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Mark J. Kennard, Mark J. Kennard, Bradley James Pusey, Bradley James Pusey ...+4 more authors

Institutions: Griffith University, Australian Government, University of Washington, Australian National University ...+1 more institutions

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Classification of natural flow regimes in Australia to support environmental flow management

MARK J. KENNARD*,†, BRADLEY J. PUSEY*,†, JULIAN D. OLDEN‡, STEPHEN J. MACKAY*, JANET L. STEIN§ AND NICK MARSH¶
*Australian Rivers Institute, Griffith University, Nathan, Qld, Australia
†Tropical Rivers and Coastal Knowledge (TRaCK) Commonwealth Environmental Research Facility, Australian Government, Canberra, ACT, Australia
‡School of Aquatic and Fishery Sciences, University of Washington, Seattle, WA, U.S.A.
§The Fenner School of Environment and Society, Australian National University, Canberra, ACT, Australia
¶eWater Cooperative Research Centre and CSIRO Land and Water, Indooroopilly, Qld, Australia

SUMMARY

1. The importance of hydrologic variability for shaping the biophysical attributes and functioning of riverine ecosystems is well recognised by ecologists and water resource managers. In addition to the ecological dependences of flow for aquatic organisms, human societies modify natural flow regimes to provide dependable ecological services, including water supply, hydropower generation, flood control, recreation and navigation. Management of scarce water resources needs to be based on sound science that supports the development of environmental flow standards at the regional scale.
2. Hydrological classification has long played an essential role in the ecological sciences for understanding geographic patterns of riverine flow variability and exploring its influence on biological communities, and more recently, has been identified as a critical process in environmental flow assessments.
3. We present the first continental-scale classification of hydrologic regimes for Australia based on 120 metrics describing ecologically relevant characteristics of the natural hydrologic regime derived from discharge data for 830 stream gauges. Metrics were calculated from continuous time series (15–30 years of record constrained within a 36-year period) of mean daily discharge data, and classification was undertaken using a fuzzy partitional method – Bayesian mixture modelling.
4. The analysis resulted in the most likely classification having 12 classes of distinctive flow-regime types differing in the seasonal pattern of discharge, degree of flow permanence (i.e. perennial versus varying degrees of intermittency), variations in flood magnitude and frequency and other aspects of flow predictability and variability. Geographic, climatic and some catchment topographic factors were generally strong discriminators of flow-regime classes. The geographical distribution of flow-regime classes showed varying degrees of spatial cohesion, with stream gauges from certain flow-regime classes often being non-contiguously distributed across the continent. These results support the view that spatial variation in hydrology is determined by interactions among climate, geology, topography and vegetation at multiple spatial and temporal scales. Decision trees were also developed to provide the ability to determine the natural flow-regime class membership of new stream gauges based on their key environmental and/or hydrological characteristics.

Correspondence: Mark J. Kennard, Australian Rivers Institute, Griffith University, Nathan, Qld 4111, Australia.
E-mail: m.kennard@griffith.edu.au

5. The need to recognise hydrologic variation at multiple spatial scales is an important first step to setting regional-scale environmental flow management strategies. We expect that the classification produced here can underpin the development of a greater understanding of flow-ecology relationships in Australia, and management efforts aimed at prescribing environmental flows for riverine restoration and conservation.

Keywords: Bayesian mixture modelling, catchment characteristics, climate, hydrologic metrics, prediction, uncertainty

Introduction

The structure and function of riverine ecosystems, and the adaptations of their constituent freshwater and riparian species, are determined by patterns of intra- and inter-annual variation in river flows (Poff *et al.*, 1997; Lytle & Poff, 2004; Naiman *et al.*, 2008). Understanding natural patterns of hydrology in time and space and the associated ecological consequences of altering these patterns of flow variability has therefore become fundamental to the assessment and management of environmental water allocations for river systems, and environmentally sustainable water management planning (Bunn & Arthington, 2002; Arthington & Pusey, 2003; Richter *et al.*, 2006). The identification of flow-regime types by means of hydrological classification underpins one of the most recent advances in environmental flow assessment methodologies, called ELOHA (Ecological Limits of Hydrological Alteration, Poff *et al.*, this volume).

