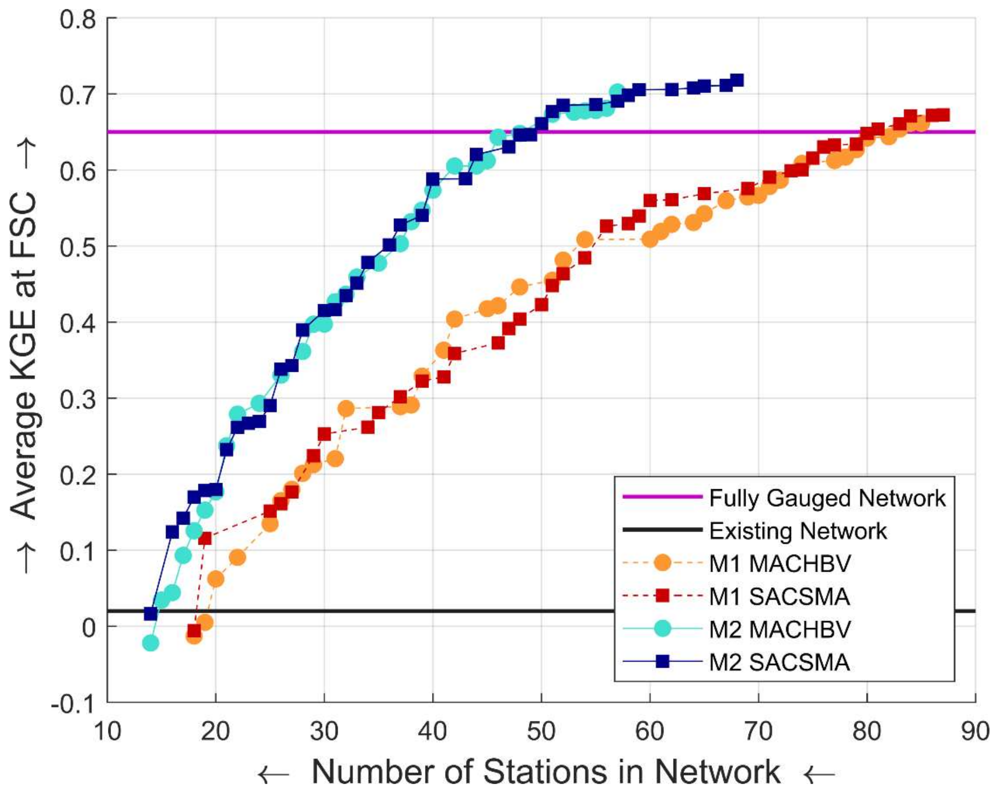


Figure 2-6: Comparative Pareto-fronts for Method 1 and Method 2 results in the Churchill River basin. Performance of the existing monitoring network and a fully gauged network, based on the calibration of the SAC-SMA model, provided as frames of reference.

Figures 2-5 and 2-6 illustrate that the Method-2 Pareto-fronts or optimal solutions, for both study areas, plateau and then truncate once a specific network size is achieved. In all instances, regardless of the study area and model selected, optimal model performance is not obtained using a fully gauged network. For the FRB, a network with 70 stations offers better performance than a fully gauged network containing an additional 36 stations. For the CRB, the best model performance is obtained using a network with 68 stations, 23 stations less dense than a fully gauged network. It is clear that merely adding more stations or observations to the calibration process does not guarantee improved model performance at FSC. Eventually, incorporating observations from additional stations can degrade model performance. This degradation can be attributed to the incorporation of time-series with erroneous measurements or utilizing observations from stations that monitor flow regimes uncharacteristic of adjoining catchments due to significant variability in representative physiographic characteristics or unaccounted for flow regulation. Instead of merely improving network density, it is more important to determine the optimal spatial distribution of potential stations to complement and augment the observations provided from the existing networks.

