

Towards a publicly-available, map-based regional software tool to estimate unregulated daily streamflow at ungauged rivers

S. A. Archfield¹, P. A. Steeves¹, J. D. Guthrie², and K. G. Ries III³

¹Massachusetts-Rhode Island Water Science Center, U.S. Geological Survey, 10 Bearfoot Road, Northborough, MA 01532, USA

²J. D. Guthrie, Rocky Mountain Geographic Science Center, U.S. Geological Survey, P.O. Box 25046 MS 516, Denver Federal Center, Denver, CO 80225, USA, jdguthrie@usgs.gov

³K. G. Ries III, Office of Surface Water, U.S. Geological Survey, 5522 Research Park Drive, Baltimore, Maryland 21228, USA, kries@usgs.gov

1 **Abstract.**

2 Streamflow information is critical for addressing any number of hydrologic problems. Often,
3 streamflow information is needed at locations which are ungauged and, therefore, have no
4 observations on which to base water management decisions. Furthermore, there has been
5 increasing need for daily streamflow time series to manage rivers for both human and ecological
6 functions. To facilitate negotiation between human and ecological demands for water, this paper
7 presents the first publicly-available, map-based, regional software tool to estimate historical,
8 unregulated daily streamflow time series (streamflow not affected by human alteration such as
9 dams or water withdrawals) at any user-selected ungauged river location. The map interface
10 allows users to locate and click on a river location, which then links to a spreadsheet-based
11 program that computes estimates of daily streamflow for the river location selected. For a
12 demonstration region in the northeast United States, daily streamflow was, in general, shown to
13 be reliably estimated by the software tool, with more difficulty estimating the highest and lowest
14 streamflows that occurred over the historical period from 1960 through 2004. The software tool
15 provides a general framework that can be applied to other regions for which daily streamflow
16 estimates are needed.

17 **Keywords:** ungauged; unged; streamflow; water availability; basin delineation; water
18 resources

19 **1. Introduction**

20 Streamflow information at ungauged rivers is needed for any number of hydrologic
21 applications; this need is of such importance that an international research initiative known as
22 Prediction in Ungauged Basins (PUB) had been underway for the past decade (2003-2012)
23 [Sivapalan *et al.*, 2003]. Concurrently, there has been increasing emphasis on the need for daily
24 streamflow time series to understand the complex response of ecology to river regulation and to
25 develop streamflow prescriptions to restore and protect aquatic habitat [Poff *et al.*, 1997; Poff *et*
26 *al.*, 2010]. Basin-wide water allocation decisions that meet both human and ecological demands
27 for water require daily streamflow time series at river locations that have ecological constraints
28 on water (locations where important or protected fish or ecological communities reside or rely on
29 for life), human constraints on water (locations on the river that are dammed or otherwise
30 managed), or locations that have both constraints. Often, these locations are unmonitored and no
31 information is available to make informed decisions about water allocation.

32 Methods to estimate daily streamflow time series at ungauged locations can be broadly
33 characterized under the topic of regionalization [Blöschl and Sivapalan, 1995], an approach
34 which pools information about streamgauges in a region and transfers this information to an
35 ungauged location. Generally there are two main categories of information that is pooled and
36 transferred to an ungauged: 1) rainfall-runoff model parameters [see Zhang and Chiew, 2009 for
37 a review] and 2) gauged streamflows, or related streamflow properties. The first category
38 assumes that rainfall-runoff models have been developed and calibrated at gauged locations
39 within a region of interest. The rainfall-runoff model parameters are then either used to
40 interpolate parameter values at an ungauged location [as examples see Abdulla and Lettenmaier,
41 1997; Seibert, 1999; Merz and Blöschl, 2004; Parajka *et al.*, 2005; Oudin *et al.*, 2008] or the

42 calibrated parameter set is directly transferred from a gauged to an ungauged catchment using
43 some measure of similarity between the gauged and ungauged location [*Merz and Blöschl*, 2004;
44 *McIntyre et al.*, 2005; *Parajka et al.*, 2005; *Oudin et al.*, 2008, *Zhang and Chiew*, 2009, *Reichl et*
45 *al.*, 2009; *Oudin et al.*, 2010]. Rainfall-runoff models are time and data intensive to develop and
46 calibrate; furthermore, no consistently successful method has been introduced to reliably
47 regionalize model parameters for ungauged locations [*Merz and Blöschl*, 2004; *McIntyre et al.*,
48 2005; *Parajka et al.*, 2005; *Oudin et al.*, 2008, *Zhang and Chiew*, 2009; *Oudin et al.*, 2010]. The
49 second category transfers information directly from a streamgauge or streamgauges to an
50 ungauged location. Examples of this type of regionalization approach include geostatistical
51 methods such as top-kriging [*Skøien and Blöschl*, 2007] and more commonly used methods such
52 as the drainage-area ratio method (as described in *Archfield and Vogel* [2010]), the MOVE
53 method [*Hirsch*, 1979], and a non-linear spatial interpolation method, applied by *Fennessey*
54 [1994], *Hughes and Smakhtin* [1996], *Smakhtin* [1999], *Mohamoud* [2008], and *Archfield et al.*
55 [2010], which all transfer a scaled historical streamflow time series from a gauged to an
56 ungauged location. These methods have the advantage of being relatively easy to apply but are
57 limited by the availability of the historical data in the study region.

58 For the software tool presented in this paper, only the second category of approaches is
59 utilized and a hybrid approach combining the drainage-area ratio and non-linear spatial
60 interpolation methods is introduced to estimate unregulated daily streamflow time series. When
61 streamflow information is presented in a freely-available software tool, this information can
62 provide a scientific framework for water-allocation negotiation amongst all stakeholders.
63 Software tools to provide streamflow time series at ungauged locations have been previously
64 published for predefined locations on a river; however few – if any – tools currently exist that

65 provide daily streamflow time series at any stream location for which this information is needed.
66 *Smakhtin and Eriyagama* [2008] and *Holtschlag* [2009] introduced software tools to provide
67 monthly streamflows for ecological streamflow assessments at predefined river locations around
68 the globe and in the Great Lakes region of the United States, respectively. *Williamson et al.*
69 [2009] developed The Water Availability Tool for Environmental Resources (WATER) to serve
70 daily streamflow information at fixed stream locations in non-karst areas of Kentucky. These
71 existing tools provide valuable streamflow information; yet, in most cases, at the monthly – not
72 daily – time step and, in all cases, for only predefined locations on a river that may not be
73 coincident with a river location of interest. The U.S. Geological Survey (USGS) StreamStats tool
74 [*Ries and others*, 2008] does provide the utility to delineate a contributing area to a user-selected
75 location on a river; however, only streamflow statistics – not streamflow time series – are
76 provided for the ungauged location.

77 The software tool presented here is one of the first such tools to provide unregulated, daily
78 streamflow time series at ungauged locations in a regional framework for any user-desired
79 location on a river. For this study, unregulated streamflow is considered to be streamflow that is
80 not altered – or regulated – by human alteration within the contributing area to the river. This
81 paper first briefly describes the methods used by the software tool. The software tool is then
82 presented and its functionality is described. The software tool can be considered a general
83 framework to provide daily streamflow time series at ungauged locations in other regions of the
84 United States and possibly other areas. Lastly the utility of the software tool to provide reliable
85 estimates of daily streamflow is demonstrated for a large basin in the northeast United States. For
86 this region, the software tool utilizes the map-based user interface of the USGS StreamStats tool

87 paired with a macro-based spreadsheet program that allows users to “point-and-click” on a river
88 location of interest and obtain the historical daily streamflow time series.

89 **2. Methods underlying the software tool**

90 Streamflow in the study region is estimated by a multi-step regionalization approach,
91 which starts with the delineation of the contributing area to the ungauged river location of
92 interest and computation of related catchment characteristics (fig. 1A). For the purposes of this
93 text, catchment and basin are used interchangeably. The flow-duration curve (FDC) for the
94 ungauged location is then obtained using these catchment characteristics (Section 2.1; fig. 1B).
95 The FDC can be considered analogous the inverse of the empirical cumulative distribution of
96 daily streamflow as it shows the probability of a particular observed streamflow being exceeded.
97 Specific quantiles on the FDC are estimated at the ungauged location by first establishing a
98 regression relation between those flow values observed at the streamgauges in the study region
99 and measurable catchment characteristics obtained for the contributing areas to those
100 streamgauges (Section 2.1; fig. 1B). Interpolation is then used to obtain the FDC values for
101 streamflows between the regression-estimated quantiles (Section 2.1; fig. 1B). Lastly, the FDC at
102 the ungauged location is transformed into a time series of streamflow by the selection (Section
103 2.2; fig. 1C) and use (Section 2.3; fig. 1D) of a donor streamgauge. To ensure that the estimated
104 streamflow represents unregulated conditions, only streamgauges whose catchments have been
105 unaffected by anthropogenic influences are utilized to develop the regional regression equations
106 and are considered as a potential donor streamgauge.

107 **2.1 Estimation of the flow-duration curve for the ungauged location**

108 Estimation of the daily FDC at an ungauged location remains an outstanding challenge in
109 hydrology. *Castellarin et al.* [2004] provides a review of several methods to estimate FDCs at
110 ungauged locations and found that no particular method was consistently better than another.
111 For this study, an empirical, piece-wise approach to estimate the FDC is used in the software tool
112 (fig. 2). This overall approach is similar to that used by *Mohamoud* [2008], *Archfield et al.*
113 [2010], and *Shu and Ourda* [2012] in that the FDC is estimated by first developing regional
114 regressions relating catchment characteristics to selected FDC quantiles and then interpolating
115 between those quantiles to obtain a continuous FDC. The selected quantiles were chosen to be
116 evenly distributed across the FDC with additional quantiles added at the tails of the FDC to
117 provide further resolution to the portions of the FDC that contain the extreme high- and low-
118 streamflow values.

