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# A framework for hydrologic classification with a review of methodologies and applications in ecohydrology

Julian D. Olden,<sup>1\*</sup> Mark J. Kennard,<sup>2</sup> Bradley J. Pusey<sup>2</sup>

<sup>1</sup> School of Aquatic and Fishery Sciences, University of Washington, Box 355020, Seattle, WA 98195, United States

<sup>2</sup> Tropical Rivers and Coastal Knowledge, National Environmental Research Program Northern Australia Hub and Australian Rivers Institute, Griffith University, Nathan, Queensland, 4111, Australia

## ABSTRACT

Hydrologic classification is one of the most widely applied tasks in ecohydrology. During the last two decades considerable effort has gone into analysis and development of methodological approaches to hydrologic classification. We review the process of hydrologic classification, differentiating between an approach based on deductive reasoning using environmental regionalization, hydrologic regionalization and environmental classification whereby environmental variables assumed to be key determinants of hydrology are analyzed, and one based on inductive reasoning using streamflow classification whereby hydrologic data is analyzed directly. We explore past applications in ecohydrology highlighting the utility of classifications in the extrapolation of hydrologic information across sparsely gauged landscapes, the description of spatial patterns in hydrologic variability, aiding water resource management, and in the identification and prioritization of conservation areas. We introduce an overarching methodological framework that depicts critical components of the classification process and summarize important advantages and disadvantages of commonly used statistical approaches to characterize and predict hydrologic classes. Our hope is that researchers and managers will be better informed when having to make decisions regarding the selection and proper implementation of methods for hydrologic classification in the future.

**KEY WORDS:** dams; flow regime; environmental flow; river regulation; hydrologic metric

30 Hydrologic classification is the process of systematically arranging streams or rivers into groups  
31 that are most similar with respect to the characteristics of their flow regime. The classification of  
32 flow regimes continues to play an important role in ecohydrology as a means to understand  
33 riverine flow variability (e.g. Mosley, 1981; Haines et al., 1988; Poff, 1996; Harris et al., 2000;  
34 Snelder et al., 2009a), explore the influence of streamflow on biological communities and  
35 ecological processes (e.g. Jowett and Duncan, 1990; Poff and Allan, 1995; Snelder et al., 2004;  
36 Kennard et al., 2007), aid hydrologic modeling in regionalization analyses (e.g. Tasker, 1982;  
37 Nathan and McMahon, 1990; Wagener et al., 2007), inventory hydrologic types for water  
38 resource management (e.g. Snelder and Biggs, 2002; Wolock et al., 2004; Arthington et al.,  
39 2006), and prioritize conservation efforts for freshwater ecosystems (e.g. Nei et al., 2007;  
40 Snelder et al., 2007). The flow regime is a key determinant of freshwater biodiversity patterns  
41 and ecological processes (Poff et al., 1997; Bunn and Arthington, 2002). Hydrologic  
42 classification has therefore been identified as a critical process in environmental flow  
43 assessments by providing a spatially explicit understanding of how much and when flow regimes  
44 vary among rivers and regions (Kennard et al., 2010b; Poff et al., 2010). Consequently,  
45 hydrologic classification is viewed as both an organizing framework and scientific tool for river  
46 research and management.

47 Challenged by the need to quantify flow similarities among rivers and map their distribution  
48 across the landscape, ecohydrologists have turned to a bewildering (and expanding) array of  
49 protocols using an equally diverse set of statistical approaches to conduct their hydrologic  
50 classification. As a result, several groups of methods are in use, and to-date no single approach  
51 has demonstrated universally accepted results. This is not entirely surprising given that despite  
52 the growing use of hydrologic classification in ecohydrology, little guidance and no synthesis on  
53 this topic has been published in the literature, and the purposes for conducting a classification  
54 vary greatly. Herein, we provide a systematic review of the process of hydrologic classification  
55 by (i) reviewing two broad classification approaches according to deductive reasoning using  
56 environmental regionalization, hydrologic regionalization and environmental classification  
57 whereby environmental variables assumed to be key determinants of hydrology are analyzed,  
58 and inductive reasoning using streamflow classification whereby hydrologic data is analyzed

59 directly; (ii) exploring past applications in ecohydrology; (iii) introducing a unifying  
60 methodological framework that depicts critical components of the classification process; and (iv)  
61 summarizing important advantages and disadvantages of commonly used statistical approaches  
62 to characterize and predict hydrologic classes. The intention of our study is to inform  
63 ecohydrologists about the critical elements of hydrologic classification, including a discussion of  
64 the important considerations and techniques available to them.  
65

## 66 APPROACHES TO HYDROLOGIC CLASSIFICATION

67 Hydrologic classification refers to a broad suite of methods that seek to characterize similarities  
68 in hydrologic properties among locations. We recognize two broad approaches that either  
69 classify locations according to attributes describing those aspects of the environment assumed to  
70 influence streamflow (the deductive approach consisting of environmental regionalization,  
71 hydrologic regionalization and environmental classification) and those that classify the emergent  
72 properties of the discharge time series (the inductive approach or streamflow classification)  
73 (Figure 1).

74 Deductive approaches to hydrologic classification are commonly used when the objective is  
75 to describe and quantify the spatial variation in flow regime attributes across broad spatial scales  
76 but where the availability of gauged or modeled hydrologic data is scarce or absent. The  
77 availability of high quality hydrologically-relevant environmental datasets (e.g. describing  
78 climate, catchment topography, soils and geology, vegetation and land use) makes deductive  
79 reasoning an appealing approach to defining spatial similarities and differences in perceived  
80 hydrologic characteristics. There are limits, however, in the particular facets of the flow regime  
81 able to be accurately quantified by this approach. Poor data quality (e.g. soil and geology) and  
82 limited understanding of hydrologic processes (e.g. groundwater-surface water connectivity) in  
83 many regions means that the ability to accurately characterize spatial variation in low flow  
84 magnitude and duration (for example) is often precluded using deductive environmental  
85 classifications.

86 Inductive approaches to hydrologic classification are typically conducted using various  
87 attributes describing different components of the riverine flow regime. This approach has the  
88 advantage of being based on direct measures of hydrology (rather than indirect environmental

89 surrogates for hydrology) but has a number of limitations including the often limited spatial  
90 coverage of stream gauges within the river network and the notoriously variable quality and  
91 quantity of discharge data available for each gauge (Kennard et al., 2010a). Key characteristics  
92 and examples of deductive and inductive approaches to hydrologic classification are presented in  
93 more detail below.

94

## 95 Deductive Approaches

### 96 Environmental regionalization

97 Environmental regionalization is commonly used to provide a spatial representation of similarity,  
98 whereby contiguous or non-contiguous regions are considered homogeneous with respect to  
99 certain environmental characteristics at a particular scale (Bryce and Clarke, 1996; Loveland and  
100 Merchant, 2004). This approach is often developed because it is not necessarily reliant on  
101 empirical flow data and can be carried out using existing maps and spatial databases (e.g. Bailey,  
102 1996; Omernik, 2004). Geographically contiguous regions, such as river basins, have been used  
103 to group streams assumed to have similar hydrologic characteristics (Table 1), although there is  
104 ample evidence that flow regimes vary greatly within river basins (Poff et al., 2006; Kennard et  
105 al., 2010b). Despite the appeal and advantages of estimating hydrologic similarity based on an  
106 environmental regionalization approach, streams and rivers within the same region (whether  
107 contiguous such as river basins or non-contiguous such as hydro-regions) are not guaranteed to  
108 be hydrologically homogenous. Kennard et al. (2010b) showed that flow regime classification  
109 of stream gauges in Australia did not correspond well to membership based on a suite of  
110 biophysical classifications schemes, including major drainage basins, freshwater ecoregions, and  
111 Köppen climate divisions. Similarly, Carlisle et al. (2010) found that the environmental drivers  
112 of streamflow vary substantially even within relatively homogenous hydrologic regions of the  
113 United States.

114

### 115 Hydrologic regionalization

116 The regionalization of hydrologic models has a long history of use in attempting to extend  
117 insights gained from well-gauged regions to ungauged or sparsely gauged regions or rivers (e.g.  
118 Tasker, 1982; Nathan and McMahon, 1990; Vogel et al., 1999; Chiang et al., 2002; Merz and

119 Bloeschl, 2004; Wagener et al., 2007). The common approach to hydrologic regionalization in  
120 ungauged basins is to delineate geographic areas of similar streamflow pattern, use regression to  
121 relate catchment environmental characteristics to hydrologic metrics describing the flow regime  
122 within these areas, and assess model reliability. Typically, only specific components of the flow  
123 regime are included, such as flood and low flow frequency (e.g. Wiltshire, 1986; Nathan and  
124 McMahon, 1990; but see Sanborn and Bledsoe, 2006). By dividing a study area into  
125 homogeneous groups that are considered to exhibit similar hydrologic characteristics, hydrologic  
126 metrics may be extrapolated with more precision, and regionalization models based on  
127 catchment characteristics may be used with greater confidence. In addition, some explanatory  
128 factors (e.g., orographic effects, geology) are not well represented by continuous variables with  
129 monotonic relation to flow, so classification prior to regionalization will likely improve the  
130 ability to extrapolate hydrologic characteristics. Often regionalization groupings encompassed  
131 geographically contiguous areas (e.g. Mosley, 1981; Hughes, 1987; Wagener et al., 2007).

132

### 133 Environmental classification

134 Environmental classification (also termed environmental domain analysis – Mackey et al., 2007)  
135 defines classes based on physical and climatic attributes that are assumed to broadly produce  
136 similar hydrological responses in stream systems. This represents a deductive approach to  
137 hydrologic classification that is often geographically-independent and depicted by a spatial  
138 mosaic of hydrologic types across the landscape (Detenbeck et al., 2000). An advantage of this  
139 approach is that it is not reliant on an extensive spatial coverage of stream gauges to characterize  
140 flow regimes. Instead, spatially comprehensive environmental datasets are often readily  
141 available (e.g. in a Geographic Information System) and suitable to the task. Numerous  
142 physical-based or geomorphic classifications of rivers have been conducted, including those  
143 based on similar topography, surficial geology and climate (e.g. Kondolf, 1995; Wolock et al.,  
144 2004; Buttle, 2006; Abell et al., 2008; Stein et al., 2009; Sawicz et al., 2011), as well as  
145 combined hydro-geomorphic typologies (e.g. Snelder and Biggs, 2002; Snelder et al., 2005;  
146 Schmitt et al., 2007, reviewed in Kondolf et al., 2003) (Table 1). We discuss two examples  
147 below.

148 The concept of hydrologic landscape regions was introduced by Winter (2001) and  
149 developed by Wolock et al. (2004) to describe non-contiguous areas for the United States that

150 reflected aggregated river basins sharing similar environmental factors (e.g. climate, soils,  
151 geology, topography) known to influence streamflow. According to this classification, a  
152 fundamental hydrologic landscape unit could be defined according to: (a) the movement of  
153 surface water, which is controlled by the slopes and permeability of the landscape; (b) the  
154 movement of ground water, which is controlled by the hydraulic characteristics of the geologic  
155 framework; and (c) atmosphere-water exchange, which is controlled by climate. Using  
156 multivariate ordination and cluster analysis, Wolock et al. (2004) assigned membership of nearly  
157 44,000 small (ca. 200 km<sup>2</sup>) watersheds in the United States to 20 hydrologic regions based on  
158 similarities in land-surface form, geologic texture, and climate characteristics (Figure 2). The  
159 hydrologic landscape region and similar concepts have proven useful in ecohydrology because  
160 they are founded on sound physical principles, yet this framework has only rarely been tested  
161 against regional hydrologic variables. Santhi et al. (2008) demonstrated that the classification  
162 approach has merit in predicting regional variations in baseflow, and Carlisle et al. (2010) found  
163 that stratification by hydrologic landscape regions improved models predicting hydrologic  
164 metrics from watershed characteristics. By contrast, McManamay et al. (2011) reported that  
165 hydrologic landscape regions showed little concordance with the hydrologic classes of Poff  
166 (1996; see below) for the continental United States, and explained < 30% of the overall  
167 variability in the hydrologic metrics.

168 A similar framework is represented by the River Environment Classification (REC) scheme  
169 for New Zealand (Snelder and Biggs, 2002). This classification is represented by a mapped  
170 hydro-geomorphic topology of rivers based on a combination of watershed climate and  
171 topography, which are assumed to be the dominant causes of variation in hydrologic character at  
172 a variety of spatial scales (Figure 3). In support of this approach, Snelder et al. (2005) found that  
173 the REC explained statistically significant amounts of variation in 13 hydrologic metrics.

174 Specifying a-priori the boundaries between classes (i.e. a ‘top-down’ approach to  
175 environmental classification) has been criticized (e.g. O’Keefe and Uys, 2000; Stein et al., 2009)  
176 as it assumes all possible classes are already known. A ‘bottom-up’ approach to the  
177 environmental classification may be preferable as it results in classes that are an emergent  
178 property of the data and reflect the shared similarities of key attributes (Mackey et al., 2007);  
179 assuming that the modeled data is representative of the total variation that exists. Although there  
180 are still subjective choices as to environmental attributes, weightings, classificatory strategy and

181 numbers of groups to include in the classification process, these decisions are explicit and  
182 therefore transparent and repeatable (Stein et al., 2009).

183       Classifications based on environmental deduction, including REC, are common in the  
184 literature because topography, surficial geology and climate are assumed to control hydrological  
185 processes (e.g. precipitation, storage and release of water by watersheds). However, they do not  
186 necessarily reflect only hydrological variation because they usually encompass more general  
187 principles concerning the causes of physical variation in streams and rivers (Snelder et al., 2005;  
188 Carlisle et al., 2010). Therefore, as mentioned previously, the choice of environmental factors to  
189 include in the analysis (and their transformation, weighting and numerical resolution), the  
190 classification method and choice of number of groups, may influence the final delineation of  
191 hydrologic regions (Snelder et al., 2007). Furthermore, some aspects of stream hydrology are  
192 poorly explained using environmental surrogates due to the coarse resolution of available data  
193 (e.g., geology layers to describe groundwater contributions), which may also limit the utility of  
194 environmentally-deduced classifications.

