Appendix 2

Protocols for hydrologic classification and a review of Australian applications

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Summary

Hydrologic classification is the process of systematically arranging streams, rivers or catchments into groups that are most similar with respect to characteristics of their flow regime. Previous classification efforts have relied on a plethora of hydrologic metrics that account for characteristics of flow variability that are hypothesised to be important in shaping ecological and physical processes in lotic ecosystems. We review the process of hydrologic classification by (i) exploring its past application in the ecological sciences; (ii) reviewing existing statistical approaches to identify and characterise hydrologic classes; and (iii) providing a methodological framework for hydrologic classification that depicts critical components of the classification process.

Ecologists have used hydrologic classification to place individual streams and rivers into a broader spatial context with the goal of maximising the transferability of knowledge among rivers of the same hydrologic class. Regionalisation analyses to predict streamflow behaviour in ungauged catchments often comprise a set of regression models based on several different classes of certain hydrological information at gauged sites. Consequently, by dividing a study area into homogeneous groups that are considered to exhibit similar hydrologic characteristics, records may be extrapolated with more precision, and regionalisation models based on catchment characteristics may be used with greater confidence.

Hydrologic classification plays a central role in environmental flow assessments aimed at the development of ecologically sustainable practices for water management. Holistic methods to assess environmental flows either implicitly or explicitly involve the hydrologic classification of rivers as they 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. Recent interest has focused on the conservation planning of freshwater ecosystems for regional-scale biodiversity and hydrologic classification may be a useful tool for the targeted management of streams, rivers or entire catchments with representative flow regimes, and therefore, representative biological communities.

A variety of classification techniques have been used in the past to derive hydrological classifications and regionalisations. These include: hierarchical and flat clustering algorithms, self-organising maps, multivariate ordination and hard and soft classification algorithms such as fuzzy clustering and Bayesian classification. We reviewed the different methods available and the information needs and processes required to satisfy several statistical assumptions and requirements. We used a protocol for classification that addresses issues about data quality and comparability, choice of classification method and assessment of results.

We also reviewed previous applications of hydrological classification in Australia, covering Australian examples of both hydrological and ecohydrological classifications but coverage of the former is not exhaustive. These prior classifications provided a means of comparing the outcomes of the classification developed in the present project.
2.1 Introduction

Hydrologic classification is the process of systematically arranging streams, rivers or catchments into groups that are most similar with respect to characteristics of their flow regime. This process has frequently been applied by hydrologists seeking to extend insights gained from well-gauged regions to ungauged or sparsely gauged regions or rivers (Bates 1994). Typically, only specific components of the flow regime are included (e.g. flood series) (Nathan and McMahon 1990; Bower et al. 2004). Hydrologic classification is playing an increasing role in the ecological sciences for understanding riverine flow variability (Mosley 1981; Haines et al. 1988; Poff 1996; Harris et al. 2000), exploring the influence of streamflow on biological communities and ecological processes (Jowett and Duncan 1990; Poff and Allan 1995; Pusey et al. 2000; Snelder et al. 2004; Monk et al. 2006, 2007), aiding hydrologic modeling in regionalisation analyses (Nathan and McMahon 1990), providing an inventory of hydrologic types for water resource management (Snelder and Biggs 2002; Wolock et al. 2004; Arthington et al. 2006), and prioritising conservation efforts for freshwater ecosystems (Nel et al. 2007; Snelder et al. 2007). Consequently, hydrologic classification has practical use as an organising framework for both river research and management purposes.

Three broad categories of hydrologic classification exist that serve to describe flow regime similarities among rivers: those according to geographic proximity, environmental attributes, or hydrologic characteristics. Geographical regions have been identified based upon political, administrative, river basin and climatic boundaries (Arnell et al. 1990). The delineated regions are located in close geographic proximity to one another, however this often does not guaranteed that the regions will be hydrological homogenous. An alternative approach is to define classes based on the environmental factors that are assumed to broadly produce similar hydrological responses. This represents a deductive approach to hydrologic classification that is often geographically-independent and depicted by a mosaic pattern of hydrologic types across the landscape (Detenbeck et al. 2000). Numerous physical-based or geomorphic classifications of rivers have been conducted; including those based on geology, topography, and climate (e.g. Kondolf 1995), as well as combined hydrogeomorphic typologies (e.g. Snelder and Biggs 2002; Snelder et al. 2005; Dollar et al. 2007; Schmitt et al. 2007; reviewed in Kondolf et al. 2003). These classifications are common, but do not reflect only hydrological variation because they encompass more general principles concerning the causes of spatial variation in ecological characteristics of streams and rivers. To overcome these difficulties, delineating patterns in hydrologic character have also been identified directly through empirically-based methods that use hydrologic metrics describing different components of the multi-facet riverine flow regime. In this application, hydrologic classification schemes attempt to provide order to inherently complex flow data by identifying and characterising similarities among rivers according to a set of diagnostic hydrologic attributes that vary spatially across the landscape (Mosley 1981; Jowett and Duncan 1990; Poff 1996; Harris et al. 2000). This approach to hydrologic classification is the focus of this section.

A number of hydrologic characteristics comprise the natural 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 (Poff et al. 1997). Accordingly, previous classification efforts have relied on a plethora of hydrologic metrics that account for characteristics of flow variability that are hypothesised to be important in shaping ecological and physical processes in lotic ecosystems (Hughes 1987; Poff and Ward 1989; Hughes and James 1989; Pusey and Arthington 1996; Richter et al. 1996; Poff et al. 1997; Puckridge et al. 1998; Clausen and Biggs 2000; Harris et al. 2000; Bunn and Arthington 2002; reviewed by Olden and Poff 2003; Bower et al. 2004; Monk et al. 2006). Many of these metrics have proven to be highly suitable for hydrologic classification. Moreover, these aspects of the hydrologic regime are likely to be most frequently altered...
by human activities such as river regulation by dams (Poff et al. 2007), and are predicted to be sensitive to global climate change (Milly et al. 2005).

