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Published

2012

Journal Title

Ecohydrology

DOI

https://doi.org/10.1002/eco.251

Olden, J.D., Kennard, M.J. & Pusey, B.J. (2012). A framework for hydrologic classification with a review of methodologies and applications in ecohydrology. *Ecohydrology*. 5: 503–518. DOI: 10.1002/eco.251.

Published version on Journal website available at:
http://dx.doi.org/10.1002/eco.251

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

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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

INTRODUCTION

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

Challenged by the need to quantify flow similarities among rivers and map their distribution across the landscape, ecohydrologists have turned to a bewildering (and expanding) array of protocols using an equally diverse set of statistical approaches to conduct their hydrologic classification. As a result, several groups of methods are in use, and to-date no single approach has demonstrated universally accepted results. This is not entirely surprising given that despite the growing use of hydrologic classification in ecohydrology, little guidance and no synthesis on this topic has been published in the literature, and the purposes for conducting a classification vary greatly. Herein, we provide a systematic review of the process of hydrologic classification by (i) reviewing two broad classification approaches according to deductive reasoning using environmental regionalization, hydrologic regionalization and environmental classification whereby environmental variables assumed to be key determinants of hydrology are analyzed, and inductive reasoning using streamflow classification whereby hydrologic data is analyzed directly; (ii) exploring past applications in ecohydrology; (iii) introducing a unifying methodological framework that depicts critical components of the classification process; and (iv) summarizing important advantages and disadvantages of commonly used statistical approaches to characterize and predict hydrologic classes. The intention of our study is to inform ecohydrologists about the critical elements of hydrologic classification, including a discussion of the important considerations and techniques available to them.

APPROACHES TO HYDROLOGIC CLASSIFICATION

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

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

Inductive approaches to hydrologic classification are typically conducted using various attributes describing different components of the riverine flow regime. This approach has the advantage of being based on direct measures of hydrology (rather than indirect environmental surrogates for hydrology) but has a number of limitations including the often limited spatial coverage of stream gauges within the river network and the notoriously variable quality and quantity of discharge data available for each gauge (Kennard et al., 2010a). Key characteristics and examples of deductive and inductive approaches to hydrologic classification are presented in more detail below.

Deductive Approaches

Environmental regionalization

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

Hydrologic regionalization

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

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

Environmental classification

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

The concept of hydrologic landscape regions was introduced by Winter (2001) and developed by Wolock et al. (2004) to describe non-contiguous areas for the United States that reflected aggregated river basins sharing similar environmental factors (e.g. climate, soils, geology, topography) known to influence streamflow. According to this classification, a fundamental hydrologic landscape unit could be defined according to: (a) the movement of surface water, which is controlled by the slopes and permeability of the landscape; (b) the movement of ground water, which is controlled by the hydraulic characteristics of the geologic framework; and (c) atmosphere-water exchange, which is controlled by climate. Using multivariate ordination and cluster analysis, Wolock et al. (2004) assigned membership of nearly 44,000 small (ca. 200 km^2) watersheds in the United States to 20 hydrologic regions based on similarities in land-surface form, geologic texture, and climate characteristics (Figure 2). The hydrologic landscape region and similar concepts have proven useful in ecohydrology because they are founded on sound physical principles, yet this framework has only rarely been tested against regional hydrologic variables. Santhi et al. (2008) demonstrated that the classification approach has merit in predicting regional variations in baseflow, and Carlisle et al. (2010) found that stratification by hydrologic landscape regions improved models predicting hydrologic metrics from watershed characteristics. By contrast, McManamay et al. (2011) reported that hydrologic landscape regions showed little concordance with the hydrologic classes of Poff (1996; see below) for the continental United States, and explained < 30% of the overall variability in the hydrologic metrics.

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

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

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

Inductive Approach

Streamflow classification

Streamflow classification involves the direct delineation of patterns in hydrologic character through inductive approaches that use attributes describing different components of the multi-faceted flow regime. In this approach, classification schemes attempt to provide order to inherently complex flow data by identifying and characterizing similarities among rivers according to a set of diagnostic hydrologic metrics that vary spatially across the landscape (e.g. Mosley, 1981; Jowett and Duncan, 1990; Poff, 1996; Hannah et al., 2000; Harris et al., 2000; Snelder et al., 2009a; Kennard et al., 2010b). Streamflow classification relies on hydrologic metrics that describe the various components of the flow regime, including the seasonal patterning of flows; timing of extreme flows; the frequency, predictability, and duration of floods, droughts, and intermittent flows; daily, seasonal, and annual flow variability; and rates of change (Olden and Poff, 2003; Figure 4). Hydrologic metrics are often selected to account for characteristics of the flow variability that are hypothesized to be important in shaping ecological and physical processes in lotic ecosystems. Many of these metrics have proven to be suitable for hydrologic classification (Kennard et al., 2010b), and are responsive to hydrologic alteration caused by human activities such as river regulation by dams, urbanization, and projected climate change (Richter et al., 1996; Bunn and Arthington, 2002).