195

## 196 Inductive Approach

### 197 Streamflow classification

198 Streamflow classification involves the direct delineation of patterns in hydrologic character  
199 through inductive approaches that use attributes describing different components of the multi-  
200 faceted flow regime. In this approach, classification schemes attempt to provide order to  
201 inherently complex flow data by identifying and characterizing similarities among rivers  
202 according to a set of diagnostic hydrologic metrics that vary spatially across the landscape (e.g.  
203 Mosley, 1981; Jowett and Duncan, 1990; Poff, 1996; Hannah et al., 2000; Harris et al., 2000;  
204 Snelder et al., 2009a; Kennard et al., 2010b). Streamflow classification relies on hydrologic  
205 metrics that describe the various components of the flow regime, including the seasonal  
206 patterning of flows; timing of extreme flows; the frequency, predictability, and duration of  
207 floods, droughts, and intermittent flows; daily, seasonal, and annual flow variability; and rates of  
208 change (Olden and Poff, 2003; Figure 4). Hydrologic metrics are often selected to account for  
209 characteristics of the flow variability that are hypothesized to be important in shaping ecological  
210 and physical processes in lotic ecosystems. Many of these metrics have proven to be suitable for



211 hydrologic classification (Kennard et al., 2010b), and are responsive to hydrologic alteration  
212 caused by human activities such as river regulation by dams, urbanization, and projected climate  
213 change (Richter et al., 1996; Bunn and Arthington, 2002).

214 Streamflow classification has been conducted for a number of purposes in ecohydrology.  
215 Previous efforts have developed classifications at basin, regional, national, continental and global  
216 scales, focusing on different components of the flow regime and applying a number of statistical  
217 methodologies (Table 2; Appendix A). For example, efforts at global or continental scales have  
218 primarily focused on flow seasonality, flood behavior or low flow characteristics of the  
219 hydrograph, whereas regional classifications have typically utilized a larger suite of hydrologic  
220 metrics. Below we provide a succinct summary of the more common applications of streamflow  
221 classification in the literature.

222  
223 Describing patterns in hydrologic variability – Streamflow classifications have commonly been  
224 developed to place individual stream sites or reaches into a broader spatial context with the goal  
225 of maximizing the transferability of knowledge among rivers of the same hydrologic class.  
226 Numerous classifications have been developed to quantify similarities in natural hydrologic  
227 characteristics at a variety of scales (Table 2). Poff (1996) identified 10 distinctive flow types –  
228 seven permanent and three intermittent - in the continental United States based on ecologically  
229 relevant hydrological characteristics describing flow variability, predictability and low- and  
230 high-flow extremes. Kennard et al. (2010b) presented a continental-scale classification of  
231 hydrologic regimes for Australia describing 12 classes of flow-regime types differing in the  
232 seasonal pattern of discharge, degree of flow permanence, variation in flood magnitude, and flow  
233 predictability and variability (Figure 5a). The geographic distributions of the flow classes varied  
234 greatly, as did differences in key hydrologic metrics. At the regional scale, Hughes and James  
235 (1989) classified streamflow types in Victoria, Australia, based on 16 hydrologic metrics  
236 computed for 138 gauges from daily time series. A low-flow classification scheme produced  
237 four distinct classes with a spatially heterogeneous distribution across the state, which was  
238 largely determined by topography. In another example, Bejarno et al. (2010) described 15  
239 natural flow typologies in the Ebro River Basin, Spain, which were characterized in terms of  
240 flow fluctuation through the year as well as timing, flow ratio and duration of the maximum and  
241 minimum flows. Groups of streams that are hydrologically distinctive at landscape scales are

242 expected to discriminate differences in ecological character (Poff et al., 1997). For example,  
243 streamflow classes are likely to have similar biological responses to both natural and human-  
244 induced variability in patterns of magnitude, frequency, duration, timing and rate of change in  
245 flow conditions. Therefore, systems that show commonalities in their hydrologic characteristics  
246 have provided a basis for testing whether hydrology influences the structure and function of  
247 biological communities in a similar fashion (e.g. Jowett and Duncan, 1990; Poff and Allan, 1995;  
248 Snelder and Lamouroux, 2010).

249  
250 Aiding water resource management – Streamflow classification based on spatial variation in  
251 stream hydrology can play a central role in river ecosystem planning (e.g., Snelder et al., 2004)  
252 and environmental flow assessments for water management. Holistic methodologies to  
253 environmental flow assessments, such as the application of the benchmarking methodology  
254 (Brizga et al., 2002), Downstream Response to Imposed Transformations (King et al., 2003), and  
255 the Ecological Limits of Hydrologic Alteration (ELOHA: Poff et al., 2010), either implicitly or  
256 explicitly involve the hydrologic classification of rivers. Streamflow classification is the first  
257 step in the ELOHA framework and serves two important purposes. First, by assigning rivers or  
258 river segments to a particular type, relationships between ecological metrics and flow alteration  
259 can be developed for an entire river type based on data obtained from a limited set of rivers of  
260 that type within the region. Thus classification can help establish the expected ecological  
261 condition of river basins by class, which alleviates the burden of developing ecological standards  
262 on a river-by-river basis. Second, a streamflow classification facilitates efficient biological  
263 monitoring and research design by informing the strategic placement of monitoring sites  
264 throughout a region to capture the range of flow conditions (Arthington et al., 2006; Poff et al.,  
265 2010). Recent efforts have also called for greater focus on how rivers in different classes vary  
266 with respect to the degree of human influence (e.g., land use, river regulation), thus providing a  
267 benchmark against which the response of biological communities to these factors can be assessed  
268 and a better understanding of the extent to which impacts and management options are  
269 conditional on river class (Peterson et al., 2009; Poff et al., 2010).

270  
271 Identifying and prioritizing conservation efforts for freshwater ecosystems – Recent interest has  
272 focused on the spatial prioritization of freshwater ecosystems for conservation of regional-scale

273 biodiversity (Abell et al., 2007). Hydrologic classification (inductive or deductive) may be a  
274 useful tool for the identification of streams, rivers or entire catchments with representative flow  
275 regimes, and therefore, representative biological communities (Nel et al., 2007). Broadly,  
276 environmental classes are often used as biodiversity surrogates as different types of  
277 environments are assumed to support different combinations of species (Margules et al., 2002).  
278 Following the premise that flow is a key driver of aquatic ecosystem structure and function,  
279 identifying streams and rivers that exhibit distinct or representative flow regimes using  
280 hydrological classification can aid in the selection of those river systems that can contribute to  
281 dynamic conservation reserves to support ecosystem resilience and maintenance of biodiversity  
282 (e.g. Nel et al., 2007; Snelder et al., 2007).

283

## 284 A FRAMEWORK FOR HYDROLOGIC CLASSIFICATION

285 Hydrologic classification should be a process that, ideally, is adequately transparent, readily  
286 interpretable, account for uncertainty and for hydrologic variability at multiple temporal and  
287 spatial scales, recognize methodological biases and robustness, and provide definable class  
288 boundaries, objective group membership, and information on the diagnostic hydrologic  
289 characteristics of each class. To maximize the ability to achieve (at least in part) these  
290 requirements, we believe that a hydrologic classification system should be based on a defensible  
291 scientific framework. Below, we provide a specific protocol to help reach this goal, highlighting  
292 all of the aforementioned approaches to hydrologic classification and focusing specifically on  
293 streamflow classification.

294

- 295 1) Define the objectives of the hydrologic classification
  - 296 a) Deductive approaches are selected when the study seeks a general description of  
297 perceived hydrologic patterns based on first principles with an emphasis on the ease of  
298 understanding. Limited availability and quality of streamflow data may also necessitate  
299 deploying a deductive approach.
    - 300 i) Environmental regionalization. The objective is to quantify environmental similarity  
301 using readily-available maps and spatial data, producing a simple classification of

302 contiguous or non-contiguous regions that are considered homogeneous with respect  
303 to certain environmental characteristics at a particular scale.

304 ii) Hydrologic regionalization. The objective is to extend insights gained from well-  
305 gauged regions to ungauged or sparsely gauged regions or rivers by relating  
306 catchment environmental characteristics to hydrologic metrics describing the flow  
307 regime within defined groups that are considered to exhibit similar hydrologic  
308 characteristics.

309 iii) Environmental classification. The objective is to classify sites according to  
310 similarities in hydrologically-relevant environmental datasets (e.g. describing climate,  
311 catchment topography, soils and geology, vegetation and land use) that are assumed  
312 to control hydrological processes (e.g. precipitation, storage and release of water by  
313 watersheds).

314 b) Inductive approaches are selected when the study seeks a stream classification based on  
315 direct measures of hydrology rather than indirect environmental surrogates for hydrology.  
316 Proceed to step #2.  
317

318 2) Acquire and evaluate the hydrologic data

319 a) Determine availability of discharge data. Data may be gauged or modeled, recorded at  
320 daily, monthly or annual time steps, span short or long time periods, and vary in  
321 geographic coverage.

322 b) Select candidate set of gauges (if using gauged discharge data). If your purpose is to  
323 classify “natural” flow regimes (the most common application in the literature), then only  
324 include gauges that are minimally affected by human activities (e.g. dams, water  
325 extraction, land-use) using best available information (e.g. spatial patterns of land-use,  
326 dam location and attributes, expert knowledge and input from water managers).

327 c) Evaluate quality of discharge data (i.e. missing data, poor measurement recordings as  
328 indicated by quality codes) and eliminate gauges with large data gaps and unsatisfactory  
329 records.

330 d) Ensure consistency of discharge measurement units among gauges (e.g.  $\text{m}^3 \cdot \text{sec}^{-1}$  vs.  
331  $\text{ML} \cdot \text{day}^{-1}$ ).

- 332 e) Evaluate temporal period (e.g. 1965-2000) and duration (i.e. 35 years) of available  
333 discharge data for each gauge, and decide on criteria for inclusion of gauge data.  
334 Important considerations include: minimum vs. fixed record length, completely  
335 overlapping vs. partially overlapping period of record, and period of record to include  
336 particular environmental events (e.g. years including significant changes in climate).  
337 Screening for long-term trends in hydrologic characteristics (e.g. based on annual values  
338 of mean, minimum, and/or maximum flows) can help to clarify the extent to which the  
339 chosen time period is likely to influence the hydrologic classification. Based on a  
340 sensitivity analysis, Kennard et al. (2010a) recommend that at least 15 years of daily  
341 discharge data is suitable for use in hydrologic classifications (to maximize precision and  
342 minimize bias in the estimation of the hydrologic metrics), provided that gauge records  
343 are contained within a discrete temporal window (i.e. preferably >50% overlap between  
344 records).
- 345 f) Evaluate spatial distribution of gauges that meet the above criteria to ensure adequate  
346 geographic coverage (e.g. representing climate regions of interest). If the spatial  
347 coverage is not sufficient, then evaluate potential for including additional gauges by:
- 348 i) Relaxing the acceptance criteria (steps 2b, c, e), and/or
  - 349 ii) Estimating missing or poor quality data in the discharge time series (step 2c) by using  
350 linear interpolation for short periods, general linear regression for longer periods, or  
351 another appropriate technique.
- 352 Note that relaxing the acceptance criteria will decrease the comparability of gauges, and  
353 estimating missing data will increase the measurement uncertainty of flow data. Both  
354 options will compromise bias and precision of classification results, although some  
355 hydrologic indices are more sensitive to record length and period overlap than others (see  
356 Kennard et al., 2010a).
- 357 g) If steps 2a-f reveal that streamflow data is not of sufficient quality and quantity, then  
358 consider deploying an deductive approach to hydrologic classification (see step 1a).  
359
- 360 3) Select hydrologic metrics
- 361 a) Select hydrologic metrics according to purpose of the study. Olden and Poff (2003)  
362 provide a comprehensive review of the most commonly used hydrologic metrics, but

363 importantly, metric selection will influence the outcome of the hydrologic classification.  
364 Considerations for metric selection include:

- 365 i) General ecological rationale: Select a suite of metrics that characterize the totality of  
366 the flow regime.
- 367 ii) Specific ecological rationale: Select individual metrics that are known or  
368 hypothesized to have ecological importance for the specific target response(s) of  
369 interest (e.g. species, community, or ecosystem properties).
- 370 iii) Driver rationale: Select a suite of metrics that is sensitive to an environmental or  
371 anthropogenic driver of interest (e.g. urbanization, river regulation, climate change).

372 b) Select hydrologic metrics that are appropriate for the temporal grain of flow data (e.g.  
373 metrics describing flow spell duration are more suited to daily or weekly data than  
374 monthly or annual data; see also Poff, 1996).

375 c) Select hydrologic metrics depending on available software and the user's experience with  
376 computer programming. Software options include dedicated hydrologic software such as  
377 the Indicators of Hydrologic Alteration (Richter et al., 1996), Hydrologic Assessment  
378 Tool (Henriksen et al., 2006), the River Analysis Package ([www.toolkit.net.au/rap](http://www.toolkit.net.au/rap)), and a  
379 number of others.

380 d) Select hydrologic metrics based on minimizing statistical redundancy among metrics. The  
381 results will inform variable selection and dimensionality reduction (e.g. indirect  
382 ordination approaches to produce composite variables, such as Principal Component  
383 Analysis) if multicollinearity among metrics is a concern (see Olden and Poff, 2003), and  
384 may lead to more robust classifications (Snelder et al., 2009b).

385 e) No hydrologic metrics are chosen. Hydrologic classification will proceed using  
386 parameter sets calculated from any number of time series tools available to analyze  
387 hydrographs, including autoregressive integrated moving average (ARIMA) models,  
388 Fourier analysis, and wavelets (e.g., Smith et al., 1998; Lundquist and Cayan, 2002; Sabo  
389 and Post, 2008).

