Improved methods for daily streamflow estimates at ungauged sites

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Received 11 October 2011; revised 11 January 2012; accepted 12 January 2012; published 18 February 2012.

[1] In this paper, improved flow duration curve (FDC) and area ratio (AR) based methods are developed to obtain better daily streamflow estimation at ungauged sites. A regression based logarithmic interpolation method which makes no assumption on the distribution or shape of a FDC is introduced in this paper to estimate regional FDCs. The estimated FDC is combined with a spatial interpolation algorithm to obtain daily streamflow estimates. Multiple source sites based AR methods, especially the geographical distance weighted AR (GWAR) method, are introduced in an effort to maximize the use of regional information and improve the standard AR method (SAR). Performances of the proposed approaches are evaluated using a jackknife procedure. The application to 109 stations in the province of Quebec, Canada indicates that the FDC based methods outperform AR based methods in all the summary statistics including *Nash*, root mean squared error (*RMSE*), and *Bias*. The number of sites that show better performances using the FDC based approaches is also significantly larger than the number of sites showing better performances using AR based methods. Using geographical distance weighted multiple sources sites based approaches can improve the performance at the majority of the catchments comparing with using the single source site based approaches.

Citation: Shu, C., and T. B. M. J. Ouarda (2012), Improved methods for daily streamflow estimates at ungauged sites, *Water Resour. Res.*, *48*, W02523, doi:10.1029/2011WR011501.

1. Introduction

[2] Daily streamflow estimation is important for planning activities related to agriculture, industry, urban water supply, navigation, and flood control. However, stream gauges and historical records are not always available at the sites where streamflow information is required. Thus, the development of methodologies for the estimation of daily streamflow time series at ungauged sites is of practical importance.

[3] The frequently used methods for daily streamflow estimation are based on deterministic rainfall-runoff models [*Singh and Frevert*, 2006]. However, determining the parameters of these models is generally time and labor intensive. Also reliable rainfall gauges which provide inputs for these models do not always exist at the locations of interest. *Smakhtin and Masse* [2000] suggested that these types of complex and information consuming methods may not always be appropriate in data-poor regions, where comparable results can be achieved by applying the pragmatic techniques of data generation.

[4] One straightforward method for obtaining daily streamflow at ungauged sites from gauged sites is the drainage area ratio (AR) method [*Stedinger et al.*, 1993]. The standard implementation of the AR method generally involves only one source site [e.g., *Mohamoud*, 2008]. Such application actually assumes that a gauged site shares the same physiographical and hydrological characteristics as the target ungauged site except for a scaling factor representing the size of the drainage basin. In reality there are several other factors, in addition to the drainage area, that have a significant influence on a catchment's unique runoff characteristics. Thus, the risk of introducing systematic errors in the streamflow estimation process at an ungauged site using the single source site area ratio (SAR) approach is high. There have been some attempts to improve the SAR by incorporating more regional information. For instance, *Stedinger et al.* [1993] used a scaling factor which has an exponential *b* derived by regional regression to get improved streamflow estimates. Nevertheless, such efforts do not materially change the initial assumption of the SAR.

[5] Another highly promising and extensively used technique for the estimation of daily streamflows at ungauged sites is associated with the use of flow duration curves. A flow duration curve (FDC) gives a summary of flow variability at a site and is interpreted as a relationship between any discharge value and the percentage of time that this discharge is equaled or exceeded [*Vogel and Fennessey*, 1994]. *Hughes and Smakhtin* [1996] proposed a FDC based nonlinear spatial interpolation approach for patching or extension of observed flow data. *Smakhtin et al.* [1997] and *Smakhtin* [1999] illustrated the steps required to use the spatial interpolation technique and flow duration curves to generate complete streamflow time series. *Smakhtin and Masse* [2000] extended the FDC based spatial interpolation method to generate daily streamflow information at ungauged sites from observed rainfall data. *Mohamoud* [2008] used a FDC based sequential generation scheme, instead of

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0043-1397/12/2011WR011501

the spatial interpolation method of *Hughes and Smakhtin* [1996], to construct daily streamflow series.

[6] The approaches developed by *Smakhtin et al.* [1997] and *Mohamoud* [2008] for generating daily streamflows are based on the estimation of the regional FDCs at the ungauged sites and using the estimated FDCs to construct the daily streamflow series. *Mohamoud* [2008] compared the regional FDC based approach with the drainage area ratio method, and the results indicated that the regional FDC based approach shows improved predictive performance. The author also found that the FDC based method exhibited less predictive uncertainty compared to the area ratio methods.

[7] Many regionalization methods for predicting FDCs at ungauged sites have been presented in the literature. *Castellarin et al.* [2004] classified the various approaches for the estimation of regional FDCs into three categories: (1) statistical approaches [*Fennessey and Vogel*, 1990; *Leboutillier and Waylen*, 1993; *Yu and Tang*, 2000; *Singh et al.*, 2001; *Yu et al.*, 2002; *Croker et al.*, 2003; *Claps et al.*, 2005], (2) parametric methods [*Quimpo et al.*, 1983; *Mimikou and Kaemaki*, 1985; *Franchini and Suppo*, 1996; *Yu et al.*, 2002; *Mohamoud*, 2008], and (3) graphical procedures [*Smakhtin et al.*, 1997].

[8] For statistical approaches, in order to predict the regional FDCs at ungauged sites, a frequency distribution needs to be selected as the parent distribution for a region of interest [*Fennessey and Vogel*, 1990]. For gauged sites in a study area, the parameters of the distribution can be locally estimated using streamflow records. For ungauged sites, the parameters of the distribution are identified using regional regression models based on physiographical and climatic characteristics.

[9] For the parametric methods, in order to predict the regional FDCs at ungauged sites, the FDCs of the catchments in a study region are assumed be represented by analytical equations such as polynomial equations. The parameters of the analytical equations for ungauged catchments are identified through regional regression equations in the same way as is carried out in statistical approaches.

[10] *Castellarin et al.* [2004] defined the graphical procedures for regional FDC estimation based on the method developed by *Smakhtin et al.* [1997]. In the paper by *Smakhtin et al.* [1997], FDCs of the gauged sites are first standardized by an index flow, and then a regional dimensionless FDC can be obtained by averaging the standardized FDCs. The index flow of an ungauged site can be estimated through regional regression. In our opinion, the main characteristic that differentiates the graphical approaches from the statistical and parametric approaches is that no assumption of distribution or shape of the regional FDC is required. In a broader sense, this should be a more appropriate definition for the graphical approaches.

[11] Although the majority of the literature on the regional estimation of FDCs has focused on the statistical and parametric approaches, most of these approaches have limited practical usefulness for the construction of complete daily streamflow information at ungauged sites. The major reason is that the current assumptions on the distribution or shape of regional FDCs only estimates a portion of the entire FDC [*Fennessey and Vogel*, 1990]. The statistical approach proposed by *Fennessey and Vogel* [1990], for instance, assumes that the distribution selected for an FDC can be fitted to the exceedance probabilities between 0.5 and 0.99. The graphical approaches which make no assumption on the distribution or shape of a FDC should probably be more suitable for complete daily streamflow estimation if properly implemented.

[12] Given the popularity of the area ratio method and the promising status of the regional FDC based approach, it seems relevant to invest additional effort on the improvement of both methods. The main objective of the present paper is to improve the FDC and area ratio based methods for daily streamflow estimation at ungauged sites by overcoming some of the major limitations in their current implementation. A rigorous assessment of these improved methods is carried out through the use of a jackknife evaluation procedure. In order to improve the standard area ratio method, we propose to develop a multiple source site area ratio (MAR) approach. The MAR approach assumes only that the target and source sites are similar to some degree, which is determined by the weighting factors controlled by a properly selected weighting scheme. Under normal circumstance, this assumption should fit better to the regional hydrological condition, and it also increases significantly the possibility of using more regional information.

[13] In order to overcome the limitations of the current statistical and parametric methods for FDC estimation which may hinder their application for complete daily streamflow estimation, we propose a regression based logarithmic interpolation (RBLI) method for FDC estimation at ungauged sites. According to the classification presented by *Castellarin et al.* [2004], the proposed approach should belong to the class of graphical approaches. However, the standardization by an index streamflow and the use of a regional dimensionless FDC [*Smakhtin et al.*, 1997] are not adopted in the RBLI approach in order to respect the unique runoff characteristics of each catchment in a study area. The major features of the proposed RBLI method for FDC estimation are (1) the method does not require any assumptions concerning the shape or the distribution of a FDC, (2) the method provides streamflow estimation for the entire range of exceedance probability values from 0% to 100% to meet the needs for the appropriate estimation of extreme streamflow events, and (3) the estimated FDCs maintain smooth and continuous curves.