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

Describing patterns in hydrologic variability – Streamflow classifications have commonly been developed to place individual stream sites or reaches into a broader spatial context with the goal of maximizing the transferability of knowledge among rivers of the same hydrologic class. Numerous classifications have been developed to quantify similarities in natural hydrologic characteristics at a variety of scales (Table 2). Poff (1996) identified 10 distinctive flow types – seven permanent and three intermittent - in the continental United States based on ecologically relevant hydrological characteristics describing flow variability, predictability and low- and high-flow extremes. Kennard et al. (2010b) presented a continental-scale classification of hydrologic regimes for Australia describing 12 classes of flow-regime types differing in the seasonal pattern of discharge, degree of flow permanence, variation in flood magnitude, and flow predictability and variability (Figure 5a). The geographic distributions of the flow classes varied greatly, as did differences in key hydrologic metrics. At the regional scale, Hughes and James (1989) classified streamflow types in Victoria, Australia, based on 16 hydrologic metrics computed for 138 gauges from daily time series. A low-flow classification scheme produced four distinct classes with a spatially heterogeneous distribution across the state, which was largely determined by topography. In another example, Bejarno et al. (2010) described 15 natural flow typologies in the Ebro River Basin, Spain, which were characterized in terms of flow fluctuation through the year as well as timing, flow ratio and duration of the maximum and minimum flows. Groups of streams that are hydrologically distinctive at landscape scales are expected to discriminate differences in ecological character (Poff et al., 1997). For example, streamflow classes are likely to have similar biological responses to both natural and human-induced variability in patterns of magnitude, frequency, duration, timing and rate of change in flow conditions. Therefore, systems that show commonalities in their hydrologic characteristics have provided a basis for testing whether hydrology influences the structure and function of biological communities in a similar fashion (e.g. Jowett and Duncan, 1990; Poff and Allan, 1995; Snelder and Lamouroux, 2010).

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

Identifying and prioritizing conservation efforts for freshwater ecosystems – Recent interest has focused on the spatial prioritization of freshwater ecosystems for conservation of regional-scale biodiversity (Abell et al., 2007). Hydrologic classification (inductive or deductive) may be a useful tool for the identification of streams, rivers or entire catchments with representative flow regimes, and therefore, representative biological communities (Nel et al., 2007). Broadly, environmental classes are often used as biodiversity surrogates as different types of environments are assumed to support different combinations of species (Margules et al., 2002). Following the premise that flow is a key driver of aquatic ecosystem structure and function, identifying streams and rivers that exhibit distinct or representative flow regimes using hydrological classification can aid in the selection of those river systems that can contribute to dynamic conservation reserves to support ecosystem resilience and maintenance of biodiversity (e.g. Nel et al., 2007; Snelder et al., 2007).

A FRAMEWORK FOR HYDROLOGIC CLASSIFICATION

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

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

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

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

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

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

2) Acquire and evaluate the hydrologic data

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

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

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

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

e) Evaluate temporal period (e.g. 1965-2000) and duration (i.e. 35 years) of available discharge data for each gauge, and decide on criteria for inclusion of gauge data. Important considerations include: minimum vs. fixed record length, completely overlapping vs. partially overlapping period of record, and period of record to include particular environmental events (e.g. years including significant changes in climate). Screening for long-term trends in hydrologic characteristics (e.g. based on annual values of mean, minimum, and/or maximum flows) can help to clarify the extent to which the chosen time period is likely to influence the hydrologic classification. Based on a sensitivity analysis, Kennard et al. (2010a) recommend that at least 15 years of daily discharge data is suitable for use in hydrologic classifications (to maximize precision and minimize bias in the estimation of the hydrologic metrics), provided that gauge records are contained within a discrete temporal window (i.e. preferably >50% overlap between records).

f) Evaluate spatial distribution of gauges that meet the above criteria to ensure adequate geographic coverage (e.g. representing climate regions of interest). If the spatial coverage is not sufficient, then evaluate potential for including additional gauges by:
   i) Relaxing the acceptance criteria (steps 2b, c, e), and/or
   ii) Estimating missing or poor quality data in the discharge time series (step 2c) by using linear interpolation for short periods, general linear regression for longer periods, or another appropriate technique.