Furthermore, the Method 2 pareto-fronts for both study areas initially exhibit a roughly linear relationship between increasing network size and improving average model performance at FSC. However, as more dense optimal networks are identified the gradient of this trend smooths out and effectively transitions into a plateau where further increasing network density offers no significant improvement to model performance. In instances where cost constraints do not force the network manager to select a smaller optimal network, this transition point identifies the best optimal network. For the FRB, the transition point occurs at network density of 55 stations and for the CRB the network density is 57 stations. Figure 2-7 and Figure 2-8 illustrate the spatial distribution of these best optimal networks, identified using both hydrological models, for the FRB and CRB, respectively.

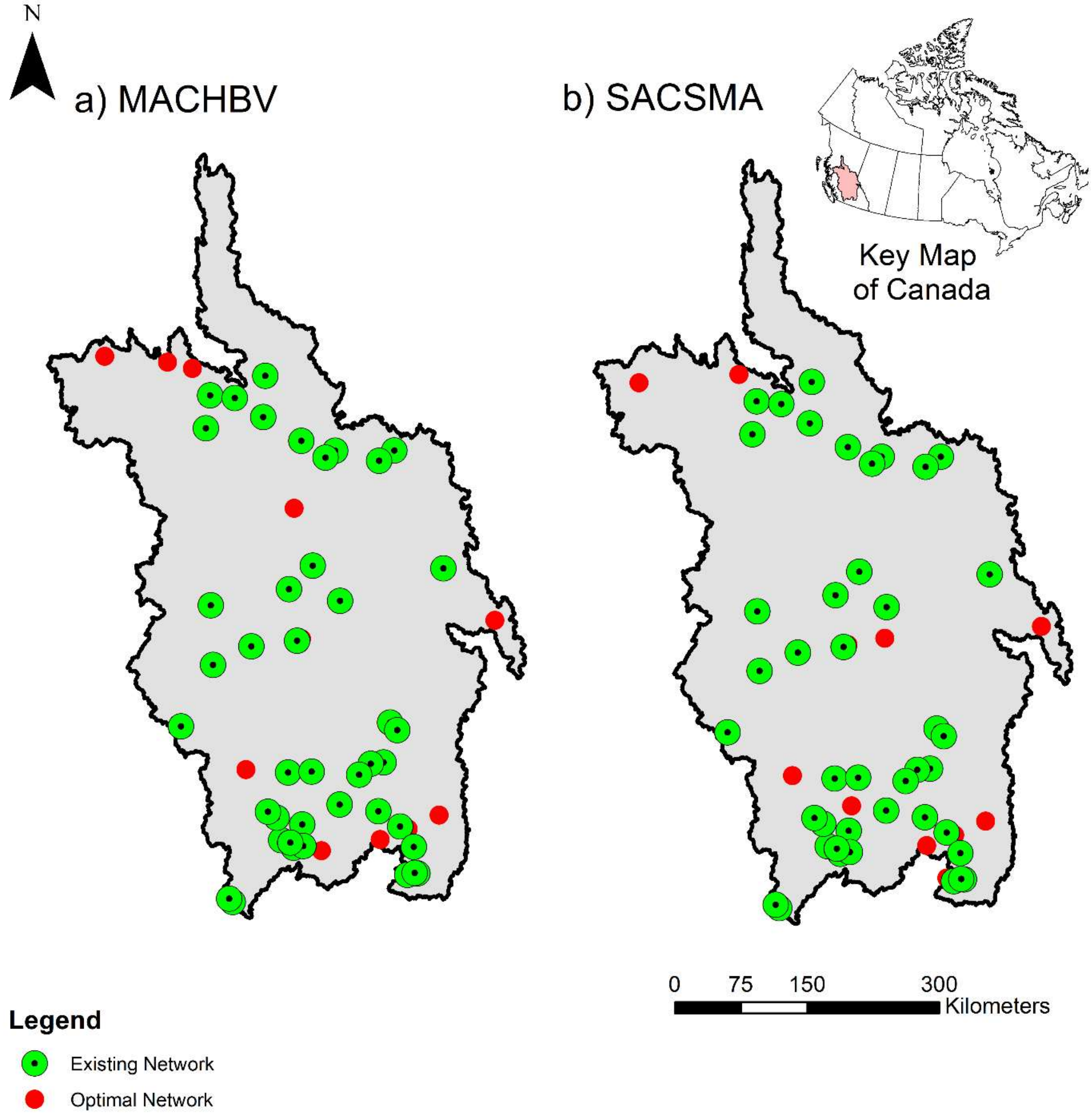


Figure 2-7: Spatial distribution of best optimal networks for FRB using **a)** MAC-HBV and **b)** SAC-SMA.