390

391 4) Compute hydrologic metrics

- 392 a) Calculate the metric values for each flow record according to decisions made in step 3.

- 393 b) Screen datasets for outliers and/or gauges potentially affected by anthropogenic activity  
394 or unknown factors (i.e. used in conjunction with step 2b). Potential approaches include:  
395 i) Examining diagnostic plots and descriptive statistics.  
396 ii) Conducting indirect ordination (e.g. Principal Component Analysis), plotting  
397 ordination scores of gauges in multi-dimensional space and looking for outliers that  
398 might be suggestive of modified flows, unique natural flows, or errors in discharge  
399 measurement, data entry or metric calculation.  
400 iii) Plotting mean daily flow (or similar hydrologic metric) against catchment area,  
401 allowing gauges with obviously different discharge (either through extraction or  
402 supplementation) to be identified.
- 403 c) Eliminate gauges if necessary.
- 404 d) Estimate uncertainty in hydrologic metrics caused by different lengths and periods of  
405 gauge records (also see step 2e). Although commonly overlooked, a robust classification  
406 system should explicitly incorporate (or in the least, examine) uncertainty in the  
407 hydrologic metrics that ultimately underlying the classification scheme. Uncertainty  
408 values can be used to weight metrics in the classification process and/or metrics with high  
409 uncertainty can be eliminated from the analysis. See Kennard et al. (2010a,b) for more  
410 details. This step is optional, but recommended.
- 411 e) Remove scale-dependence of flow magnitude metrics (if required, depending on  
412 objectives of the study) by standardizing values by catchment area, mean daily flow, or a  
413 similarly suitable variable.
- 414
- 415 5) Conduct the hydrologic classification
- 416 a) Select hydrologic metrics to include in classification analysis. Choice of metrics might  
417 also be dependent on statistical assumptions/requirements (data type, normality, etc.) of  
418 classification approach. Selections might include:  
419 i) All flow metrics.  
420 ii) Subset(s) of metrics describing separate components of flow regime (this decision  
421 depends on the purpose for classification).

- 422           iii) Subset(s) of metrics that are non-redundant (i.e. low multicollinearity) and highly  
423           informative (i.e. explaining dominant gradients of variation that exist in the larger set  
424           of metrics). See Olden and Poff (2003) for more details.
- 425       b) Decide whether metric transformations and/or standardizations are required (again, this  
426       depends on statistical assumptions/requirements of classification approach).
- 427       c) Conduct hydrologic classification analysis using a statistical approach that corresponds  
428       with the objective of classification and capability of the researcher. Ordination analyses  
429       may also be conducted to complement hydrologic classification, explore the extent of  
430       hydrologic variability and examine for natural clusters of stream gauges and/or outliers.  
431       See Methodologies section below.
- 432       d) Delineate and decide on the number of hydrologic classes (i.e. clusters) based on  
433       objective (statistical) criteria, ecological rationale and/or considering a trade-off between  
434       resolution of hydrological variability and complexity (number of classes). Depending on  
435       the purpose of the classification, each approach may be legitimate for deciding on the  
436       number of classes. Assign class membership. See Methodologies section below.
- 437       e) Examine classification results for outliers and eliminate gauges if necessary; repeat steps  
438       5b-d.
- 439
- 440   6) Interpret and/or spatially-model the hydrologic classification
- 441       a) Assess the predictive performance of the hydrologic classifier using an independent  
442       dataset containing gauges not included in the classification (e.g., cross-validation)  
443       according to an appropriate statistical approach (e.g. coefficient of agreement such as  
444       Cohen's Kappa statistic). When model performance is poor and the uncertainty of  
445       classifications are high, this may indicate an inadequate understanding of watershed  
446       behavior or an inability to know or estimate the salient hydrologic characteristics. The  
447       result is a classification system with low power and utility.
- 448       b) Diagnose the distinguishing characteristics of the hydrologic classes using numerical,  
449       statistical, graphical, and descriptive approaches.
- 450       c) Examine geographic distribution of gauge class membership.
- 451       d) Depending on the study purpose, model class membership of gauges based on upstream  
452       physiographic characteristics (e.g. drainage area, stream slope, soil type) and climatic



453 variables (e.g. precipitation, temperature, evapotranspiration) of the watershed using an  
454 appropriate statistical approach (e.g. logistic regression, discriminant function analysis,  
455 classification tree). Assuming adequate model performance (see Snelder et al., 2007 for  
456 discussion) the user can predict hydrologic class membership by applying model at the  
457 river segment scale. See Methodologies section below.

458

## 459 METHODOLOGIES FOR STREAMFLOW CLASSIFICATION

460 The objective of streamflow classification is to ascribe objects (i.e., streams, rivers, catchments)  
461 to empirically-based groupings or classes, so as to maximize the similarity between the members  
462 of each group and minimize the similarity between groups. By virtue of the many ways that the  
463 various components of the flow regime can be characterized (see Olden and Poff, 2003), the  
464 statistical techniques for organizing rivers into hydrologic classes are numerous and vary in their  
465 output. Below we discuss some of the more common approaches to streamflow classification,  
466 and examine some important considerations with respect to delineating and deciding on the  
467 number of hydrologic classes (i.e. clusters) and assigning class membership.

468

469 Ordination approaches to exploring hydrologic variability

470 Multivariate ordination is typically used to explore continuous patterns in hydrologic variability  
471 among sites (e.g. Lins, 1997; Clausen and Biggs, 2000) and complement clustering-based  
472 classifications that assign sites to classes (see below). Commonly employed approaches include  
473 Principal Component Analysis (PCA) or non-metric multidimensional scaling. Ordination  
474 approaches do not produce a classification; rather the relative hydrological  
475 similarity/dissimilarity of different objects (i.e. gauging locations) is displayed in multivariate  
476 space of reduced dimensionality, thus allowing the investigator to visually determine whether  
477 objects group together in well-defined sets or form contrastingly poorly-defined and overlapping  
478 groups. One property of most classification algorithms is that they force a grouped structure on  
479 what may otherwise be a continuously varying distribution and ordination is a useful tool to  
480 assess whether any such grouping is warranted. Other approaches for exploring hydrologic  
481 variation, although rarely used, include graphical representation of multi-dimensional data using  
482 Andrews curves (Andrews, 1972) and a range of pictorial techniques that involve “entertaining

483 transmogrifications” (Nathan and McMahon, 1990) of cartoon faces, trees, castles, and  
484 dragonflies (see Chernoff, 1973).

485

486 Clustering approaches to developing a streamflow classification

487 Hierarchical clustering has been most commonly applied for streamflow classification. These  
488 algorithms produce a classification of objects (typically presented as a dendrogram), starting  
489 with each stream site (gauge) in a separate cluster and combining clusters until only one is left  
490 (agglomeration approach) or by splitting larger clusters into smaller ones (divisive approach).  
491 As pointed out by Nathan and McMahon (1990), a major consideration encountered when using  
492 cluster analysis for streamflow classification is the plethora of different computational  
493 algorithms and distance/dissimilarity measures available. Unfortunately, different clustering  
494 algorithms applied to the same set of data can produce classifications that are substantially  
495 different because each approach implicitly imposes structure on the data. Therefore, the choice  
496 of algorithm used in hydrologic classification is paramount.

497 Seven algorithms for agglomerative hierarchical clustering have been commonly applied in  
498 the past (Table 2), including (i) single linkage; (ii) complete linkage; (iii) average linkage (either  
499 weighted or unweighted); (iv) centroid linkage; (v) median linkage; (vi) density linkage; and  
500 (vii) Ward’s minimum-variance algorithm. Each algorithm has both strengths and weaknesses  
501 (see Gordon (1987) for a good overview from a statistical perspective), but perhaps the most  
502 relevant feature for streamflow classification is the tendency of algorithms to ‘distort’ space, thus  
503 affecting the clustering results (see Everitt et al., 2001). The ‘chaining’ effect, in which  
504 dissimilar objects are sequentially drawn into the same cluster, is an example of space  
505 contraction and is commonly produced by the single linkage algorithm. Such approaches tend to  
506 identify highly distinctive groups and may see their greatest use in conservation when  
507 practitioners are seeking to reveal unique and rare hydrologic environments. By contrast, space  
508 dilation refers to the process of favoring the fusion of clusters together, and is typical of the  
509 complete linkage algorithm. These approaches tend to produce groups of equal size and may be  
510 best applied in hydrologic regionalization to ensure adequate sample sizes to establish statistical  
511 relationships. Lastly, space-conserving methods, such as average linkage, merge clusters in a  
512 manner that best balances space contraction and dilation, and therefore, the resulting dendrogram  
513 best represents the original data structure. The choice of clustering algorithm will depend on the

514 objective of the classification exercise, but for most applications we would recommend space  
515 conserving approaches, such as average linkage or Ward's algorithm. The latter is quite  
516 beneficial because it maximizes the cophenetic correlation between the original and dendrogram  
517 distances and eliminates group size dependencies on the clustering results. Selection of an  
518 appropriate (dis)similarity index is also important, but for continuous variables such as the  
519 majority of commonly used hydrologic metrics, standardized Euclidean distance remains the  
520 most popular. However, other indices have favorable properties (i.e., minimizing the influence  
521 of large distances) and may be preferred (see Legendre and Legendre, 1998).

522       Partitional clustering techniques have also been applied for streamflow classification. This  
523 family of methods seeks to identify clusters of equal distinction, and thus is not represented in a  
524 hierarchy. Examples include K-means, K-median, K-modes and K-medoids algorithms, where  
525 K-means is by far the most commonly used. This algorithm groups cases according to a distance  
526 measure (typically Euclidian distance) from initial, randomly chosen cluster centers of a  
527 predetermined number, and then it iteratively redefines cluster centers as the means of the cases  
528 in the latest cluster, until cases no longer change in membership (Everitt et al., 2001). The  
529 method is efficient for large datasets, and results are often sufficient, although subjectivity of the  
530 initial number of clusters and the location of their centroids in n-dimensional space must be  
531 considered.

532       While the hierarchical clustering procedures are not influenced by initialization and local  
533 minima, the partitional clustering procedures are influenced by initial guesses (number of  
534 clusters, cluster centers, etc.). The partitional clustering procedures are dynamic in the sense that  
535 objects can move from one cluster to another to minimize the objective function. By contrast,  
536 the objects committed to a cluster in the early stages cannot move to another in hierarchical  
537 clustering procedures. The relative merits of the hierarchical and partitional clustering methods  
538 resulted in the development of hybrid-clustering methods that are a blend of these methods. For  
539 example, Rao and Srinivas (2006a) used a partitional clustering procedure to identify groups of  
540 similar catchments by refining the clusters derived from agglomerative hierarchical clustering  
541 using the K-means algorithm. Similarly, Kahya et al. (2007) considered results of an average  
542 linkage algorithm to help identify an optimal number of hydrologic classes of Turkey streams for  
543 subsequent flat classification using K-means.

544

545 Determining the number of hydrologic classes

546 Determining the number of distinct classes is a problem inherent to most if not all conventional  
547 clustering techniques. For partitional algorithms, the number of clusters must be predetermined  
548 before the patterns of input data have been analyzed. For hierarchical algorithms, selection of  
549 the degree of cluster distinction between tiers is subjective. Several approaches for optimizing  
550 the number of clusters have been discussed in the literature and are relevant for hydrologic  
551 classification (Milligan and Cooper, 1985). In hierarchical clustering, partitions are achieved by  
552 selecting one of the solutions in the nested sequence of clusters that comprise the hierarchy. This  
553 is equivalent to cutting down the dendrogram at a particular height in which the appearance of  
554 distinct classes is present. Although this procedure is commonly used, it does carry with it the  
555 high possibility of influence from a priori expectations. More formal methods for determining  
556 the number of clusters are reviewed by Milligan and Cooper (1985). Among the many they  
557 reviewed, the authors identified “best” approaches – including those based on the ratio of  
558 between-cluster to within-cluster sums of squares.

559 Expert opinion can also guide the selection process. Snelder and colleagues (Snelder and  
560 Hughey, 2005; Snelder et al., 2007) suggest that the definition of most classifications cannot be  
561 entirely objective as it rare that all parts of the hydrological space are represented, thus no  
562 optimal number of classes exists. Moreover, where classifications serve some managerial utility,  
563 then trade-offs between resolution of hydrological variability and complexity (number of classes)  
564 may be needed and are then guided by other than mathematical elegance (i.e. simple  
565 pragmatism). To date, we fear that the lack of application and consensus about which rule to  
566 apply have resulted in informal and subjective criteria in the selection of hydrologic classes. We  
567 urge that investigators become more explicit on the criteria that they apply.

568

569 Assigning class membership: hard vs. soft classification

570 Clustering algorithms can lead to either hard or soft (i.e. fuzzy) classifications. A hard clustering  
571 method is based on the assumption that stream sites can be divided into non-overlapping clusters  
572 (i.e. hydrologic class) with well-defined boundaries between them, and each site is assigned to a  
573 single cluster with a high degree of certainty. In other words, a stream is classified as belonging  
574 to a cluster on the basis of distance (or dissimilarity) between itself and the cluster centroid in the  
575 multi-dimensional space of attributes depicting the flow variation.

576 It is reasonable to suppose, however, that most streams partially resemble several other  
577 streams and therefore a hard assignment to one class (cluster) may not be justified.  
578 Consequently, identifying classes with vague boundaries between them is preferable, compared  
579 to crisp classification with well-defined boundaries as in the case of hard clustering. The fuzzy  
580 set theory that straddles ordination, classification and clustering analysis (Roberts, 1986) is a  
581 natural way to represent such a situation. Fuzzy partitional clustering allows a stream site to  
582 belong to all the regions simultaneously with a certain degree of membership. The distribution  
583 of membership of a stream among the fuzzy clusters specifies the strength with which the stream  
584 belongs to each class and is useful to identify ambiguous sites. A threshold to maximum  
585 membership values can be applied to derive crisp, vector-based representations from raster,  
586 fuzzy classifications. Rao and Srinivas (2006b) argue that given the inadequacies of  
587 conventional stream classification methods, fuzzy representations of hydrologic variability  
588 present an appealing alternative.