   Note that relaxing the acceptance criteria will decrease the comparability of gauges, and estimating missing data will increase the measurement uncertainty of flow data. Both options will compromise bias and precision of classification results, although some hydrologic indices are more sensitive to record length and period overlap than others (see Kennard et al., 2010a).

g) If steps 2a-f reveal that streamflow data is not of sufficient quality and quantity, then consider deploying an deductive approach to hydrologic classification (see step 1a).

3) Select hydrologic metrics
   a) Select hydrologic metrics according to purpose of the study. Olden and Poff (2003) provide a comprehensive review of the most commonly used hydrologic metrics, but

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

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

b) Select hydrologic metrics that are appropriate for the temporal grain of flow data (e.g. metrics describing flow spell duration are more suited to daily or weekly data than monthly or annual data; see also Poff, 1996).
c) Select hydrologic metrics depending on available software and the user's experience with computer programming. Software options include dedicated hydrologic software such as the Indicators of Hydrologic Alteration (Richter et al., 1996), Hydrologic Assessment Tool (Henriksen et al., 2006), the River Analysis Package (www.toolkit.net.au/rap), and a number of others.
d) Select hydrologic metrics based on minimizing statistical redundancy among metrics. The results will inform variable selection and dimensionality reduction (e.g. indirect ordination approaches to produce composite variables, such as Principal Component Analysis) if multicollinearity among metrics is a concern (see Olden and Poff, 2003), and may lead to more robust classifications (Snelder et al., 2009b).
e) No hydrologic metrics are chosen. Hydrologic classification will proceed using parameter sets calculated from any number of time series tools available to analyze hydrographs, including autoregressive integrated moving average (ARIMA) models, Fourier analysis, and wavelets (e.g., Smith et al., 1998; Lundquist and Cayan, 2002; Sabo and Post, 2008).

4) Compute hydrologic metrics
   a) Calculate the metric values for each flow record according to decisions made in step 3.

b) Screen datasets for outliers and/or gauges potentially affected by anthropogenic activity or unknown factors (i.e. used in conjunction with step 2b). Potential approaches include:
   i) Examining diagnostic plots and descriptive statistics.
   ii) Conducting indirect ordination (e.g. Principal Component Analysis), plotting ordination scores of gauges in multi-dimensional space and looking for outliers that might be suggestive of modified flows, unique natural flows, or errors in discharge measurement, data entry or metric calculation.
   iii) Plotting mean daily flow (or similar hydrologic metric) against catchment area, allowing gauges with obviously different discharge (either through extraction or supplementation) to be identified.

c) Eliminate gauges if necessary.

d) Estimate uncertainty in hydrologic metrics caused by different lengths and periods of gauge records (also see step 2e). Although commonly overlooked, a robust classification system should explicitly incorporate (or in the least, examine) uncertainty in the hydrologic metrics that ultimately underlying the classification scheme. Uncertainty values can be used to weight metrics in the classification process and/or metrics with high uncertainty can be eliminated from the analysis. See Kennard et al. (2010a,b) for more details. This step is optional, but recommended.

e) Remove scale-dependence of flow magnitude metrics (if required, depending on objectives of the study) by standardizing values by catchment area, mean daily flow, or a similarly suitable variable.

5) Conduct the hydrologic classification
   a) Select hydrologic metrics to include in classification analysis. Choice of metrics might also be dependent on statistical assumptions/requirements (data type, normality, etc.) of classification approach. Selections might include:
      i) All flow metrics.
      ii) Subset(s) of metrics describing separate components of flow regime (this decision depends on the purpose for classification).

iii) Subset(s) of metrics that are non-redundant (i.e. low multicollinearity) and highly informative (i.e. explaining dominant gradients of variation that exist in the larger set of metrics). See Olden and Poff (2003) for more details.

b) Decide whether metric transformations and/or standardizations are required (again, this depends on statistical assumptions/requirements of classification approach).

c) Conduct hydrologic classification analysis using a statistical approach that corresponds with the objective of classification and capability of the researcher. Ordination analyses may also be conducted to complement hydrologic classification, explore the extent of hydrologic variability and examine for natural clusters of stream gauges and/or outliers. See Methodologies section below.

d) Delineate and decide on the number of hydrologic classes (i.e. clusters) based on objective (statistical) criteria, ecological rationale and/or considering a trade-off between resolution of hydrological variability and complexity (number of classes). Depending on the purpose of the classification, each approach may be legitimate for deciding on the number of classes. Assign class membership. See Methodologies section below.

e) Examine classification results for outliers and eliminate gauges if necessary; repeat steps 5b-d.