[14] The RBLI approach integrates two techniques: regional regression for percentile flow estimation and logarithmic interpolation to obtain discharge between fixed exceedance percentage points. The use of regional regression in the RBLI method to estimate a number of selected percentiles at the ungauged sites is similar to the procedures used by *Yu* et al., [2002] and *Mohamoud* [2008], although no logarithmic interpolation was used in those procedures. A logarithmic interpolation method was implemented by *Hughes and Smakhtin* [1996] and *Smakhtin* [1999]. However, a regional regression procedure was not used in these two papers.

[15] The FDC based approaches for daily streamflow estimation developed in the present paper utilize the RBLI method for FDC estimation at ungauged sites and the spatial interpolation method by *Hughes and Smakhtin* [1996] to transfer the streamflow sequence information to the

destination sites from the source sites. Two types of FDC based approaches using single and multiple source sites, respectively, are implemented. Three different weighting schemes are also proposed to be used with the multiple source sites FDC based approach. Significant efforts are made in the present paper to investigate the optimal physiographical variables in regional regression equations, the optimal weighting schemes, the optimal number of source sites, and the effects of several key measures including geographical distance, area ratio, and drainage area on model performances. This investigation allows us to provide an objective evaluation of the proposed methods and guidance for their application in the future.

[16] According to the literature review, all the published studies on using the FDC and area ratio based method for daily streamflow estimation [e.g., *Smakhtin et al.*, 1997; *Smakhtin*, 1999; *Mohamoud*, 2008] are evaluated based on selected sample watersheds, although many chose to use sample study sites because of the limited availability of reliable data or because of physical considerations. To obtain an unbiased evaluation of the proposed approaches, we use a jackknife procedure in the present paper. For a given study region, the main benefit of the jackknife procedure is that the results are not dependent on the specific sample site selection.

2. Methodology

2.1. Regional FDC Based Methods for Daily Streamflow Estimation at Ungauged Sites

2.1.1. Overview

[17] In this paper the FDC based methods are implemented in two types: a single source site FDC based method (SFDC) and a multiple source site FDC based method (MFDC). Sections 2.1.2, 2.1.3 and 2.1.4 provide details concerning the three major steps to implement the SFDC method. The first two steps of the SFDC method are devoted to the construction of the FDCs at the gauged sites and ungauged sites, respectively. The third step of the SFDC method deals with the use of a spatial interpolation algorithm to obtain the streamflow estimates at ungauged sites.

[18] The MFDC approach combines the prediction from the selected source sites according to a weighting scheme, while prediction from each source site is generated according to the procedure of the SFDC method. The source sites selection and weighting schemes, which are the major focuses when implementing the MFDC method, are discussed in section 2.1.5.

2.1.2. Construction of FDC at Gauged Sites

[19] In order to construct the FDCs at gauged sites, we need to rank the observed streamflows q_i, $i = 1, 2, \ldots, n$ in descending order at each site, where n is the number of events on record. Thus i is the rank of an event, and q_1 and q_n are the largest and smallest streamflow events, respectively. Then we need to calculate the plotting position p_i for the ith event using the following Weibull plotting formula:

$$p_i = P(Q > q_i) = \frac{i}{n+1}, \qquad (1)$$

where p_i represents the probability of all streamflow events greater than the discharge value q_i. The flow duration curve can be constructed by plotting q_i versus its corresponding plotting position p_i.

2.1.3. Regression Based Logarithmic Interpolation Method for Regional FDC Estimation at Ungauged Sites

[20] The regression based logarithmic interpolation (RBLI) method applied in this paper to obtain the complete FDCs at ungauged sites involves two steps. The first step is to estimate the quantiles Q_p at a number of fixed percentage points in the FDCs of the gauged and ungauged sites. In this paper, 17 fixed percentage points (0.01%, 0.1%, 0.5%, 1%, 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, 95%, 99%, and 99.99%) are selected. For a gauged site, the quantiles at these fixed percentage points can be directly estimated from its flow record. Extreme quantiles at 0.01% and 99.99% need at least 27 years of data to be directly estimated using the Weibull plotting position formula. Thus for gauges with less than 27 years of record, logarithmic extrapolation (as shown in equation (5)) is used to estimate quantiles at 0.01%, while the lowest flow in the records, which corresponds to exceedance probability of 99.97% or higher in our study area, are set for the quantile estimate at 99.99%.

[21] To obtain the estimation at an ungauged site, a stepwise regression technique is used to indentify the physiographical variables that are most influential to the estimation of the quantiles corresponding to the fixed percentage points. The selected variables are used to establish the regional regression equation for the entire study region using the following equation:

$$Q_p = a \times V_1^b \times V_2^c \times V_3^d \cdots, \qquad (2)$$

where $V_1, V_2, V_3 \ldots$ are the selected site physiographic or climatic characteristics used for the estimation of the quantile Q_p; p is one of the 17 fixed percentage points; $b, c, d \ldots$ are the model parameters; and a is a multiplicative error term and a multiplicative parameter of the model. Equation (2) is frequently logarithmically transformed into a linear equation (3)

$$\ln Q_p = \ln a + b \ln V_1 + c \ln V_2 + d \ln V_3 \cdots \qquad (3)$$

so that standard multivariable linear regression techniques can be applied. Once the parameters of equation (3) are identified based on the information of at the gauged sites, estimates of quantiles at the ungauged sites can be easily obtained by supplying the independent variables in equation (3) with the catchment descriptors of the ungauged sites. As an alternative approach, Q_p can be normalized by drainage area as suggested by *NERC* [1980].

[22] The second step of the RBLI approach is to use logarithmic interpolation to obtain estimates of the quantiles corresponding to the percentage points between the fixed percentage points, and thus construct the complete FDCs at the ungauged sites. Suppose that we want to obtain the estimate of the discharge y at the percentage point x, we need to locate its nearest fixed percentage points on both sides x_i and x_{i-1} and their corresponding discharge y_i and y_{i-1}. The

discharge y can be simply estimated using the following equation:

$$\ln(y) = \ln(y_i) + \frac{\ln(y_i) - \ln(y_i)}{x_{i-1} - x_i} \times (x - x_i). \quad (4)$$

In some rare cases we need to estimate discharges that correspond to an exceedance probability x below 0.01% or above 99.99%. In the case of $x < 0.01\%$, the following logarithmic extrapolation is used to estimate the daily streamflow y:

$$\ln(y) = \ln(Q_{0.01\%}) + \frac{\ln(Q_{0.01\%}) - \ln(Q_{0.1\%})}{0.01\% - 0.1\%} \times (x - 0.1\%). \quad (5)$$

For $x > 99.99\%$., the corresponding quantile y is set to be equal to $Q_{99.99\%}$ since extrapolating beyond 99.99% results frequently in unrealistic negative flows especially for smaller catchments.

2.1.4. Spatial Interpolation Technique for Daily Streamflow Estimation

[23] The spatial interpolation algorithm was proposed by *Hughes and Smakhtin* [1996] for streamflow patching or extension, and the steps for using the method for daily streamflow estimation at ungauged sites were provided in detail by *Smakhtin* [1999]. To estimate the discharge Q_d at the destination site for a given date, we need to locate the date and corresponding discharge Q_s at the source site Then we need to look up the observed flow duration curve of the source site and identify the percentage point p that corresponds to Q_s. Since the source site and the destination site are assumed to have an equivalent exceedance probability for a given daily streamflow event, the estimated discharge Q_d for the destination site corresponding to the percentage point p can be directly read from the estimated flow duration curve for the destination site.

2.1.5. Source Sites Selection and Weighting Schemes

[24] Since the spatial interpolation method is a data transferring technique to generate streamflow at destination sites from the gauged source sites, proper selection of the source sites is of crucial importance to the quality of the prediction at the destination sites. The works of *Hughes and Smakhtin* [1996] and *Smakhtin* [1999] advocate the use of multiple sources sites since the influence on the streamflow series at the destination site cannot generally be reflected from single source site streamflow records. *Hughes and Smakhtin* [1996] suggested that nearest gauges on the same river, its tributaries or adjacent streams can be used as source sites. The source sites are selected based on their geographical distance to the destination sites in the present paper.