589 Another fuzzy partitional method available is Bayesian mixture modeling (Gelman et al.,  
590 2004). In this approach, the observed distribution of data is modeled as a mixture of a finite  
591 number of component distributions in order to determine the number of distributions, their  
592 parameters, and object memberships (Webb et al., 2007). The approach is fully probabilistic and  
593 uncertainty can be explicitly reported in terms of data specification, class specification and the  
594 final classification chosen. Multiple plausible classifications are produced, which are then  
595 ranked on their estimated marginal likelihoods to select the most parsimonious classification that  
596 is guaranteed to have the highest posterior probability; the probability of the model being correct  
597 given the data (Gelman et al., 2004; Webb et al., 2007). To date, Kennard et al. (2010b)  
598 represents the only application of fuzzy clustering for streamflow classification; here, the authors  
599 used 120 hydrologic metrics to quantify the likelihood of 830 stream gauges to belong to 12  
600 flow-regime types across Australia (Figure 5a).

601  
602 Predicting landscape patterns of streamflow classes

603 Knowledge of probable class membership within a streamflow classification allows hydrologic  
604 behavior to be predicted for a target site or stream. For example, hydrologists frequently use  
605 regression models developed for specific clusters within a classification to predict hydrology of a  
606 novel stream (i.e. regionalization) after determining to which class it should belong (Lin and

607 Wang, 2006). The key issue, therefore, is how class membership for novel locations is  
608 determined given that geographic proximity alone is not always a sufficient rationale (Ouarda et  
609 al., 2001; Poff et al., 2006). Several methods are available to predict class membership using  
610 upstream physiographic characteristics (e.g., drainage area, stream slope, soil type) and climatic  
611 variables (e.g., precipitation, temperature, evapotranspiration) of the watershed based on an  
612 appropriate statistical model. Linear discriminant analysis (LDA) is one such method in which  
613 linear combinations of potential predictor variables are used to allocate group membership. LDA  
614 has a number of requirements and assumptions that are not always met when applied to  
615 environmental data (e.g., multivariate normality of predictor variables), however LDA has been  
616 appropriately used in a variety of ecohydrological analyses (e.g. Pusey and Arthington, 1996;  
617 Detenbeck et al., 2005; Jowett and Duncan, 1990; Sanborn and Bledsoe, 2006). Alternative non-  
618 parametric and/or machine learning methods are available (see Olden et al., 2008; Kampichler et  
619 al., 2010) and have been used to allocate cluster group membership in hydrologic analyses (e.g.,  
620 Reidy Liermann et al., 2011). For example, classification trees were used by Kennard et al.  
621 (2010b) to identify a subset of climatic and landscape variables that were able to predict flow  
622 regime class membership with a relatively high success rate of 62.1% (Figure 5b). In another  
623 example, Snelder et al. (2009a) used boosted regression trees and watershed variables describing  
624 climate, topography, and geology, to predict natural flow classes for stream segments in France  
625 with 87% accuracy.

626 The examples above all involve a two-step process; the classification is developed and then  
627 potential predictor variables are assessed and combined to predict class membership. Lin and  
628 Wang (2006) suggest that this is an inefficient process and describe a machine learning approach  
629 based on self-organizing maps (SOM: Kohonen 2000) in which cluster analysis and  
630 discrimination analysis is performed in one analysis. Their SOM-based cluster and  
631 discrimination analysis produces three maps in a single step for use in classification. The feature  
632 density and discrimination maps can be used to assign unknown catchments to classes at one  
633 time, eliminating the step of post-clustering discriminant analysis for each unknown catchment.  
634 As well, the ability to define the number of clusters at multiple resolutions from the feature and  
635 density maps is argued as a key advantage of the method.

636 The capacity to predict streamflow class membership provides, in addition to increased  
637 knowledge of what factors drive hydrologic variation, a means by which a classification may be

638 extrapolated to all locations within the spatial domain of the input variables. Thus, a map of flow  
639 regime variation can be constructed. For example, Snelder et al. (2009a) developed a natural  
640 flow regime classification of continental France using non-hierarchical K-means cluster analysis.  
641 Boosted regression tree models were used to predict the likelihood of gauging stations belonging  
642 to identified clusters based on watershed characteristics and these models were used to  
643 extrapolate the classification to all ~115,000 segments of a national river network. Snelder and  
644 Hughey (2005) and Arthington et al. (2006) argue that such a spatial framework has practical  
645 use. A spatially explicit classification aids in exploring the influence of streamflow on biological  
646 communities and ecological processes, prioritizing conservation efforts for freshwater  
647 ecosystems and guiding river management strategies.

648

649

## CONCLUSION

650 Hydrologic classification is increasingly being used to guide and aid the management of aquatic  
651 resources. No single classification will suit all purposes, as classification is a tool not an end in  
652 itself. Rather, different approaches and many different means of classifying locations, stream  
653 reaches or catchments are available and the choice of which approach and which classification  
654 method is employed depends on the availability of data and the desired purpose of the  
655 classification. In the case where high quality hydrologic information is sparse or lacking for  
656 some areas, the deductive approach is appropriate. This approach varies from simple  
657 environmental or hydrologic regionalizations in which region membership is qualitatively  
658 assigned, to regionalizations in which membership is quantitatively assigned based on  
659 similarities across a number of environmental (climatic, topographic etc) variables that are  
660 assumed to have direct influence on streamflow. The inductive approach, in contrast, is based on  
661 quantitative classification, achieved by a variety of methods, in which classification group  
662 membership is based on similarity in various metrics describing aspects of the flow regime for  
663 individual locations. Whatever the approach used, the steps taken in the formation of a  
664 classification need to be explicitly described including criteria used for data selection, data  
665 treatment and assessment, metric selection and rationale, and classification method including  
666 explicit rationale for derivation of final group number. These steps are integral to the framework  
667 described here.

668

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## REFERENCES

- 681 Abell R, Allan JD, Lehner B. 2007. Unlocking the potential of protected areas for freshwaters.  
682 *Biological Conservation* 134: 48-63.
- 683 Acreman MC, Sinclair CD. 1986. Classification of drainage basins according to their physical  
684 characteristics; an application for flood frequency analysis in Scotland. *Journal of Hydrology*  
685 84: 365-380.
- 686 Andrews DF. 1972. Plots of high dimensional data. *Biometrics* 28: 125-136.
- 687 Arthington AH, Bunn SE, Poff NL, Naiman RJ. 2006. The challenge of providing environmental  
688 flow rules to sustain river ecosystems. *Ecological Applications* 16: 1311-1318.
- 689 Assani AA, Tardif S. 2005. Classification and characterization of natural flow regimes in Quebec  
690 (Canada). Factors of spatial variability – an eco-geographical approach. *Revue Des Sciences*  
691 *De L'Eua* 18: 247-266.
- 692 Baeza Sanz D, Garcia del Jalon D. 2005. Characterisation of streamflow regimes in central  
693 Spain, based on relevant hydrobiological parameters. *Journal of Hydrology* 310: 266–279.
- 694 Bailey RG. 1996. *Ecosystem Geography*. Springer-Verlag, New York.
- 695 Bejarano MD, Marchamalo M, de Jalón DG, Tánago MG. 2010. Flow regime patterns and their  
696 controlling factors in the Ebro basin (Spain). *Journal of Hydrology* 385: 323-335.



697 Bower D, Hannah DM, McGregor GR. 2004. Techniques for assessing the climatic sensitivity of  
698 river flow regimes. *Hydrological Processes* 18: 2515–2543.

699 Brizga SO, Arthington AH, Pusey BJ, Kennard MJ, Mackay SJ, Werren GL, Craigie NM Choy  
700 SJ. 2002. Benchmarking, a 'top-down' methodology for assessing environmental flows in  
701 Australian rivers. In *Proceedings of International Conference on Environmental Flows for*  
702 *Rivers, Cape Town, SA.*

703 Bryce SA, Clarke SE 1996. Landscape-level ecological regions: linking state-level ecoregion  
704 frameworks with stream habitat classifications. *Environmental Management* 20: 297–311.

705 Bunn SE, Arthington AH. 2002. Basic principles and ecological consequences of altered flow  
706 regimes for aquatic biodiversity. *Environmental Management* 30: 492-507.

707 Burn DH, Arnell NW. 1993. Synchronicity in global flood responses. *Journal of Hydrology* 144:  
708 381–404.

709 Buttle J. 2006. Mapping first-order controls on streamflow from drainage basins: the T3  
710 template. *Hydrologic Processes* 20: 3415-3422.

711 Carlisle DM, Falcone J, Wolock DM, Meador MR, Norris RH. 2010. Predicting the natural flow  
712 regime: models for assessing hydrological alteration in streams. *River Research and*  
713 *Application* 26: 118-136.

714 Chang FJ, Tsai MJ, Tsai WP, Herricks EE. 2008. Assessing the ecological hydrology of natural  
715 flow conditions in Taiwan. *Journal of Hydrology* 354: 75–89.

716 Chernoff H. 1973. Using faces to represent points in k-dimensional space graphically. *Journal of*  
717 *the American Statistics Association* 68: 361 368.

718 Chiang S-M, Tsay T-K, Nix SJ. 2002. Hydrologic regionalization of watersheds I: Methodology  
719 development. *Journal of Water Resource Planning and Management* 128: 3-11.

720 Clausen B, Biggs BJF. 2000. Flow variables for ecological studies in temperate streams:  
721 groupings based on covariance. *Journal of Hydrology* 237: 184-197.

722 Detenbeck NE, Batterman SL, Brady VL, Brazner JC, Snarski VM, Taylor DL, Thompson J,  
723 Arthur JW. 2000. A test of watershed classification systems for ecological risk assessment.  
724 *Environmental Toxicology and Chemistry* 19: 1174-1181.

725 Detenbeck NE, Brady VJ, Taylor DL, Snarski VM, Batterman SL. 2005. Relationship of stream  
726 flow regime in the western Lake Superior basin to watershed type characteristics. *Journal of*  
727 *Hydrology* 309: 258–276.

728 Dettinger MD, Diaz HF. 2000. Global characteristics of stream flow seasonality and variability.  
729 *Journal of Hydrometeorology* 1: 289-310.

730 Everitt, BS, Landau S, Leese M. 2001. *Cluster Analysis* (fourth ed), Arnold, London (2001)

731 Fielding AH, Bell JF. 1997. A review of methods for the assessment of prediction errors in  
732 conservation presence/absence models. *Environmental Conservation* 24: 38-49.

733 Finlayson BL, McMahon TA. 1988. Australia vs. the World: A comparative analysis of  
734 streamflow characteristics. Pp 17-40 In: Werner RF (ed.), *Fluvial Geomorphology of*  
735 *Australia*, Academic Press, Sydney.

736 Gelman A, Carlin JB, Stern HS, Rubin DB. 2004. *Bayesian Data Analysis*. 2nd edition.  
737 Chapman and Hall/CRC Press, Boca Raton, Florida.

738 GeoSciences Australia. 2006. GEODATA TOPO 250K Series 3. Shape Files Format.  
739 Commonwealth of Australia (GeoSciences Australia), Canberra, ACT, Australia.

740 Gordon A. 1987. A review of hierarchical classification. *Journal of the Royal Statistical Society*.  
741 *Series A (General)*. 150: 119–137.

742 Gottschalk L, Lundager J, Lundquist D, Solantie R, Tollan A. 1979. Hydrologic regions in the  
743 Nordic countries. *Nordic Hydrology* 10: 273-286.

744 Gottschalk L. 1985. Hydrological regionalization of Sweden. *Hydrological Science* 30: 65-83.

745 Haines AT, Findlayson BL, McMahon TA. 1988. A global classification of river regimes.  
746 *Applied Geography* 8: 255-272.

747 Hannah DM, Smith BPG, Gurnell AM, McGregor GR. 2000. An approach to hydrograph  
748 classification. *Hydrological Processes* 14: 317-338.

749 Hannah DM, Kansakar SR, Gerrard AJ, Rees G. 2005. Flow regimes of Himalayan rivers of  
750 Nepal: nature and spatial patterns. *Journal of Hydrology* 308: 18-32.

751 Harris NM, Gurnell AM, Hannah DM, Petts GE. 2000. Classification of river regimes: a context  
752 for hydroecology. *Hydrological Processes* 14: 2831-2848.

753 Henriksen JA, Heasley J, Kennen JG, Newsand S. 2006. Users' manual for the hydroecological  
754 integrity assessment process software (including the New Jersey Assessment Tools): U.S.  
755 Geological Survey, Biological Resources Discipline, Open File Report 2006-1093, 71 p.

756 Hughes DA, Hannart P. 2003. A desktop model used to provide an initial estimate of the  
757 ecological instream flow requirements of rivers in South Africa. *Journal of Hydrology* 270:  
758 167-181.

759 Hughes JMR. 1987. Hydrological characteristics and classification of Tasmanian rivers.  
760 Australian Geographical Studies 25: 61–82.

761 Hughes JMR, James B. 1989. A hydrological regionalization of streams in Victoria, Australia,  
762 with implications for stream ecology. Australian Journal of Marine and Freshwater  
763 Resources 40: 303-326.

764 Jowett IG, Duncan MJ. 1990. Flow variability in New Zealand rivers and its relationship to in-  
765 stream habitat and biota. New Zealand Journal of Marine and Freshwater Research 24: 305-  
766 317.

767 Kachroo RK, Mkhanda SH, Parida BP. 2000. Flood frequency analysis of southern Africa: I.  
768 Delineation of homogeneous regions. Hydrological Science 45: 437-447.