119 With the exception of streamflows having less than or equal to a 0.01 probability of being
120 exceeded (streamflows with a probability of being exceeded less than 1 percent of the time),
121 selected quantiles on the FDC are estimated from regional regression equations and a continuous
122 FDC is log-linearly interpolated between these quantiles to obtain a continuous FDC (fig. 2).
123 Relations between streamflow quantiles at the 0.02, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.4, 0.5, 0.6,
124 0.7, 0.75, 0.8 and 0.85 exceedance probabilities are estimated by independently regressing each
125 streamflow quantile against catchment characteristics (fig. 2). In this approach, catchment
126 characteristics (the independent variables) are regressed against the streamflow quantiles (the
127 dependent variable) to determine which catchment characteristics have a statistically significant
128 relation with each streamflow quantile. The catchment characteristics tested for inclusion in the
129 regression equations are based on the availability of the spatial data layers in the particular study
130 area of interest and, therefore, vary from region to region. In practice, multiple linear regression

131 is typically applied using the logarithms of the streamflow values and catchment characteristic
 132 values, with the form of the regression equation as:

$$133 \quad Y = a_0 + \sum_{i=1}^M a_i X_i + \varepsilon \quad (1)$$

134 where Y is a vector of the log-transformed values of the streamflow quantile across the
 135 study streamgauged, X_i 's are the vectors of the log-transformed values of the observed catchment
 136 characteristics, a_0 is a constant term estimated by the regression, a_i 's are the coefficients
 137 estimated by the regression, M is the total number of catchment characteristics and ε is the vector
 138 of the model residuals.

139 *Mohamoud* [2008] and *Archfield et al.* [2010] observed that when regressions with
 140 catchment characteristics are used across all quantiles on the FDC, there is increased potential
 141 for the estimated quantiles to violate the constraint that streamflows must decrease as the
 142 exceedance probability increases because the uncertainty in the flow estimates is greatest at the
 143 lowest portion of the FDC. As confirmed by *Archfield et al.* [2010], when all streamflow
 144 quantiles were regressed against catchment characteristics, there was no constraint to ensure that
 145 estimated streamflows decreased with increasing exceedance probability and some estimated
 146 streamflow values were larger at higher exceedance probabilities than streamflows estimated at
 147 lower exceedance probabilities. Thus, the inherent structure of the data that ensures streamflow
 148 quantiles decrease with increasing exceedance probability was not preserved—a physical
 149 impossibility. To enforce physical consistency, relations between streamflow quantiles at the 0.9,
 150 0.95, 0.98, 0.99 and 0.999938 exceedance probabilities were estimated by regressing
 151 streamflows at these quantiles against one another and using these relations to recursively
 152 estimate streamflows (fig. 2). Regressing quantiles against one another ensures that this
 153 constraint is not violated. In this case, the form of the regression equation is equivalent to that of

154 equation (1) for the case where i equals 1. This is an alternative approach to that used by
 155 *Mohamoud* [2008], who suggested discarding any estimated quantiles that violate the constraint
 156 that streamflows must decrease with increasing exceedance probability.

157 Using the regression equations to solve for the selected quantiles, the continuous, daily
 158 FDC is then determined by log-linear interpolation between the quantiles and ensuring that the
 159 interpolation passes through each quantile estimated by regression. *Arcfield et al.* [2010] showed
 160 that estimated streamflows determined by log-linear interpolation for exceedance probabilities of
 161 0.01 or less do not match the shape of the FDC and this interpolation method creates a bias in the
 162 estimated streamflows, which can substantially overestimate the peak streamflows. The shape of
 163 the FDC at the highest streamflows is curved such that an alternative interpolation scheme such
 164 as parabolic or cubic splines is not capable of capturing the shape. Instead of using another
 165 interpolation method, streamflows from a donor streamgauge are scaled by catchment area to
 166 estimate the highest streamflows at the ungauged location (fig. 2). This is predicated on the
 167 assumption that the shape of the left tail of the FDC is better approximated by the observed
 168 streamflow at a donor streamgauge than by a curve fit. Therefore, for streamflows having less
 169 than or equal to a 0.01 probability of being exceeded, streamflows are scaled by a drainage-area
 170 ratio approach (eqn. 2) in conjunction with the selected donor streamgauge:

$$q_{p_u} = \frac{A_u}{A_g} q_{p_g} \quad (2)$$

171 where q_{p_u} is the value of the streamflow quantile at the ungauged location for
 172 exceedance probability, p , A_u is the contributing drainage area to the ungauged location, A_g is
 173 the contributing drainage area to the donor streamgauge, and q_{p_g} is the value of the streamflow

174 quantile at the donor streamgauge for exceedance probability, p . Whereas this piecewise
175 interpolation of the FDC – particularly at the tails – seems admittedly untidy, it is important to
176 note that previous studies choose to ignore the estimation of the tails of the FDC because of the
177 substantial challenges associated with their estimation [*Mohamoud, 2008 and Shu and Ourda,*
178 2012].

179 2.2 Selection of the donor streamgauge

180 The donor streamgauge is used for two purposes in the streamflow estimation approach:
181 1) to estimate streamflows that have less than a 1-percent chance of being exceeded, and 2) to
182 transform the estimated FDC into a time series of streamflow at the ungauged location. For the
183 direct transfer of streamflow time series from a gauged to an ungauged location, several methods
184 have been used to select the donor catchment. The most common method is the selection of the
185 nearest donor catchment [*Mohamoud, 2008; Patil and Stieglitz, 2012; Shu and Ourda, 2012*].
186 Also recently, *Archfield and Vogel* [2010] hypothesized that the cross-correlation between
187 concurrent streamflow time series could be an alternative metric to select the donor streamgauge.
188 For one streamflow transfer method – the drainage area ratio – *Archfield and Vogel* [2010]
189 showed that the selection of the donor streamgauge with the highest cross-correlation results in a
190 substantial improvement to the estimated streamflows at the ungauged location. Using this result,
191 *Archfield and Vogel* [2010] introduced a new method – the map correlation method – to estimate
192 the cross-correlation between an ungauged location and a donor streamgauge.

193 Based on the findings of *Archfield and Vogel* [2010], the donor streamgauge is selected
194 by the map-correlation method; however, the software tool provides information on the
195 similarity of the selected donor streamgauge to the ungauged location in terms of both distance

196 and similarity in catchment characteristics should the user prefer to use another selection method.
 197 Through the use of geostatistics, the map-correlation method selects the donor streamgauge
 198 estimated to have the highest cross-correlation between concurrent streamflow time series at the
 199 donor streamgauge and the ungauged location. For a given donor streamgauge, the cross-
 200 correlations between daily streamflow at the donor streamgauge and the other study
 201 streamgauges in the region are computed. Ordinary kriging [Isaaks and Srivastava,1989] is used
 202 to create a relational model – termed the variogram model – for the separation distances between
 203 the study streamgauges and the differences in observed cross-correlation. There are several
 204 commonly-used variogram model forms [Isaaks and Srivastava,1989]; Archfield and Vogel
 205 [2010] use a spherical variogram model because of its relatively simple formulation and its
 206 visual agreement with the majority of the sample variograms. The spherical variogram, here
 207 represented as the covariance function and as presented in Ribeiro Jr. and Diggle [2001], has the
 208 form

$$209 \quad C(h) = \begin{cases} \sigma^2 \left(1 - 1.5 \frac{h}{a} + 0.5 \left(\frac{h}{a} \right)^3 \right), & \text{if } h < 0 \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

210 where $C(h)$ is the covariance function variogram model (also referred to as the correlation
 211 function), h is the separation distance between streamgauges, σ^2 is the partial sill, and a is the
 212 range parameter. Following from traditional geostatistics techniques for ordinary kriging as
 213 presented in Isaaks and Srivastava [1989] and as applied by Archfield and Vogel [2010], the
 214 variogram model is then used to map the cross-correlation between the donor streamgauge and
 215 any location within the study region, including an ungauged location of interest. This mapping is
 216 repeated for each possible donor streamgauge in the study region so that estimates of the cross-
 217 correlation between the ungauged location and all possible donor streamgauges can be obtained.

218 The software tool then selects the donor streamgauge resulting in the highest estimated cross-
219 correlation with the ungauged location. Additional details on the map correlation method are
220 described in *Archfield and Vogel* [2010].

221 **2.3 Generation of streamflow time series**

222 With a donor streamgauge selected and estimated daily FDC at the ungauged location, a
223 time series of daily streamflow for the simulation period is then constructed by use of the QPPQ
224 transform method [*Fennessey*, 1994; *Hughes and Smakhtin* [1996]; *Smakhtin*, 1999; *Mohamoud*,
225 2008; *Archfield et al.* 2010; *Shu and Ourda*, 2012]. The term QPPQ-transform method was
226 coined by *Fennessey* [1994]; however, this method has been published by *Smakhtin* [1999],
227 *Mohamoud* [2008], and *Archfield et al.* [2010] under names including “non-linear spatial
228 interpolation technique” [*Hughes and Smakhtin*, 1996; *Smakhtin*, 1999] and “reshuffling
229 procedure” [*Mohamoud*, 2008]. The method assumes that the exceedance probability associated
230 with a streamflow value on a given day at the donor streamgauge also occurred on the same day
231 at the ungauged location. For example, if the streamflow on October, 1, 1974 was at the 0.9
232 exceedance probability at the donor streamgauge, then it is assumed that the streamflow on that
233 day at the ungauged location also was at the 0.9 exceedance probability. To implement the
234 QPPQ-transform method, a FDC is assembled from the observed streamflows at the donor
235 streamgauge (fig. 1C). The exceedence probabilities at the donor and ungauged FDC are then
236 equated (fig. 1D) and the date that each exceedence probability occurred at the donor
237 streamgauge is transferred to the ungauged catchment (fig. 1D).