[25] Suppose there are n source sites selected to transfer the information to the ungauged site, the streamflow estimate at the ungauged site for a given day can be computed as the weighted average of the estimates of the n source sites. The computation of the combined estimate Q_d at the ungauged site from the n source sites can be obtained using the equation:

$$Q_d = \sum_{j=1}^{n} w_j Q_{dj} / \sum_{j=1}^{n} w_j, \quad (6)$$

where Q_{dj} is the estimation from the source site j and w_j is the weight assigned to the source site j. The values of the weights in equation (6) should be based on the similarity between the target and source sites. In the present paper we propose and evaluate the following three weighting schemes designed for site similarity measure: geographical distance weighted (GW), drainage area weighted (AW), and physiographical descriptor weighted (PW) schemes., The MFDC methods using the three weighting schemes (GW, AW, and PW) are denoted using GWFDC, AWFDC, and PWFDC, respectively. The weights w_j in equation (6) can be computed as

$$w_j = \frac{1/d_j}{\sum_{j=1}^{n} 1/d_j}, \quad (7)$$

where d_j is the similarity distance measure between the destination site and source site j. It is frequently expressed as an Euclidean distance measure, and it is computed using equations (8), (9), and (10) for the geographical distance weighed, drainage area weighted, and physiographical descriptor weighed schemes respectively:

$$d_j = \sqrt{(X_j - X)^2 + (Y_j - Y)^2}, \quad (8)$$

$$d_j = \sqrt{(AREA_j - AREA)^2}, \quad (9)$$

$$d_j = \sqrt{(V_{1j} - V_1)^2 + (V_{2j} - V_2)^2 \cdots + (V_{kj} - V_k)^2}, \quad (10)$$

where X_j and Y_j are the easting and northing of the centroid of the source site j, X and Y are the easting and northing of the centroid of the target site, $AREA_j$ is the drainage area of the source site j, $AREA$ is the drainage area of the target site, $V_{1j}, V_{2j}, \ldots, V_{kj}$ are the selected physiographical variables of the source site j, and $V_1, V_2, \ldots, V_k$ are the k selected physiographical variables of the target site. The drainage area weighted method can be considered as a special situation of the physiographical descriptor weighted method, in which the drainage area is the only physiographical variable used in equation (10). Since the catchment area is frequently considered as the most important variable in many hydrological regionalization procedures, and it is also the only scaling factor used in the AR method for streamflow estimation at ungauged sites, the area weighted scheme is considered in this paper even if the variable catchment area will appear in equation (10).

2.2. Single and Multiple Source Sites Based Area Ratio Methods

[26] The FDC based approaches developed in the present paper are compared to the AR based methods. Two types of implementation of the AR methods are applied: the single source site area ratio method (SAR) and the multiple source sites area ratio method (MAR). The SAR method is one of the most used and the easiest way to obtain regional

estimates of the runoff at ungauged sites. The streamflow at an ungauged site is estimated by

$$Q_y = \frac{A_y}{A_x} Q_x, \quad (11)$$

where A_x and A_y are the drainage area of the ungauged and gauged site, respectively, Q_x is the observed streamflow at a gauged site, and Q_y is the estimated discharge at an ungauged site.

[27] The MAR approach is a novel method proposed in this work, and it generates the streamflow prediction at an ungauged site as the weighted average of the predictions from the source sites. In the present paper, the same weighting schemes developed for the FDC based approaches in section 2.1.5 are applied to the MAR method. Thus, multiple predictions from the source sites are combined using equation (6). The three weighting schemes (GW, AW, and PW) introduced in section 2.1.5 are used to obtain the weights in equation (6), and the resulting three weighted AR models (GWAR, AWAR, and PWAR) are compared with the FDC based methods and the SAR method.

2.3. Evaluation Method

[28] The performance of the daily streamflow prediction approaches is evaluated using a jackknife evaluation procedure [*Miller*, 1964] in this paper. A number of studies [e.g., *McCuen*, 2005; *Shu and Ouarda*, 2007] pointed out that the advantage of the jackknife procedure is that model accuracy obtained using the procedure is independent of the calibration data. In jackknifing, the streamflow record of one catchment in the study area is held out from the database, thus the catchment is considered as "ungauged." Then the FDC and daily streamflow for the site that is held out are estimated using the data from the remaining sites. This process is continued until regional estimates of the FDCs and streamflows are obtained using the proposed models for all the sites in the study area.

[29] A set of three indices is used to evaluate the FDC and AR based methods proposed in this paper. These indices are the Nash efficiency criterion (*NASH*) [*Nash and Sutcliffe*, 1970], the root mean square error (*RMSE*), and the bias (*BIAS*). For a given site, they are computed using the following equations:

$$NASH = 1 - \frac{\sum_{i=1}^{n} (q_i - \hat{q}_i)^2}{\sum_{i=1}^{n} (q_i - q_m)^2}, \quad (12)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (q_i - \hat{q}_i)^2}, \quad (13)$$

$$BIAS = \frac{1}{n}\sum_{i=1}^{n} (q_i - \hat{q}_i), \quad (14)$$

where n is the total number of daily streamflow values being estimated, q_i and $\hat{q}_i$ are respectively the ith measured and estimated daily streamflow, and q_m is the mean of the observed daily streamflow series.

3. Application

3.1. Study Area

[30] The various approaches developed in this paper are applied to the hydrometric station network of Quebec, Canada. According to the following criteria, 109 hydrometric stations managed by the ministry of the environment of Quebec (MENVIQ) services are selected:

[31] (1) The minimum continuous streamflow record length is 10 years.

[32] (2) Each selected site should present a natural flow regime.

[33] (3) The historical record of the selected sites should pass the Kendall test of stationarity [*Kendall*, 1975] and the nonparametric independence test of *Wald and Wolfowitz* [1943]. For the Kendall test, a sample of N independent and identically distributed random variables is tested at the selected significance level. The Wald-Wolfowitz test checks a randomness hypothesis for two flow series.

[34] The locations of the selected hydrometric stations are shown in Figure 1. The area of these catchments ranges from 219 to 96,600 km^2. The minimum, mean, maximum, and standard deviation of the record length of the selected stations are 10, 29, 71, and 11 years, respectively.

[35] The analysis conducted in the present paper relies on three types of data: physiographical, meteorological, and hydrological data. The sources of the physiographical and hydrological data are the hydrological database and the topographic digital maps provided by the Ministry of the Environment of the Province of Quebec, Canada (MENVIQ). Meteorological variables were extracted from the historical database of the MENVIQ meteorological network across the province of Quebec by using an interpolation technique [*Shu and Ouarda*, 2007]. The list of physiographical and meteorological variables selected based on their relevance for this study are: basin area (BV), the fraction of the basin area covered with lakes (PLAC), the fraction of the basin area occupied by forest (PFOR), basin mean slope (PMBV), annual mean degree-days over 0°C (DJBZ), annual mean total precipitations (PTMA), summer mean liquid precipitation (PLME), annual mean degree-days over 13°C (DJH13), average number of days with temperature over 27°C (NJH27) and curve number (NCM). The summary statistics including minimum, mean, maximum, and standard deviation of these variables are presented in Table 1.

3.2. Results and Discussion

3.2.1. Regional FDC Estimation at Ungauged Sites

[36] Following the major steps described in section 2.1, constructing the FDC at ungauged sites requires estimation of the 17 selected quantiles, and the estimation is based on the regional regression equation (3). For each of the 17 quantiles, a stepwise regression technique is used to select the independent variables in equation (3). The candidate variables and their corresponding transformation methods are listed in Table 1. The stepwise regression algorithm applied in this paper is implemented in the MATLAB environment. The algorithm selects the single best performing variable for the first step. It then steps through each of the remaining variables, keeping a variable if the null hypothesis that the variable would have a zero coefficient can be rejected based on the p value of an F statistics, and

