



Hydrometric network design using streamflow signatures and indicators of hydrologic alteration



James M. Leach^{a,*}, Kurt C. Kornelsen^b, Jos Samuel^c, Paulin Coulibaly^{a,b}

^a Department of Civil Engineering, McMaster University, 1280 Main Street West, Hamilton, Ontario L8S 4L7, Canada

^b School of Geography and Earth Sciences, McMaster University, 1280 Main Street West, Hamilton, Ontario L8S 4L7, Canada

^c Yukon Research Centre, Yukon College, 500 College Drive, Whitehorse, Yukon Y1A 5K4, Canada

ARTICLE INFO

Article history:

Received 16 April 2015

Received in revised form 14 August 2015

Accepted 21 August 2015

Available online 29 August 2015

This manuscript was handled by Andras Bardossy, Editor-in-Chief, with the assistance of Wolfgang Nowak, Associate Editor

Keywords:

Entropy

Hydrologic signatures

Indicators of hydrologic alteration

Hydrometric networks

Multi-objective optimization

Spatial variability

SUMMARY

This study highlights the impacts that the selected hydrologic characteristics of a basin have on the spatial variability of hydrometric networks. The study was conducted using streamflow monitoring networks in two Canadian basins, specifically in the Hamilton, Halton, Credit Valley basins of Ontario and the Columbia River basin of British Columbia. The Dual Entropy-Multiobjective Optimization (DEMO) model which has been demonstrated to be sufficiently robust for designing optimum networks in a large basin was used in these analyses. In addition to the entropy functions, the spatial variability of flow networks was examined by either excluding or including hydrologic signatures and indicators of hydrologic alteration (IHA) of a basin. The entropy functions are used to identify optimal trade-offs between the maximum possible information content and the minimum shared information among stations. The hydrologic signatures are used to quantify hydrological response characteristics among sub-basins, and the IHAs, which are normally used to determine how a hydrologic regime has been altered by an impact, are instead used to quantify differences between sub-basins. It was found that the optimal locations for the new stations were well captured by the objective functions. Also, new stations covered a wider area when hydrological signatures and IHAs were considered, enhancing the objective functions. The inclusion of streamflow signatures increased emphasis on the headwaters whereas the inclusion of IHAs increased emphasis on the downstream and disturbed regions. Accounting for such spatial variability in designing hydrometric networks is crucial in obtaining an optimal network.

© 2015 Elsevier B.V. All rights reserved.

1. Introduction

Given the inherent importance of hydrometric data and the increasing pressures on water resources, it is important that an optimum hydrometric network be designed to maximize the information gained from the network (Mishra and Coulibaly, 2009). Mishra and Coulibaly (2009) reviewed various methodological developments in hydrometric network design and reported that the most efficient methods for water monitoring network evaluation and design are generalized least square (Tasker and Stedinger, 1989), entropy-based methods (Caselton and Husain, 1980; Husain, 1979, 1987, 1989; Krstanovic and Singh, 1992a,b), and multi-objective optimization methods (Kollat et al., 2008). The generalized least square method is used to estimate regional regression equations and parameters to predict flow at ungauged

locations (Tasker and Stedinger, 1989). However, the data used in this method is assumed to be stationary which may not be appropriate (NRC, 1992; Milly et al., 2008). The merit of an entropy-based method (Shannon, 1948) is that entropy directly defines information and quantifies uncertainty (Harmancioglu and Singh, 1998; Mishra and Coulibaly, 2010; Mogheir et al., 2006). A fundamental basis of this approach is that the lower the transinformation values between stations, the lower the shared information between these stations and therefore, the more independent the stations are. On the other hand, the larger the transinformation values, the larger the duplicity of the same information and therefore, the more dependent the stations are (Mishra and Coulibaly, 2010). This approach requires exhaustive and repetitive computations to determine the optimal locations of new stations to be added (Husain, 1989; Mishra and Coulibaly, 2010). The most advanced network design models involve a combination of entropy-based and optimization methods (Alfonso et al., 2010, 2012; Rianna et al., 2012; Samuel et al., 2013). Using binary

* Corresponding author.

E-mail address: leachjm@mcmaster.ca (J.M. Leach).

(on/off) decision variables in the optimization method, the model has the capability to easily seek the optimal trade-offs between several entropy functions by systematically selecting values from within a reliable set of all existing and potential stations. The precise locations of new stations to be added can be well detected and defined.

Accounting for spatial and temporal variability is an important component for designing optimum hydrometric networks. In particular, it is critical to provide accurate and qualitative hydrological information of the entire area covered by the networks (Husain, 1989; Mishra and Coulibaly, 2009). Studies for evaluating and designing optimum networks have been discussed in the literature; however, not many studies have thoroughly evaluated the spatial variability of the optimum networks. This would include using the variation of temporal data resolutions and/or either incorporating or excluding informative hydrological variables in designing optimum hydrometric networks. Mishra and Coulibaly (2009) stated that optimum hydrometric networks should present the hydrological variables needed, the appropriate time interval of the variables observed, the density of the existing network and the accuracy of the data for end users. The use of limited data records, the selection of inappropriate sampling intervals, and/or the exclusion of informative hydrological/physiographic variables in designing optimum hydrometric networks may limit the network models in: (a) optimizing the space-time trade-off between the locations of the existing and potential new stations, and between hydrological variables needed, (b) searching for the optimum locations of new additional stations from all available potential locations, and (c) generating and obtaining the most informative spatial distributions of optimal networks. These analyses are important for evaluating spatial distribution of optimum networks however, to the best of our knowledge very few studies have examined such analyses. The impact of seasonality on streamflow network design has been recently reported by Mishra and Coulibaly (2014), but the study didn't attempt to consider catchment characteristics or hydrologic signatures to account for basin spatial variability in the hydrometric network design. This study aims to fill that specific gap, and resorts to a combined entropy – multiobjective optimization method that facilitate the use of various objective functions.