769 Kahya E, Demirel MC, Piechota TC. 2007. Spatial grouping of annual streamflow patterns in  
770 Turkey. Paper presented at Hydrology Days, Colorado State Univ. (Available at:  
771 [http://hydrologydays.colostate.edu/Papers\\_2007/Demirel\\_Kahya\\_paper.pdf](http://hydrologydays.colostate.edu/Papers_2007/Demirel_Kahya_paper.pdf)).

772 Kampichler C, Wieland R, Calmé S, Weissenberger H, Arriaga-Weiss S. 2010. Classification in  
773 conservation biology: A comparison of five machine-learning methods. Ecological  
774 Informatics 5: 441-450.

775 Kennard MJ, Olden JD, Arthington AH, Pusey BJ, Poff NL. 2007. Multi-scale effects of flow  
776 regime, habitat, and their interaction on fish assemblage structure in eastern Australia.  
777 Canadian Journal of Fisheries and Aquatic Sciences 64: 1346-1359.

778 Kennard MJ, Pusey BJ, Mackay SJ, Olden JD, Marsh N. 2010a. Quantifying uncertainty in  
779 estimation of hydrologic metrics for ecohydrological studies. River Research and  
780 Applications 26: 137-156.

781 Kennard MJ, Pusey BJ, Olden JD, Mackay SJ, Stein JL, Marsh N. 2010b. Classification of  
782 natural flow regimes in Australia to support environmental flow management. Freshwater  
783 Biology 55: 171-193.

784 King JM, Brown CA, Sabet H. 2003. A scenario-based holistic approach to environmental flow  
785 assessments for rivers. River Research and Applications 19: 619-640.

786 Kohonen T. 2000. Self organizing maps. 3<sup>rd</sup> edition. Berlin: Springer-Verlag. 521 pp.

787 Kondolf GM. 1995. Cases studies and reviews. Geomorphological stream channel classification  
788 in aquatic habitat restoration: uses and limitations. Aquatic Conservation: Marine and  
789 Freshwater Ecosystems 5: 127-141.

790 Kondolf GM, Montgomery DR, Piégay H, Schmitt L. 2003. Geomorphic classification of rivers  
791 and streams. Pp 169-202. In GM Kondolf and H Piégay, (ed.). Tools in Fluvial  
792 Geomorphology. Wiley, New York.

793 Krasovskaia I. 1997. Entropy-based grouping of river flow regimes. *Journal of Hydrology* 202:  
794 173-191.

795 Legendre P, Legendre L. 1998. Numerical Ecology, 2nd edition. Elsevier Scientific, Amsterdam,  
796 The Netherlands. 870 pp.

797 Lin G-F, Wang C-M. 2006. Performing cluster analysis and discrimination analysis of  
798 hydrological factors in one step. *Advances Water Research* 29: 1573–1585.

799 Lins HF. 1997. Regional streamflow regimes and hydroclimatology of the United States. *Water*  
800 *Resources Research* 33: 1655-1667.

801 Loveland TR, Merchant JM. 2004. Ecoregions and ecoregionalization: geographical and  
802 ecological perspectives. *Environmental Management* 34: 1–13.

803 Lundquist JD, Cayan DR. 2002. Seasonal and spatial patterns in diurnal cycles in streamflow in  
804 the western United States. *Journal of Hydrometeorology* 3: 591–603.

805 Mackey BG, Berry SL, Brown T. 2007. Reconciling approaches to biogeographical  
806 regionalization: a systematic and generic framework examined with a case study of the  
807 Australian continent. *Journal of Biogeography* 35: 213–229.

808 Margules CR, Pressey RL, Williams PH. 2002. Representing biodiversity: data and procedures  
809 for identifying priority areas for conservation. *Journal of Biosciences* 27: 309-326.

810 McMahon TA, Vogel RM, Peel MC, Pegram GGS. 2007a. Global streamflows – Part 1:  
811 Characteristics of annual streamflows. *Journal of Hydrology* 347: 243-259.

812 McMahon TA, Peel MC, Vogel RM, Pegram GGS. 2007b. Global streamflows – Part 3: Country  
813 and climate zone characteristics. *Journal of Hydrology* 347: 272-291.

814 McManamay RA, Orth DJ, Dolloff CA, Frimpong EA. 2011. Regional frameworks applied to  
815 hydrology: Can landscape-based frameworks capture the hydrologic variability? *River*  
816 *Research and Applications*, in press. DOI: 10.1002/rra.1535.

817 Meigh JR, Farquharson FAK, Sutcliffe JV. 1997. A worldwide comparison of regional flood  
818 estimation methods and climate. *Hydrology Science* 42: 225-244.

819 Merz B, Bloeschl G. 2004. Regionalization of catchment model parameters. *Journal of*  
820 *Hydrology* 287: 95-123.

821 Milligan GW, Cooper MC. 1985. An examination of procedures for determining the number of  
822 clusters. *Psychometrika* 50: 159-179.

823 Mkhandi SH, Kachroo RK. 1996. Regional flood frequency analysis for southern Africa.  
824 Xiièmes Journées Hydrologiques De L'orstom. Montpellier, 10-11th October 1996.

825 Monk WA, Peters DL, Curry RA, Baird DJ. 2011. Quantifying trends in indicator  
826 hydroecological variables for regime-based groups of Canadian river. *Hydrological*  
827 *Processes*, in press. DOI: 10.1002/hyp.8137.

828 Monk WA, Wood PJ, Hannah DM, Wilson DA, Extence CA, Chadd RP. 2006. Flow variability  
829 and macroinvertebrate community response within riverine systems. *River Research and*  
830 *Applications* 22: 595–615.

831 Mosley MP. 1981. Delimitation of New Zealand hydrologic regions. *Journal of Hydrology* 49:  
832 179-192.

833 Nathan RJ, McMahon TA. 1990. Identification of homogeneous regions for the purposes of  
834 regionalization. *Journal of Hydrology* 121: 217-238.

835 Nel JL, Roux, DJ, Maree G, Kleynhans CJ, Moolman J, Reyers B, Rouget M, Cowling RM.  
836 2007. Rivers in peril inside and outside protected areas: a systematic approach to  
837 conservation assessment of river ecosystems. *Diversity and Distributions* 13: 341-352.

838 O'Keefe JH, Uys MC. 2000. The role of classification the conservation of rivers. Pages 445-458  
839 in Boon PJ, Davies BR. and Petts GE. (eds), *Global perspectives on river conservation:*  
840 *Science policy and practice*. John Wiley & Sons, Chichester.

841 Olden JD, Poff NL. 2003. Redundancy and the choice of hydrologic indices for characterizing  
842 streamflow regimes. *River Research and Applications* 19: 101-121.

843 Olden JD, Lawler JJ, Poff, NL. 2008. Machine learning methods without tears: a primer for  
844 ecologists. *The Quarterly Review in Biology* 83: 171-193.

845 Omernik JM. 2004. Perspectives on the nature and definition of ecological regions.  
846 *Environmental Management* 34: S1–S13.

847 Ouarda TBMJ, Girard C, Cavadias GS, Bobee B. 2001. Regional flood frequency estimation  
848 with canonical correlation analysis. *Journal of Hydrology* 254: 157–173.

849 Pardé M. 1955. *Fleuves et rivières*. Collection Armand Colin, Paris, 224 pp.

850 Pegg MA, Pierce CL. 2002. Classification of reaches in the Missouri and lower Yellowstone  
851 rivers based on flow characteristics. *River Research and Applications* 18: 31–42.

852 Peterson JT, Jackson CR, Shea CP, Li G. 2009. Development and evaluation of a stream channel  
853 classification for estimating fish responses to changing streamflow. *Transactions of the*  
854 *American Fisheries Society* 138: 1123-1137.

855 Poff NL. 1996. A hydrogeography of unregulated streams in the United States and an  
856 examination of scale-dependence in some hydrological descriptors. *Freshwater Biology* 36:  
857 71-91.

858 Poff NL, Allan D, Bain MB, Karr JR, Prestegard KL, Richter BD, Sparks RE, Stromberg JC.  
859 1997. The natural flow regime: a paradigm for river conservation and restoration. *Bioscience*  
860 47: 769-784.

861 Poff NL, Allan JD. 1995. Functional organization of stream fish assemblages in relation to  
862 hydrological variability. *Ecology* 76: 606-627.

863 Poff NL, Olden JD, Pepin DM, Bledsoe BP. 2006. Placing global stream flow variability in  
864 geographic and geomorphic contexts. *River Research and Applications* 22:149-166.

865 Poff NL, Richter BD, Arthington AH, Bunn SE, Naiman RJ, Kendy E, Acreman M, Apse C,  
866 Bledsoe BP, Freeman MC, Henriksen J, Jacobson RB, Kennen JG, Merritt DM, O’Keeffe  
867 JH, Olden JD, Rogers K, Tharme RE, Warner A. 2010. The ecological limits of hydrologic  
868 alteration (ELOHA): a new framework for developing regional environmental flow  
869 standards. *Freshwater Biology* 55: 147-170.

870 Puckridge JT, Sheldon F, Walker KF, Boulton AJ. 1998. Flow variability and the ecology of  
871 large rivers. *Marine and Freshwater Research* 49: 55-72.

872 Pusey BJ, Arthington AH. 1996. Streamflow variability within the Burdekin River. *Proceedings*  
873 *of the 23rd Hydrology and Water Resources Symposium*. Pp. 213–220. Australian Institute of  
874 Engineers, Barton.

875 Rao AR, Srinivas VV. 2006a. Regionalization of watersheds by hybrid-cluster analysis. *Journal*  
876 *of Hydrology* 318: 37-56.

877 Rao AR, Srinivas VV. 2006b. Regionalization of watersheds by fuzzy cluster analysis. *Journal*  
878 *of Hydrology* 318: 57-79.

879 Reidy Liermann CA, Olden JD, Beechie TJ, Kennard MJ, Skidmore PB, Konrad CP, Imaki H.  
880 2011. Hydrogeomorphic classification of Washington State rivers to support emerging  
881 environmental flow management strategies. *River Research and Applications*, in press. DOI:  
882 10.1002/rra.1541

883 Richter BD, Baumgartner JV, Powell J, Braun DP. 1996. A method for assessing hydrologic  
884 alteration within ecosystems. *Conservation Biology* 10: 1163-1174.

885 Roberts DW. 1986. Ordination on the basis of fuzzy set theory. *Vegetatio* 66: 123-131.

886 Sabo JL, Post DM. 2008. Quantifying periodic, stochastic, and catastrophic environmental  
887 variation. *Ecological Monographs* 78: 19-40.

888 Sanborn SC, Bledsoe, BP. 2006. Predicting streamflow regime metrics for ungauged streams in  
889 Colorado, Washington, and Oregon. *Journal of Hydrology* 325: 241–261.

890 Santhi C, Allen PM, Muttiah RS, Arnold JG, Tuppad, P. 2008. Regional estimation of base flow  
891 for the conterminous United States by hydrologic landscape regions. *Journal of Hydrology*  
892 351: 139-153.

893 Sawicz K, Wagener T, Sivapalan M, Troch PA, Carrillo G. 2011. Catchment classification:  
894 empirical analysis of hydrologic similarity based on catchment function in the eastern USA.  
895 *Hydrology and Earth System Sciences Discussions* 8: 4495-4534.

896 Schmitt L, Maire G, Nobelis P, Humbert J. 2007. Quantitative morphodynamic typology of  
897 rivers: a methodological study based on the French Upper Rhine basin. *Earth Surface*  
898 *Processes and Landforms* 32: 1726-1746.

899 Smith LC, Turcotte DL, Isacks BL. 1998. Stream flow characterization and feature detection  
900 using a discrete wavelet transform. *Hydrological Processes* 12: 233–249.

901 Snelder TH, Biggs BJJ. 2002. Multi-scale river environment classification for water resources  
902 management. *Journal of the American Water Resources Association* 38: 1225-1240.

903 Snelder TH, Lamouroux N. 2010. Co-variation of fish assemblages, flow regimes and other  
904 habitat factors in French rivers. *Freshwater Biology* 55: 881–892.

905 Snelder TH, Hughey KFD. 2005. On the use of an ecologic classification to improve water  
906 resource planning in New Zealand. *Environmental Management* 36: 741–756.

907 Snelder TH, Weatherhead M, Biggs BJJ. 2004. Nutrient concentration criteria and  
908 characterization of patterns in trophic state for rivers in heterogeneous landscape. *Journal of*  
909 *the American Water Resources Association* 40: 1-13.

910 Snelder TH, Biggs BJJ, Woods RA. 2005. Improved eco-hydrological classification of rivers.  
911 *River Research and Applications* 21: 609–628.

912 Snelder TH, Dey KL, Leathwick JR. 2007. A procedure for making optimal selection of input  
913 variables for multivariate environmental classifications. *Conservation Biology* 21: 365–375.

914 Snelder TH, Lamouroux N, Leathwick JR, Pella H, Sauquet E, Shankar U. 2009a. Predictive  
915 mapping of the natural flow regimes of France. *Journal of Hydrology* 373: 56–67.

916 Snelder TH, Lehmann A, Lamouroux N, Leathwick JR, Allenbach K. 2009b. Strong influence of  
917 variable treatment on the performance of numerically defined ecological regions.  
918 *Environmental Management* 44: 658–670.

919 Snelder TH, Booker D, Lamouroux N. 2011. A method to assess and define environmental flow  
920 rules for large jurisdictional regions. *Journal of the American Water Resources Association*,  
921 in press. DOI: 10.1111/j.1752-1688.2011.00556.x

922 Stein JL, Hutchinson MF, Pusey BJ, Kennard MJ. 2009. Ecohydrological classification based on  
923 landscape and climate data. Appendix 8. In: Pusey BJ, Kennard MJ, Stein JL, Olden JD,  
924 Mackay SJ, Hutchinson MF, Sheldon F. (eds), *Ecohydrological Regionalisation of Australia:  
925 A Tool for Management and Science*. Innovations Project GRU36, Final Report to Land and  
926 Water Australia. Available at <http://lwa.gov.au/products/pn22591>.