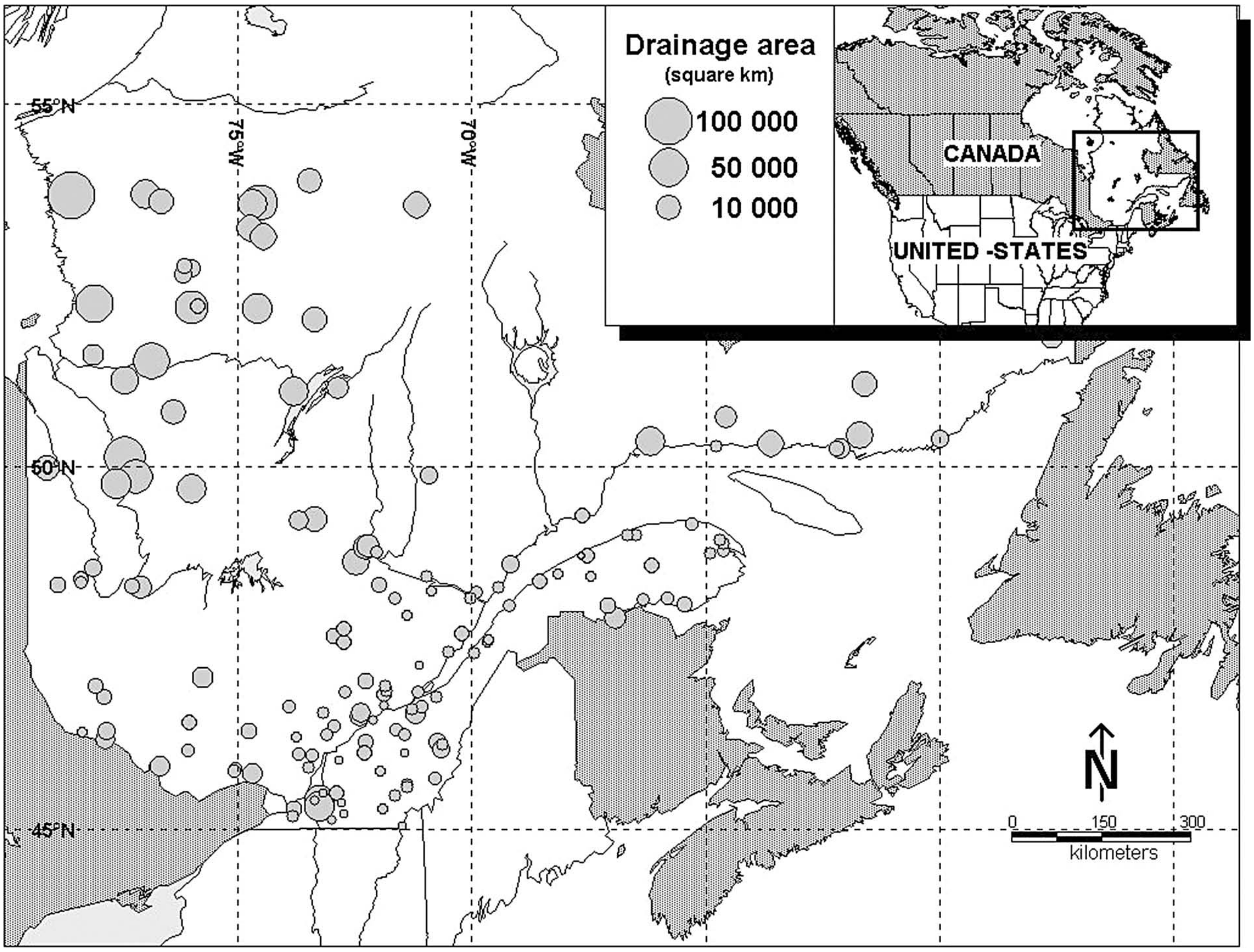

Figure 1. Location of hydrometric stations across the province of Quebec, Canada.

discarding it otherwise. The entrance and exit tolerances on the p values are 0.05 and 0.10, respectively. The variables selected by the stepwise regression for each quantile are shown in Table 2. As expected, the drainage area was selected by all the stepwise regression procedures. Except for the estimation of $Q_{99.9}$, the estimation of all quantiles shows a very high coefficient of determination. A number of descriptive statistics: the minimum, mean, maximum, and standard deviation of the estimates listed in Table 2 also show a very close match between the estimated and observed values.

[37] Suppose $d1$ and $d2$ are two of the fixed percentage points defined in section 2.1.3, there are five cases in which the relationship "if $d1 < d2$, then $Q_{d1} > Q_{d2}$" are not preserved. Four of the cases happen for $d1 = 99\%$ and $d2 = 99.9\%$; and one case happens at $d1 = 0.01\%$ and $d2 = 0.1\%$. The uncertainties for the estimates are generally higher at the extremes of the FDCs. To deal with these problems, we use the following relationships: If $d1 = 99\%$, and $d2 = 99.9\%$, while $Q_{d1} < Q_{d2}$, we set $Q_{d1} = Q_{d2}$; if $d1 = 0.01\%$, $d2 = 0.1\%$, while $Q_{d1} < Q_{d2}$, Q_{d1} is extrapolated using equation (5).

Table 1. Descriptive Statistics of the Selected Physiographical and Meteorological Variables

Variable	Unit	Notation	Transformation	Min	Mean	Max	Std
Basin area	km^2	BV	Log	219	7080	96,600	13,182
% of the basin occupied by lakes	%	PLAC	$\sqrt{}$	0.10	7.33	32.00	6.83
% of the basin occupied by forest	%	PFOR	–	29.00	84.84	99.80	15.03
Basin mean slope	%	PMBV	Log	0.19	2.49	6.95	1.08
Annual mean degree-days < 0°C	degree-day	DJBZ	Log	920.60	1688.10	2963.10	553.39
Annual mean total precipitation	mm	PTMA	Log	646	986	1508	162
Summer mean liquid precipitation	mm	PLME	–	306.00	454	657	74
Annual mean degree-days > 13°C	degree-day	DJH13	–	70.20	312.77	734.10	138.76
Average number of days with temperature > 27°C	number of days	NJH27	–	0.80	11.78	36.60	7.10
Curve number	–	NCM	–	22	45.02	75.30	12.29

Table 2. Results of the Estimation of the 17 Percentile Flows

Percentile Flow	Variables	R^2	Observed Min	Observed Mean	Observed Max	Observed Std	Estimated Min	Estimated Mean	Estimated Max	Estimated Std
$Q_{0.01}$	BV, PLAC, PTMA	0.90	79.2	901.8	6710.0	1016.0	97.2	881.7	5392.3	949.1
$Q_{0.1}$	BV, PLAC, PTMA, PFOR, NJH27	0.95	58.0	767.5	6250.3	974.9	61.2	748.4	5842.4	913.1
$Q_{0.5}$	BV, PLAC, PTMA, PFOR, DJH13	0.96	41.7	608.1	5231.8	812.1	45.4	593.7	4889.1	758.2
Q_1	BV, PLAC, PTMA, PFOR, DJH13	0.97	31.4	535.9	4713.5	727.2	37.6	528.2	4384.6	694.9
Q_5	BV, PLAC, PTMA, DJBZ, DJH13	0.98	15.1	369.0	3885.0	570.8	19.0	363.4	3718.1	546.5
Q_{10}	BV, PLAC, DJBZ, DJH13, PLME	0.99	9.6	282.0	3280.0	473.3	10.6	279.2	3232.0	461.1
Q_{20}	BV, NJH27, DJH13, PLME	0.99	5.2	204.3	2680.0	374.6	5.6	205.0	2891.5	385.0
Q_{30}	BV, NJH27, DJH13, PLME	0.99	3.0	165.8	2260.0	316.1	3.4	167.1	2568.9	334.0
Q_{40}	BV, PLAC, NJH27, DJH13, PLME	0.99	2.0	137.9	1890.0	268.7	2.2	138.9	2217.6	286.2
Q_{50}	BV, PLAC, NJH27, PLME, NCM	0.99	1.4	112.8	1520.0	220.7	1.5	114.6	1901.6	243.2
Q_{60}	BV, PLAC, NJH27, PLME, NCM	0.99	0.9	89.2	1160.0	175.4	1.1	90.6	1508.4	193.1
Q_{70}	BV, PLAC, PFOR, DJH13, PLME	0.99	0.6	65.3	779.0	126.8	0.9	65.8	1029.3	135.8
Q_{80}	BV, PLAC, PFOR, DJH13, PLME	0.98	0.4	48.3	561.0	93.9	0.7	47.9	711.2	95.4
Q_{90}	BV, PLAC, PFOR, PLME, NCM	0.97	0.2	38.2	462.0	75.8	0.4	38.0	584.2	77.5
Q_{95}	BV, PLAC, PFOR, DJH13, PLME	0.97	0.2	33.5	408.0	67.1	0.3	33.3	523.7	69.2
Q_{99}	BV, PLAC, PFOR, DJH13, PLME	0.96	0.1	27.5	348.0	56.8	0.2	28.1	507.6	63.5
$Q_{99.9}$	BV, DJH13	0.72	0.0	22.3	320.0	48.6	0.02	21.0	467.7	53.8

[38] In order to assess the reliability of the regional FDC estimation, the relative error distribution plots (relative error bands) developed by *Castellarin et al.* [2004] and *Castellarin et al.* [2007] are used. For a given site i and duration d, relative error $e_{i,d}$ between the empirically estimated FDC $\widehat{q_{i,d}}$ and jackknifed FDC $q_{i,d}$ can be computed as

$$e_{i,d} = \frac{\widehat{q_{i,d}} - q_{i,d}}{q_{i,d}}. \tag{15}$$

Thus for a given duration d, we can compute the various statistics of relative error (such as mean, median, and 75% and 90% percentiles, etc.) across all the stations in the study area. By connecting these statistics for different durations, relative error bands are formed (shown in Figure 2). The 50%, 75% and 90% percentile of the relative errors are generally contained within 5%, 8%, and 18% bands, respectively, except at the extreme high and low durations.