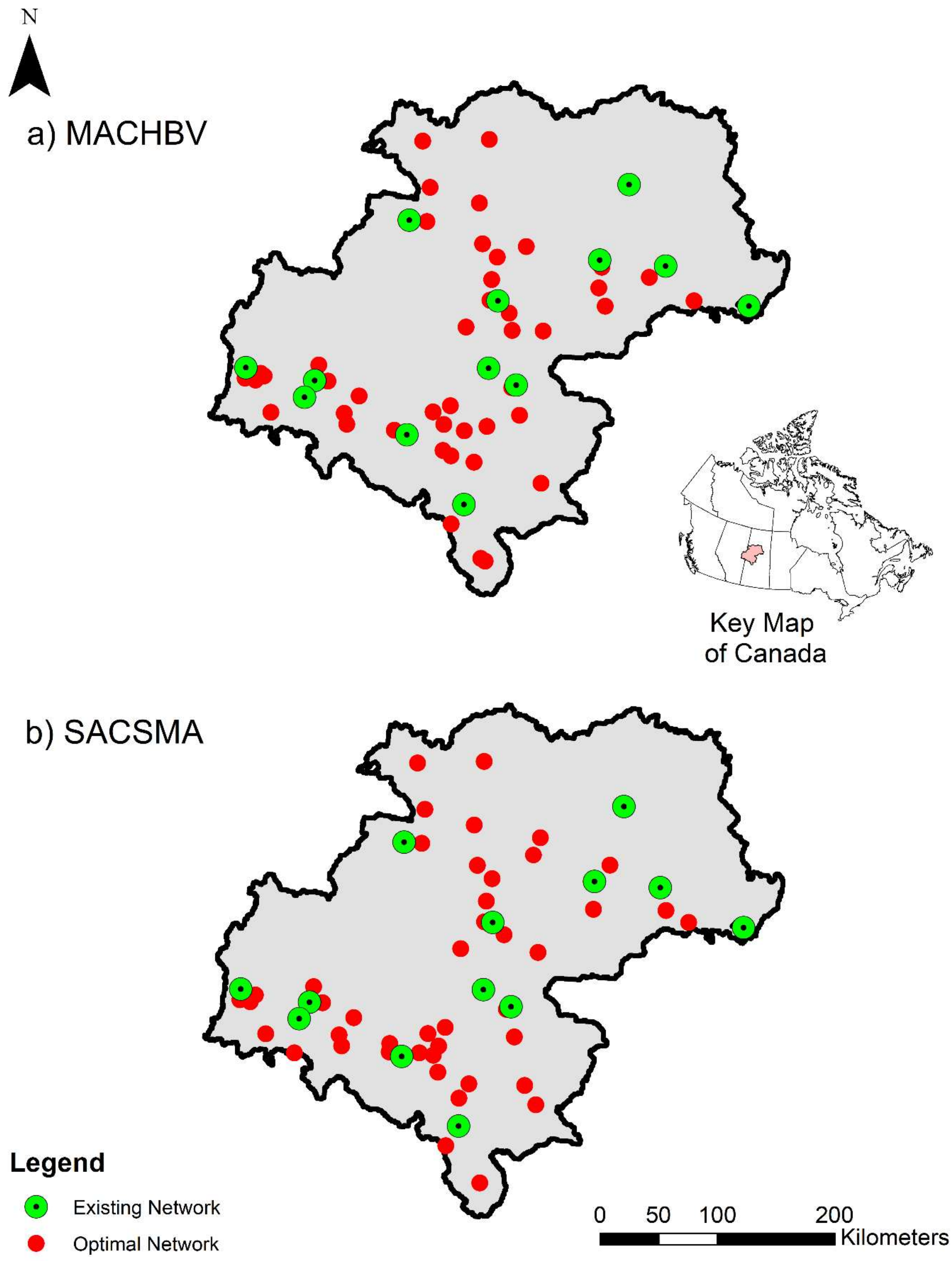


Figure 2-8: Spatial distribution of best optimal networks for CRB using **a)** MAC-HBV and **b)** SAC-SMA

Figures 2-7 and 2-8 indicate that the spatial distribution of the best optimal networks are only slightly sensitive to model selection. For the FRB, the best optimal networks identified using the two hydrological models are 67 percent similar. The similarity percentage for the CRB is 77 percent. More importantly, for network designs facilitated by both rainfall-runoff models the best optimal networks identified by Method 2 provide better performance and are generally significantly less dense networks than the best performing networks identified using Method 1. Overall, the Method 2 results indicate that embedding models into a MOEA enables the identification of smaller less costly networks that more effectively meet user needs when compared with the networks identified using the traditional approach of applying hydrological models as a post-processing mechanism.

2.5.3 Bubble Maps to Assess Spatial Distribution of Optimal Networks

Bubble maps were crafted to visually assess the spatial distribution of all Pareto-optimal solutions identified using both methods. The number of optimal networks identified ranged from 7-41 depending on the study area and model selection. It is impractical to present different network maps for each optimal network identified in this investigation individually. Instead, the information presented in the bubble maps is based on average or aggregated statistics pertaining to a single optimal solution set. As a result, eight different maps or scenarios are presented, one for each method, study area, and model combination. Each node or bubble represents a single station or catchment. Nodes are sized to reflect the selection frequency of a given station within the corresponding solution set. Node shape distinguishes between catchments based on flood sensitivity. Non-FSC are plotted with solid blue square markers. On the other hand, FSC are represented with circles, shaded using a red-green color gradient. The color of FSC catchment markers reflects average model performance at that catchment outlet or station, considering all model calibration results for the associated scenario. Figure 2-9 presents all bubble maps related to the FRB, while Figure 2-10 does the same for the CRB. Nodes were plotted at the centroid of catchments, as opposed to catchments outlets, for both Figures 2-9 and 2-10 to reduce node crowding and improve visualization.