6) Interpret and/or spatially-model the hydrologic classification

a) Assess the predictive performance of the hydrologic classifier using an independent dataset containing gauges not included in the classification (e.g., cross-validation) according to an appropriate statistical approach (e.g. coefficient of agreement such as Cohen's Kappa statistic). When model performance is poor and the uncertainty of classifications are high, this may indicate an inadequate understanding of watershed behavior or an inability to know or estimate the salient hydrologic characteristics. The result is a classification system with low power and utility.

b) Diagnose the distinguishing characteristics of the hydrologic classes using numerical, statistical, graphical, and descriptive approaches.

c) Examine geographic distribution of gauge class membership.

d) Depending on the study purpose, model class membership of gauges based on upstream physiographic characteristics (e.g. drainage area, stream slope, soil type) and climatic variables (e.g. precipitation, temperature, evapotranspiration) of the watershed using an appropriate statistical approach (e.g. logistic regression, discriminant function analysis, classification tree). Assuming adequate model performance (see Snelder et al., 2007 for discussion) the user can predict hydrologic class membership by applying model at the river segment scale. See Methodologies section below.

METHODOLOGIES FOR STREAMFLOW CLASSIFICATION

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

Ordination approaches to exploring hydrologic variability

Multivariate ordination is typically used to explore continuous patterns in hydrologic variability among sites (e.g. Lins, 1997; Clausen and Biggs, 2000) and complement clustering-based classifications that assign sites to classes (see below). Commonly employed approaches include Principal Component Analysis (PCA) or non-metric multidimensional scaling. Ordination approaches do not produce a classification; rather the relative hydrological similarity/dissimilarity of different objects (i.e. gauging locations) is displayed in multivariate space of reduced dimensionality, thus allowing the investigator to visually determine whether objects group together in well-defined sets or form contrastingly poorly-defined and overlapping groups. One property of most classification algorithms is that they force a grouped structure on what may otherwise be a continuously varying distribution and ordination is a useful tool to assess whether any such grouping is warranted. Other approaches for exploring hydrologic variation, although rarely used, include graphical representation of multi-dimensional data using Andrews curves (Andrews, 1972) and a range of pictorial techniques that involve "entertaining transmogrifications” (Nathan and McMahon, 1990) of cartoon faces, trees, castles, and dragonflies (see Chernoff, 1973).

Clustering approaches to developing a streamflow classification

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

Seven algorithms for agglomerative hierarchical clustering have been commonly applied in the past (Table 2), including (i) single linkage; (ii) complete linkage; (iii) average linkage (either weighted or unweighted); (iv) centroid linkage; (v) median linkage; (vi) density linkage; and (vii) Ward’s minimum-variance algorithm. Each algorithm has both strengths and weaknesses (see Gordon (1987) for a good overview from a statistical perspective), but perhaps the most relevant feature for streamflow classification is the tendency of algorithms to ‘distort’ space, thus affecting the clustering results (see Everitt et al., 2001). The ‘chaining’ effect, in which dissimilar objects are sequentially drawn into the same cluster, is an example of space contraction and is commonly produced by the single linkage algorithm. Such approaches tend to identify highly distinctive groups and may see their greatest use in conservation when practitioners are seeking to reveal unique and rare hydrologic environments. By contrast, space dilation refers to the process of favoring the fusion of clusters together, and is typical of the complete linkage algorithm. These approaches tend to produce groups of equal size and may be best applied in hydrologic regionalization to ensure adequate sample sizes to establish statistical relationships. Lastly, space-conserving methods, such as average linkage, merge clusters in a manner that best balances space contraction and dilation, and therefore, the resulting dendrogram best represents the original data structure. The choice of clustering algorithm will depend on the objective of the classification exercise, but for most applications we would recommend space conserving approaches, such as average linkage or Ward's algorithm. The latter is quite beneficial because it maximizes the cophenetic correlation between the original and dendrogram distances and eliminates group size dependencies on the clustering results. Selection of an appropriate (dis)similarity index is also important, but for continuous variables such as the majority of commonly used hydrologic metrics, standardized Euclidean distance remains the most popular. However, other indices have favorable properties (i.e., minimizing the influence of large distances) and may be preferred (see Legendre and Legendre, 1998).