Hydrologic classification is the process of systematically arranging streams, rivers or catchments into types that are most similar with respect to characteristics of their flow regime. The classification of hydrological regimes has long played a critical role in the ecological sciences for understanding geographic patterns of riverine flow variability (e.g. Haines, Finlayson & McMahon, 1988; Poff & Ward, 1989; Harris *et al.*, 2000), exploring the influence of streamflow on biological communities and ecological processes (e.g. Jowett & Duncan, 1990; Poff & Allan, 1995), prioritising conservation efforts for freshwater ecosystems (e.g. Higgins *et al.*, 2005; Snelder, Dey & Leathwick, 2007) and guiding river management strategies (e.g. Snelder, Biggs & Woods, 2005; Arthington *et al.*, 2006). Environmental water allocations, scenario testing and risk analysis of various management options, and planning for the impacts of global climate change, all need to be based on our understanding of, and capacity to predict, the ecological consequences of changes in hydrologic regime (Poff *et al.*, 2003; Stewardson & Gippel, 2003; Richter *et al.*, 2006). The ability to do so is constrained unless we know how much and when flow regimes vary among rivers and regions, and the extent to which such variation influences biological patterns and ecological processes in riverine ecosystems.

A key foundation of the natural flow paradigm (*sensu* Poff *et al.*, 1997) is that the long-term physical characteristics of flow variability have strong ecological consequences at local to regional scales, and at time intervals ranging from days (ecological effects) to millennia (evolutionary effects) (Lytle & Poff, 2004). Critical components of the flow regime include the magnitude and seasonal pattern 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 in discharge events (Richter *et al.*, 1996; Poff *et al.*, 1997; Bunn & Arthington, 2002). Spatial variation in these hydrologic characteristics is determined by variations in climate and mediated by catchment geology, topography and vegetation (Winter, 2001). These factors interact at multiple spatial and temporal scales to influence physical habitat for aquatic and riparian biota, the availability of refuges, the distribution of food resources, opportunities for movement and migration, and conditions suitable for reproduction and recruitment (Naiman *et al.*, 2008).

Given the importance of hydrologic variability for shaping the biophysical attributes and functioning of riverine ecosystems, rivers that have similar hydrological characteristics should also have similar assemblage composition, species traits and community functioning (Poff & Ward, 1989). Extending this notion, Arthington *et al.* (2006) and Poff *et al.* (this volume) suggested that ecological responses to a given anthropogenic change in flow regime should be similar in rivers of a similar initial natural flow regime. If true, this provides researchers and managers with a powerful foundation for predicting future responses to flow-regime changes whether it arises from localised basin-specific impacts or global climate change. Moreover, the outcomes of flow restoration exercises may be better planned and implemented. The ability to identify and classify spatial patterns in ecologically relevant flow-regime characteristics is therefore an important first step in achieving these goals (Arthington *et al.*, 2006; Poff *et al.*, this volume).

Hydrological classifications have previously been attempted in Australia at various scales, using a variety of methods, and usually describing only a subset of ecologically relevant flow-regime components. Finlayson & McMahon (1988) applied the Haines *et al.* (1988) global classification of stream flow seasonality at a continental scale. Other continental scale classifications of climate and catchment environmental attributes with a direct relevance to hydrology have also been undertaken (e.g. Hutchinson *et al.*, 2005; Stein *et al.*, 2008). Hydrologic classifications have been derived for particular regions (e.g. Hughes & James, 1989; Leigh & Sheldon, 2008; Moliere, Lowry & Humphrey, 2009) and individual catchments (e.g. Thoms & Parsons, 2003). A continental scale multi-metric classification of ecologically relevant aspects of the flow regime has not yet been undertaken and few studies have examined the environmental mechanisms responsible for spatial variation in flow-regime characteristics (but see Nathan & McMahon, 1990; Moliere *et al.*, 2009).

In this paper, we present the first continental-scale classification of hydrologic regimes for Australia. The classification is based on multiple hydrologic metrics describing the key ecologically relevant flow-regime characteristics using discharge data from a large set of stream gauges throughout the country. We attempt to gain insight into the mechanisms responsible for shaping broad-scale variation in flow regimes by using combinations of environmental variables describing catchment topography, surficial geology and substrate, vegetative cover and climate to explain and predict flow-regime class membership of stream gauges. We also develop a decision tree to enable new stream gauges (i.e. not used in the present analyses) to be assigned to a flow-regime class based on a subset of key discriminating hydrological characteristics. This facility is also important for predicting the type of flow regime existing prior to human impacts. By addressing these objectives, we aim to improve our understanding of spatial variation in natural flow regimes throughout Australia and provide the ability to determine the natural flow-regime class membership of new stream gauges based on their key environmental and/or hydrological characteristics. We expect that the hydrological classification produced here can underpin the development of a greater understanding of the interaction between hydrology and ecology in Australian rivers, and support management efforts aimed at prescribing environmental flows for riverine restoration and conservation.