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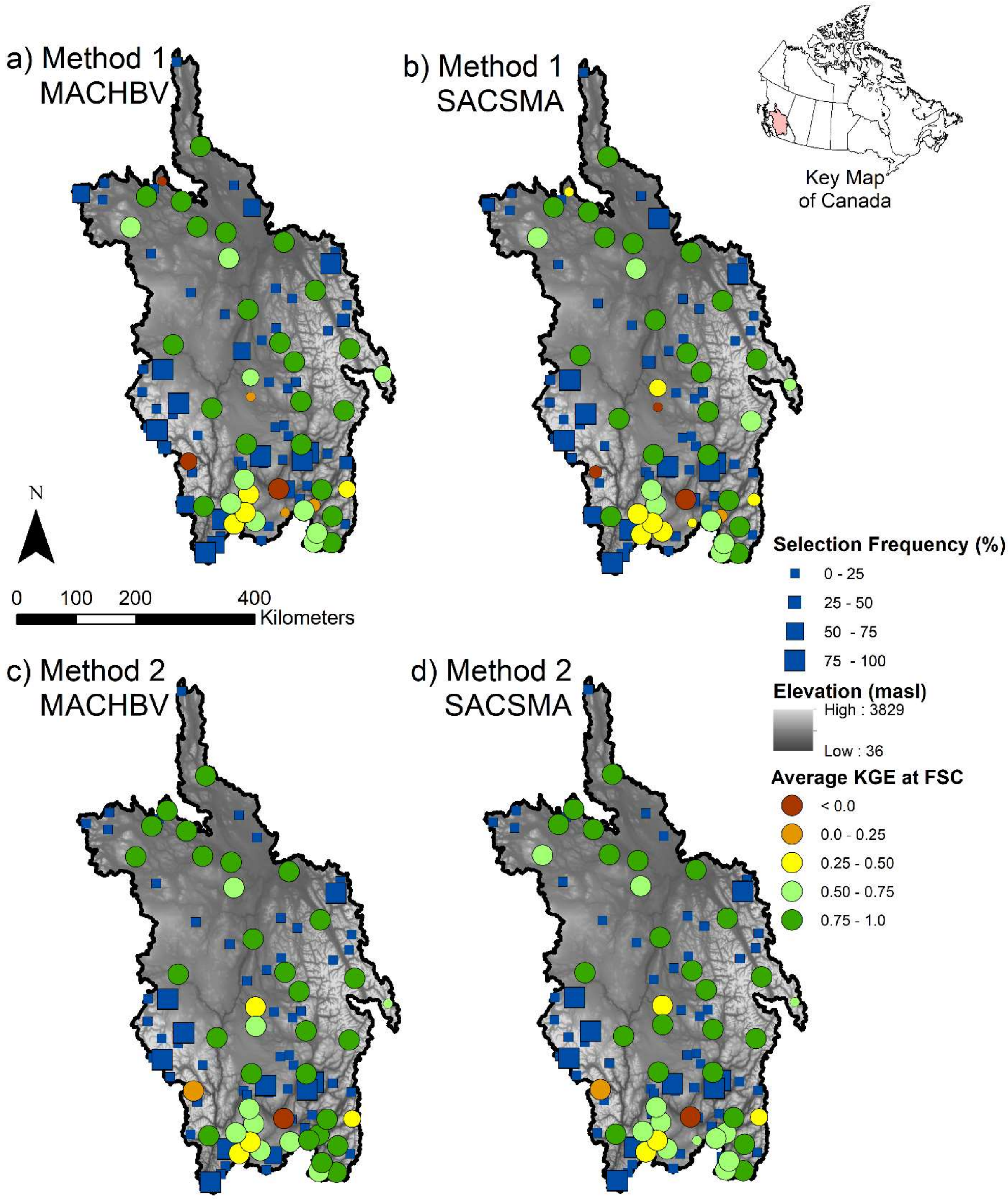

Figure 2-9: Bubble maps for the Fraser River basin based on non-dominated networks identified using Method 1 and Method 2 with both the MAC-HBV and SAC-SMA models. Stations gauging non-FSC demarcated using blue squares, FSC represented by circles shaded using a red-green color gradient.