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

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

Determining the number of hydrologic classes

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

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

Assigning class membership: hard vs. soft classification

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

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

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

Predicting landscape patterns of streamflow classes

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

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

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

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

CONCLUSION

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

ACKNOWLEDGMENTS

We thank Chris Konrad, Ton Snelder and an anonymous reviewer for constructive comments that greatly improved the final paper. Funding was gratefully provided by the USGS National Gap Analysis Program (JDO), the U.S. Environmental Protection Agency Science To Achieve Results (STAR) Program (Grant No. 833834) (JDO), and the Tropical Rivers and Coastal Knowledge (TRaCK) Research Hub through the Australian Rivers Institute, Griffith University (MJK, BJP and JDO). TRaCK receives major funding for its research through the Australian Government's Commonwealth Environment Research Facilities initiative; the Australian Government's Raising National Water Standards Program; Land and Water Australia; the Fisheries Research and Development Corporation; the National Environmental Research Program and the Queensland Government's Smart State Innovation Fund.

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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)[1] and non-hierarchical (K-means[1], fuzzy partitioning c-means algorithm[2]) clustering.	Rao and Srinivas, 2006a[1]; Rao and Srinivas, 2006b[2]
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)
Basin				
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
Regional				
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
National/Continental				
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

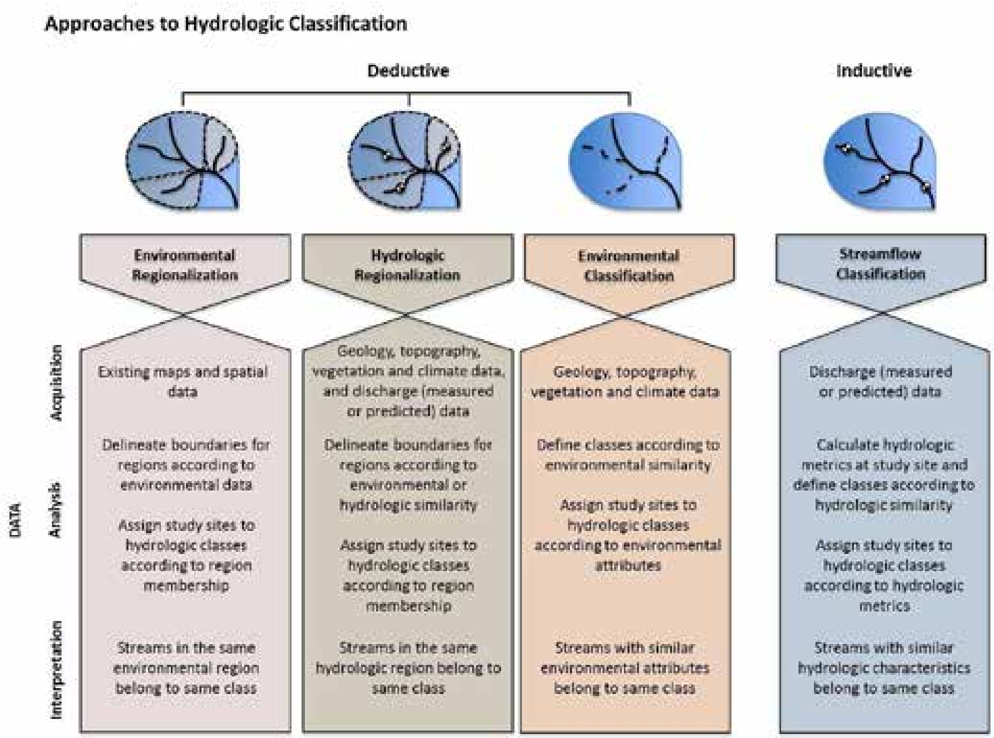
Figure 1. Two main approaches to hydrologic classification based on deductive (environmental regionalization, hydrologic regionalization or environmental classification) and inductive (streamflow classification) reasoning.

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

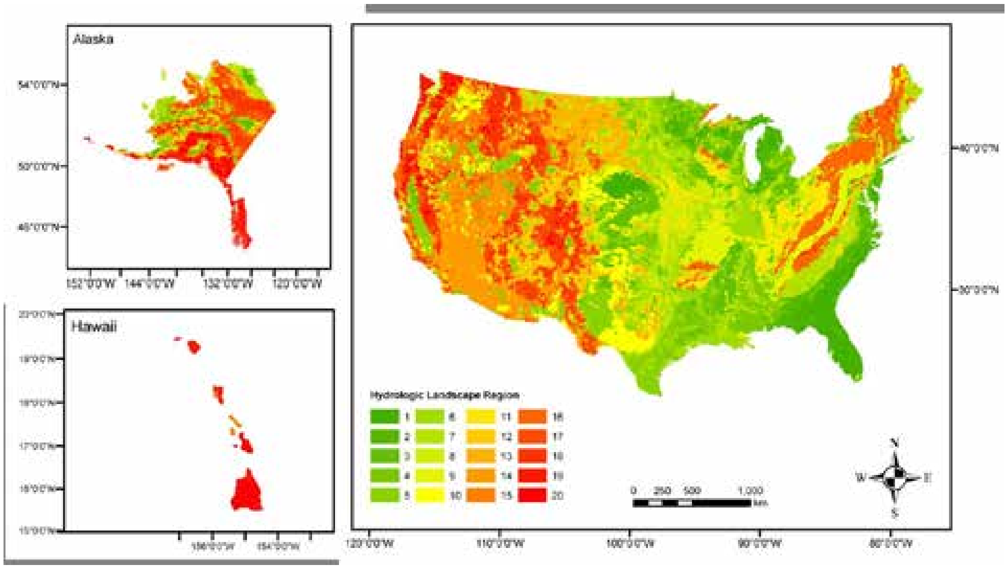
Figure 3. The REC classification for New Zealand. River classes refer to a combination of climate type: warm-extremely-wet (WX), warm-wet (WW), warm-dry (WD), cool-extremely-wet (CX), cool-wet (CW) and cool-dry (CD); and source of flow: glacial-mountain (/GM), mountain (/M), hill (/H), low-elevation (/L) and lake (/LK). The width of the lines representing the rivers has been scaled to 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.