3.2.2. Performance of FDC Based and Area Ratio Based Methods

[39] In this study, both FDC based and ARbased methods are implemented with both single and multiple sources sites. For the single source site approach, the site geographically closest to the target site is selected as the source site. The performance indices for the FDC based method with single source site (SFDC) and AR method with single source site (SAR) are shown in the first two rows of Table 3. The performances of the two MFDC approaches, geographical

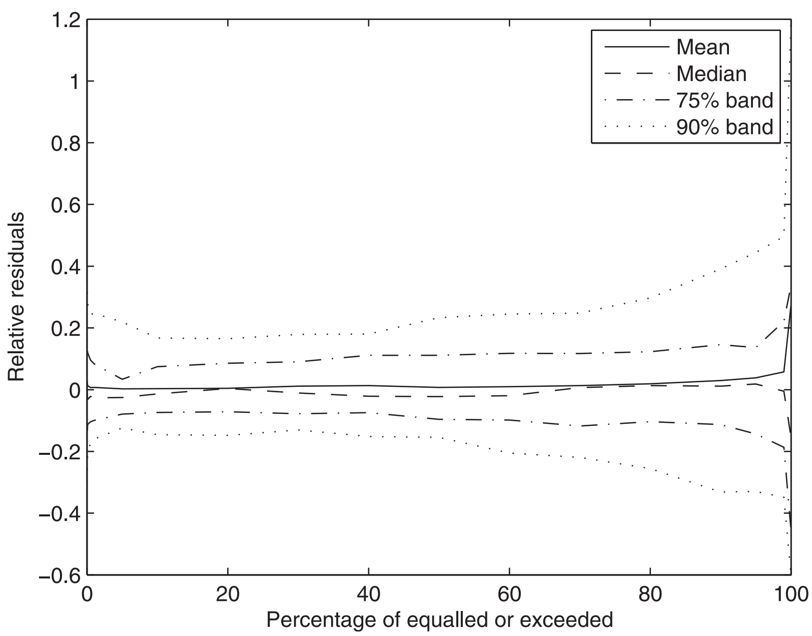

Figure 2. Distribution of relative residuals for the study area: mean, median, and bands containing 75% and 90% of the relative errors.

Table 3. Performance Indices of the FDC and AR Based Approaches Using a Jackknife Procedure

Method	Notation	*Nash* Mean	*Nash* % of sites > 0.75	*RMSE* Mean	*BIAS* Mean
Single source FDC	SFDC	0.63	42.2%	59.72	−0.49
Single source AR	SAR	0.53	37.6%	66.79	0.51
Geographical distance weighted FDC	GWFDC	0.72	65.1%	51.57	−0.46
Geographical distance weighted AR	GWAR	0.67	56.9%	55.75	2.66
Drainage area weighted FDC	AWFDC	0.70	54.1%	52.18	−0.65
Area weighted AR	AWAR	0.63	45.0%	57.90	2.14
Physiographical descriptor weighted FDC	PWFDC	0.71	53.2%	52.16	−0.71
Physiographical descriptor weighted AR	PWAR	0.65	51.4%	58.61	2.13

distance weighted FDC based method (GWFDC) and area ratio method (GWAR) using four source sites, are presented in the third and fourth rows of Table 3. The other four multiple source sites based approaches listed in the last four rows of Table 3 are discussed in detail in section 3.2.4. The performance indices reported in Table 3, except column 4, are computed as the mean of the performance indices at each site of the entire study region as an indication of the overall performance of each approach. Additionally, periods that observed data are not available at target sites are not included in the evaluation. The actual source sites for a given target site may vary over time since at a given time each approach is looking for the best available source sites with observed flow record.

[40] Compared to the SAR method, the SFDC method shows a much better performance in terms of *Nash* and *RMSE* indices. Similar patterns can be observed when comparing the GWAR method with the GWFDC method. The FDC based methods generally slightly overestimate, while the AR based methods generally underestimate streamflows. The multiple source sites based GWAR and GWFDC approaches perform much better than the single source site based SAR and SFDC, respectively, in terms of *Nash* and *RMSE*. The GWFDC method leads to a slight decrease in *BIAS* compared to the SFDC method, while there is a large increase in *BIAS* when using the GWAR method in comparison to the SAR method. The overall performance of the FDC based approaches is much higher than the area ratio based methods in terms of the summary performance indices.

[41] Differences in the goodness-of-fit measure *Nash* at each site between the FDC based methods and the AR based methods are shown in Figure 3. Positive bars in Figure 3 indicate that the FDC based methods are superior to the AR based methods at the site referred to on the horizontal axis, while negative bars in Figure 3 indicate that the AR based methods are superior. Bars exceeding 1 in Figure 3 are truncated to ensure a better representation of the scales of the remaining bars. In Figure 3a it can be seen that the SFDC method shows a better performance at 61 sites, and at 16 sites of which, the SFDC shows an improvement in the *Nash* value that is larger than 0.15, a level considered as significant in this study. The SAR method shows a better performance at 48 sites, while at only 5 sites the SAR leads to an improvement in the *Nash* value larger than 0.15.

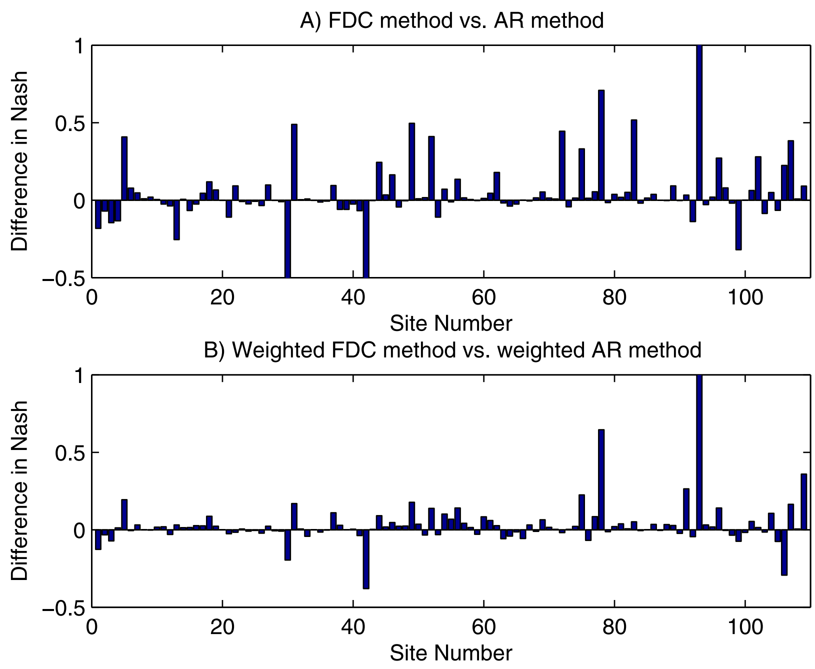

Figure 3. FDC based method versus AR based method.

[42] Figure 3b indicates that the GWFDC method shows a better performance at 67 sites, and at 9 sites, the SFDC shows an improvement in the *Nash* value that is larger than 0.15. The GWAR method shows a better performance at 42 sites, while at only 3 sites it shows an improvement in the *Nash* larger than 0.15. Based on these observations, we can conclude that the FDC based methods outperform the AR based methods at the majority of the sites. The FDC based methods lead to a significantly better performance (difference in *Nash* over 0.15) at three times more sites than the AR based methods. Overall, the patterns observed in Figure 3 confirm the conclusions derived from the summary statistics in Table 3.

[43] The differences in the performance index *Nash* between single and multiple sources at each site are presented in Figure 4. Figures 4a and 4b illustrate these results for the FDC based and AR based methods, respectively. Positive bars in Figure 4 indicate that using multiple source sites leads to a superior performance, while negative bars indicate that using multiple source sites actually reduces performance. In Figure 4a it can be seen that the GWFDC method leads to a better performance at 86 sites, and at 22 sites the GWFDC method shows a significant improvement in the *Nash* value (>0.15). Although the GWFDC method ends up with an underperformance at 23 sites, only one of them is significant. Figure 4b indicates that the GWAR method leads to a better performance at 81 sites, and at 34 sites the GWAR method shows a significant improvement in the *Nash* value. The GWAR method show a reduced performance at 28 sites. However, the performance reduction at only four of these sites is significant. Overall, we can conclude that the multiple source sites approaches show a significantly better performance than the single source site approach at the vast majority (>74%) of the sites.