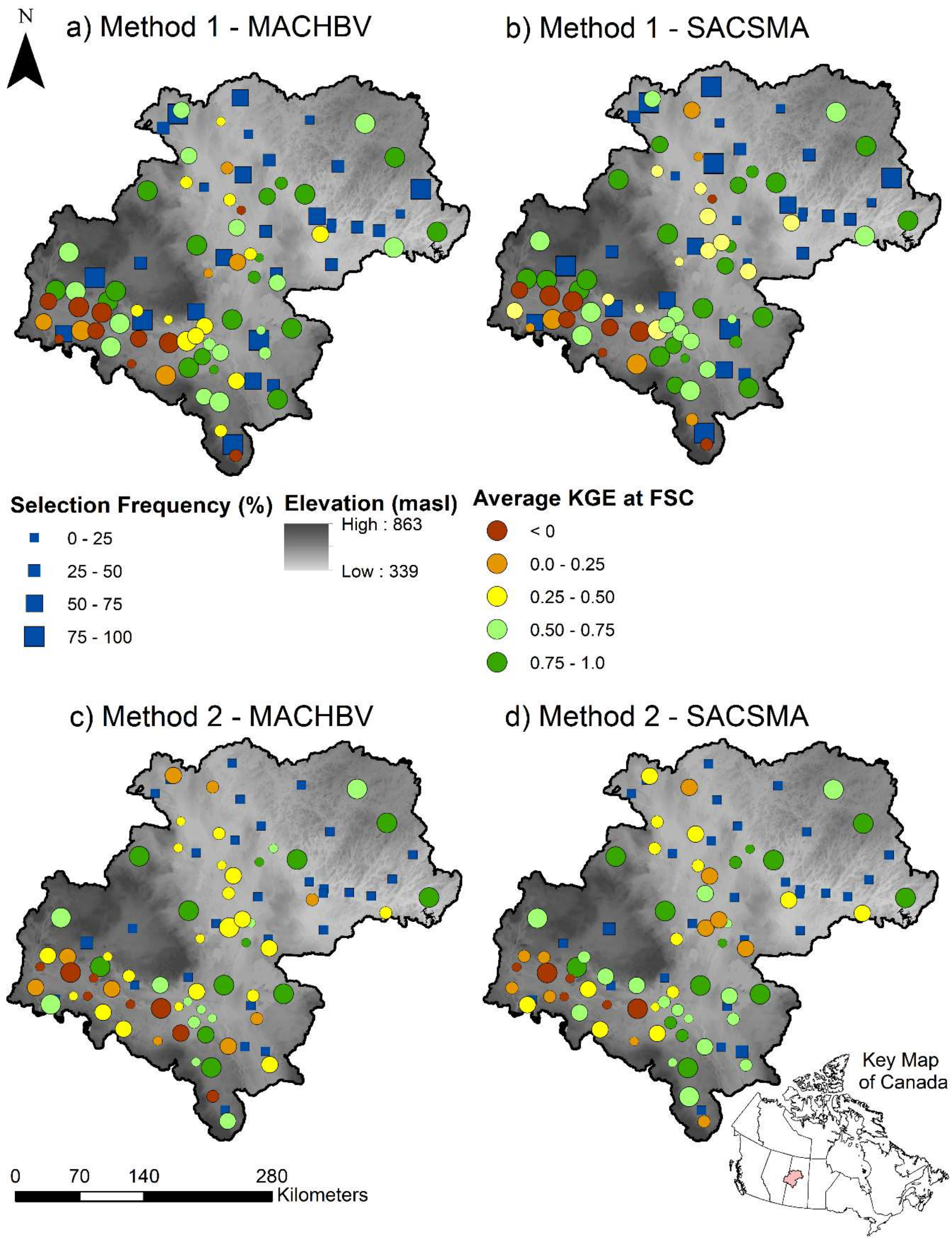

Figure 2-10: Bubble maps for the Churchill River basin based on non-dominated networks identified using Method 1 and Method 2 with both the MAC-HBV and SAC-SMA models. Stations gauging non-FSC demarcated using blue squares, FSC represented by circles shaded using a red-green color gradient.

It is essential to note that the results represented by the bubble maps are based on averaged results across the entire optimal solutions sets identified for a given design scenario. Therefore, an individual optimal network should not be simply selected by choosing some combination of the more frequently selected stations, because doing so would not guarantee selection of an actual optimal network. Nevertheless, the aggregated and averaged results presented by these maps allow for further evaluation of the differences between the two design methods and how sensitive the identification of optimal networks are spatially to model selection. When comparing the two methods using Figures 2-9 and 2-10, the FSC are on average more frequently gauged and better modelled by the optimal solution sets identified using Method 2. This is visually apparent from the larger and greener nodes at FSC for the Method 2 maps. Non-FSC are also generally less frequently selected by networks identified using Method 2 in comparison to networks identified using Method 1. In terms of model-model comparisons for Method 2, the most frequently selected stations (large nodes, reflecting a selection frequency greater than 50%) are consistently the same for both rainfall-runoff models with only slight variations. Average model performance at FSC is also only slightly sensitive to model selection.