927 Tasker GD. 1982. Comparing methods of hydrologic regionalization. *Water Resources Bulletin*  
928 18: 965-970.

929 Vogel RM, Wilson I, Daly C. 1999. Regional regression models of annual streamflow for the  
930 United States. *Journal of Irrigation and Drainage Engineering* 125: 148–157.

931 Wagener T, Sivapalan M, Troch P, Woods R. 2007. Catchment classification and hydrologic  
932 similarity. *Geography Compass* 1: 1-31.

933 Ward D, Stein J, Carew R, Kennard M. 2010. Hydrosystem delineation, environmental  
934 attribution and classification. Chapter 4. In Kennard MJ. (ed), *Identifying high conservation  
935 value aquatic ecosystems in northern Australia*. Interim Report for the Department of  
936 Environment, Water, Heritage and the Arts and the National Water Commission. *Tropical  
937 Rivers and Coastal Knowledge (TRaCK)* Commonwealth Environmental Research Facility,  
938 Charles Darwin University. Available at: <http://track.gov.au/publications/registry/843>.

939 Webb JA, Bond NR, Wealands SR, Mac Nally R, Quinn GP, Vesk PA, Grace MR. 2007.  
940 Bayesian clustering with AutoClass explicitly recognises uncertainties in landscape  
941 classification. *Ecography* 30: 526-536.

942 Wiltshire SE. 1986. Identification of homogeneous regions for flood frequency analysis.  
943 *Journal of Hydrology* 84: 287-302.



- 944 Winter TC. 2001. The concept of hydrologic landscapes. *Journal of the American Water*  
945 *Resources Association* 37: 335–349.
- 946 Wolock DM, Winter TC, McMahon G. 2004. Delineation and evaluation of hydrologic-  
947 landscape regions in the United States using geographic information system tools and  
948 multivariate statistical analyses. *Environmental Management* 34: S71-S88.
- 949 Zhang Y, Xia J, Bunn SE, Arthington AH, Mackay S, Kennard M. 2011. Classification of flow  
950 regimes for environmental flow assessment in regulated rivers: the Huai River Basin, China.  
951 *River Research and Applications*, in press. DOI: 10.1002/rra.1483.
- 952 Zoppou C, Nielsen OM, Zhang L. 2002. Regionalization of daily stream flow in Australia using  
953 wavelets and K means analysis. CMA Research Report MRR02-003, Australian National  
954 University, Canberra. Available at:  
955 <http://www.maths.anu.edu.au/research.reports/mrr/02/003/>

Table 1. Examples of deductive regionalization/classifications of environmental attributes (inferred as key determinants of riverine flow regimes). Environmental data types: Spatial Location (SL) (e.g. latitude & longitude, catchment boundaries), Climate (C), Catchment Topography (T), Soils/Geology (SG), Vegetation (V), Flow (F), Land Use (LU). A brief description of classification methodology is also provided (see references for more details). The spatial units analyzed included individual stream segments or watersheds of varying spatial resolution with the exception of Mkandi and Kachroo (1996). All examples used gauged streamflow data to externally validate the classifications with the exception of Wolock et al. (2004).

Scale/Location	Environmental attributes	Geographic dependence	Classification methodology	Reference(s)
Africa (Southern)	SL, C, T, F	Dependent	Regions delineated based on subjective interpretation of environmental attributes.	Mkandi and Kachroo, 1996
Australia	C, T, SG, V, F	Independent	Non-hierarchical iterative clustering method based on Gower similarity of objects to groups.	Stein et al., 2009 (see also Ward et al., 2010)
Australia (South-eastern)	SL, C, T, SG	Independent	Clustering (using a range of similarity measures and clustering methods) and Andrew's curves to identify group outliers and evaluate within-group cohesiveness.	Nathan and McMahon, 1990
New Zealand	C, T, SG, V	Independent	Top-down hierarchical method whereby river segments were classified individually according to various differentiating criteria.	Snelder and Biggs, 2002; Snelder et al., 2005
Scotland	C, T, SG	Independent	Hierarchical clustering using Ward's algorithm and maximum likelihood.	Acreman and Sinclair, 1986
USA	C, CT, SG	Independent	Ordination (Principal Component Analysis) and clustering (using a minimum variance criterion and the nearest neighbor chain algorithm)	Wolock et al., 2004
USA (Indiana)	C, T, SG, V	Independent	Hierarchical (single linkage, complete linkage, Ward's algorithm) <sup>1</sup> and non-hierarchical (K-means <sup>1</sup> , fuzzy partitioning c-means algorithm <sup>2</sup> ) clustering.	Rao and Srinivas, 2006a <sup>1</sup> ; Rao and Srinivas, 2006b <sup>2</sup>
USA (Eastern)	C, T, SG, V	Independent	Non-hierarchical clustering using fuzzy partitioning Bayesian mixture algorithm.	Sawicz et al., 2011

Table 2. Examples of inductive streamflow classifications. Flow regime attributes: Magnitude (M), Frequency (F), Duration (D), Timing (T), Rate of Change (R). Temporal scale of the flow regime attributes analyzed: Daily (D), Weekly (W), Monthly (M), Annual (A). A brief description of classification methodology, instances of external validation of the classifications (i.e. using independent environmental data unless otherwise stated) and method for prediction of class membership at new locations is also provided. See references for more details and Appendix A for a complete listing of past streamflow classifications.

Scale/Location	Flow attributes	Temporal scale	Classification methodology	Reference(s)
<b>Basin</b>				
Huai R., China	M, F, D, T	M, A	Ordination (Principal Component Analysis), hierarchical clustering (Ward's algorithm) and external validation.	Zhang et al., 2011
Ebro R., Spain	M, D, T	M	Hierarchical clustering (unspecified cluster algorithm), external validation and prediction (logistic regression).	Bejarano et al., 2010
Missouri and Yellowstone R., USA	M, T	M, A	Hierarchical clustering (centroid linkage).	Pegg and Pierce, 2002
<b>Regional</b>				
Victoria, Australia	M, F, D, T	D	Ordination (Principal Component Analysis), hierarchical clustering (average linkage) and external validation.	Hughes and James, 1989
Quebec, Canada	M, D, T, R	M	Ordination (Principal Component Analysis), heuristic classification method based on rules and signs of loadings on PCs and external validation.	Assani and Tardif, 2005
Washington, USA	M, F, D, T, R	D, M, A	Non-hierarchical clustering using fuzzy partitioning Bayesian mixture algorithm, external validation and prediction (random forest classifier).	Reidy Liermann et al., 2011
<b>National/Continental</b>				
Australia	F, T	D	Wavelet analysis and non-hierarchical clustering (K-means).	Zoppou et al., 2002
Australia	M, D, F, T, R	D	Non-hierarchical clustering using fuzzy partitioning Bayesian mixture algorithm and external validation.	Kennard et al., 2010b
Canada	M, T	W	Hierarchical clustering (Ward's method).	Monk et al., 2011
France	M, T	M	Proportion of flow within each of four seasons, together with the source of water (i.e. snow melt, glacier melt, rainfall).	Pardé, 1955
France	M, D, F, T, R	D	Ordination (Principal Component Analysis), non-hierarchical clustering (K-means), external validation and prediction (boosted regression trees).	Snelder et al., 2009a
New Zealand	M, F	D, A	Hierarchical clustering (Two-way indicator species analysis) and external validation.	Jowett and Duncan, 1990

Scale/Location	Flow attributes	Temporal scale	Classification methodology	Reference(s)
Scandinavia	M, T	M, A	Two-step approach: (1) Flow regime class discriminating criteria based on the time of occurrence of the highest (3 classes) and lowest (2 classes) of monthly flow, (2) entropy based groupings based on interannual variation in monthly flows.	Krasovskaia, 1997
South Africa, Lesotho and Swaziland	T, M	M	Index of flow variability divided into classes using cumulative deviations from homogeneity plots.	Hughes and Hannart, 2003
Tanzania	M, F	A	Three-step process: (1) Geographic information was used to identify likely homogeneous regions that are geographically continuous; (2) Each region was checked for similarity in the statistics of observed flood data. Based on this step, regions obtained in step (1) were modified; (3) A test of homogeneity was applied to confirm that the delineated regions are statistically homogeneous.	Kachroo et al., 2000
United Kingdom	M, T	M	Hierarchical clustering (Ward's algorithm) and external validation (qualitative environmental information and quantitative biological data).	Monk et al., 2006
United Kingdom	M, T	M	Hierarchical (Ward's algorithm) and non-hierarchical (K-means) clustering and external validation.	Bower et al., 2004 (see also Harris et al., 2000; Hannah et al., 2000)
United States	M, F, D, T	D, M, A	Hierarchical clustering (density linkage).	Poff, 1996
Global				
	M	A	Two-step approach: (1) initial groupings based on regions of similar climatic conditions (based largely on Köppen's climate regions); (2) Hierarchical clustering (average linkage) of stream gauges based on an index of flood magnitude.	Burn and Arnell, 1993
	M, T	M	Non-hierarchical clustering (K-means).	Dettinger and Diaz, 2000
	M, T	M, A	Hierarchical clustering (average linkage) and external validation.	Haines et al., 1988 (see also Finlayson and McMahon, 1988)
	M, F	A	Examined regional variation in mean annual flood magnitudes and flood frequency curves, where regions were defined using an empirical approach based firstly on physical and climatic characteristics, and second, by evaluation of the homogeneity of flood frequency curves within the defined regions.	Meigh et al., 1997
	M	M	No actual streamflow classification but examined regional variation in individual hydrologic attributes at a global scale.	McMahon et al., 2007a, b
	M, F, D, T R	D, M, A	Ordination (Semi Strong Hybrid Multidimensional Scaling), hierarchical clustering (average linkage) and external validation.	Puckridge et al., 1998

## FIGURE CAPTIONS

Figure 1. Two main approaches to hydrologic classification based on deductive (environmental regionalization, hydrologic regionalization or environmental classification) and inductive (streamflow classification) reasoning.

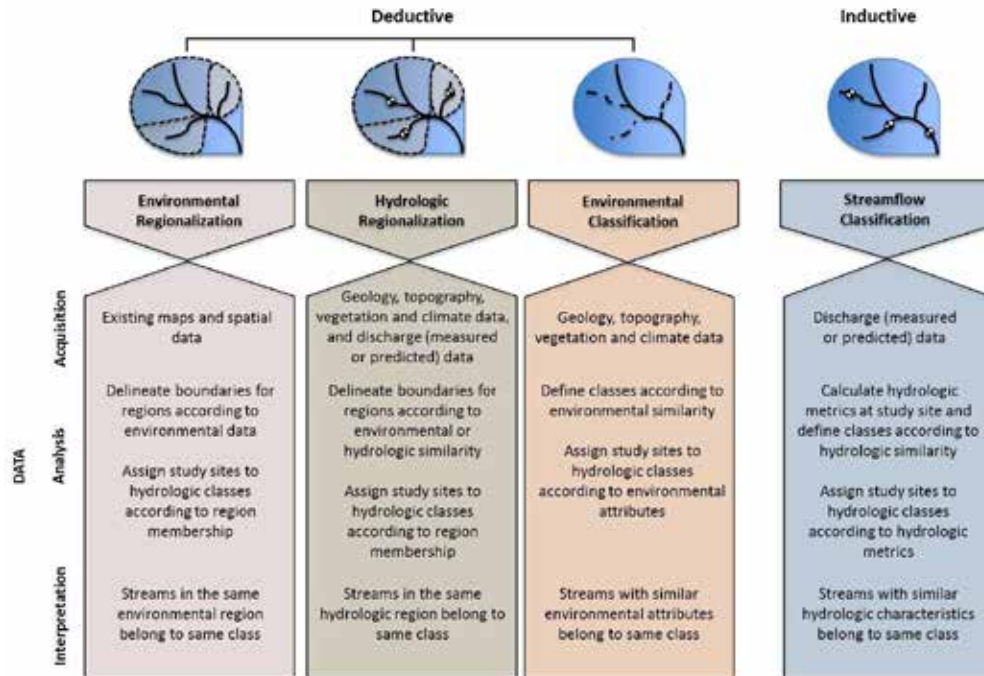
Figure 2. Hydrologic landscape regions of the United States after Wolock et al. (2004).

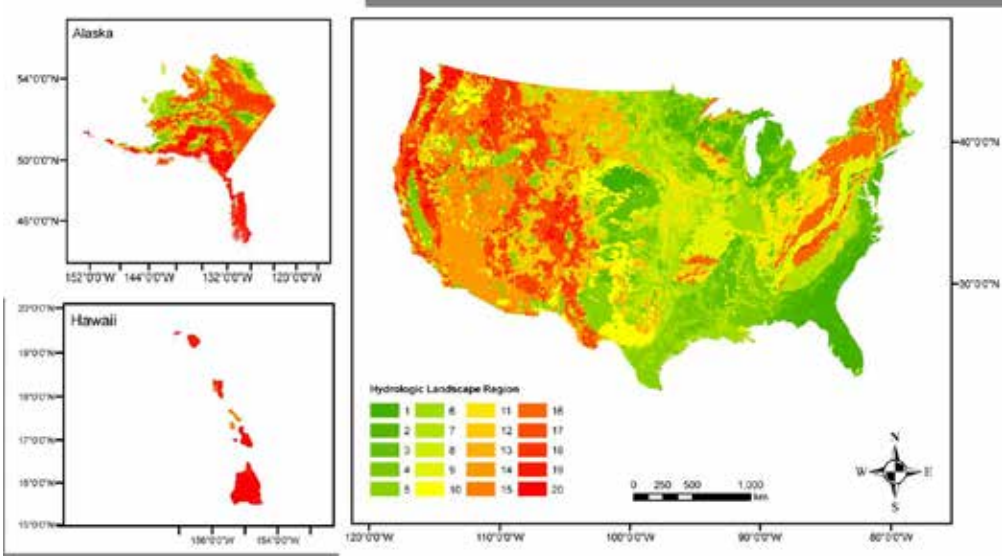
Figure 3. The REC classification for New Zealand. River classes refer to a combination of climate type: warm-extremely-wet (WX), warm-wet (WW), warm-dry (WD), cool-extremely-wet (CX), cool-wet (CW) and cool-dry (CD); and source of flow: glacial-mountain (/GM), mountain (/M), hill (/H), low-elevation (/L) and lake (/LK). The width of the lines representing the rivers has been scaled according to the mean flow in each river segment. Modified from Snelder et al. (2011), and provided courtesy of Ton Snelder.