Researchers have applied a number of statistical approaches and used a variety of hydrologic metrics in attempts to develop hydrologic classifications at catchment, regional, national, continental and global scales (Table 2.1). For example, efforts at global or continental scales have primarily focused on certain aspects of the hydrograph such as seasonality, flood behaviour or low flow characteristics, whereas regional classifications have utilised a larger suite of hydrologic metrics. Challenged by the need to quantify flow similarities among rivers and map their distribution across hydrologic landscapes (sensu Winter 2001), ecologists have turned to a bewildering array of statistical approaches using an equally diverse set of protocols to conduct their hydrologic classification (Table 2.1). During the last two decades considerable effort has gone into analysis and development of methodological approaches to hydrologic classification. As a result, several groups of methods are in use, and to-date no single approach has been demonstrated to yield universally acceptable results. Consequently, most researchers reach into their same statistical toolbox when required to tackle a classification problem and are unaware of important considerations and new techniques available to them.

Herein, we review the process of hydrologic classification by (i) exploring its past application in the ecological sciences; (ii) reviewing existing statistical approaches to identify and characterise hydrologic classes; and (iii) providing a methodological framework for hydrologic classification that depicts critical components of the process in order that researchers will be better informed regarding the selection and proper implementation of methods for hydrologic classification. To close, we also review the outcomes of prior attempts to classify Australian rivers and suggest an appropriate way to proceed with a classification of Australian flow regime types.

2.2 Ecological applications of hydrologic classification

Hydrologic classification has been conducted for a number of purposes in ecology. Below we briefly highlight some of the more common applications of hydrologic classification in the literature.

2.2.1 Increasing our understanding of flow variability among streams and rivers by identifying hydrologic classes

Ecologists have used hydrologic classification to place individual streams and rivers into a broader spatial context with the goal of maximising the transferability of knowledge among rivers of the same hydrologic class and to show broader application of intensely studied sites to unstudied sites (Table 2.1). Hydrologic classes are expected 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. Consequently, 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. Poff and Ward 1989; Jowett and Duncan 1990; Poff and Allan 1995; Snelder et al. 2004). Recent efforts have also focused 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.
2.2.2 Hydrologic classification for the purposes of guiding regionalisation analyses

Classification has a long history of use in the regionalisation of hydrologic models that attempt to achieve continuous streamflow predictions in ungauged basins (e.g., Tasker 1982; Nathan and McMahon 1990; Abdulla and Lettenmaier 1997; Merz and Bloeschl 2004; Wagener et al. 2007; Yadav et al. 2007). Regionalisation analyses often comprise a set of regression models based on several different classes of certain hydrological information at gauged sites. Consequently, by dividing a study area into homogeneous groups that are considered to exhibit similar hydrologic characteristics, records may be extrapolated with more precision, and regionalisation models based on catchment characteristics may be used with greater confidence.

2.2.3 Developing environmental flow recommendations for water resource management

Hydrologic classification plays a central role in environmental flow assessments (Tharme 2003) aimed at the development of ecologically sustainable practices for water management (Richter et al. 2006). Holistic methodologies to environmental flow assessments, such as the application of the benchmarking methodology (Brizga et al. 2002), Downstream Response to Imposed Transformations (DRIFT: King et al. 2003), and the Ecological Limits of Hydrologic Alteration (ELOHA: Poff et al. in review), either implicitly or explicitly involve the hydrologic classification of rivers to varying extents. Arthington et al. (2006) describe how the classification of undeveloped rivers 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. As a result, environmental flow rules for rivers with detailed data can provide interim recommendations for rivers in the same class where data are sparse and the response of biota to hydrological patterns is unknown but may be assumed to be similar to those occurring in hydrologically similar rivers for which flow ecology relationships are known.

2.2.4 Identifying and prioritising conservation efforts for freshwater ecosystems

Recent interest has focused on the conservation planning of freshwater ecosystems for regional-scale biodiversity (e.g., Saunders et al. 2002, Moilanen et al. 2008). Hydrologic classification may be a useful tool for the selection of streams, rivers or entire catchments with representative flow regimes, and therefore, representative biological communities (Nel et al. 2007, Poff et al. 2007).

2.3 Methodological approaches to hydrologic classification

The strategy of hydrologic classification is to ascribe objects (i.e., streams, rivers, catchments) to empirically-based groupings or classes, so as to maximise the similarity between the members of each group and minimise the similarity between groups. Because of the many ways that magnitude and variability of flow can be characterised (Olden and Poff 2003) analysing hydrologic metrics using a multivariate approach is an effective means to determine similarities or differences among and/or within rivers. The multivariate techniques for identifying classes of river and organising them into a hydrologic topology are numerous and vary in output properties, such as whether the classes are hierarchical or flat, whether boundaries between classes are hard (i.e. defined) or soft (i.e. fuzzy), and/or whether rivers can belong to one or more classes (described in detail below). As Nathan and McMahon (1990) point out, a major problem encountered when using cluster analysis for hydrologic classification is the
plethora of different linkage algorithms and distance measures available. Unfortunately, different clustering techniques applied to the same set of data will often produce structures that are substantially different. This is because the choice of a clustering method implicitly imposes a structure on the population and is often tantamount to defining a structure. Therefore, the choice of statistical approach used in hydrologic classification is critical. Below we provide a preliminary review of different methodologies that have been used to develop hydrologic classifications in the past, and finish by describing differences between hard versus soft classifications.