For the FRB almost all FSC are included as part of the optimal networks identified using Method 2. FSC are also very well modelled on average throughout the watershed, with the notable exception of a group of spatially clustered catchments in the south-eastern extents of the study area. A few non-FSC catchments are selected in more than 50% of optimal solutions, indicating that they provide valuable information for enhancing average model performance at downstream FSC. Regarding the CRB, some FSC are selected more frequently than others. There is also notable variation in how well individual FSC are modelled on average. Many FSC are infrequently selected but well modelled (small green nodes), representing points where streamflow can be effectively estimated without point-source observations to influence model calibration.

For the CRB non-FSC catchments are infrequently selected as part of the optimal networks identified by Method 2. These results indicate that including observed discharge records from non-FSC does not consistently enhance model performance at the priority FSC within the CRB. While not suitable for selection of an individual optimal network, the bubble maps provide a useful visualization of which FSC within a watershed are effectively modelled, where models are unable to accurately simulate observed time-series, and which stations are frequently included in the optimal networks designed to satisfy user needs using a model based approach.

2.6 Conclusions

The collection of accurate and reliable hydrometric data are integral to many streamflow modeling applications. Multi-objective optimization tools that utilize entropy-based optimization objectives are capable of designing robust monitoring networks based on information theory. However, these methods are limited in their ability to account for the relationship between data collection and model application needs. This study proposes and investigates a model embedding approach that integrates hydrological model into MOEA to identify optimal streamflow networks more appropriate for hydrologic modeling application. The proposed method is compared to the traditional approach where hydrologic models are used as post-processors of DEMO solutions. A key advantage of the proposed method is that by embedding hydrological models directly into the optimization algorithms, a continuous evaluation of the relationship between data collection and model application is possible. The primary design objectives were to maximize model performance at user-defined flood sensitive catchments and minimize network size. Evaluation of networks, according to these criteria, provides network managers with a means to quantify the benefit of increasing network density. The analysis was performed to design streamflow monitoring networks in two large western Canadian watersheds. A network reduction design was considered for the well gauged Fraser River basin, whereas a network augmentation design was performed for the sparsely gauged Churchill River basin. Two different rainfall-runoff models, MAC-HBV and SAC-SMA, were leveraged to guide the network design processes.

Embedding hydrological models into the optimization algorithm consistently identified networks, regardless of network size, that provided superior model performance when compared to the networks identified using hydrologic models as a post-processing mechanism. For all design scenarios, the benefit of adding additional stations in terms of model performance has an upper limit after which there is no more benefit. Networks that covers better the FSC tended to result in the best calibration scores at these user-defined locations. However, whether the gauging of non-FSC improves model performance at flood sensitive locations was case-specific. While both models offered similar levels of overall performance, the spatial distribution of optimal networks was slightly sensitive to model selection.

Although more computationally demanding than traditional entropy-based network design schemes, the methodologies proposed in this study are highly flexible, allowing for decision-makers to design networks according to specific user-defined design criteria. The selection of which catchments to prioritize during model calibration, and by extension, during the overall design process, can be readily changed to reflect user needs. In addition to prioritizing stations that gauge FSC, stations could also be prioritized to reflect economic or practical constraints. The model performance criteria used as design objectives can also be easily modified. While KGE was selected as the primary design objective for this study to identify networks most suitable for general streamflow modeling, other criteria could be used to emphasize the modeling of peak flows for flood forecasting applications or base flows for drought assessment. Different hydrological models other than SAC-SMA or MAC-HBV could also be used in the design process. Future research should further investigate the applicability of using multi-objective optimization algorithms with embedded hydrological models to design monitoring networks for different engineering applications, such as flood forecasting or drought prediction.