238 **3. Software tool**

239 The software tool can be considered a general framework to provide daily streamflow
240 time series at ungauged locations in other regions of the United States and possibly other areas.
241 Furthermore, all data and methods underlying tool are freely available. Whereas the tool is a
242 general framework for providing a map-based, “point-and-click” approach to estimate daily
243 streamflow at an ungauged river location of interest, the underlying data, including the river
244 network and catchment characteristics, are specific to the region of interest. Much like other
245 modeling frameworks, the software tool must be calibrated based on the data available in the
246 region of interest. Details of the functionality of the regional tool presented in this study follow.
247 Additional details on the customization of the catchment delineation for application to other
248 regions is discussed in Section 4.

249 The software tool initially interfaces with the USGS StreamStats tool (*Ries et al.*, 2008 or
250 <http://streamstats.usgs.gov>) to delineate a catchment area for any user-selected location on a river
251 and to compute the catchment characteristics needed to estimate the FDC at the ungauged
252 location (fig. 1). The selection of the donor streamgauge, the computation of the FDC and the
253 estimate of the time series of daily streamflow is then executed by a Microsoft Excel spreadsheet
254 program with Visual Basic for Applications (VBA) coding language. The spreadsheet itself,
255 which contains the VBA source code, can be used independently of the StreamStats interface and
256 is, therefore, able to be customized to interface with other watershed delineation tools or with
257 any study area for which the methods in Section 2 have been applied. Additionally, any macro-
258 enabled spreadsheet program could be used in place of the Microsoft Excel spreadsheet program.

259 The catchment delineation portion of the software tool is handled by the USGS
260 StreamStats tool, which operates within a web browser, and is accessible at
261 <http://streamstats.usgs.gov>. The StreamStats tool implements a watershed delineation process

262 described in *Ries et al.* [2008] and contains basin-wide spatial data layers of the catchment
263 characteristics needed to solve the regional regression equations described in Sections 2.2 and
264 3.2. The map navigation tools provided in the StreamStats user interface are used to locate a
265 point along the stream of interest. In addition to the stream network, users can view satellite
266 imagery, topographic maps, and street maps to find the river location of interest. This
267 background information can then be used to locate the ungauged river location of interest (fig.
268 3A). Users simply click on the river location of interest and the catchment boundary will be
269 delineated and displayed on the map (fig. 3A). Once the catchment is delineated, pressing a
270 command button will open a new browser window that shows a table of the catchment
271 characteristics for the selected location (fig. 3B). StreamStats uses the processes described by
272 *ESRI, Inc.* [2009] for catchment delineation and computation of catchment characteristics.
273 StreamStats also provides a command button to export a shapefile of the contributing catchment
274 (fig. 3A) for use in other mapping applications.

275 Once the catchment characteristics are determined for the ungauged location of interest,
276 the user opens the spreadsheet program and inputs the catchment characteristics into the
277 spreadsheet program to compute the daily streamflow (fig. 4); the spreadsheet program contains
278 five worksheets (figs. 4A-E). The spreadsheet opens on the *MainMenu* worksheet, which
279 provides additional instruction and support contact information (fig. 4A). The user enters the
280 catchment characteristics summarized by StreamStats (fig. 4B) into the *BasinCharacteristics*
281 worksheet (fig. 4B) and then presses the command button to compute the unregulated daily
282 streamflows. The program then follows the process outlined in figures 1B to 1D and Section 2.
283 The estimated streamflows are, in part, computed from regional regression equations that were
284 developed using the catchment characteristics from the approach discussed in Section 2.1.

285 Streamflows estimated for ungauged catchments having characteristics outside the range of
286 values used to develop the regression equations are highly uncertain because these values were
287 not used to fit the regression equations. Therefore, the software tool includes a message in the
288 *BasinCharacteristics* worksheet (fig. 4B) next to each characteristic that is outside the respective
289 ranges of those characteristics used to solve the regression equations.

290 The *ReferenceGaugeSelection* worksheet (fig. 4C) displays information about the
291 ungauged catchment and donor streamgauge that was selected by the map correlation method
292 described in Section 2.2; however, additional measures of similarity between the donor and
293 ungauged location are also provided, including the percent difference between catchment
294 characteristics at the ungauged location and the donor streamgauge as well as the distance
295 between the ungauged location and donor streamgauge (fig. 4C). The estimated cross-correlation
296 resulting from the map-correlation method is also reported (fig. 4C). If a user selects a new donor
297 streamgauge, they then press the update button (fig. 4C) and daily streamflows will be
298 recomputed using the newly selected donor streamgauge. The *ContinuousFlowDuration*
299 worksheet (fig. 4D) displays the estimated FDC, and the *ContinuousDailyFlow* worksheet (fig.
300 4E) displays the estimated daily time series for the ungauged site.

301 **3.1. Demonstration area**

302 The methods described in Sections 2 were applied to the Connecticut River Basin (CRB),
303 located in the northeast United States, and incorporated into a basin-specific tool termed the
304 Connecticut River UnImpacted Streamflow Estimator (CRUISE) tool. The CRUISE tool is freely
305 available for download at <http://webdmamrl.er.usgs.gov/s1/sarch/ctrtool/index.html>. The CRB is
306 located in the northeast United States and covers an area of approximately 29,000 km². The

307 region is characterized by a temperate climate with distinct seasons. Snowfall is common from
308 December through March, with generally more snow falling in the northern portion of the CRB
309 than in the south. The geology and hydrology of the study region are heavily affected by the
310 growth and retreat of glaciers during the last ice age, which formed the present-day stream
311 network and drainage patterns [Armstrong *et al.*, 2008]. The retreat of the glaciers filled the river
312 valleys with outwash sands and gravel as well as fine- to coarse-grained lake deposits
313 [Armstrong *et al.*, 2008], and these sand and gravel deposits have been found to be important
314 controls on the magnitude and timing of base flows in the southern portion of the study region
315 [Ries and Friesz, 2000]. The CRB has thousands of dams along the mainstem and tributary rivers
316 that are used for hydropower, flood control, and water supply just as the CRB is home to a
317 number of important fish species that rely on the river for all or part of their life cycle. To
318 understand how dam management can be optimized to meet both human and ecological needs for
319 water, unregulated daily streamflows are needed to provide inflow time series to dams that can
320 be routed through operation and optimization models being developed in the CRB.

321 **3.2. Estimation of daily streamflow in the demonstration area**

322 Data from streamgauges located within the CRB and surrounding area are used in the
323 CRUISE tool to estimate unregulated daily streamflow time series at ungauged locations (table
324 1). The study streamgauges have at least 20 years of daily streamflow record and have minimal
325 regulation in the contributing catchments to the streamgauges [Armstrong *et al.*, 2008; Falcone
326 *et al.*, 2010]. Previous work in the southern portion of the study area by Archfield *et al.* [2010]
327 showed that, from a larger set of 22 catchment characteristics, the contributing area to the
328 streamgauge, percent of the contributing area with surficial sand and gravel deposits, and mean
329 annual precipitation values for the contributing area are important variables in modeling

330 streamflows at ungauged locations. For this reason, these characteristics were summarized for
331 the study streamgauges and used in the streamflow estimation process. Contributing area to the
332 study streamgauges ranges from 0.5 km² to 1,845 km² with a median value of 200 km². Mean
333 annual precipitation ranges from 101 cm per year to 157 cm per year with a median value of 122
334 cm per year. Percent of the contributing area with surficial sand and gravel ranges from 0 percent
335 to 67 percent with a median value of 9.5 percent. Streamflow in the CRUISE tool is estimated
336 for a 44-yr (16,071-d) period spanning October 1, 1960 through September 30, 2004 using the
337 methods described in Section 2.

338 Streamflow quantiles at the 0.02, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.4, 0.5, 0.6, 0.7, 0.75, 0.8
339 and 0.85 exceedance probabilities were determined from the observed streamflow time series
340 and regressed against the contributing area to the streamgauge, percent of the contributing area
341 with surficial sand and gravel deposits, and mean annual precipitation values for the contributing
342 area using the conventions described in *Archfield et al.* [2010]. Regression equations were
343 developed using weighted, least-squares multiple linear regression. Regression weights were
344 applied to the dependent variables and computed as a function of the number of days of observed
345 streamflow on which the estimated streamflow statistic was based. Natural-log transformations
346 of the dependent variables (streamflow quantiles at selected exceedance probabilities) and
347 independent variables (catchment characteristics) were made to effectively linearize the relations
348 between the variables. Bias correction factors were estimated using the Smearing Estimator
349 (Duan, 1983) to remove bias in the regression estimates of the streamflow quantiles when
350 transferred out of logarithmic space. All non-zero regression coefficients in the regression
351 equations (table 2) were significantly different from zero at the 0.05 significance level. Residuals
352 (observed minus regression-estimated streamflow values) (plotted in log space) were generally

353 homoscedastic and normally distributed. Variables in the final equations had variance-inflation
354 factors of less than 2.5, meaning the correlations between the independent variables are minimal.
355 Regression-coefficient values and goodness of fit values are shown in table 2.

356 To enforce physical consistency as described in Section 2.1, streamflow quantiles at the
357 0.9, 0.95, 0.98, 0.99 and 0.999938 exceedence probabilities were recursively regressed against
358 one another (fig. 5). This approach also exploits the strong structural relation of the observed
359 quantiles, as observed in figure 5. Linear regression equations were fit between the observed
360 quantiles to establish a relation between the quantiles (fig. 5); this relation was then carried
361 recursively through the estimation of the FDC. For example, streamflow at the 85-percent
362 exceedence probability is obtained by solving the multiple-linear regression equation that is a
363 function of basin characteristics. However, streamflow at the 90-percent exceedence probability
364 is obtained by the relation fit between the streamflows at the 85- and 90-percent exceedence
365 probabilities (fig 5). Only the estimated streamflow at the 85-percent exceedence probability is
366 needed to estimate the streamflow at the 90-percent exceedence probability. Subsequent
367 streamflow quantiles are estimated from the relation between one quantile and another (fig. 5).
368 The remainder of the FDC curve was then estimated as described in Section 2.1.