2.3.1 Hierarchical and flat clustering algorithms

Both hierarchical and flat clustering algorithms have been used to develop hydrologic classifications (Table 2.1). Hierarchical clustering proceeds iteratively by either combining smaller clusters into larger ones (agglomerative), or by splitting larger clusters to smaller ones (divisive) to produce a classification of objects typically presented as a dendrogram of clusters. Flat clustering techniques identify clusters of equal distinction, and thus are not represented in a hierarchy. Certain algorithms can be adapted to provide either hierarchical or flat classifications.

Gordon (1987) provides a good overview from a statistical perspective. Rao and Srinivas (2006) outline eight common algorithms for agglomerative hierarchical clustering of rivers according to their flow regimes: 1) single linkage or nearest neighbor; 2) complete linkage or furthest neighbor; 3) average linkage (UPGMA); 4) weighted average linkage; 5) centroid; 6) median or weighted pair-group centroid; 7) density or k-linkage; and 8) Ward’s algorithm. The k-means algorithm is a commonly employed divisive clustering technique for non-hierarchical classification. The algorithm groups cases according to Euclidian distance from initial, randomly chosen cluster centers of a predetermined number. Then it iteratively redefines cluster centers as the means of the cases in the latest cluster, until cases no longer change membership. The method is efficient for large datasets, and results are often sufficient, although subjectivity of the initial cluster centroids must be considered.

Hierarchical and flat clustering methods can be used in tandem to optimise hydrologic classification (called hybrid clustering). For example, Rao and Srinivas (2006) used a partitional clustering procedure to identify groups of similar catchments by refining the clusters derived from agglomerative hierarchical clustering algorithms using the k-means algorithm. Similarly, Kahya et al. (2007) considered results of a hierarchical, average-linkage algorithm to help identify an optimal number of clusters for subsequent flat classification using k-means.

Determining the number of clusters is a problem inherent to most if not all conventional clustering techniques. For flat algorithms, the number of clusters must be predetermined before the patterns of input data have even been analysed. For hierarchical algorithms, selection of the degree of cluster distinction between tiers is subjective. Several approaches for optimising the number of clusters have been discussed in the literature.

2.3.2 Self-organising maps

Machine learning approaches provide a powerful set of tools for analysing complex ecological data (Olden et al. 2008). Self-organising maps (SOM; Kohonen 1982, 2000) provide a means of representing high-dimensional data in a low-dimensional view; typically a two-dimensional map. The goal is for the map to retain topological properties of the input data, in contrast to information losses common to other data-reduction techniques such as principal component analysis. Using SOM as a framework for performing cluster analysis and discrimination analysis of hydrological factors in one step has been presented by Lin and Wang (2006) as a novel and efficient method for hydrologic classification. Their
SOM-based cluster and discrimination analysis (SOMCD) 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 top advantage of the method.

2.3.3 Multivariate ordination

Multivariate ordination techniques, including principal components analysis (PCA) and principal coordinate analysis, have been used to develop (or aid in) hydrologic classification (Table 2.1). PCA involves a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible (Legendre and Legendre 1998). In many applications, the composition scores from a small number of principal components are retained and then clustered to identify rivers with similar flow regimes (Table 2.1).

2.3.4 Hard versus 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 feature vectors can be divided into non-overlapping clusters with well-defined boundaries between them. Each feature vector is assigned to one of the clusters with a degree of membership equal to unity. In other words, a catchment is classified as belonging to a cluster on the basis of distance (or dissimilarity) between the catchment and the cluster centroid in the multi-dimensional space of attributes depicting the flood response of catchments. A brief review of hard clustering algorithms in regionalisation is found in Srinivas et al. (2002) and Rao and Srinivas (2003).

It is reasonable to suppose, however, that most catchments partially resemble several catchments and therefore assigning a catchment to one region (cluster) or another may not be justified. Consequently, identification of regions with vague boundaries between them is preferable, compared to crisp regions with well-defined boundaries as in the case of hard clustering. The fuzzy set theory (Zadeh 1965), which straddles ordination classification and clustering analysis (Roberts 1986), is a natural way to represent such a situation. Fuzzy partitional clustering allows a catchment to belong to all the regions simultaneously with a certain degree of membership. The distribution of membership of a catchment among the fuzzy clusters specifies the strength with which the catchment belongs to each region. The knowledge of this distribution is particularly useful to identify ambiguous catchments. A threshold to maximum membership values can be applied to derive crisp, vector-based representations from raster, fuzzy classifications. Rao and Srinivas (2006) argue that given the intricate process interactions controlling channel morphology and the inadequacies of conventional stream classification methods, fuzzy representations of in-stream habitat 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 (Cheeseman and Stutz 1996; Webb et al. 2007). 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 (Cheeseman and Stutz 1996; Gelman et al. 2004; Webb et al. 2007).
Table 2.1. Examples of hydrologic classifications of riverine flow regimes. Flow regime attributes: Magnitude (M), Frequency (F), Duration (D), Timing (T), Rate of Change (R). Temporal scale (of the flow regime attributes analysed): Daily (D), Monthly (M), Annual (A). NOTE: This table presents the results from a preliminary review of the literature.