2.7 Declaration of Competing Interests

The authors declare no known competing interests.

2.8 Acknowledgments

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Chapter 3. Conclusions and Recommendations

3.1 General Conclusions

Model-based design strategies provide a highly adaptable methodology for user-directed designs of hydrometric monitoring networks. Potential streamflow monitoring network configurations for two large Canadian river basins were investigated using two distinct research methods. Method 1 employs a modified DEMO process to identify a set of Pareto-optimal networks using intermediate, entropy-based, design objectives. Data records from Pareto-optimal networks identified by DEMO are then used to calibrate semi-distributed SAC-SMA and MAC-HBV models separately for each of the two study areas. Thereafter, each candidate network is reassessed for non-dominance based on the primary design objectives, which are derived in part from model calibration scores.

The newly proposed Method 2 embeds the semi-distributed hydrological models and their calibration process into the MOEA. Pareto-optimal networks are then directly identified according to the primary design objectives. It was determined that while Method 2 required significantly more computational resources, it consistently identified solutions that outperform those identified by Method 1, regardless of network density. As network density increases, the incremental benefit of adding additional stations on improving average model performance at user-defined catchments diminishes until an inflection point is reached. After the inflection point, further increasing network density degrades average model performance. The relationship between network size and model performance is dependent on the size and configuration of the baseline network, and which model is selected to facilitate the network design.

The spatial distribution of station selection frequency and average model performance at flood sensitive catchments was compared for all design scenarios using Bubble maps. Method to method and model to model comparisons across the varying design scenarios show results are highly case-specific, and that general trends in model-based network design are difficult to predict a priori. Thus, the continued use of computationally demanding optimization and model-based design strategies is validated. Furthermore, the design framework presented with this research can be easily modified to address problem specific characteristics because the variation of the optimization objectives allows for problem-orientated designs. For instance, the model performance statistics used in this study could have been varied to favor the modeling of peak flows or baseflow conditions, thereby identifying networks more suitable for flood forecasting and drought monitoring applications, respectively.

3.2 Recommendations and Future Research

It is recommended that when using a model-based network design strategy that models be embedded into the optimization algorithms if computationally feasible. Integrating the models allows for direct optimization according to model performance statistics, which provides better results than when models are applied as a post-processing mechanism. It is also recommended that minimizing network size be included as a primary design objective. The results of this research shown that the incremental benefit of adding additional stations with respect to enhancing model performance decrease significantly once a certain network density is achieved. If network size is not considered as a design objective, the relationship between network cost and network performance cannot be easily quantified. Potentially resulting in the installation of more expensive monitoring networks that offer minimal performance benefits when compared with other design alternatives.

For future research, it is recommended that the methodology used in this investigation be applied for a wider variety of study areas and network types. For instance, the same model-based design strategies could be leveraged to design precipitation, groundwater, and snowpack monitoring networks. Further application of the proposed methods could validate or expand upon the trends and findings established by this initial study. The sensitivity of results to model selection and the selection of model performance criteria should also be more robustly investigated by applying the proposed methodologies repeatedly for one study area using many different combinations of hydrological models and model performance statistics. Perhaps, using models and design objective combinations that are more suited to the modeling of specific portions of the hydrograph will emphasis the gauging of stations in distinct spatial regions.

Finally, there is a need to develop new design strategies that can address the challenges associated with climate change. Currently, historical time-series observed at existing stations are used in conjunction with synthetic time-series generated for potential station locations. Therefore, a ten-year historical time record may be used to design a network intended to function with minimal changes for 20 or more years into the future, without any consideration for the impacts associated with climate change. By leveraging global and regional climate models to generate projected hydrometric time-series, it is possible to assess the sensitivity of network design strategies, including those presented in this investigation, to a dynamic and variable climate.

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