369 Mapping of the cross-correlation for each of the study streamgauges was applied using
370 the general approach described in Section 2.3 and in *Archfield and Vogel* [2010]. *Archfield and*
371 *Vogel* [2010] use the Pearson r correlation coefficient to model the cross-correlation across their
372 study region. In this study, the Spearman rho cross-correlation metric is utilized. The Spearman
373 rho cross-correlation metric is a non-parametric measure of cross-correlation that uses the ranks
374 of the data; therefore, it is resistant to outliers and has fewer assumptions than the more
375 commonly used Pearson r correlation coefficient [*Helsel and Hirsch*, 2002]. As described by

376 *Archfield and Vogel* [2010], spherical variogram models were fit for each study streamgauge.
377 Variogram model (eqn. 3) parameters and root-mean-square errors between observed cross-
378 correlations and cross-correlations estimated by the variogram model are shown in table 2. The
379 donor streamgauge and estimated FDC were then used to obtain continuous daily streamflow at
380 the ungauged location, as described in Section 2.3.

381 **3.3. Performance of estimated streamflows**

382 To evaluate the utility of the underlying methods to estimate unregulated, daily
383 streamflow at ungauged locations, a leave-one-out cross validation for 31 study streamgauges
384 (fig. 6) was applied in conjunction with the methods described in Sections 2 and 3.2. These 31
385 study streamgauges were selected because they have observed streamflow covering the entire 44-
386 yr historical period of streamflow estimated by the CRUISE tool. In the leave-one-out cross
387 validation, each of the 31 study streamgauges was assumed to be ungauged and removed from
388 the methods described in Sections 2 and 3.2. The methods were then reapplied without inclusion
389 of the removed site. Using the catchment characteristics of the removed site, daily streamflow
390 was determined and compared to the observed streamflow data at the removed streamgauge. This
391 cross-validation procedure ensured that the comparison of observed and estimated streamflow at
392 each of the study streamgauges represented the truly ungauged case because the streamgauge
393 was not used in any part of the methods development. This procedure was repeated for each of
394 the 31 validation streamgauges to obtain 31 estimated and observed streamflow time series from
395 which to assess the performance of the study methods.

396 Goodness of fit between observed and estimated streamflows was evaluated using the
397 Nash-Sutcliffe efficiency value [*Nash and Sutcliffe*, 1970], which was computed from both the
398 observed and estimated streamflows as well as the natural logarithms of the observed and

399 estimated streamflows (fig. 6A). The natural logarithms of the observed and estimated
400 streamflows were taken to scale the daily streamflow values so that the high and low streamflow
401 values were more equally weighted in the calculation of the efficiency metric. Efficiency values
402 were mapped to determine if there was any spatial bias in the model performance (fig. 6B).
403 Selected hydrographs were also plotted to visualize the interpretation of the efficiency values
404 (figs. 6C-E).

405 The values in figure 4 show that the streamflows estimated by the CRUISE tool generally
406 have good agreement with the observed streamflows at the 31 validation streamgauges. The
407 minimum efficiency computed from the transformed daily streamflows is 0.69 and the maximum
408 value is 0.92 (fig. 6A), with an efficiency value equal to 1 indicating perfect agreement between
409 the observed and estimated streamflows. The efficiency values for the untransformed observed
410 and estimated streamflows range from 0.04 to 0.92 (fig. 6A). Despite this, the CRUISE tool
411 appears to result in high efficiency values across all validation sites (fig. 6). Streamgauges in the
412 northern portion of the basin have lower efficiency values than streamgauges in the middle and
413 southern portions of the basin; however, it should be noted from the hydrographs in figure 4 that
414 the CRUISE tool is able to represent the daily features of the hydrographs at the validation
415 streamgauges even though the efficiency values are relatively lower in the northern portion of the
416 study area. The efficiency values and hydrograph comparisons demonstrate that the CRUISE
417 tool can provide a reasonable representation of natural streamflow time series at ungauged
418 catchments in the basin.

419 **4. Discussion**

420 As described, the software tool can be viewed as a general framework to provide
421 estimates of daily streamflow in a publicly-available, map-based manner. Whereas, the
422 StreamStats user-interface was developed specifically for the CRB, the watershed delineation
423 and catchment characteristic algorithms underlying StreamStats is universally available across
424 the globe through the ArcHydro platform [ESRI, Inc., 2009]. To utilize the ArcHydro platform, a
425 properly networked stream data layer is needed, which uniquely identifies each stream reach and
426 provides such information as flow direction [Reis *et al.*, 2008]. Such a network is freely available
427 for the United States and is termed the National Hydrography Dataset (NHD) [available at:
428 <http://nhd.usgs.gov/>]. It is likely that other regions around the globe already have such a dataset
429 developed. In addition to the stream network, region-wide spatial data layers of catchment
430 characteristics are needed so that these characteristics can be computed at the ungauged location
431 and used to solve the regression equations. If the stream network and spatial data layers of
432 catchment characteristics are readily available, this software framework can be easily applied
433 towards a map-based tool to provide estimates of daily streamflow. The underlying in the macro-
434 enabled spreadsheet can then be customized to the catchment characteristics, fitted regression
435 equations, and fitted variogram models to link with the catchment delineation.

436 There are several limitations to the methods described in the software tool. Notably, the
437 software tool assumes that the topographic surface water divides of the catchment are coincident
438 with the underlying groundwater divides. Therefore, the tool assumes that water draining to the
439 stream location of interest is contained entirely within the topographic catchment divides. For
440 regions dominated by groundwater flow, this assumption may not be valid. The methods
441 underlying the tool also currently do not account for routing, which is an important consideration
442 for large catchment areas whose response to precipitation events may exceed more than a few

443 days. Lastly, the purpose of the software tool is to provide reliable estimates of historical
444 streamflow time series for an ungauged location and non-stationarity is not explicitly considered
445 in the underlying methods. By excluding streamgauges in the methods development that may
446 have been affected by human use such as dams or water withdrawals, the effects of non-
447 stationarity are seemingly minimized; however, no attempt was made to explicitly remove study
448 streamgauges affected by climate non-stationarity in the daily streamflow signal.

449 **5. Summary and conclusions**

450 This paper presents one of the first publicly available, map-based software tools to provide
451 unregulated daily streamflow time series (streamflow not affected by human regulation such as
452 dams or water withdrawals) for any user-selected river location in a particular study region. In
453 this study, the software tool was developed and presented for the Connecticut River Basin – a
454 large river basin located in the northeast United States. For other regions, this study presents an
455 overall framework which can be applied toward development of a region-specific tool to
456 estimate daily streamflow at any user-selected river location. The software tool is available at
457 <http://webdmamrl.er.usgs.gov/s1/sarch/ctrtool/index.html> and requires only an internet
458 connection, a web browser program, and a macro-based spreadsheet program. Furthermore, the
459 underlying data used to develop the tool and the source code are freely-available and adaptable
460 to other regions. Daily streamflow is estimated by a four-part process: 1) delineation of the
461 drainage area and computation of the basin characteristics for the ungauged location, 2) selection
462 of a donor streamgauge, 3) estimation of the daily flow-duration curve at the ungauged location,
463 and 4) use of the donor streamgauge to transfer the flow-duration curve to a time series of daily
464 streamflow. The software tool, when applied to the Connecticut River Basin, provided reliable
465 estimates of observed daily streamflows at 31 validation streamgauges across the basin. This

466 software framework and underlying methods can be used to develop map-based, daily-
467 streamflow estimates needed for water management decisions at ungauged stream locations for
468 this and potentially other regions.

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485 **References**

- 486 Abdulla, F. A., and D. P. Lettenmaier (1997), Development of regional parameter estimation
487 equations for a macroscale hydrologic model, *J. Hydrol.*, 197(1-4), 230-257, ISSN 0022-
488 1694, doi: 10.1016/S0022-1694(96)03262-3.
- 489 Archfield, S. A., and R. M. Vogel, 2010. Map correlation method: Selection of a reference
490 streamgage to estimate daily streamflow at ungauged catchments, *Water Resour. Res.*, 46,
491 W10513, doi:10.1029/2009WR008481.
- 492 Archfield, S., R. Vogel, P. Steeves, S. Brandt, P. Weiskel, and S. Garabedian, 2010. The
493 Massachusetts Sustainable-Yield Estimator: A decision-support tool to assess water
494 availability at ungauged sites in Massachusetts, U.S. Geological Survey Scientific
495 Investigations Report 2009-5227, 41 p. plus CD-ROM.
- 496 Armstrong, D. S., G. W. Parker, and T. A. Richards, 2008. Characteristics and classification of
497 least altered streamflows in Massachusetts, U.S. Geological Survey Scientific
498 Investigations Report, 20075291, 113 p. plus CD-ROM.
- 499 Castellarin, A., G. Galeati, L. Brandimarte, A. Montanari, and A. Brath, 2004. Regional flow-
500 duration curves: reliability for ungauged basins, *Adv. Water Resour.*, 27, 10, 953-965
- 501 ESRI, Inc., 2009. Arc-Hydro Tools - Tutorial, Version 1.3 - January 2009, ESRI, Inc., Redlands,
502 CA, available at http://andersonruhoff.googlepages.com/ArcHydro_Tutorial.pdf.
- 503 Falcone, J. A., D. M. Carlisle, D. M. Wolock, and M. R. Meador, 2010. GAGES: A stream gage
504 database for evaluating natural and altered flow conditions in the coterminous United
505 States, *Ecology*, 91, 612.