3.2.3. Optimal Number of Source Sites

[44] In the literature, the majority of the studies using the AR method are based on a single source site. As for the FDC based method, *Mohamoud* [2008] used a single source site to predict daily streamflow at ungauged sites. The study by *Hughes and Smakhtin* [1996] recommended that up to five sites can be used as source sites. Instead of using an arbitrarily selected number of source sites, an exploratory study based on the jackknife resampling procedure is used in this paper to objectively determine the optimal number of source sites that can be used with the FDC based method and the AR method. By sequentially increasing the number of source sites from one to ten, the performances of the two methods are examined based on several selected indices. By plotting the number of source sites against the selected performance indices obtained using the jackknife procedure, objective conclusions regarding the optimal number of source sites can be drawn.

[45] The results of the exploratory study of the optimal number of source sites are shown in Figure 5. As described in section 2.1.5, the source sites are selected here based on their closeness (geographical distance) to the target site. The geographical distance weighting scheme is applied to combine the multiple predictions from the source sites. It can be seen in Figure 5 that the performances of the FDC based method and the AR method in terms of *Nash* and *RMSE* indices increase sharply when the number of source sites increases from one to four, and no significant change is observed when more source sites are included. This

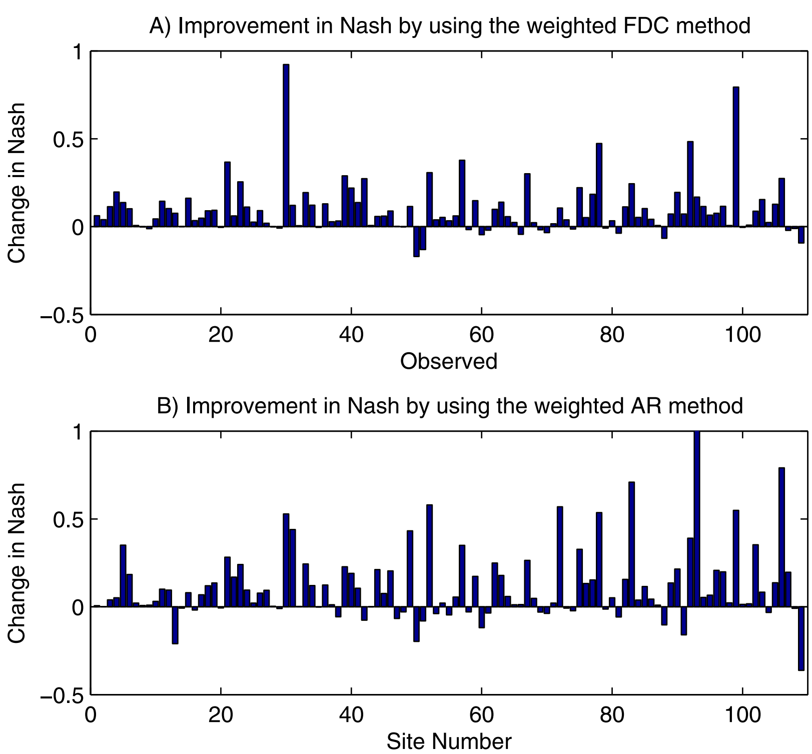

Figure 4. Single source site versus multiple source sites.

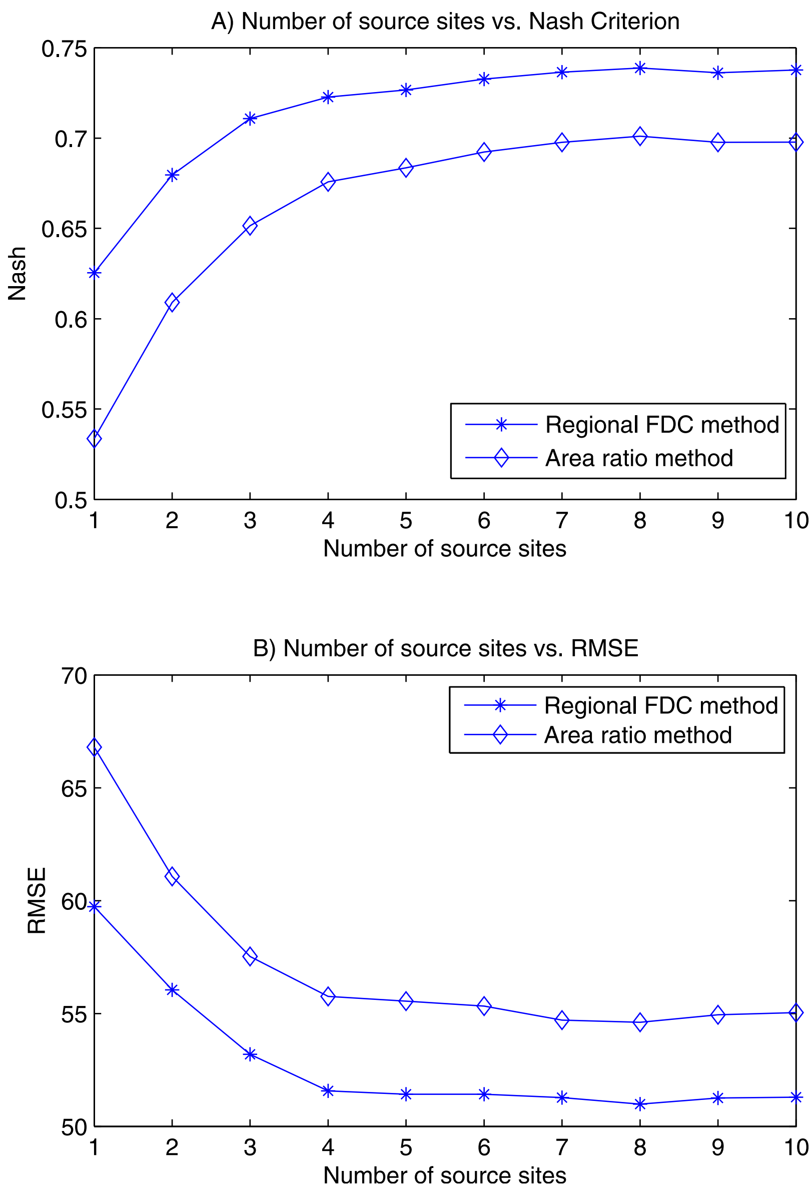

Figure 5. Performance of estimation methods as a function of the number of source sites.

phenomenon could lead to the conclusions that the optimal number of source sites for our study region is four; and two to four sources sites should always be preferred over a single source site if they are available.

[46] Another result that can be observed from Figure 5 is that the AR method benefits significantly more than the FDC based method by using multiple source sites. For example, the *Nash* for the AR method increases from 0.53 to 0.61 with a 0.08 gain when the number of source sites increases from one to two as opposed to a 0.04 gain for the FDC based method. This phenomenon can be best explained by the source of regional information obtained by the two methods. The AR method obtains both the magnitude and sequence of the streamflow information from the selected source sites. The FDC based method only obtains the sequence information from the source sites directly, while the magnitude information of the streamflow series is acquired during the regional estimation of the FDC. Regional FDC estimation gives the FDC based methods the potential to obtain the magnitude information from the entire region. Thus when only one source site is used, the FDC based method actually uses much more regional information than the AR method, which in turn diminishes its potential for additional information gain when more source sites are used.

3.2.4. Optimal Weighting Scheme for the Source Sites

[47] The FDC based method and the AR method with four source sites weighted by the three weighting schemes described in section 2.1.5 are applied to the study area The variables used for geographical distance and area weighting schemes are apparent according to equations (8) and (9). Still we need to specify the variables used for the physiographical descriptor based weighting scheme. The variables selected for the weighting scheme of PWFDC and PWAR methods are *BV*, *PMBV*, and *PTMA*, and the updated equation (10) using these variables is

$$d_j = \sqrt{\left(\frac{\ln BV_j - \ln BV}{\sigma \ln BV}\right)^2 + \left(\frac{\ln PMBV_j - \ln PMBV}{\sigma \ln PMBV}\right)^2 + \left(\frac{\ln PTMA_j - \ln PTMA}{\sigma \ln PTMA}\right)^2}, \tag{16}$$

where ln stands for the log transformation of a variable, and σ stands for the standard deviation of a variable.

[48] The results of the evaluation for the three weighting schemes are presented in the third to eighth rows of Table 3. From this table we can observe that the GWFDC method provides better results than the rest of the approaches in terms of all performance indices. We also observe that the geographical distance based weighting scheme outperforms the drainage area and physiographical descriptors based weighting schemes when the same prediction method is used. The results also suggest that the physiographical descriptors weighted method outperforms the drainage area weighted method when the same prediction method is used.