Entropy is a powerful tool that can be used in this respect, as it provides a quantitative measure of the information content within a hydrometric network (Singh, 1997; Mishra and Coulibaly, 2010). Coulibaly et al., 2013a found current hydrometric monitoring network density was insufficient in many areas of Canada when compared to World Meteorological Organization (WMO) (WMO, 2008) recommendations; thereby leading to the development of the Combined Regionalization and Dual Entropy-Multiobjective Optimization (CR-DEMO) model by Samuel et al. (2013) to determine the optimum locations for new hydrometric stations to be added in various regions.

In this model, a regionalization approach was used to estimate flows in potential locations for new additional stations and the dual entropy multi-objective optimization (DEMO) approach was used to identify optimal entropy function trade-offs between the maximum possible information content (joint entropy) and the minimum shared information (total correlation) among the stations. It should be noted that in Samuel et al. (2013) and similar studies (Alfonso et al., 2010, 2012; Rianna et al., 2012) the entropy functions (i.e. joint entropy and total correlation) were computed using streamflow data alone. The main limitation of these methods was that only flows or water level data were used to compute and optimize the trade-off entropy functions. This may limit the models' ability to optimally search for the best compromise between streamflow and other variables which contribute to the generation and variability of flows, such as precipitation, temperature, and physical characteristics including land use/cover.

CR-DEMO is able to capture the information content of the networks (Samuel et al., 2013); however, it remains to be determined if this translates to the hydrological behaviors of the basins. Additional objective functions that can quantify the hydrologic behaviors of each basin were included in CR-DEMO to determine if the spatial variability in the optimal networks found by the model was enhanced. Sawicz et al. (2011) defined six hydrologic signatures: runoff ratio, baseflow index, snow day ratio, slope of the flow duration curve, streamflow elasticity, and rising limb density, to quantify hydrological response characteristics and catchment functional behaviors. These six key signatures were selected from a large number of indices (Yadav et al., 2007) having small correlation among variables and having an interpretable link to catchment responses. They concluded that these signatures can be used to detect how catchments respond to precipitation and temperature inputs, classification of catchment, transferability of hydrological information, and generalization of hydrologic understanding and catchment responses (Sawicz et al., 2011). These six hydrologic signatures are used in this current study, particularly to better quantify hydrological response characteristics of each sub-basin where the potential new hydrometric stations may be installed. Richter et al. (1996) developed a method for assessing hydrologic alterations by grouping several streamflow parameters into five groups: Monthly magnitude, Magnitude and duration of annual extremes, Timing of annual extremes, Frequency and duration of high and low pulses, and Rate and frequency of change in conditions. These indicators of hydrologic alteration (IHA) parameters can be used to assess the impact that human influences have on the hydrologic regimes of river systems (Richter et al., 1996). Monk et al. (2011) evaluated the IHA parameters and identified those that were most important in Canadian rivers. The impact of each IHA group (Richter et al., 1996) and those identified by Monk et al. (2011) was evaluated in the selected study area by Coulibaly et al. (2013b) and it was found that the IHA parameters selected by Monk et al. (2011) adequately represented most hydrologic alterations in the basin. Therefore, only the IHA parameters selected by Monk et al. (2011) were used herein.

This research will expand on the CR-DEMO approach of Samuel et al. (2013), by evaluating the impact of additional objective functions in CR-DEMO based on streamflow signatures (Sawicz et al., 2011) and IHAs (Monk et al., 2011). The spatial distributions of optimum networks obtained by including or excluding these informative hydrologic signatures and IHA parameters in designing optimum networks were compared and the differences highlighted. In this study, the aim was to explore the effects of incorporating informative hydrologic/physiographic variables on the spatial distributions of optimum networks. As indicated earlier, the focus here is to account for basin spatial variability in the design of optimal hydrometric networks. The study used two Canadian basins, namely the Columbia River basin (CRB) in British Columbia and the Hamilton, Halton, Credit Valley (HHCV) basins in southern Ontario. These basins vary in several aspects such as elevation, land cover, land use, and size; all of which impact the hydrologic characteristics of the basins. They were chosen to provide very different study areas for testing the robustness of CR-DEMO with the inclusion of streamflow signatures and IHAs.

2. Study area and data used

Two study areas were selected for this research. The first is a combined watershed that includes the Hamilton, Halton and Credit Valley watersheds of Ontario as seen in Fig. 1a. The combined watersheds have an approximate total surface area of 2300 km² and contain 23 active streamflow monitoring stations. Combined, the watersheds are approximately 80% rural agricultural/forested

Download English Version:

<https://daneshyari.com/en/article/6410779>

Download Persian Version:

<https://daneshyari.com/article/6410779>

[Daneshyari.com](https://daneshyari.com)