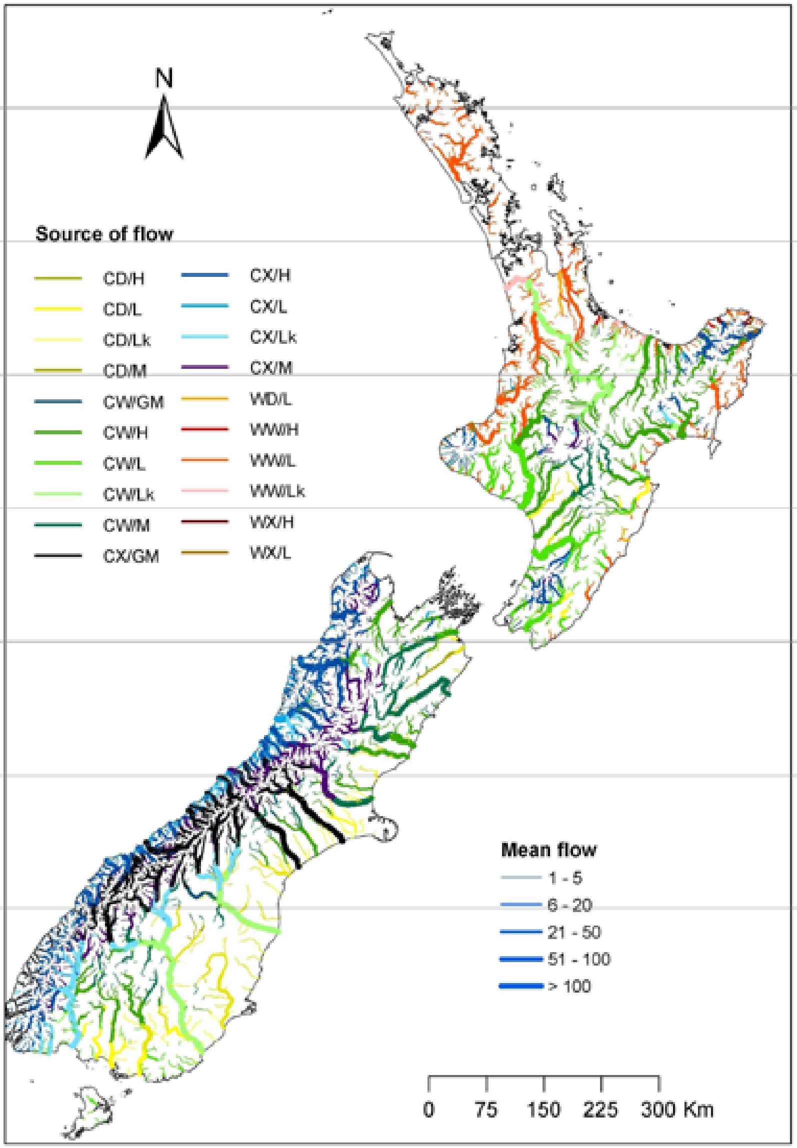
Figure 5. (a) Hydrologic classification of flow-regime types for 830 stream gauges in Australia from Kennard et al. (2010b). Australian drainage divisions (thick lines) and State and Territory borders (dashed lines) are shown. (b) Inset figure shows predicted flow regime types of north-eastern Australian 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).