3.2.5. Effects of the Area Ratio and Geographical Distance on the Performances of the Estimation Methods

[49] Since the attributes "geographical distance" and "area ratio" play significant roles in the proposed approaches, it is the intention of section 3.2.5 to examine the relationship between these attributes and the estimation methods. Since the multiple source sites approaches make it very

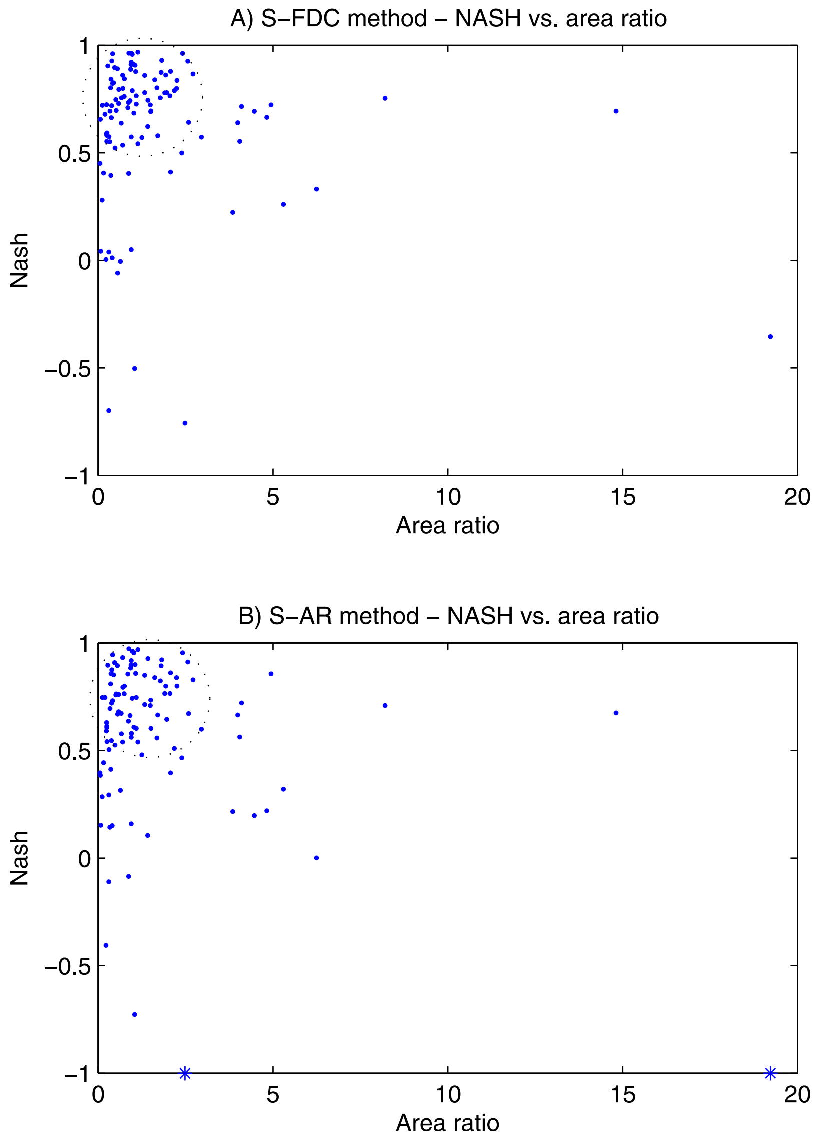

Figure 6. Effects of area ratio on the performance of prediction methods.

difficult to obtain a good composite measure on the attributes, the analysis of the effects of the two attributes is based on the SFDC and SAR methods. The plots of *Nash* versus area ratio and *Nash* versus geographical distance using the two estimation methods are shown in Figures 6 and 7, respectively. There are two sites with *Nash* values below -1 when using the SAR approach, and the two sites are plotted on the horizontal axis and marked using * in Figures 6b and 7b.

[50] Although the FDC and AR based methods use completely different mechanisms to obtain the estimates of the magnitude of the streamflow, the general patterns of the results generated by the two approaches as observed in Figures 6 and 7 are actually quite similar. Highly clustered areas (circled by a dash line) can be observed in Figures 6a and 6b, and the areas contain the majority of the sites associated with relatively good performances and low area ratios. For sites with an area ratio greater than three, the SFDC method generally has a better performance. This result is expected since the AR method is generally not suitable for use when the area ratio is higher than 1.5 [*Lumia*, 1991]. From Figures 7a and 7b, we can see that both approaches perform very well at several sites whose source sites are located at a very small geographical distance. However, with the increase in geographical distance, patterns in the performance become diverse, although the majority of the sites still have *Nash* values over 0.5 when the distance is below 100 km. For sites with a distance measure above 100 km, the FDC method generally has a better performance than the SAR, and the SAR approach has an extremely bad performance (*Nash* < -1) at two of the sites (marked by *).

3.2.6. Relationship Between Drainage Area and Model Performance

[51] In section 3.2.6 we divide the sites in the study area into five classes (very small, small, medium, large, and very large) according to their drainage area, so that each class has essentially the same number of sites. The division of the classes, the four methods under comparison, and the performance of each class are shown in Table 4. The

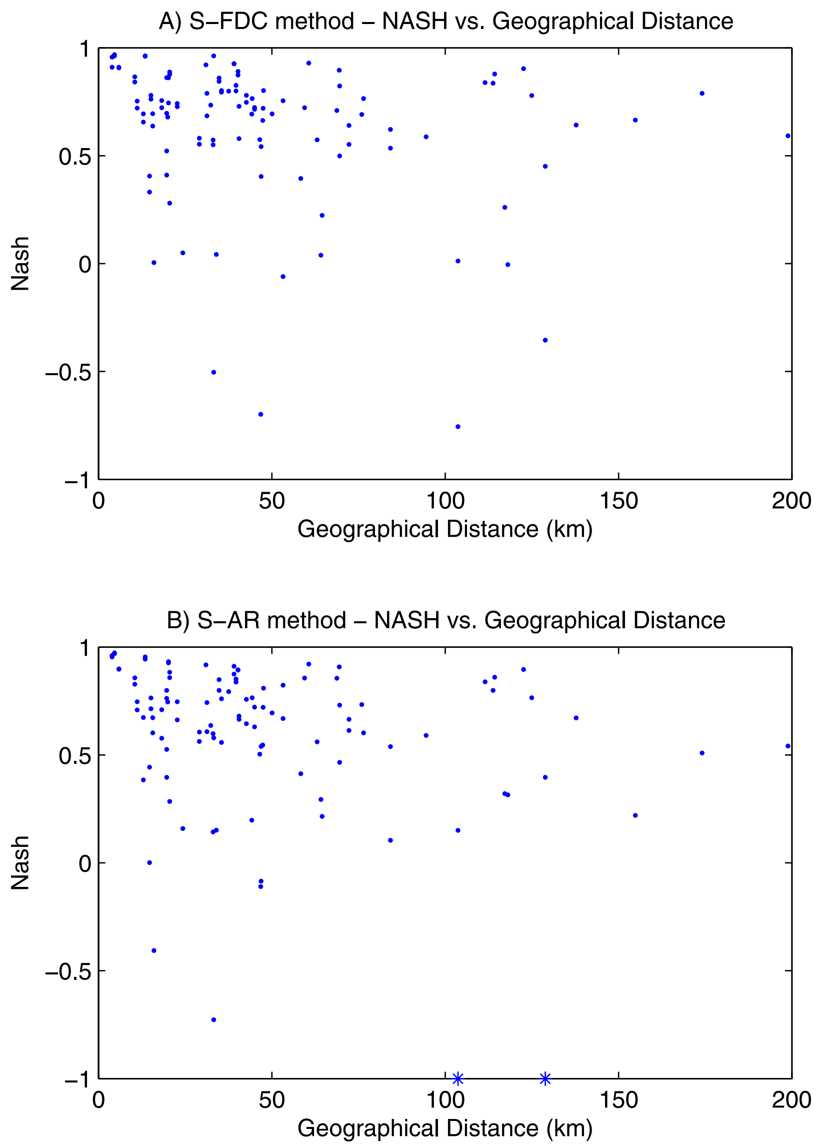

Figure 7. Effects of geographical distance on the performance of prediction methods.