- 506 Fennessey, N. M., 1994. A hydro-climatological model of daily streamflow for the northeast
507 United States, Ph.D. dissertation, Tufts University, Department of Civil and
508 Environmental Engineering.
- 509 Helsel, D., and R. Hirsch, 2002. Statistical Methods in Water Resources Techniques of Water
510 Resources Investigations, Book 4, Chapter A3, U.S. Geological Survey.
- 511 Hirsch, R., 1979. Evaluation of some record reconstruction techniques, *Water Resour. Res.*, 15,
512 6, 1781-1790, ISSN 0043-1397.
- 513 Holtschlag, D.J., 2009. Application guide for AFINCH, analysis of flows in networks of
514 channels) described by NHDPlus, U.S. Geological Survey Scientific Investigations
515 Report 2009-5188, 106 p.
- 516 Hughes, D.A., and V.U. Smakhtin, 1996. Daily flow time series patching or extension: a spatial
517 interpolation approach based on flow duration curves: *Hydrolog. Sci. J.*, 41, 6, 851–871.
- 518 Isaaks, E. H., and R. M. Srivastava (1989), *An Introduction to Applied Geostatistics*, first ed.,
519 Oxford University Press, New York.
- 520 Mahoamoud, Y. M., 2008. Prediction of daily flow duration curves and streamflow for ungauged
521 catchments using regional flow duration curves, *Hydrolog. Sci. J.*, 53, 4, 706-724.
- 522 McIntyre, N., H. Lee, H.S. Wheater, A. Young and T. Wagener (2005), Ensemble prediction of
523 runoff in ungauged watersheds *Water Resour. Res.*, 41, W12434, doi:
524 10.1029/2005WR004289.
- 525 Merz, R. and G. Blöschl (2004), Regionalisation of catchment model parameters, *J. Hydrol.*,
526 287(1-4), 95-123, ISSN 0022-1694, doi: 10.1016/j.jhydrol.2003.09.028.

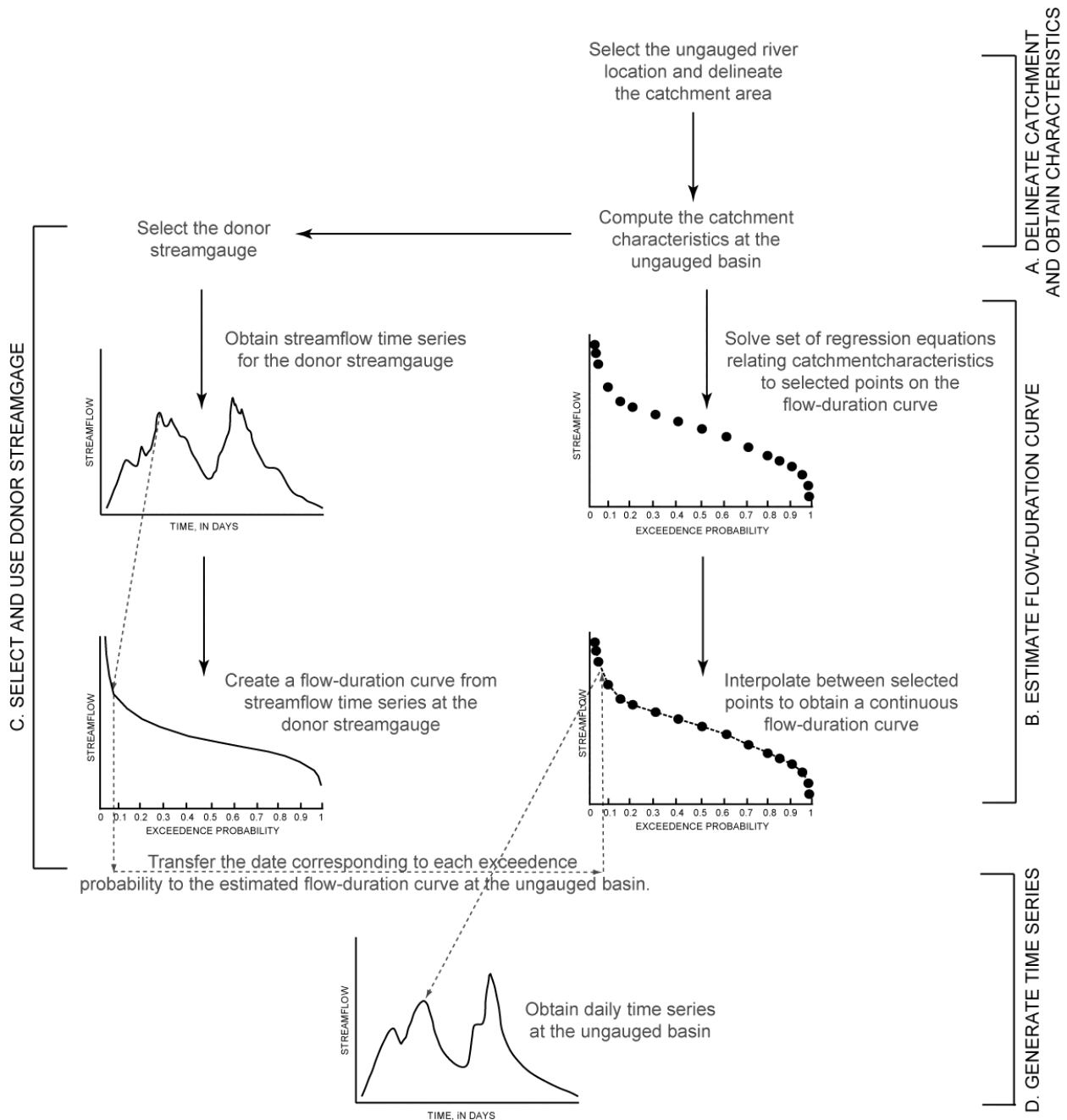
- 527 Nash, J. E., and J. V. Sutcliffe, 1970. River flow forecasting through conceptual models part I - a
528 discussion of principles, *J. of Hydrol.*, 10, 3, 282–290.
- 529 Patil, S. and Stieglitz, M.: Controls on hydrologic similarity: role of nearby gauged catchments
530 for prediction at an ungauged catchment, *Hydrol. Earth Syst. Sci.*, 16, 551-562,
531 doi:10.5194/hess-16-551-2012, 2012.
- 532 Oudin, L., V. Andréassian, C. Perrin, C. Michel, and N. Le Moine (2008), Spatial proximity,
533 physical similarity, regression and ungauged catchments: A comparison of
534 regionalization approaches based on 913 French catchments, *Water Resour. Res.*, 44,
535 W03413, doi:10.1029/2007WR006240.
- 536 Oudin, L., A. Kay, V. Andréassian, and C. Perrin (2010), Are seemingly physically similar
537 catchments truly hydrologically similar?, *Water Resour. Res.*, 46, W11558,
538 doi:10.1029/2009WR008887.
- 539 Parajka, J., R. Merz, and G. Blöschl (2005), A comparison of regionalisation methods for
540 catchment model parameters. *Hydrol. Earth Syst. Sc.*, 9(3), 157-171.
- 541 Poff, N.L., J.D. Allen, M.B. Bain, J.R. Karr, K.L. Prestgaard, B.D. Richter, R.E. Sparks, and
542 J.C. Stromberg, 1997. The natural-flow regime—A paradigm for river conservation and
543 restoration: *Bioscience*, 47, 769–784.
- 544 Poff N.L., Richter B., Arthington A., Bunn S.E., Naiman R.J., Kendy E., Acreman M., Apse C.,
545 Bledsoe B.P., Freeman M., Henriksen J., Jacobsen R.B., Kennen J., Merritt D.M.,
546 O’Keefe J., Olden J., Rogers K., Tharme R.E., Warner A., 2010, The ecological limits of
547 hydrologic alteration (ELOHA): a new framework for developing regional environmental
548 flow standards, *Freshwater Biology* 55: 147–170.

- 549 Reichl J, Western A., McIntyre N and Chiew F. (2009), Optimisation of a similarity measure for
550 estimating ungauged streamflow, *Water Resour. Res.*, doi:10.1029/2008WR007248.
- 551 Ries, K. G., III; Guthrie, J. G.; Rea, A. H.; Steeves, P. A.; Stewart, D. W., 2008. StreamStats: A
552 Water Resources Web Application, U.S. Geological Survey Fact Sheet 2008-3067, 6 p.,
553 available on line at <http://pubs.usgs.gov/fs/2008/3067/>.
- 554 Seibert, J. (1999) Regionalization of parameters for a conceptual rainfall–runoff model, *Agric.*
555 *For. Met.*, 98, 279–293.
- 556 Shu, C., and T. B. M. J. Ouarda, 2012, Improved methods for daily streamflow estimates at
557 ungauged sites, *Water Resour. Res.*, 48, W02523, doi:10.1029/2011WR011501.
- 558 Skøien, J. O., and G. Blöschl, 2007. Spatiotemporal topological kriging of runoff time series,
559 *Water Resour. Res.*, 43, 9, doi:10.1029/2006WR005760.
- 560 Smakhtin, V. U., 1999. Generation of natural daily flow time-series in regulated rivers using a
561 non-linear spatial interpolation technique, *Regul. Rivers: Res. Mgmt*, 15, 311-323.
- 562 Smakhtin V.U. and N. Eriyagama, 2008. Developing a software package for global desktop
563 assessment of environmental flows. *Environ. Model. Softw.* 23, 12, December 2008.
564 1396-1406. doi:10.1016/j.envsoft.2008.04.002.
- 565 Williamson, T.N., K.R. Odom, J.K. Newson, A.C. Downs, H.L. Nelson Jr., P.J. Cinotto and
566 M.A. Ayers, 2009. The Water Availability Tool for Environmental Resources,
567 WATER)—A water-budget modeling approach for managing water-supply resources in
568 Kentucky—Phase I—Data processing, model development, and application to non-karst
569 areas: U.S. Geological Survey Scientific Investigations Report 2009–5248, 34 p.