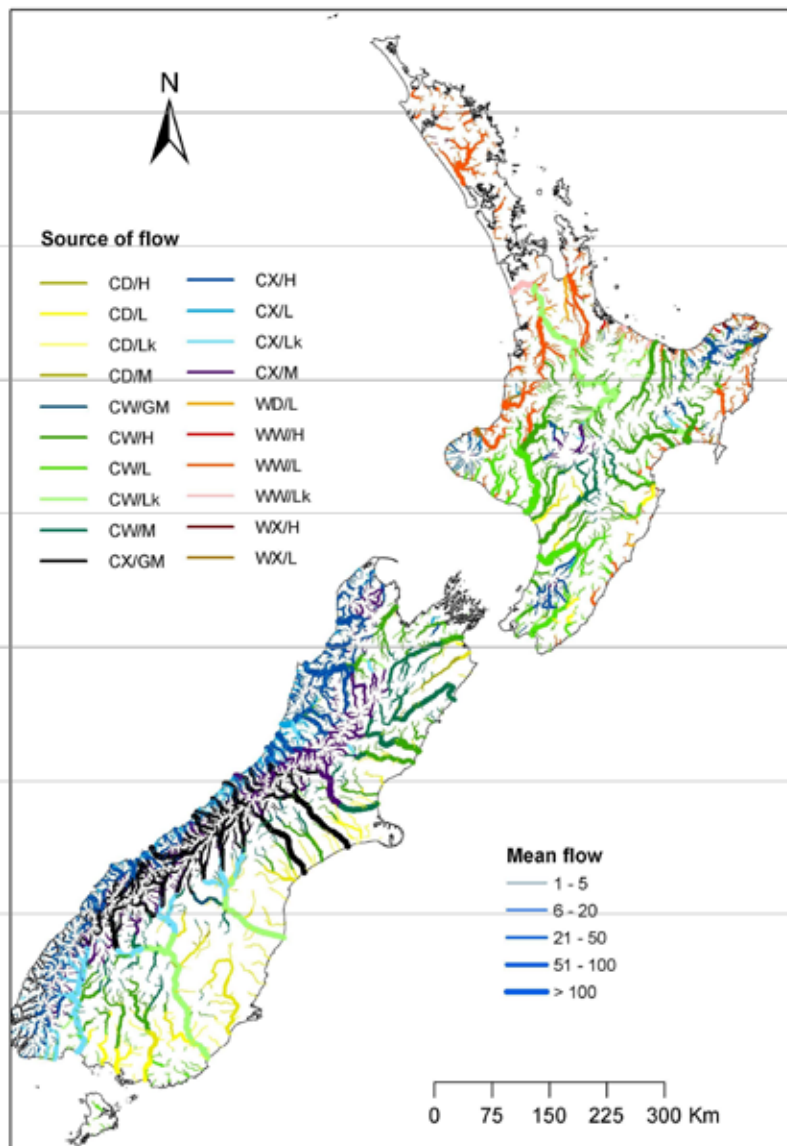
Figure 4. Different components of the flow regime may be characterized over varying temporal scales for use in streamflow classifications.

Figure 5. (a) Hydrologic classification of flow-regime types for 830 stream gauges in Australia from Kennard et al. (2010b). Australian drainage divisions (thick lines) and State and Territory borders (dashed lines) are shown. (b) Inset figure shows predicted flow regime types of north-eastern Australian streams based on climate and catchment topographic characteristics and derived using a classification tree predictive model (see Kennard et al., 2010b). This figure incorporates data that are copyrighted by the Commonwealth of Australia (GeoSciences Australia, 2006).

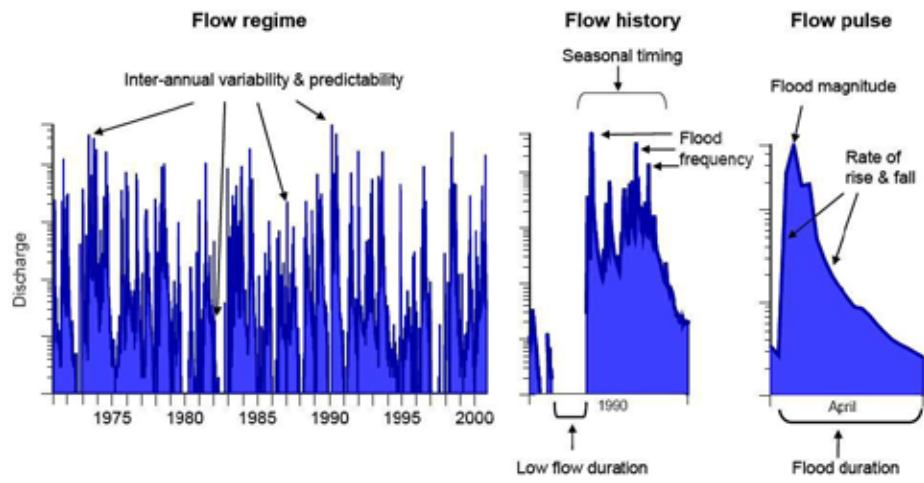
## Approaches to Hydrologic Classification

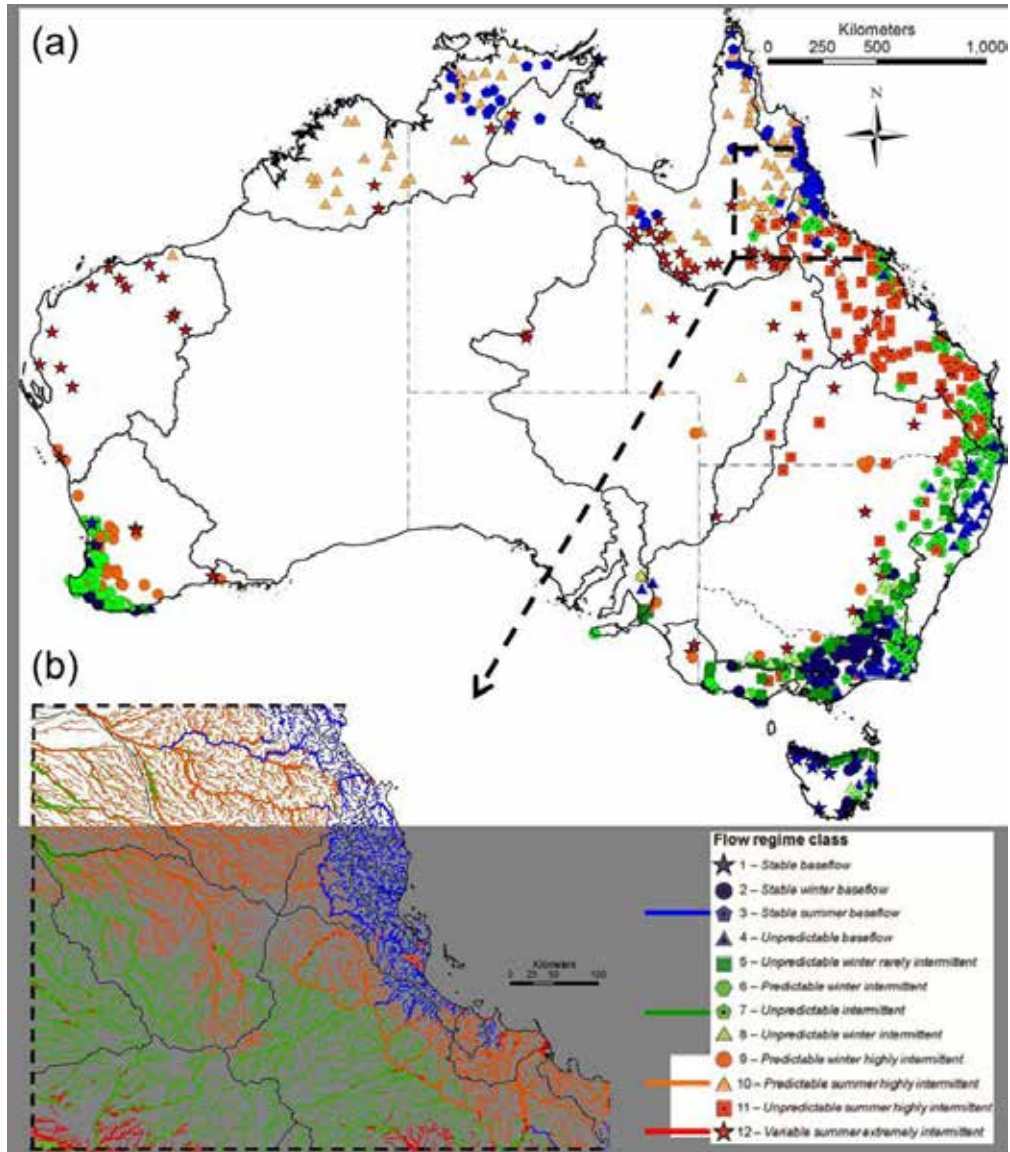












**Appendix A.** Examples of inductive streamflow classifications. Flow regime attributes: Magnitude (M), Frequency (F), Duration (D), Timing (T), Rate of Change (R). Temporal scale of the flow regime attributes analyzed: Daily (D), Weekly (W), Monthly (M), Annual (A). A brief description of classification methodology, instances of external validation of the classifications (i.e. using independent environmental data unless otherwise stated) and method for prediction of class membership at new locations is also provided. See references for more details.

Scale/Location	Flow attributes	Temporal scale	Classification methodology	Reference(s)
<b>Basin</b>				
Burdekin R., Australia	M, F, D, T	D, M, A	A-priori classification of stream gauges (based on stream size and relative catchment position) and ordination (Discriminant Functions Analysis) of streamflow attributes	Pusey and Arthington, 1996
Condamine–Balonne R., Australia	M, F, D, T, R	D, M, A	Ordination (Semi Strong Hybrid Multidimensional Scaling) and hierarchical clustering (average linkage)	Thoms and Parsons, 2003
Huai R., China	M, F, D, T	M, A	Ordination (Principal Component Analysis), hierarchical clustering (Ward's algorithm) and external validation	Zhang <i>et al.</i> , 2011
Ebro R., Spain	M, D, T	M	Ordination (Principal Component Analysis), hierarchical clustering (unspecified cluster algorithm), external validation and prediction (logistic regression)	Bejarano <i>et al.</i> , 2010
Tagus R., Spain	M, F, D, T	D, M, A	Hierarchical clustering (unspecified cluster algorithm)	Baeza Sanz and García del Jalón, 2005
Missouri and Yellowstone R., USA	M, T	M, A	Hierarchical clustering (centroid linkage)	Pegg and Pierce, 2002
<b>Regional</b>				
Victoria, Australia	M, F, D, T	D	Ordination (Principal Component Analysis), hierarchical clustering (average linkage) and external validation	Hughes and James, 1989
Tasmania, Australia	M, F, D, T	D	Ordination (Principal Coordinate Analysis), hierarchical clustering (complete linkage) and external validation	Hughes, 1987
South-eastern Australia	M, D, F	D	No actual streamflow classification but examined regional variation in flow regime attributes using ordination (Semi Strong Hybrid Multidimensional Scaling)	Growns and Marsh, 2000
Gulf of Carpentaria region, Australia	M, D, F	D	Ordination (Semi Strong Hybrid Multidimensional Scaling) and hierarchical clustering (average linkage)	Leigh and Sheldon, 2008
Quebec, Canada	M, D, T, R	M	Ordination (Principal Component Analysis), heuristic classification method based on rules and signs of loadings on PCs and external validation	Assani and Tardif, 2005

Scale/Location	Flow attributes	Temporal scale	Classification methodology	Reference(s)
Southern Taiwan	M, T, F		Clustering and external validation (discrimination) using self-organizing maps	Lin and Wang, 2006
Alabama, Georgia and Mississippi, USA	M, T	M	Ordination (Principal Component Analysis), hierarchical clustering (average linkage) and external validation	Chiang <i>et al.</i> , 2002a,b
Arizona, New Jersey, Pennsylvania, Texas, USA	M, F	D, A	Hierarchical clustering (complete linkage) and external validation	Tasker, 1982
<b>National/Continental</b>				
Australia	M, D, F, T, R	D	Non-hierarchical clustering using fuzzy partitioning Bayesian mixture algorithm and external validation	Kennard <i>et al.</i> , 2010b
Australia	F, T	D	Wavelet analysis and non-hierarchical clustering (K-means)	Zoppou <i>et al.</i> , 2002
Austria	M, T	D	Ordination (Principal Component Analysis), non-hierarchical clustering (K-medoids) and external validation	Laaha and Blöschl, 2006
Canada	M, T	W	Hierarchical clustering (Ward's method)	Monk <i>et al.</i> , 2011
France	M, T	M	Proportion of flow within each of four seasons, together with the source of water (i.e. snow melt, glacier melt, rainfall)	Parde, 1955
France	M, D, F, T, R	D	Ordination (Principal Component Analysis), non-hierarchical clustering (K-means), external validation and prediction (boosted regression trees)	Snelder <i>et al.</i> , 2009a
Mediterranean countries (Portugal, France, Italy, Cyprus, Morocco, Algeria, Tunisia, Israel)	M, D, F, T, R	D, M, A	Ordination (Principal Components Analysis), hierarchical clustering (group average) and external validation	Oueslati <i>et al.</i> , 2010
Nepal	M, T	M	Hierarchical clustering (Ward's algorithm)	Hannah <i>et al.</i> , 2005 (see also Harris <i>et al.</i> , 2000; Hannah <i>et al.</i> , 2000; Bower <i>et al.</i> , 2004)
New Zealand	M	D	Hierarchical clustering (Ward's algorithm )	Mosley, 1981
New Zealand	M, F	D, A	Hierarchical clustering (Two-way indicator species analysis) and external validation	Jowett and Duncan, 1990
New Zealand	M, F, D, T, R	D	Hierarchical clustering (flexible beta)	Snelder <i>et al.</i> , 2005
Russia	M, T	M	Proportion of flow within each of four seasons, together with the source of water (i.e. snow melt, glacier melt, rainfall and groundwater)	Lvovich, 1973