<table>
<thead>
<tr>
<th>Spatial Scale</th>
<th>Location</th>
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<th>Temporal scale</th>
<th>Classification methodology</th>
<th>Reference(s)</th>
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<td>D, M, A</td>
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<td></td>
<td>Victoria, Australia</td>
<td>D</td>
<td>PCA &amp; average linkage clustering</td>
<td>Hughes and James (1989)</td>
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<td></td>
<td>Tasmania, Australia</td>
<td>D</td>
<td>PCA &amp; complete linkage clustering</td>
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<td>D, M</td>
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<td>M</td>
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<td>M, A</td>
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<td>Spatial Scale</td>
<td>Location</td>
<td>Flow attributes</td>
<td>Temporal scale</td>
<td>Classification methodology</td>
<td>Reference(s)</td>
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<td></td>
<td>Russia</td>
<td>M, T</td>
<td>M</td>
<td>Proportion of flow within each of four seasons, together with estimation of the genetic origin of flow (i.e. snow melt, glacier melt, rainfall and groundwater). The mean average monthly flow pattern satisfying the discriminating criteria is assigned a certain regime type.</td>
<td>Lvovich (1973) (see Krasovskaia (1997))</td>
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<td>Global</td>
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<td>M</td>
<td>A</td>
<td>M</td>
<td>Two-step approach: (1) initial groupings based on regions of similar climatic conditions (based largely on Koppen's Climate Classification). A hierarchical agglomerative cluster analysis using the within-group average method was subsequently used to create a smaller number of groups based on similarity in annual maximum discharge.</td>
<td>Burn and Arnell (1993)</td>
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<td>M, F</td>
<td>A</td>
<td>M</td>
<td>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.</td>
<td>Meigh et al. (1997)</td>
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<td>M, F, D, T R</td>
<td>D, M, A</td>
<td>D, M, A</td>
<td>Agglomerative hierarchical fusion (flexible UPGMA) on the Bray–Curtis matrix</td>
<td>Puckridge et al. (1998)</td>
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2.4 A framework and protocol for hydrologic classification

Hydrologic classification should be an objective process, transparent, readily interpretable, explicitly account for uncertainty and for variability at multiple temporal and spatial scales, explicitly regard methodological biases and robustness, and provide definable class boundaries, objective group membership, and information on the diagnostic hydrologic characteristics of each class. We believe that for a hydrologic classification system to be widely adopted it must be founded on a defensible scientific framework (Figure 2.1). Below, we provide specific guidelines for achieving this goal.

1. Define purpose of the study, geographic region of interest and objectives of the hydrologic classification.

2. Acquire and assess hydrologic data

   a) What discharge data are available (gauged versus modeled data, temporal grain – daily, monthly or annual, time period, geographic coverage)?

   b) Select candidate set of gauges (if using gauged discharge data).

   c) If your purpose is to classify 'natural' flow regimes, then select gauges that are not likely to be affected by anthropogenic factors (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, etc.).

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

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

   f) Evaluate temporal period (e.g. 1965–2000) and duration (i.e. 35 years) of available discharge data for each gauge.

   g) Decide on criteria for acceptance of gauges (i.e. minimum versus fixed record length, completely overlapping versus partially overlapping period of record, period of record to include particular years, such as years including significant changes in climate).

   h) Evaluate geographic locations of gauges to ensure adequate spatial coverage (i.e. representing climate regions of interest).

   i) If the spatial coverage is not adequate, then evaluate potential for including additional gauges by:

      i. relaxing the acceptance criteria (step 2g), and/or

      ii. estimating missing data in the discharge time series (step 2d) by using linear interpolation for short periods, general linear regression for longer periods, or some other 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 accuracy and precision of classification results (although some hydrologic metrics are more sensitive to record length and period overlap than others).
3. **Choose hydrologic metrics to include in the hydrologic classification**

   a) The selection of metrics depends primarily on purpose of the study (step 1). One might be interested in selecting a large number of metrics to characterise all facets of the flow regimes, or individual metrics of known/hypothesised ecological importance (see Olden and Poff 2003).
      i. General ecological rationale: set of metrics to characterise the totality of the flow regime.
      ii. Specific ecological rationale: individual metrics of known/hypothesised ecological importance for specific species, community, or ecosystem properties.
      iii. Driver rationale: metrics that are sensitive to an environmental or anthropogenic driver of interest (e.g. urbanisation, river regulation, climate change).

   b) Selection depends on temporal grain of flow data.

   c) Selection depends on intended software used to calculate metrics and practical capability of the researcher. Software options include dedicated hydrologic software (Indicators of Hydrologic Alteration (IHA): Richter et al. 1996; Hydrologic Assessment Tool (HAT): Henriksen et al. 2006; River Analysis Package (www.toolkit.net.au/rap) versus statistical/mathematical software.

   d) Selection based on quantifying statistical redundancy among metrics using univariate and multivariate approaches. The results will inform variable selection and dimensionality reduction (e.g. indirect ordination approaches to produce composite variables) if multicollinearity among metrics is a concern (see Olden and Poff 2003).

   e) No choice. Hydrologic classification will proceed using the raw discharge time series.

4. **Compute hydrologic metrics**

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

   b) Screen datasets for outliers and/or gauges potentially affected by anthropogenic activity by:
      i. Examining diagnostic plots and descriptive statistics
      ii. Conducting indirect ordination (e.g. principal components analysis), plotting ordination scores of gauges in 2-dimensional space and looking for outliers that might be suggestive of modified flows, unique natural flows, or measurement/data entry errors
      iii. Plotting mean daily flow (or similar hydrologic metric) against catchment area (gauges with obviously lower discharge than expected for a given catchment size may be effected by water extraction).

   c) Eliminate gauges if necessary.

   d) Remove scale-dependence of flow magnitude metrics (if required, depending on objectives of the study) by standardising metrics by catchment area or mean daily flow.