570 Zhang, Y., and F. H. S. Chiew, 2009. Relative merits of different methods for runoff predictions
571 in ungauged catchments, *Water Resour. Res.*, 45, W07412, doi:10.1029/2008WR007504.

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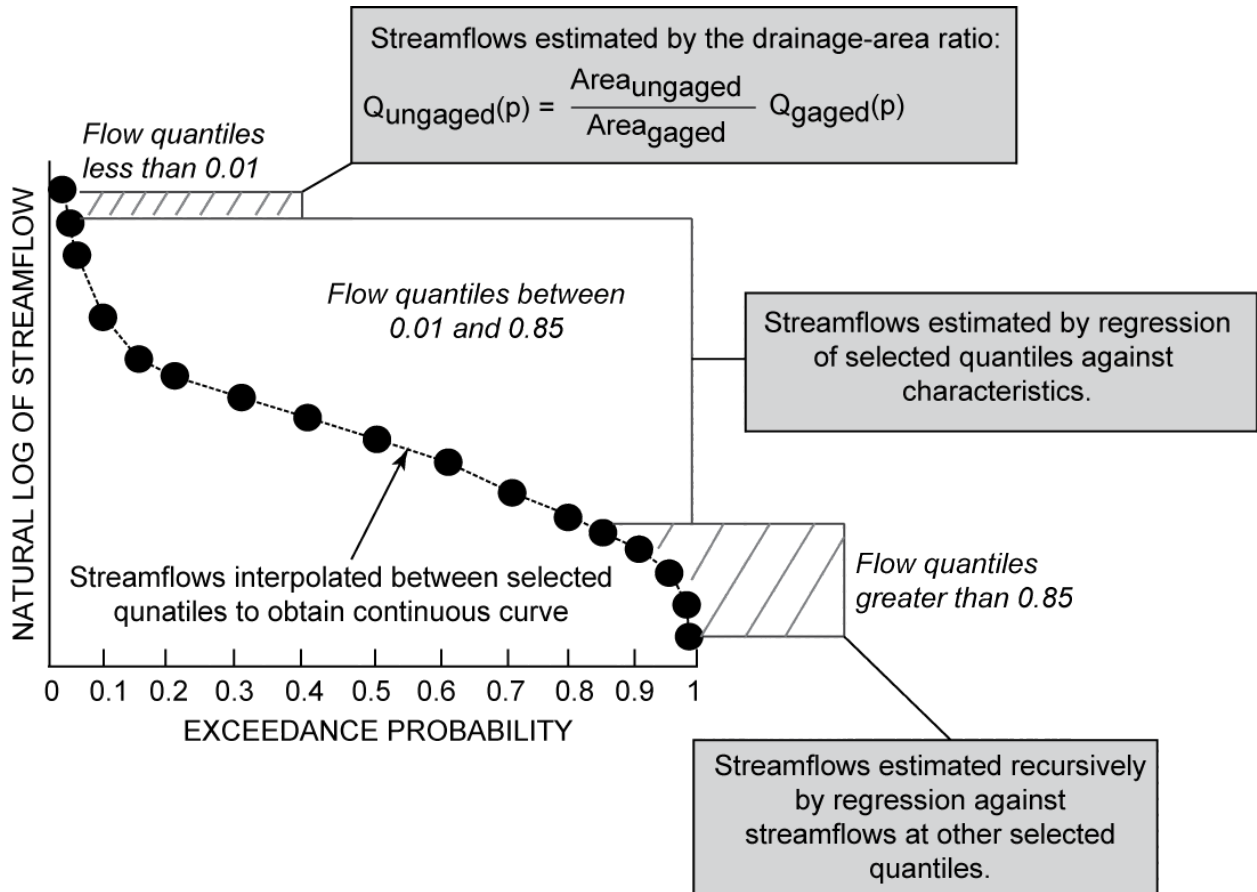


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576 Figure 1. Diagram of the process to estimate unregulated, daily streamflow at ungauged
 577 locations. An ungauged river location is selected and the catchment characteristics are computed
 578 (A). The flow-duration curve is then estimated using regression relations between the catchment
 579 characteristics and selected points on the flow-duration curve (B). A donor streamgauge is then
 580 selected (C) and used to transfer the estimated flow-duration curve into a time series of daily
 581 streamflow at the ungauged location (D).

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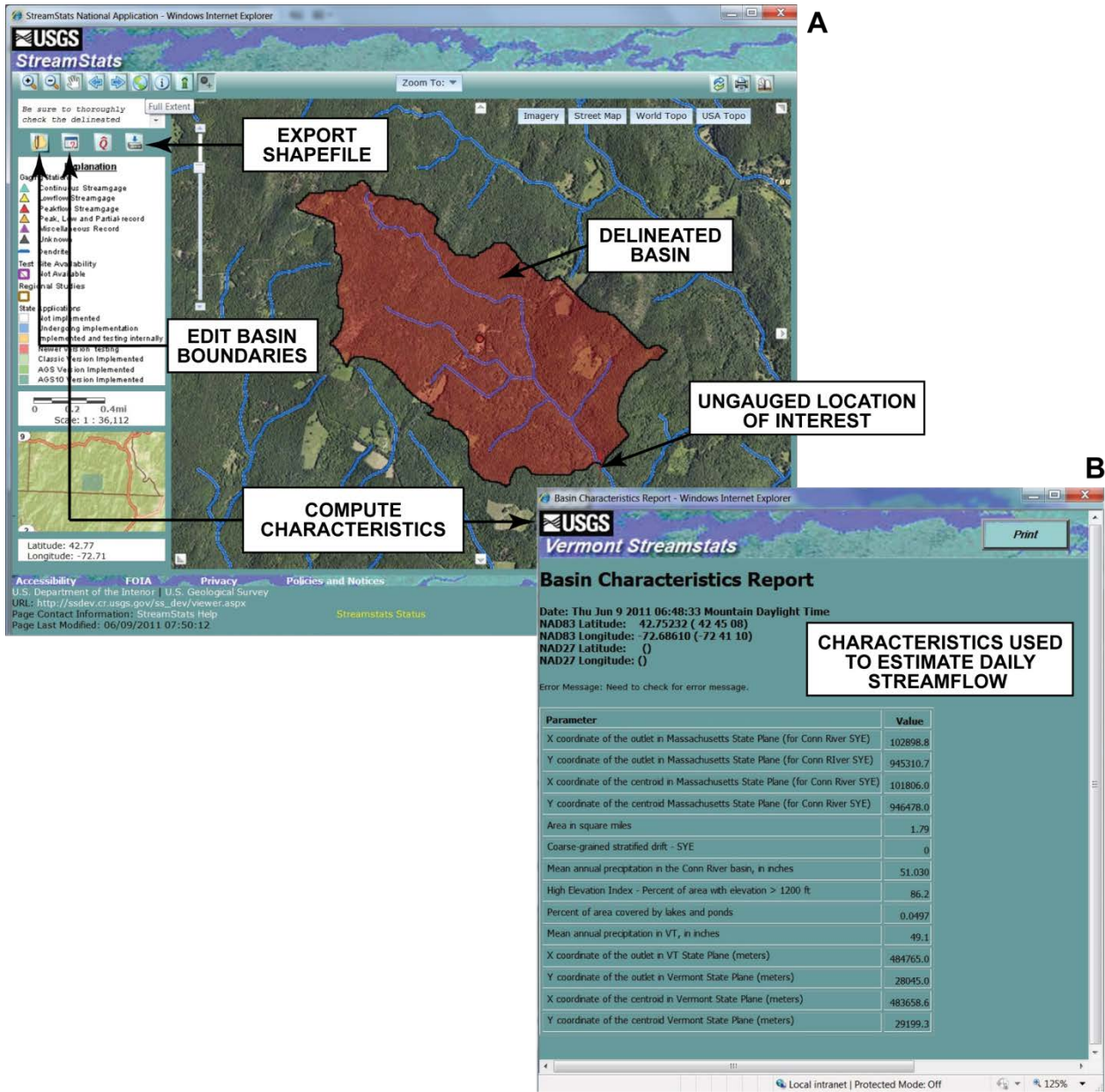


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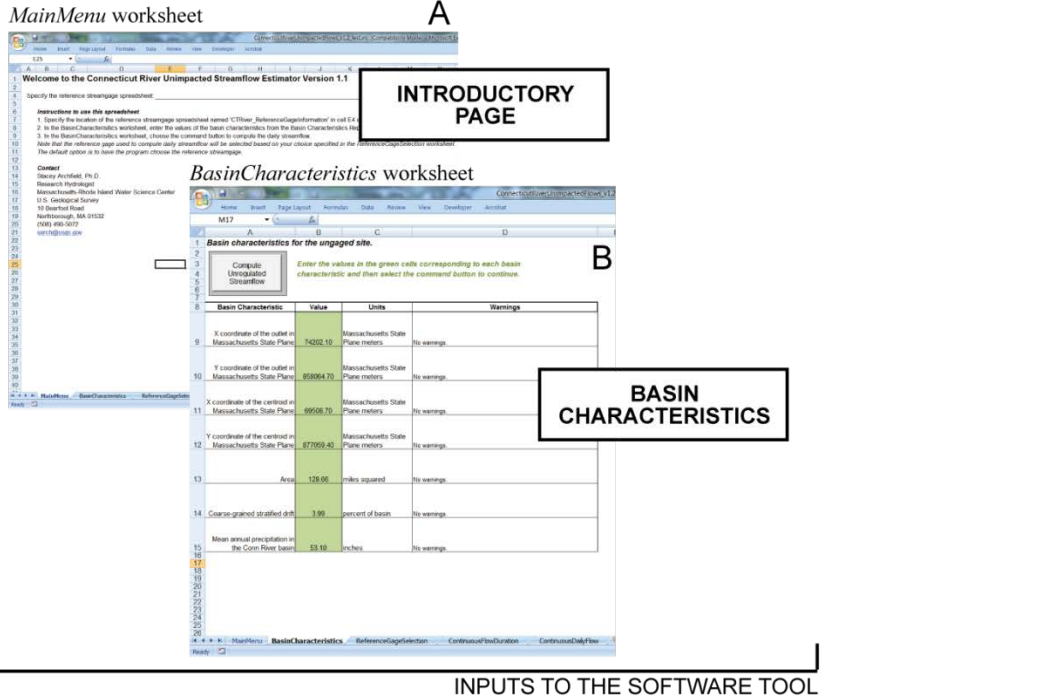
585 Figure 2. Diagram showing the methods used to estimate a continuous, daily flow duration at an
 586 ungauged location.