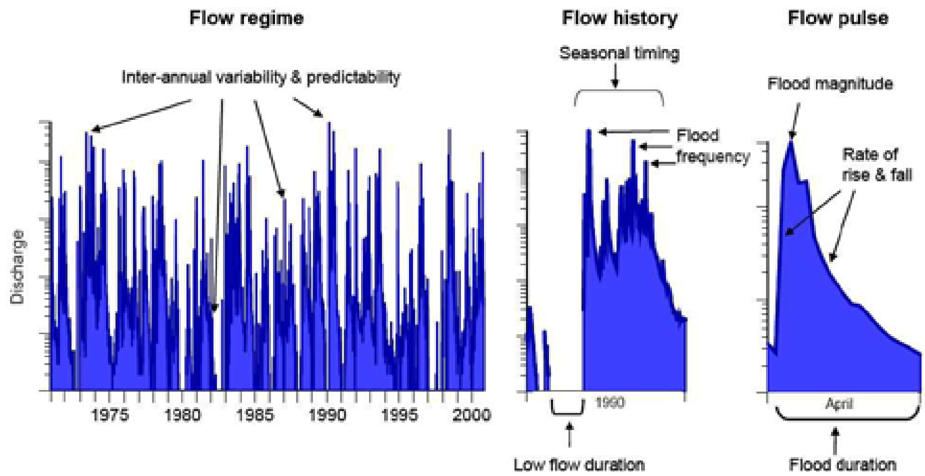


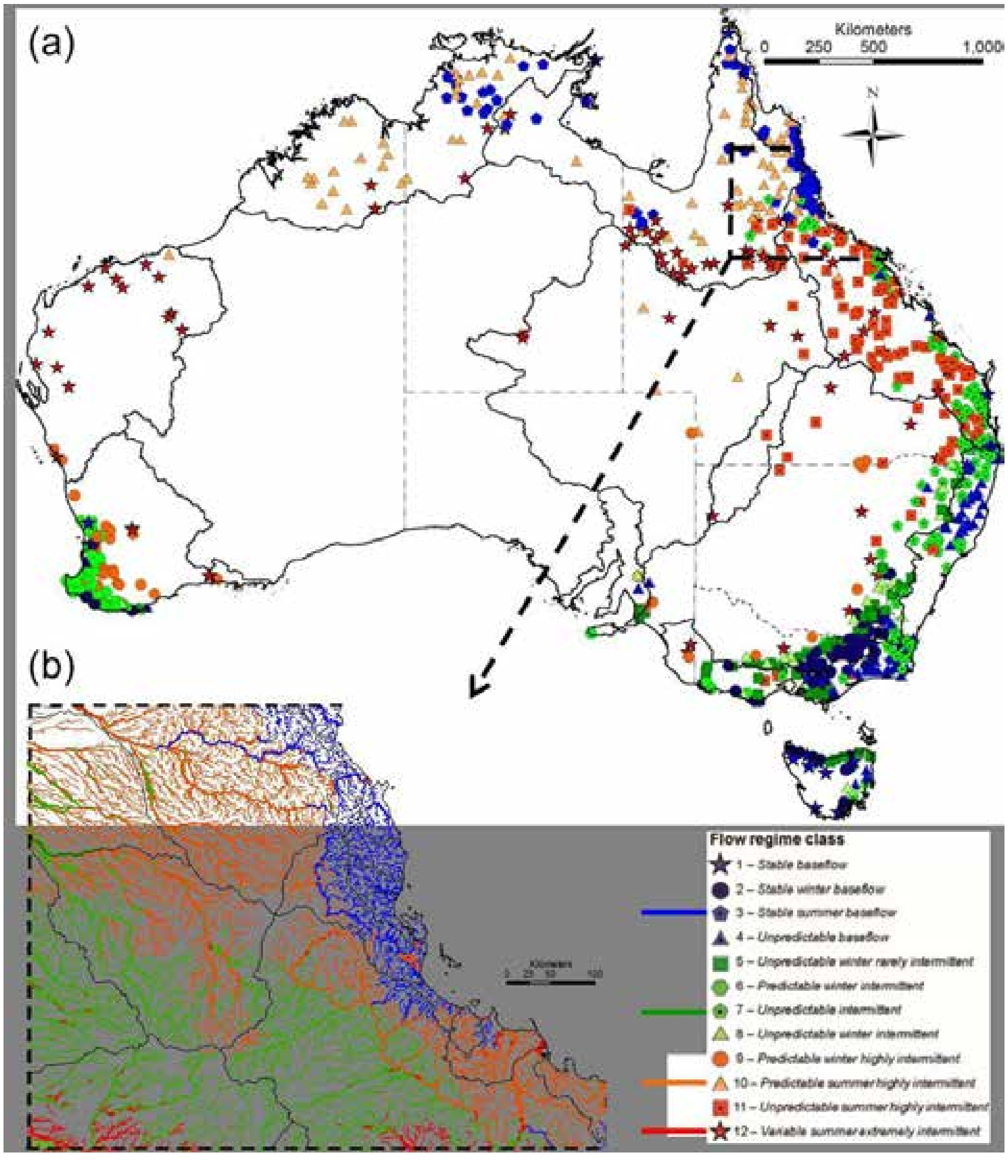
Approaches to Hydrologic Classification
Deductive
Inductive
Environmental Regionalization
Hydrologic Regionalization
Environmental Classification
Streamflow Classification
DATA
Acquisition
Analysis
Interpretation
Existing maps and spatial data
Geology, topography, vegetation and climate data, and discharge (measured or predicted) data
Geology, topography, vegetation and climate data
Discharge (measured or predicted) data
Delineate boundaries for regions according to environmental data
Delineate boundaries for regions according to environmental or hydrologic similarity
Define classes according to environmental similarity
Calculate hydrologic metrics at study site and define classes according to hydrologic similarity
Assign study sites to hydrologic classes according to region membership
Assign study sites to hydrologic classes according to region membership
Assign study sites to hydrologic classes according to environmental attributes
Assign study sites to hydrologic classes according to hydrologic metrics
Streams in the same environmental region belong to same class
Streams in the same hydrologic region belong to same class
Streams with similar environmental attributes belong to same class
Streams with similar hydrologic characteristics belong to same class