5. **Conduct the hydrologic classification**

   a) Choose statistical approach depending on objective of classification, software and capability of the researcher (see review below).

   b) Decide which hydrologic metrics to include in classification analysis:
      i. All flow metrics
ii. Subset(s) of metrics describing separate components of flow regime (this decision depends on the reason for classification, see step 1)

iii. Prune the total number of flow metrics to a smaller set of high-information, non-redundant flow metrics (see Olden and Poff 2003)

iv. Choice of metrics might also be dependent on statistical assumptions/requirements (data type, normality, etc.) of classification approach.

c) Decide whether metric transformations/standardisations are required.
d) Choose appropriate distance/similarity measure (if required).
e) Conduct classification analysis.
f) Delineate clusters, and decide on the number of hydrologic classes (i.e. clusters), class membership, and probabilities of class membership (see below).
g) Examine classification results for outliers and eliminate gauges if necessary; repeat steps 5d–f.

6. Interpret the hydrologic classification

a) Describe hydrologic characteristics of hydrologic classes, numerically, statistically, graphically, and verbally.
b) Examine geographic distribution of gauge class membership (e.g. using a Geographic Information System).
c) Optionally, validate the classification model using an independent dataset containing gauges not included in the classification or based on a set of environmental variables describing each gauge that are considered the most important for shaping flow regime characteristics (i.e. the results of a physical-based classification).
1. Define study purpose of the study, geographic region of interest and objectives of classification.

2. Acquire and assess hydrologic data
   a) What discharge data is available?
   b) Select candidate set of gauges
   c) Eliminate gauges with modified flow regimes
   d) Eliminate gauges with poor quality data
   e) Ensure consistency of discharge measurement units
   f) Evaluate temporal period and duration of record
   g) Decide on criteria for acceptance of gauges with respect to 2f.
   h) Evaluate geographic coverage of gauges
   i) Evaluate potential for including additional gauges by:
      i. relaxing acceptance criteria (Step 2g), and/or
      ii. estimating missing data in time series (Step 2d)

3. Choose hydrologic metrics to characterize flow regimes
   a) Depends on purpose of the study
      i. General ecological rationale (all facets of the flow regime)
      ii. Specific ecological rationale: individual metrics of ecological importance
      iii. Driver rationale: metrics that are sensitive to environmental drivers
   b) Depends on temporal grain of flow data
   c) Depends on software used to calculate metrics and researcher capability
   d) Removal of statistical redundancy
   e) No choice (time series)

4. Calculate hydrologic metrics
   a) Calculate metrics
   b) Screen datasets for outliers and/or unnatural flow regimes by:
      i. Examining diagnostic plots and descriptive statistics
      ii. Conducting indirect ordination and plotting ordination scores in 2-dimensional space
      iii. Plotting hydrologic metrics against catchment area
   c) Eliminate gauges if necessary
   d) Remove scale-dependence of flow magnitude metrics (if required)

5. Conduct the hydrologic classification
   a) Choose statistical approach
   b) Decide which hydrologic metrics to include in classification analysis:
      i. All flow metrics
      ii. Subset(s) of metrics for separate components of flow regime
      iii. Small set of high information, non-redundant flow indices.
      iv. Dependent on statistical assumptions/requirements of classification approach.
   c) Decide whether metric transformations/standardisations are required
   d) Choose appropriate distance/similarity measure (if required)
   e) Conduct classification analysis
   f) Delineate clusters
   g) Examine for outliers, eliminate gauges if necessary, repeat step 5d.

6. Interpret the hydrologic classification
   a) Describe hydrologic characteristics of clusters
   b) Examine geographic distribution of gauge cluster membership
   c) External validation using independent environmental data

Figure 2.1. A protocol for the process of hydrologic classification.
2.5 The development and application of hydrological classifications in Australia

Hydrological classification of Australian rivers has been previously undertaken at a variety of spatial scales (Bates 1994). Typically, these undertakings have been primarily motivated by the need to extend known relationships about hydrological data to poorly gauged areas to assist in water management and civil engineering projects (i.e. bridge construction). In addition, some of the studies reviewed here do not consider actual daily flow data but consider environmental data that act as proxies for flow and frequently model a limited subset of hydrological parameters (i.e. flood series or low flows) using hydrological parameters that are not commonly used by biologists or that are not immediately perceived to have ecological relevance (McMahon and Finlayson 2003). Rarely are such studies undertaken with any ecological applicability in mind. Typically also, such endeavors are referred to as regionalisations rather than classifications as the primary intent is the derivation of mathematical relationships describing hydrological behaviour for a given region (e.g. Nathan and McMahon 1990). It is not our intent to review these studies here but to focus on ecologically-oriented classifications (although strictly hydrological studies do reveal some noteworthy insights into the nature of Australian flow regimes and such studies are discussed).