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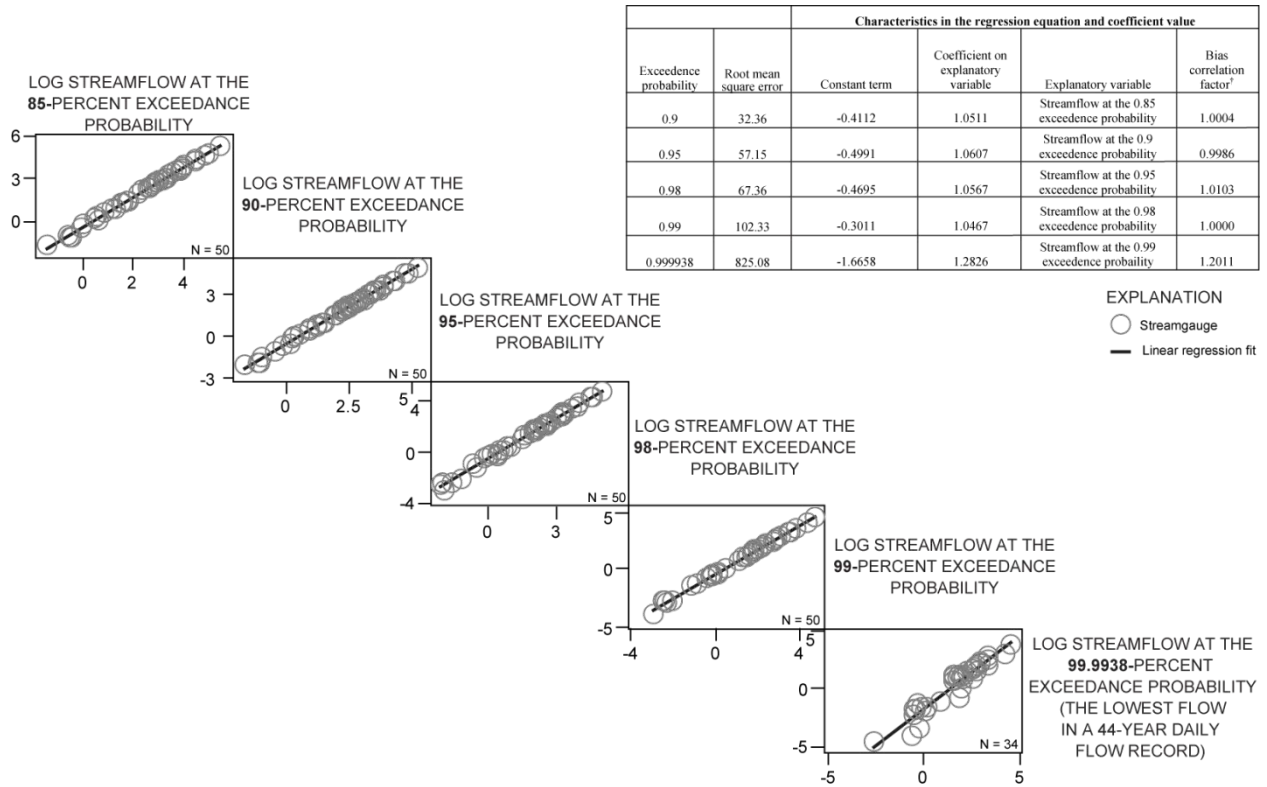
Figure 3. Screen captures showing the map portion of the software tool used to estimate daily, unregulated time series. The program delineates a catchment (or basin, as named in the tool) for the ungauged location selected by the user (A) and summarizes the catchment characteristics (B). The user also has the option to export the shapefile of the delineated catchment or edit the catchment boundaries (A).



OUTPUT FROM THE SOFTWARE TOOL

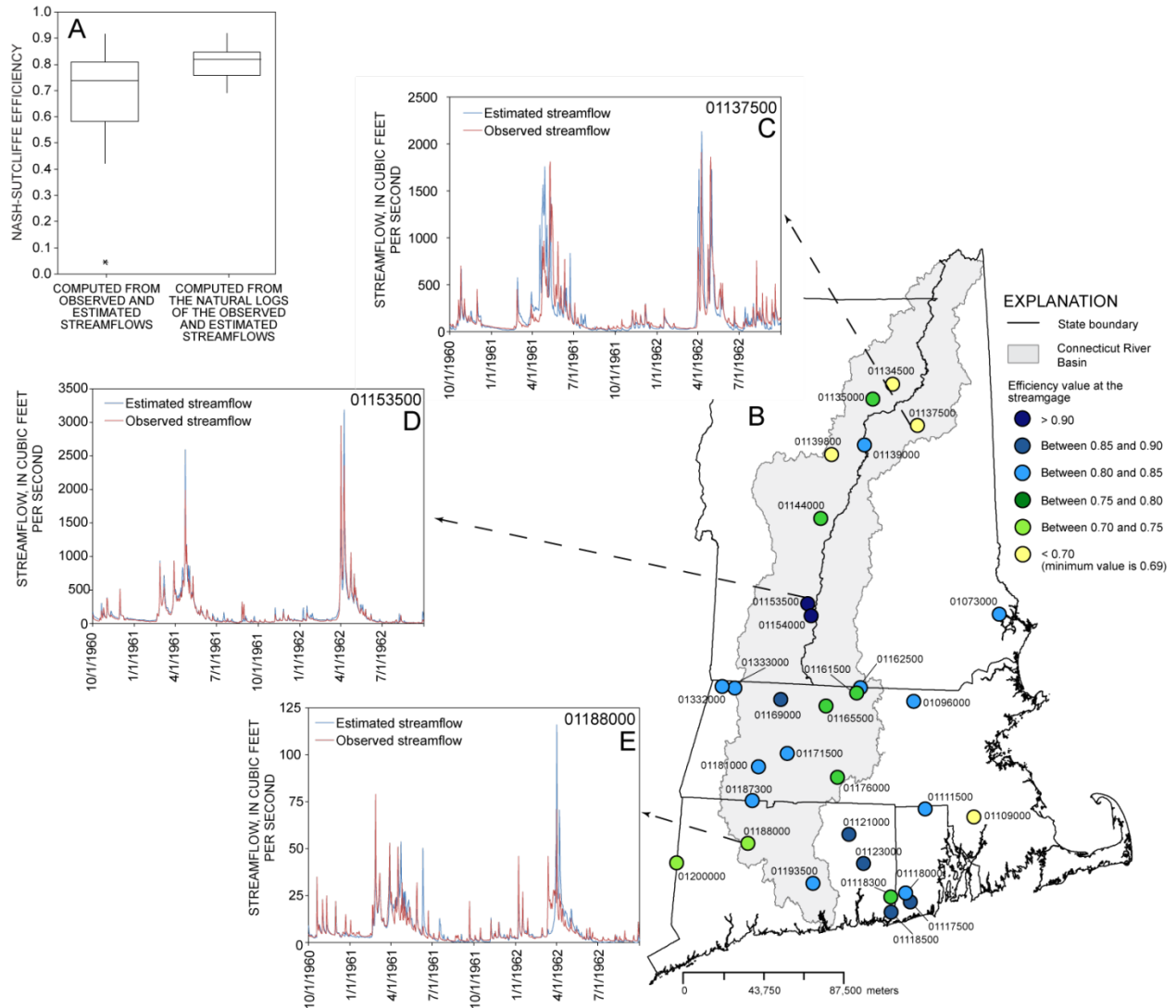
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Figure 4. Screen captures showing the spreadsheet portion of the software tool used to estimate daily, unregulated streamflow time series. After reading the introductory page (A), the user inputs the catchment characteristics (or basin characteristics, as named in the tool) into the BasinCharacteristics worksheet (B). The spreadsheet program then selects the donor streamgauge (C) and generates the flow-duration curve (D) and the daily streamflow time series (E).



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Figure 5. Relations between streamflows at the 0.9, 0.95, 0.98, 0.99 and 0.999938 exceedence probabilities and the corresponding goodness of fit values resulting from a least-squares linear regression to estimate streamflows recursively from other streamflow quantiles. (†, Bias correction factor computed from *Duan* (1983).)



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614 Figure 6. Range of efficiency values computed between the observed and estimated streamflows
 615 at the 31 validation streamgauges (A), spatial distribution of efficiency values resulting from log-
 616 transformed observed and estimated daily streamflow at 31 validation streamgauges (B) and
 617 selected hydrographs of observed and estimated streamflow for the period from October 1, 1960
 618 through September 30, 1962 (C-E). The boxplot (A) shows the median, interquartile ranges and
 619 the upper and lower limits (defined as 75th percentile \pm 1.5 * (75th percentile - 25th percentile)).
 620 Values outside of the upper and lower limits are shown as an asterisk.

621 Table 1. List of streamgauges used to estimate unregulated, daily streamflow at ungauged
 622 locations in the Connecticut River Basin.