Scale/Location	Flow attributes	Temporal scale	Classification methodology	Reference(s)
Scandinavia	M, T	M	Flow regime class discriminating criteria based on the time of occurrence of the highest (3 classes) and lowest (2 classes) of mean monthly flow	Gottschalk <i>et al.</i> , 1979; Krasovskaia and Gottschalk, 2002
Scandinavia	M, T	M, A	Two-step approach: (1) Flow regime class discriminating criteria based on the time of occurrence of the highest (3 classes) and lowest (2 classes) of monthly flow, (2) entropy based groupings based on interannual variation in monthly flows	Krasovskaia, 1997
Scandinavia and western Europe	M, T	M	Flow regime class discriminating criteria based on the time of occurrence of the highest (3 classes) and lowest (2 classes) of mean monthly flow	Krasovskaia, 1995
South Africa, Lesotho and Swaziland	T, M	M	Index of flow variability divided into classes using cumulative deviations from homogeneity plots	Hughes and Hannart, 2003
Sweden	M, T	M	Ordination (Principal Component Analysis) and hierarchical clustering (average linkage)	Gottschalk, 1985
Taiwan	M, D, F, R	D	Non-hierarchical clustering (K-means) and self-organizing maps	Chang <i>et al.</i> , 2008
Tanzania	M, F	A	Three-step process: (1) Geographic information was used to identify likely homogeneous regions that are geographically continuous; (2) Each region was checked for similarity in the statistics of observed flood data. Based on this step, regions obtained in step (1) were modified; (3) A test of homogeneity was applied to confirm that the delineated regions are statistically homogeneous	Kachroo <i>et al.</i> , 2000
Turkey	M	A	Non-hierarchical clustering (K-means)	Kayha <i>et al.</i> , 2007
United Kingdom	M, T	M	Hierarchical clustering (Ward's algorithm) and external validation (qualitative environmental information and quantitative biological data)	Monk <i>et al.</i> , 2006
United Kingdom	M, T	M	Hierarchical clustering (average linkage)	Harris <i>et al.</i> , 2000 (see also Hannah <i>et al.</i> , 2000)
United Kingdom	M, T	M	Hierarchical (Ward's algorithm) and non-hierarchical (K-means) clustering and external validation	Bower <i>et al.</i> , 2004 (see also Harris <i>et al.</i> , 2000; Hannah <i>et al.</i> , 2000)
United Kingdom (and other regions)	M, T, F, D		Hierarchical clustering (Ward's algorithm) and external validation	Stahl, 2001
United States	M, T	Y	No actual streamflow classification but examined regional variation in flow regime attributes using ordination (Principal Component Analysis)	Lins, 1985
United States	M, F, D, T	D, M, A	Non-hierarchical clustering (K-means) and external validation	Poff and Ward, 1989
United States	M, F, D, T	D, M, A	Hierarchical clustering (density linkage)	Poff, 1996

Scale/Location	Flow attributes	Temporal scale	Classification methodology	Reference(s)
<b>Global</b>				
	M	A	Two-step approach: (1) initial groupings based on regions of similar climatic conditions (based largely on Köppen's climate regions); (2) Hierarchical clustering (average linkage) of stream gauges based on an index of flood magnitude	Burn and Arnell, 1993
	M, T	M	Non-hierarchical clustering (K-means)	Dettinger and Diaz, 2000
	M, T	M	Hierarchical clustering (average linkage)	Finlayson and McMahon, 1988
	M, T	M, A	Hierarchical clustering (average linkage) and external validation	Haines <i>et al.</i> , 1988
	M, F	A	Examined regional variation in mean annual flood magnitudes and flood frequency curves, where regions were defined using an empirical approach based firstly on physical and climatic characteristics, and second, by evaluation of the homogeneity of flood frequency curves within the defined regions.	Meigh <i>et al.</i> , 1997
	M	M	No actual streamflow classification but examined regional variation in individual hydrologic attributes at a global scale	McMahon <i>et al.</i> , 2007
	M, F, D, T R	D, M, A	Ordination (Semi Strong Hybrid Multidimensional Scaling), hierarchical clustering (average linkage) and external validation	Puckridge <i>et al.</i> , 1998

## References

- Assani AA, Tardif S. 2005. Classification and characterization of natural flow regimes in Quebec (Canada). Factors of spatial variability – an eco-geographical approach. *Revue Des Sciences De L'Eua* **18**: 247-266.
- Baeza Sanz D, García del Jalón D. 2005. Characterisation of streamflow regimes in central Spain, based on relevant hydrobiological parameters. *Journal of Hydrology* **310**: 266–279.
- Bejarano MD, Marchamalo M, de Jalón DG, Tánago MG. 2010. Flow regime patterns and their controlling factors in the Ebro basin (Spain). *Journal of Hydrology* **385**: 323-335.
- Bower D, Hannah DM, McGregor GR. 2004. Techniques for assessing the climatic sensitivity of river flow regimes. *Hydrological Processes* **18**: 2515–2543.

- Chang FJ, Tsai MJ, Tsai WP, Herricks EE. 2008. Assessing the ecological hydrology of natural flow conditions in Taiwan. *Journal of Hydrology* **354**: 75–89.
- Chiang SM, Tsay TK, Nix SJ. 2002a. Hydrologic regionalization of watersheds. I: Methodology development. *Journal of Water Resources Planning and Management* **128**: 3–11.
- Chiang SM, Tsay TK, Nix SJ. 2002b. Hydrologic regionalization of watersheds. II: Applications. *Journal of Water Resources Planning and Management* **128**: 12–20.
- Dettinger MD, Diaz HF. 2000. Global characteristics of stream flow seasonality and variability. *Journal of Hydrometeorology* **1**: 289–310.
- Finlayson BL, McMahon TA. 1988. Australia vs. the World: A comparative analysis of streamflow characteristics. Pp 17-40 In: Werner RF (ed.), *Fluvial Geomorphology of Australia*, Academic Press, Sydney.
- Gottschalk L, Lundager J, Lundquist D, Solantie R, Tollan A. 1979. Hydrologic regions in the Nordic countries. *Nordic Hydrology* **10**: 273-286.
- Gottschalk L. 1985. Hydrological regionalization of Sweden. *Hydrological Science* **30**: 65-83.
- Growns J, Marsh N. 2000. Characterisation of flow in regulated and unregulated streams in eastern Australia. Technical Report, Cooperative Research Centre for Freshwater Ecology. 66 pp.
- Haines AT, Findlayson BL, McMahon TA. 1988. A global classification of river regimes. *Applied Geography* **8**: 255-272.
- Hannah DM, Smith BPG, Gurnell AM, McGregor GR. 2000. An approach to hydrograph classification. *Hydrological Processes* **14**: 317-338.
- Hannah DM, Kansakar SR, Gerrard AJ, Rees G. 2005. Flow regimes of Himalayan rivers of Nepal: nature and spatial patterns. *Journal of Hydrology* **308**: 18-32.
- Harris NM, Gurnell AM, Hannah DM, Petts GE. 2000. Classification of river regimes: a context for hydroecology. *Hydrological Processes* **14**: 2831-2848.

- Hughes DA, Hannart P. 2003. A desktop model used to provide an initial estimate of the ecological instream flow requirements of rivers in South Africa. *Journal of Hydrology* **270**: 167-181.
- Hughes JMR. 1987. Hydrological characteristics and classification of Tasmanian rivers. *Australian Geographical Studies* **25**: 61–82.
- Hughes JMR, James B. 1989. A hydrological regionalization of streams in Victoria, Australia, with implications for stream ecology. *Australian Journal of Marine and Freshwater Resources* **40**: 303-326.
- Jowett IG, Duncan MJ. 1990. Flow variability in New Zealand rivers and its relationship to in-stream habitat and biota. *New Zealand Journal of Marine and Freshwater Research* **24**: 305-317.
- Kachroo RK, Mkhanda SH. 2000. Flood frequency analysis of southern Africa: I. Delineation of homogeneous regions. *Hydrological Science* **45**: 437-447.
- Kahya E, Demirel MC, Piechota TC. 2007. *Spatial grouping of annual streamflow patterns in Turkey*. Paper presented at Hydrology Days, Colorado State Univ. (Available at: [http://hydrologydays.colostate.edu/Papers\\_2007/Demirel\\_Kahya\\_paper.pdf](http://hydrologydays.colostate.edu/Papers_2007/Demirel_Kahya_paper.pdf)).
- Kennard MJ, Pusey BJ, Olden JD, Mackay SJ, Stein JL, Marsh N. 2010b. Classification of natural flow regimes in Australia to support environmental flow management. *Freshwater Biology* **55**: 171-193.
- Krasovskaia I. 1995. Quantification of the stability of river flow regimes. *Hydrological Science* **40**: 587-598.
- Krasovskaia I. 1997. Entropy-based grouping of river flow regimes. *Journal of Hydrology* **202**: 173-191.
- Krasovskaia I, Gottschalk L. 2002. River flow regimes in a changing climate. *Hydrological Science* **47**: 597-609.
- Laaha G, Blöschl G. 2006. A comparison of low flow regionalization methods - catchment grouping. *Journal of Hydrology* **323**: 193–214.
- Leigh C, Sheldon F. 2008. Hydrological changes and ecological impacts associated with water resource development in large floodplain rivers in the Australian tropics. *River Research and Applications* **24**: 1251–1270
- Lin G-F, Wang C-M. 2006. Performing cluster analysis and discrimination analysis of hydrological factors in one step. *Advances Water Research* **29**: 1573–1585.



- Lins HF. 1985. Streamflow variability in the United States: 1931-78. *Journal of Climate Applications and Meteorology* **24**: 463-471.
- Lvovich MI. 1973. *The World's Water*. Mir, Moscow, 213 pp.
- McMahon TA, Vogel RM, Peel MC, Pegram GGS. 2007. Global streamflows – Part 1: Characteristics of annual streamflows. *Journal of Hydrology* **347**: 243-259
- Meigh JR, Farquharson FAK, Sutcliffe JV. 1997. A worldwide comparison of regional flood estimation methods and climate. *Hydrology Science* **42**: 225-244.
- Monk WA, Peters DL, Curry RA, Baird DJ. 2011. Quantifying trends in indicator hydroecological variables for regime-based groups of Canadian river. *Hydrological Processes*, in press. DOI: 10.1002/hyp.8137.
- Monk WA, Wood PJ, Hannah DM, Wilson DA, Extence CA, Chadd RP. 2006. Flow variability and macroinvertebrate community response within riverine systems. *River Research and Applications* **22**: 595–615.
- Mosley MP. 1981. Delimitation of New Zealand hydrologic regions. *Journal of Hydrology* **49**: 179-192.
- Oueslati O, De Girolamo AM., Abouabdillah A, Lo Porto A. 2010. Attempts to flow regime classification and characterisation in Mediterranean streams using multivariate analysis. *Advances in Statistical Hydrology*, International Workshop Proceedings, May 23-25, 2010 Taormina, Italy.
- Parde M. 1955. *Fleuves et rivières*. Collection Armand Colin, Paris, 224 pp.
- Pegg MA, Pierce CL. 2002. Classification of reaches in the Missouri and lower Yellowstone rivers based on flow characteristics. *River Research and Applications* **18**: 31–42.
- Poff NL. 1996. A hydrogeography of unregulated streams in the United States and an examination of scale-dependence in some hydrological descriptors. *Freshwater Biology* **36**: 71-91.
- Poff NL, Ward JV. 1989. Implications of streamflow variability and predictability for lotic community structure: a regional analysis of streamflow patterns. *Canadian Journal of Fisheries and Aquatic Sciences* **46**: 1805-1818.

- Puckridge JT, Sheldon F, Walker KF, Boulton AJ. 1998. Flow variability and the ecology of large rivers. *Marine and Freshwater Research* **49**: 55-72.
- Pusey BJ, Arthington AH. 1996. Streamflow variability within the Burdekin River. *Proceedings of the 23rd Hydrology and Water Resources Symposium*. Pp. 213–220. Australian Institute of Engineers, Barton.
- Snelder TH, Biggs BJB, Woods RA. 2005. Improved eco-hydrological classification of rivers. *River Research and Applications* **21**: 609-628.
- Snelder TH, Lamouroux N, Leathwick JR, Pella H, Sauquet E, Shankar U. 2009a. Predictive mapping of the natural flow regimes of France. *Journal of Hydrology* **373**: 56-67.
- Stahl K. 2001. *Hydrological drought: A study across Europe*. PhD Dissertation, Albert Ludwig University, Freiburg, Germany.
- Tasker GD. 1982. Comparing methods of hydrologic regionalization. *Water Resources Bulletin* **18**: 965-970.
- Thoms MC, Parsons M. 2003. Identifying spatial and temporal patterns in the hydrological character of the Conadmine-Balonne river, Australia, using multivariate statistics. *River Research and Applications* **19**: 443–457.
- Zhang Y, Xia J, Bunn SE, Arthington AH, Mackay S, Kennard M. 2011. Classification of flow regimes for environmental flow assessment in regulated rivers: the Huai River Basin, China. *River Research and Applications* DOI: 10.1002/rra.1483.
- Zoppou C, Nielsen OM, Zhang L. 2002. *Regionalization of daily stream flow in Australia using wavelets and K means analysis*. CMA Research Report MRR02-003, Australian National University, Canberra. Available at: <http://www.maths.anu.edu.au/research.reports/mrr/02/003/>