2.5.1 Classification at the basin scale

Studies that have examined ecohydrological variation within a single river or a basin (i.e. catchment) that consists of several rivers are considered first. Thoms and Parson (2003) undertook a classification of flow data from 43 locations within the Condamine-Balonne River, which with the Maranoa River forms a major headwater source of the Darling River. They used 73 years of modeled daily flow data for two water resource development scenarios (no development scenario and current water resource development scenario) to calculate many summary flow statistics (227 and 230 for the two scenarios, respectively), addressing most key facets of the flow regime (Poff et al. 1997) across three temporal scales (pulse, history and regime). The similarity matrix upon which classification (UPGMA) and ordination (Semi Strong Hybrid Multidimensional Scaling) analyses were based, was estimated using the Gower Index which standardises units across each variable. Prior standardisation of magnitude variables (i.e. by reference to catchment area or median daily flow) was not employed. No redundancy analysis was conducted prior to multivariate analyses and all variables were allowed into each analysis. Significant redundancy is evident in the pictorial representations of significant correlation (as determined by the principal axis correlation analysis) between objects and attributes in ordination space. Six groups of locations (modeled gauges) were formed by the classification aligned down the river in a sequence corresponding to spatial variation in a previously described geomorphic/river classification sequence for the study area. Although this sequential alignment of flow regime and geomorphology may have arisen because magnitude variables were not scaled to become essentially dimensionless prior to inclusion in the multivariate analyses, Thoms and Parsons (2003) argue the interaction between flow and channel morphology determines the regime state particularly with respect to spatial variation in temporal facets of the regime. These authors demonstrated that different sets of temporal parameters, equating to the time scales described above, became dominant contributors to the regime signature within various geomorphic zones.
Pusey and Arthington (1996) examined the spatial variation in the hydrologic regime of the Burdekin River in central Queensland. A common 19 year period of daily flow records for 26 gauges arrayed throughout the catchment was examined. Gauges were grouped a priori, based on landscape attributes (geographic position, subdrainage membership and river type) and a moderately concordant pattern of spatial variation in freshwater fish structure (Pusey et al. 1998). The investigation was primarily focused on describing spatial variation in hydrological variability and the choice of metrics used was consequently limited (n = 15) to statistics describing the variability of flows across different time periods (CV of daily, monthly and yearly flows), metrics quantifying predictability (Colwell’s P) of monthly minimum, monthly maximum, monthly totals and ratio of maximum to minimum daily flows, and an annual exceedance frequency of a low flow threshold. Average annual and daily flows were also included but these metrics were not standardised (made dimensionless) prior to analysis. A formal examination of redundancy was not performed, but an analysis of the relationship between catchment area and hydrological metrics demonstrated that across all gauges, only mean annual and daily flow were related to catchment area. However, within some of the a priori formed groups, catchment area was correlated with up to six parameters in addition to mean annual flow. Discriminant functions analysis (stepwise) was used to test whether discharge regime varied predictably throughout the catchment. Eleven of the 15 parameters, including mean annual flow, varied significantly between groups and consequently highly significant concordance between flow regime and position in the catchment was detected (100% successful classification). Spatial variation in flow regime was largely due to gradients in perenniality and the variability of minimum, maximum and mean daily flows and was related to spatial variation in rainfall and underlying geology. The resultant classification was discussed with respect to the difficulty of setting environmental flow limits in systems of contrasting variability and origins of that variability.

Ransley et al. (2007) used a GIS map-based approach to classify and spatially model stream-aquifer connectivity in the Border Rivers catchment of the Murray-Darling. Stream-aquifer connectivity was identified as being both economically (i.e. with respect to water allocation) as well as ecologically important (i.e. environmental flow and water quality management). The authors, building on similar approaches developed for the rivers of inland NSW (Braaten and Gates 2002), identified four key determinants of connectivity. These were:

- depth to the water table (DWT – estimated from existing bore hole data from state agencies)
- stream bed sediments (SBS – derived from Layer 2 gridded (1.1 km² grain) NLWRA (1999) soil saturated hydraulic conductivity national data set)
- geology (G – existing maps and state water agency lithological logs for low-lying areas classed as undifferentiated alluvium)
- geomorphology (GM – Multi resolution Valley Bottom Flatness Index derived from the 9 inch DEM).

Values were scaled and combined according to the formula: connectivity index = 3DWT + 5SBS + 5G + 2GM; qualitatively classified as low, medium and high, and mapped. The relevance of the resultant classification to ecological management was not developed although the authors suggest that the method has value as a ‘first cut’ approach to identifying areas where groundwater/surface water interactions may be important. The extent to which this method can be extended elsewhere relies on the availability of spatial information and the resolution (grain) of that information and to this effect, may be limited in its application to much of northern Australia where geology is coarsely mapped.
Map-based GIS information, gauged and modeled flow data, and waterhole characteristics (e.g., size, persistence etc.) were combined in a very comprehensive analysis of the hydrology of the Lake Eyre basin (McMahon et al. 2005). Although the various data elements were not combined to produce a formal classification of flow regimes in the basin, the development of a model to explain spatial variation in water balance flows clearly identifies major hydrological differences across the basin. Laut et al. (1985) undertook a hydrological classification of the sub-basins of the Macleay Valley in New South Wales with the main intent being the development of relationships between catchment characteristics and streamflow with a view to extension to other catchments. Readily available landscape information was used to provide an explicitly derived classification of sub-basins based on the assumption that hydrologic similarity is a function of landscape similarity and rainfall similarity. The authors used a combination of analyses developed for numerical taxonomy (classification and ordination); the first time such approaches had been used in hydrological investigations in Australia. Landscape attributes were grouped into five classes: topography (5 attributes), aspect (3), wetland type (7), landcover (9) and lithology (9). Similarity was estimated using a combination of the Gower and Bray Curtis measures and the NEWCLAS algorithm. This study found significant relationships between the combined landscape and rainfall functions and various aspects of hydrology for nine gauged stations throughout the catchment, demonstrating the link between these functions and streamflow.

2.5.2 Classification at the regional scale

Several classification exercises have been undertaken for various parts or regions of south-eastern Australia. Spatial distribution of flow regime variation in Tasmanian rivers was undertaken by Hughes (1987) in the first Australian study to use multivariate techniques to spatially model streamflow at the regional scale. Hughes (1987) used daily flow data, varying in length from 15–81 years, to compute 13 flow metrics (mostly at the monthly and annual time scales) from 77 gauges distributed across 69 basins. Magnitude variables were not made dimensionless prior to analysis and no formal analysis of redundancy was undertaken. It is clear from the Principal Component’s analysis and regression analyses however that many variables were correlated with mean annual runoff.