Alaska
152°0'0"W
144°0'0"W
132°0'0"W
120°0'0"W
Hawaii
Hydrologic Landscape Region
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
0 250 500 1,000
km
N
W
E
S
40°0'0"N
30°0'0"N
120°0'0"W
110°0'0"W
100°0'0"W
90°0'0"W
80°0'0"W


N
Source of flow
CD/H
CD/L
CD/Lk
CD/M
CW/GM
CW/H
CW/L
CW/Lk
CW/M
CX/GM
CX/H
CX/L
CX/Lk
CX/M
WD/L
WW/H
WW/L
WW/Lk
WX/H
WX/L
Mean flow
1 - 5
6 - 20
21 - 50
51 - 100
> 100
0 75 150 225 300 Km


Flow regime
Inter-annual variability & predictability
Discharge
1975
1980
1985
1990
1995
2000
Flow history
Seasonal timing
Flood
frequency
1990
Low flow duration
Flow pulse
Flood magnitude
Rate of
rise & fall
April
Flood duration



(a)
Kilometers
0 250 500 1,000
N
(b)
Flow regime class
1 – Stable baseflow
2 – Stable winter baseflow
3 – Stable summer baseflow
4 – Unpredictable baseflow
5 – Unpredictable winter rarely intermittent
6 – Predictable winter intermittent
7 – Unpredictable intermittent
8 – Unpredictable winter intermittent
9 – Predictable winter highly intermittent
10 – Predictable summer highly intermittent
11 – Unpredictable summer highly intermittent
12 – Variable summer extremely intermittent

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)
Basin				
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 *et al.*, 2011
Ebro R., Spain	M, D, T	M	Ordination (Principal Component Analysis), hierarchical clustering (unspecified cluster algorithm), external validation and prediction (logistic regression)	Bejarano *et al.*, 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
Regional				
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 *et al.*, 2002a,b
Arizona, New Jersey, Pennsylvania, Texas, USA	M, F	D, A	Hierarchical clustering (complete linkage) and external validation	Tasker, 1982
National/Continental				
Australia	M, D, F, T, R	D	Non-hierarchical clustering using fuzzy partitioning Bayesian mixture algorithm and external validation	Kennard *et al.*, 2010b
Australia	F, T	D	Wavelet analysis and non-hierarchical clustering (K-means)	Zoppou *et al.*, 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 *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)	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 *et al.*, 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 *et al.*, 2010
Nepal	M, T	M	Hierarchical clustering (Ward's algorithm)	Hannah *et al.*, 2005 (see also Harris *et al.*, 2000; Hannah *et al.*, 2000; Bower *et al.*, 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 *et al.*, 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 *et al.*, 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 *et al.*, 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 *et al.*, 2000
Turkey	M	A	Non-hierarchical clustering (K-means)	Kayha *et al.*, 2007
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 clustering (average linkage)	Harris *et al.*, 2000 (see also Hannah *et al.*, 2000)
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 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)
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	Hierarchical clustering (average linkage)	Finlayson and McMahon, 1988
	M, T	M, A	Hierarchical clustering (average linkage) and external validation	Haines *et al.*, 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.*, 2007
	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

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