Table 4. Relationship Between Drainage Area and Model Performance

	Nash				
Notation	Very Small Area <= 725.5	Small Area > 725.5 Area <= 1340	Medium Area > 1340 Area <= 3058	Large Area > 3058 Area <= 10,690	Very Large Area > 10,690
SFDC	0.50	0.71	0.66	0.71	0.55
SAR	0.47	0.71	0.64	0.65	0.20
GWFDC	0.63	0.78	0.73	0.81	0.66
GWAR	0.61	0.76	0.73	0.80	0.48

performance measure *Nash* is computed as the mean of the *Nash* of the sites in each class. For all the estimation methods in Table 4, the performance at the very small and very large classes are significantly worse than the rest of the classes. Large differences between the large and very large classes in *Nash* values by using the SAR and GWAR methods are especially notable. The very bad performance of the AR based methods at the very large class confirms the observation in section 3.2.5 since those very large sites are generally associated with high area ratios. The performances of the AR and FDC based approaches using either single or multiple source sites are comparable at small and medium classes. It is also observed in Table 4 that all the multiple source sites based approaches significantly outperform their single source site counterparts. For example, the differences between SFDC and SAR for large and very large classes are 0.06 and 0.35, while the differences shrink to 0.01 and 0.18 when using their multiple source sites version.

3.2.7. Streamflow Statistics Comparison

[52] Table 5 shows the comparison between the observed and modeled streamflow statistics including mean, variance, skewness, and lag 1 autocorrelation. These statistics are averaged over the entire study area. For statistics including mean, variance, and lag 1 autocorrelation, the difference between modeled and observed results are all very small. For skewness, the FDC based approaches slightly overperform the AR based approaches. The statistics at each catchment for two approaches including GWFDC (represented by circles) and GWAR (represented by dots) are shown in Figure 8. GWFDC and GWAR approaches are both very good in predicting the mean and variance of the streamflow. Characteristics of highly skewness or low autocorrelation are more difficult to preserve.

4. Conclusions and Future Work

[53] In the present paper, improved FDC and AR based methods are developed to obtain better daily streamflow estimates at ungauged sites. A regression based logarithmic interpolation method is introduced to estimate regional FDCs at ungauged sites. The method overcomes some of the major limitations in the current statistical or parametric methods by eliminating the assumption of the distribution or shape of a FDC. The FDC estimation method is combined with a spatial interpolation algorithm to obtain daily streamflow estimates at ungauged sites. For the AR based methods, the major contribution of this paper is to introduce the multiple source sites based AR methods, especially the geographical distance weighted AR method.

Table 5. Statistics Computed From Observed and Modeled Daily Streamflow Time Series

	Observed	GWFDC	GWAR	SFDC	SAR
Mean	140.46	140.66	137.54	140.84	140.02
Variance	114.66	115.88	111.12	113.5	106.35
Skewness	2.98	2.90	2.70	2.88	2.58
Lag 1 autocorrelation	0.95	0.96	0.96	0.95	0.95

[54] The FDC and AR based methods developed in the present paper are implemented with both single and multiple source sites, although multiple source sites based approaches are the major focus. A jackknife resampling procedure is used to evaluate the proposed approaches. Based on the evaluation and a number of exploratory and comparative studies, the following is a summary of the major conclusions. The conclusions are based on the application in the selected catchments in Quebec, Canada, thus these conclusions may not be generalized to other areas.

[55] 1. The single and multiple source sites FDC based methods outperform the single and multiple source sites area based AR methods, respectively. The FDC based method shows better performance in all the summary statistics including *Nash*, *RMSE*, and *Bias*. The number of sites that show a better performance using the FDC based approaches is also significantly larger than the number of sites using the AR based methods. At very large catchments, the AR based method could lead to very bad performances, and in such cases the FDC based approach should be used.

[56] 2. Significant improvements can be obtained by using multiple source sites instead of single source site. Compared to the standard AR method, the geographical distance weighted AR method shows an improvement at 81 (or 74%) of the sites. Compared to the single source FDC approach, the geographical distance weighted FDC method shows an improvement at 86 (or 79%) of the sites.

[57] 3. Among the three weighting schemes (geographical distance weighted, drainage area weighted, and physiographical descriptor weighted) used to weight the contribution of each source site to the final estimation at a destination site, the geographical distance based weighting scheme performs best for both FDC and AR based methods.

[58] 4. The exploratory studies to examine the optimal number of source sites for this case study suggest that using four source sites can provide optimal solution for both FDC and AR based methods, and little improvement can be observed by adding additional source sites.

[59] 5. The performances of the FDC and AR methods are better at sites with smaller area ratio and geographical distance from a source site. Under unusual situations where either the area ratio or geographical distance is very large, the FDC can perform noticeably better than the AR method.

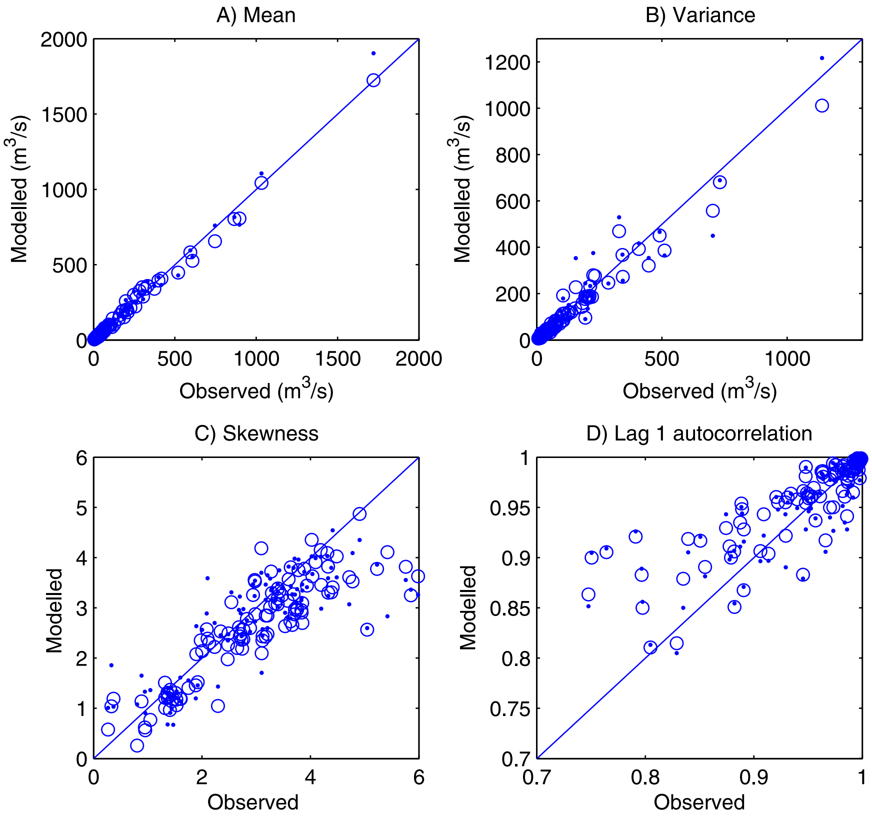

Figure 8. Comparison between observed and modeled flow statistics at each catchment.

[60] For a few sites, the extreme quantiles at 0.01% and 99.99% exceedance probability are extrapolated linearly in the logarithmic domain. The advantage of this approach is that a longer series of gauging stations are included in the regression analysis. However, the uncertainty associated with the extrapolation is likely to be introduced into the estimation at ungauged catchments. As an alternative method, the sites with a short record can be excluded in the estimation of the extreme quantiles, and the regression analysis will only be based on catchment with a longer flow record. Although the alternative approach provide estimates with less gauging stations, the uncertainty is easier to be quantified.

[61] Two research areas that require significant extra efforts to improve upon the approaches developed in this paper are: (a) introducing regionalization techniques to improve the FDC based estimation methods developed in this paper; and (b) extending the methods developed in this paper to deal with nonstationary situations. Regionalization methods have been successfully used to estimate the extreme flow events at ungauged site in recent years [e.g., Burn, 1990; *Ouarda et al.*, 2001, 2006, 2008; *Shu and Ouarda*, 2007]. Since the estimation of the regional FDCs used in this paper is based on the entire study area, improved estimation of the percentiles used for FDC construction can be obtained by applying the methodology to the homogeneous regions (neighborhoods) identified by the regionalization methods. The approaches developed in this paper require that the flow series of the catchments are stationary, but approaches have been developed to handle nonstationary cases [*Leclerc and Ouarda*, 2007]. Thus efforts should be devoted to the extension of the AR and FDC methods to the case of nonstationary streamflow series since ignoring the nonstationarity could lead to significant under- or overestimation [*Leclerc and Ouarda*, 2007].

[62] **Acknowledgments.** The financial support provided by the Natural Sciences and Engineering Research Council of Canada (NSERC) is gratefully acknowledged. This paper is significantly improved by following the suggestions of the reviewers, Attilio Castellarin and Giuliano Di Baldassarre.

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