Four distinctive and spatially significant groups were recognised by classification. Spatial arrangement was largely determined by topography and climate (Figure 2.2).

- **Group 1** streams were typically located on the north-western coastal zone of Tasmania and were distinguished by intermediate runoff values (mean = 410 mm), moderate CV of annual flows (0.52), moderate skewness of annual flows (0.75), comparatively high CVs of monthly (0.75), maximum (0.66) and minimum (1.19) flows lows, low variability of peak flows (0.29) but high variability of low flows (0.66).
- **Group 2** streams were located in the south-east corner of the island and were characterised by low runoff (142 mm), high CV of annual flow (0.87), high skewness of annual flows (1.04) and high CVs of annual (0.87), monthly (0.70), maximum (0.67) and minimum flows (1.14).
- **Group 3** streams were located in the southwestern portion of the island and were characterised by high runoff (1347 mm), very low CV of annual flow (0.23) and low skewness (0.46) and low CVs of monthly (0.49), maximum (0.44) and minimum (0.67) flows.
Group 4 streams were located inland from Tasmania’s northern coast and were characterised by moderately high runoff (762 mm), low CV annual flow and skewness (0.36 and 0.15, respectively), low to moderate CVs of monthly and monthly maximum flows (0.65 and 0.54, respectively) but high variability in low flows (CV = 0.91).

Figure 2.2. Distribution of flow regime types in Tasmania (Hughes 1987).

Hughes and James (1989) extended this type of examination in a study aimed at providing an objective classification of streamflow types in Victoria, based on quantitative streamflow records, for the purposes of informing stream ecology research and providing a predictive capacity for ungauged locations. Streamflow data were obtained from 138 gauges distributed across 117 basins. A total of 16 hydrologic metrics (no standardisation for variation in magnitude) were computed for each location from daily time series spanning at least 15 years. No flow data prior to 1950 were used so as to exclude the influence of a major climate shift occurring around this time. Two separate classifications (average linkage cluster) were conducted: one based on the entire flow record (13 metrics) and the other limited to the low flow period (7 metrics). The low flow classification produced four distinct classes with a spatially heterogeneous distribution across the state. The entire classification (5 groups) exhibited significant spatial clustering (see Figure 2.3) and spatial distribution of flow types was largely determined by topography and coincided with a previously described climatic regionalisation (Whetton 1988). Hughes and James (1989) described the major hydrologic differences between classification groups and attempted to ascribe ecological importance to these differences.
In a hydrologic regionalisation study, Nathan and McMahon (1990) applied a range of multivariate techniques in an investigation of the relationship between catchment and discharge characteristics for streams of south-eastern Australia (including eastern Victoria and south-eastern NSW). The focus of the study was on methods to determine the applicability of derived relationships for extension to ungauged catchments and was further focused on the low flow character of the hydrograph. Catchments examined were typically small (1–250 km²) and discharge record length averaged only 17 years. A total of 19 catchment-related variables were estimated and included catchment area and basin morphometry, rainfall, vegetative cover and underlying geology. The study examined the outcome of using different clustering techniques and similarity measures, and different variable weighting on regional groups. The authors further examined the utility of Andrew’s curves for identifying group outliers and tightening within-group cohesiveness. The spatial arrangement of the various groups derived from each classification was not displayed and the study focused more on identifying problems and biases associated with different analytical approaches. Nonetheless, this study did identify the utility of using catchment-related variables to predict hydrology across a large area.

Growns and Marsh (2000) undertook an analysis of flow regime variation across 107 gauging locations (including 10 simulated time series) in south eastern Australian (Victoria to southern Queensland) using a common 20 year daily flow series. Data from both regulated and unregulated streams were used. A total of 333 metrics were calculated and subsequently reduced to 91 variables after cross correlation redundancy analysis. The resultant attributes were then subjected to ordination (Semi Strong Hybrid Multidimensional Scaling) based on the
The analysis clearly identified differences in the flow regimes of regulated and unregulated streams. Unregulated streams were differentiated principally on the basis of a gradient in intermittency/permanency.

Leigh and Sheldon (2008) undertook an analysis of spatial variation in hydrology in rivers of the Gulf of Carpentaria Queensland, with a definite focus on ecological relevance. A total of 15 gauges spread across seven major catchments (Nicholson, Leichardt, Flinders, Gilbert, Mitchell, Coleman and Wenlock rivers) were examined. Daily discharge data were standardised by catchment area (i.e. converted to runoff). Partial removal of the effect of differing catchment size was achieved by inclusion of gauges from catchments only in excess of 1000 km². Twenty years of records were used and although time periods for each gauge were not common across all gauges, substantial temporal overlap was present as many records commenced in either 1967 or 1968, or 1970, 1972 or 1973. A total of 29 metrics was computed for each gauge covering the magnitude, duration and variability facets of the discharge regime. No formal examination of redundancy was undertaken prior to multivariate analyses and all variables were range standardised prior to analysis. The sample by sample (gauge) association matrix was estimated using the Euclidean distance measure, and the resultant ordination and classification based on this matrix were achieved by Non Metric Multidimensional Scaling and group average clustering, respectively. Classification resulted in the formation of two groups differentiated by permanence and ‘flashiness’ of discharge. A second classification based solely on variables relating to seasonal differences in wet and dry season discharge resulted in the formation of three groups, of which one group essentially related to one of the groups formed in the earlier classification. The two types of regimes were described as a ‘tropical regime’ (Nicholson, Gregory, Mitchell and Wenlock rivers) characterised by permanent regular discharge with major differences in nature and predictability of dry and wet season behaviour, and a ‘dryland regime’ (Flinders, Leichardt, Gilbert rivers and large tributaries of the Mitchell River) characterised by ephemerality, flash flooding and extended periods of zero discharge. Comparison of discharge metrics under natural and potentially modified regimes for the Flinders and Leichardt Rivers was achieved by reference to the water resource development conditions in the Darling River.