Station Number	Station name	Period of record
01073000	Oyster River near Durham, NH	December 15, 1934 - December 31, 2004
01082000	Contocook River at Peterborough, NH	July 7, 1945 - September 30, 1977
01084500	Beard Brook near Hillsboro, NH	October 1, 1945 - September 30, 1970
01085800	West Branch Warner River near Bradford, NH	May 22, 1962 - September 30, 2004
01086000	Warner River at Davisville, NH	October 1, 1939 - September 30, 1978
01089000	Soucook River near Concord, NH	October 1, 1951 - September 30, 1987
01091000	South Branch Piscataquog River near Goffstown, NH	July 27, 1940 - September 30, 1978
01093800	Stony Brook tributary near Temple, NH	May 1, 1963 - September 30, 2004
01096000	Squannacook River near West Groton, MA	October 1, 1949 - December 31, 2004
01097300	Nashoba Brook near Acton, MA	July 26, 1963 - December 31, 2004
01105600	Old Swamp River near South Weymouth, MA	May 20, 1966 - July 24, 2006
01105730	Indian Head River at Hanover, MA	July 8, 1966 - July 24, 2006
01106000	Adamsville Brook at Adamsville, RI	October 1, 1940 - September 30, 1978
01108000	Taunton River near Bridgewater, MA	October 1, 1929 - April 23, 1976
01109000	Wading River near Norton, MA	June 1, 1925 - December 31, 2004
01111300	Nipmuc River near Harrisville, RI	March 1, 1964 - September 30, 1991
01111500	Branch Riverb at Forestdale, RI	January 24, 1940 - December 31, 2004
01117500	Pawcatuck River at Wood River Junction, RI	December 7, 1940 - December 31, 2004
01118000	Wood River Hope Valley, RI	March 12, 1941 - December 31, 2004
01118300	Pendleton Hill Brook near Clarks Falls, CT	October 1, 1958 - December 31, 2004
01118500	Pawtucket River at Westerly, RI	November 27, 1940 - December 31, 2004
01120000	Hop Brook near Columbia, CT	October 1, 1932 - October 6, 1971
01121000	Mount Hope River near Warrentville, CT	October 1, 1940 - December 31, 2004
01123000	Little River near Hanover, CT	October 1, 1951 - December 31, 2004
01127880	Big Brook Near Pittsburg Nh	December 1, 1963 - January 1, 1984
01133000	East Branch Passumpsic River near East Haven, VT	October 1, 1948 - September 1, 1979
01133500	Passumpsic River near St. Johnsbury, VT	May 1, 1909 - July 1, 1919
01134500	Moose River at Victory, VT	January 1, 1947 - May 12, 2010
01135000	Moose River at St. Johnsbury, VT	August 1, 1928 - September 1, 1983
01137500	Ammonoosuc River at Bethlehem Junction, NH	August 1, 1939 - May 12, 2010
01139000	Wells River at Wells River, VT	August 1, 1940 - May 12, 2010
01139800	East Orange Branch at East Orange, VT	June 1, 1958 - May 12, 2010
01140000	South Branch Waits River near Bradford, VT	April 1, 1940 - September 1, 1951
01141800	Mink Brook near Etna, NH	August 1, 1962 - September 1, 1998
01142000	White River near Bethel, VT	June 1, 1931 - September 1, 1955
01144000	White River at West Hartford, VT	October 1, 1951 - May 12, 2010
01145000	Mascoma River at West Canaan, NH	July 1, 1939 - September 1, 1978
01153500	Williams River near Rockingham, VT	June 1, 1940 - September 1, 1984
01154000	Saxtons River at Saxtons River, VT	June 20, 1940 - September 30, 1982
01155000	Cold River at Drewsville, NH	June 23, 1940 - September 30, 1978
01161500	Tarbell Brook near Winchendon, MA	May 29, 1916 - September 6, 1983
01162500	Priest Brook near Winchendeon, MA	October 1, 1936 - December 31, 2004
01165500	Moss Brook at Wendell Depot, MA	June 1, 1916 - September 30, 1982
01169000	North River at Shattuckville, MA	December 13, 1939 - December 31, 2004
01169900	South River near Conway, MA	January 1, 1967 - December 31, 2004
01171500	Mill River at Northampton, MA	November 18, 1938 - December 31, 2004
01174000	Hop Brook near New Salem, MA	November 19, 1947 - September 30, 1982
01174900	Cadwell Creek near Belchertown, MA	July 13, 1961 - September 30, 1997
01175670	Sevenmile River near Spencer, MA	December 1, 1960 - December 31, 2004
01176000	Quaboag River at West Brimfield, MA	August 19, 1912 - December 31, 2004
01180000	Sykes Brook at Knightville, MA	June 20, 1945 - July 18, 1974
01181000	West Branch Westfield at Huntington, MA	September 1, 1935 - December 31, 2004
01187300	Hubbard River near West Hartland, CT	August 4, 1959 - December 31, 2004
01187400	Valley Brook near West Hartland, CT	October 1, 1940 - September 30, 1972

01188000	Burlington Brook near Burlington, CT	October 1, 1931 - December 31, 2004
01193500	Salmon River near East Hampton, CT	October 1, 1928 - December 31, 2004
01194500	East Branch Eightmile River near North Lyme, CT	October 1, 1937 - October 6, 1981
01198000	Green River near Great Barrington, MA	October 1, 1951 - September 30, 1971
01198500	Blackberry River at Canaan, CT	October 1, 1949 - October 20, 1971
01199050	Salmon Creek at Lime Rock, CT	October 1, 1961 - December 31, 2004
01200000	Ten Mile River, CT	October 1, 1930 - April 4, 1988
01332000	North Branch Hoosic River at North Adams, MA	June 22, 1931 - September 30, 1990
01333000	Green River at Williamstown, MA	September 20, 1949 - December 31, 2004

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625 Table 2. Number of streamgauges, goodness of fit values, explanatory variables, and estimated
 626 regression parameters for streamflow quantiles estimated from catchment characteristics using
 627 multiple least squares regression.

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629 [†, Bias correction factor computed from *Duan* (1983)]

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Exceedence probability	General regression information		Estimated regression coefficients					
	Number of stream-gauges used to develop regression equation	Percent root mean square error	Constant term	Drainage area	Average annual precipitation.	Percent of basin that is underlain by sand and gravel deposits	Y-location of the basin centroid	Bias correlation factor [†]
0.02	51	1.49	-26.5758	0.9590	2.3262	0	1.4462	1.0103
0.05	51	0.62	-19.3148	0.9775	1.7521	0	1.0457	1.0023
0.1	51	0.73	-2.1224	0.9982	0.9106	0	0	1.0015
0.15	51	0.60	-2.9777	1.0050	1.0589	0	0	0.9972
0.2	51	0.86	-3.6935	1.0037	1.1920	0	0	0.9957
0.25	51	1.32	-4.6684	1.0110	1.3890	0	0	0.9950
0.3	51	1.86	-5.5394	1.0137	1.5688	0	0	0.9950
0.4	51	3.00	-6.7591	1.0206	1.8000	0	0	0.9960
0.5	51	3.86	-7.6803	1.0269	1.9577	0	0	0.9982
0.6	50	4.40	-8.3466	1.0184	2.0123	0.0804	0	1.0184
0.7	50	6.61	-8.4500	1.0480	1.9072	0.0949	0	1.0278
0.75	50	9.24	-8.7450	1.0655	1.9073	0.1040	0	1.0243
0.8	50	13.58	-9.1085	1.0951	1.9008	0.1251	0	1.0379
0.85	50	21.20	-9.3154	1.1239	1.8480	0.1515	0	1.0565

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632 Table 3. Variogram model parameters and root-mean-square error value resulting from a leave-
 633 one-out cross validation of the variogram models.
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Station Number	Variance parameter	Range parameter	Root-mean-square error
01073000	0.0411	697945.4362	0.0399
01085800	0.0115	267272.8077	0.0388
01089000	0.0112	269793.6063	0.0462
01093800	0.0147	267272.7273	0.0416
01096000	0.0389	607472.9297	0.0469
01097300	0.0261	374218.0554	0.0488
01105600	0.0621	557922.7912	0.0488
01105730	0.0677	547625.3299	0.0447
01109000	0.0588	489036.3840	0.0487
01111300	0.0444	435141.4397	0.0470
01111500	0.0649	664951.4696	0.0452
01117500	0.0964	846131.5260	0.0548
01118000	0.0680	547336.8809	0.0456
01118300	0.0541	478962.6030	0.0421
01118500	0.1548	1255724.6703	0.0469
01121000	0.0440	467562.3777	0.0442
01123000	0.0487	476803.1943	0.0457
01127880	0.0475	451474.0307	0.0241
01134500	0.0585	593052.1148	0.0491
01135000	0.0828	885228.5293	0.0574
01137500	0.0421	469510.7730	0.0194
01139000	0.0354	483627.8140	0.0309
01139800	0.0224	369057.2000	0.0255
01141800	0.0116	267272.7273	0.0264
01144000	0.0155	302281.0433	0.0328
01153500	0.0135	267272.7081	0.0409
01154000	0.0129	213818.1818	0.0470
01161500	0.0187	337256.6753	0.0447
01162500	0.0176	291135.1932	0.0436
01165500	0.0291	445510.0450	0.0417
01169000	0.0190	317944.4643	0.0402
01169900	0.0245	398758.9250	0.0442
01171500	0.0310	393869.0688	0.0454
01174000	0.0249	330495.4703	0.0443
01174900	0.0321	412573.1453	0.0430
01175670	0.0366	486730.2368	0.0463
01176000	0.0357	526274.7021	0.0498
01181000	0.0333	502453.4839	0.0426
01187300	0.0566	846080.6046	0.0422
01188000	0.0313	454196.0564	0.0427
01193500	0.0412	435477.5668	0.0445
01199050	0.0212	368184.1116	0.0414
01200000	0.0401	538909.4325	0.0444
01332000	0.0114	175180.2029	0.0370
01333000	0.0148	267272.7273	0.0341

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