The Flinders River was also included in a comparison of discharge regimes in three rivers across northern Australia (Moliere 2006, Moliere et al. 2006). Daily discharge series (but not continuous data as whole years with missing data were excluded; Moliere 2006) covering at least 20 years of data were analysed for 13 gauges within the Daly River catchment in the Northern Territory, six within the Fitzroy River in the Kimberley region, Western Australia, and nine within the Flinders River drainage of the Gulf of Carpentaria, Queensland. Eight discharge metrics were calculated for each catchment (in addition to catchment area). Mean annual discharge was not made dimensionless prior to analysis but a formal redundancy analysis was conducted and this variable and two others were removed prior to analysis. Comparison between classification solutions (based on Euclidean distance and group average linkage cluster) revealed that only two variables, CV of annual discharge (CV) and the proportion of zero flow days (ZFD), drove most of the spatial variation and the final classification presented was based on these variables alone. Four hydrologic groups were identified and described as:

1. perennial (mean CV = 0.80, mean frequency of zero flow days = 0.06)
2. seasonal (CV = 0.82, ZFD = 0.46)
3. dry seasonal (CV=1.24, ZFD = 0.68)
4. seasonal intermittent (CV = 1.74, ZFD = 0.86).
Substantial geographic congruence was identified with eight of the Daly river gauges being allocated to the perennial group (plus one Fitzroy River gauge), five Fitzroy River gauges (plus one Daly River and one Flinders River) being allocated to the seasonal group, and seven Flinders River gauges (plus one Daly River) being allocated to the dry seasonal group. The fourth group, seasonal intermittent, contained two Daly River gauges and one Flinders River gauge. In those cases where gauges from one river were allocated to a group different from other gauges within that river, Moliere *et al.* (2006) demonstrated that these anomalous gauges were located in specific subcatchments with a dissimilar climate and geology. The authors noted that flood related parameters were not useful discriminators between groups perhaps because flood generation processes were associated with large scale meteorological processes common across the entire region. Moliere *et al.* (2006) went on to determine that four landscape variables: drainage density, mean catchment slope, mean average rainfall and elevation; were able to significantly predict spatial variation in CV and ZFD and suggested that these parameters were useful in predicting classification group membership in ungauged rivers.

### 2.5.3 Classification at the continental scale

Not surprisingly given the size of the task, efforts at providing a continent wide classification of Australian riverine discharge regimes have been limited. Comparison of certain aspects of the hydrologic regime of Australian rivers with elsewhere in the world has occurred (see Finlayson and McMahon 1988; Puckridge *et al.* 1998; McMahon *et al.* 2007a, b, c) but has not been extended to a similar comprehensive analysis within Australia. Nevertheless, some large-scale studies have been undertaken within Australia. For example, McMahon and Finlayson (2003) provided a map of the continent divided into the various seasonality regimes identified by Haines *et al.* (1988) (Figure 2.4).

![Figure 2.4. Application of the Haines *et al.* (1988) discharge regime seasonality classification to Australia (from McMahon and Finlayson 2003).](image)
Zoppou et al. (2002) used modeled daily discharge data at 286 gauges distributed throughout the continent but heavily concentrated in south-eastern Australia (only four gauges in the Northern Territory, 10 in south-western Western Australia and domination of Queensland gauges by those from the Burdekin River) to examine discharge regime signatures across a range of time scales. They employed wavelet transformations to decompose the discharge regime into variation at different time scales (1, 2, 4 days, 64 days… ≈1 year, 2 years, 3 years…90 years) and then employed k-means clustering to group gauges according to the energy spectrum of the wavelets. Twelve classification types were identified and in which random variations were the dominant signal. One group (3) was characterised by a dominant annual signature and many stations within this group were located in south-western WA or Victoria (i.e. a Mediterranean signal). Another group with a dominant annual signature (10) was distributed across Victoria, NSW and Queensland. The outcomes of this classification, whilst apparently mathematically elegant, are difficult to interpret and harder still to attribute ecological significance.

2.6 Conclusion

A number of conclusions may be drawn from the Australian examples of hydrological classification described in this short review.

• First, despite a comparatively long history during which some basin-wide and regional classifications have been produced, an interpretable, ecologically relevant and quantitatively objective continent-wide classification of hydrologic regimes has not been produced.

• Second, a variety of techniques have been employed in regional and basin-centred classifications of stream discharge but all have had drawbacks associated with metric redundancy, comprehensiveness of hydrologic metrics used, standardisation of metrics and methodological approaches. In part, this reflects the original intent of the studies and the period in which they were undertaken.

• Third, no Australian studies have formally addressed the implications of record length and period of record overlap for estimation of hydrologic metrics.

• Fourth, hydrologists have, not surprisingly, and until recently, tended to be more interested in classification as a means of extending insights gained into ungauged catchments than they are in the ecological relevance of the spatial variation in regime. However, regionalisation exercises for the purposes of extension into ungauged catchments have revealed that a relatively small group of landscape and climatic attributes are capable of predicting many individual aspects of hydrology and by extension, may be used to model or predict hydrologic regime (Laut et al. 1985; McMahon et al. 2005; Ransley et al., 2007).

Clearly, the most effective way in which a continent wide classification incorporating hydrologic rigor and ecological relevance can be progressed is by the production of a classification based on similarities in hydrologic metrics (an empirical approach) following the protocol outlined above, in tandem with the development of regionalisations based on landscape and climatic attributes (a deductive approach).
2.7 References