Methods

Study area – climate and geography

The Australian continent is notable for its generally low topography (average elevation = 330 m.a.s.l., maximum = 2745 m.a.s.l.), large inland arheic and endorheic river basins and low gradient coastal exorheic river basins (Bridgewater, 1987). The climate is diverse (12 of the 30 Koeppen-Geiger climate classes represented) but most of the continent is within two arid climate classes (Peel, Finlayson & McMahon, 2007). The climate is dominated by the dry sinking air of the subtropical high pressure belt that moves north and south with the seasons such that most rainfall in the north occurs during the austral summer (i.e. monsoonal wet) whilst most rainfall in the south occurs in the austral winter (i.e. temperate wet) and is associated with complex low pressure weather systems originating in the Southern Ocean and South Pacific Ocean. Low rainfall (average = 451 mm year^{-1}), high mean annual temperatures (21.5 °C) and high rates of evaporation (typically in excess of rainfall) typically lead to low runoff (McMahon *et al.*, 2007). Spatial variations in runoff separate the continent into two distinct areas, a humid coastline and an arid interior, with the greatest proportion of total runoff occurring in the northern and north-eastern coastal areas (88% from only 26% of the land area), and the least recorded in arid and semi-arid regions (75% of the continent receives <12.5 mm of annual runoff). Pronounced temporal variations in runoff are also characteristic of much but not all of Australia, particularly relative to other regions of the world (Puckridge *et al.*, 1998).

Quantifying characteristics of the flow regime

Discharge data. Mean daily discharge data for an initial set of 2686 gauges with >10 years of record were acquired from Australian state and territory water resources agencies. These gauges were screened and a subset fulfilling the following criteria were selected: (i) little or no hydrologic modification due to human activities; (ii) a period of hydrologic record ≥15 years within the period 1st January 1965 to 31st December 2000, preferably extending throughout a common year (i.e. 1980); and (iii) continuous mean daily discharge data where possible. Our objective was to maximise the number and spatial coverage of gauges available for inclusion in subsequent analyses whilst ensuring that stream gauges were comparable in terms of data quality and quantity. Criterion 1 was assessed as follows. Stream gauges potentially subject to hydrologic modifications due to dams, weirs, interbasin transfers and water extraction were identified using available information on the location of major dams and weirs (e.g. ANCOLD Inc., 2002), discussion with colleagues from water resource management agencies and other institutions, as well as by examining GIS layers of the locations of major canals and pipelines (GeoSciences Australia., 2006). Potential human impacts on flow regimes were also evaluated using the River Disturbance Index (RDI; Stein, Stein & Nix, 2002). This index comprises indirect measures of flow-regime disturbance due to impoundments, flow diversions and levee banks, and catchment disturbance due to urbanisation, road infrastructure and land use activities. This information was summarised for the catchment upstream of each gauge and was used as a guide to identify and exclude gauges subject to intense human disturbances. Criterion 2 was based on the conclusions of Kennard *et al.* (2009) that estimation of hydrologic metrics based on at least 15 years of discharge record was suitable for use in hydrologic classification analyses that aim to characterise spatial variation in hydrologic regimes, provided that the discharge records were contained within a discrete temporal window (i.e. preferably >50% overlap between records).

A total of 830 stream gauges met all of the screening criteria. While the hydrologic regimes of some of these stream gauges are likely affected by human activities to some extent, this represents our best efforts to identify the subset of least-disturbed stream gauges in Australia. The majority of selected stream gauges (76%, 630 of 830 gauges) had continuous daily flow data with the remainder being most frequently (80%) characterised as missing less than 30 days (i.e. <0.6% of record). Missing periods of record were infilled using linear interpolation or regression (see Kennard *et al.*, 2008). The period of record for all gauges was within the years 1965–2000 and 85% included the year 1980 (Fig. 1a). The majority of gauges (>60%) had at least 20 years of record and only 7% of gauges had 15 years of data (Fig. 1b), the minimum length of record for inclusion in the classification. Most stream gauges also overlapped substantially in their period of discharge record (e.g. *c.* 90% of gauges overlapped by more than 50%) (Fig. 1b). The geographical location and length of discharge record for each of the 830 gauges is shown in Fig. 2. Gauge density was greatest (>0.4 gauges per 1000 km^2) for the eastern coastal region of Australia (i.e. drainage division I, II and III) and least (<0.02 gauges per 1000 km^2) for the two arid internally draining basins (X and XI). Few gauges that were unaffected by human activity were available in the Murray-Darling Basin (division IV), except in headwater tributaries. Tropical northern Australia (i.e. drainage divisions VIII and IX) was generally characterised by gauges with short record lengths (i.e. ≤20 years) compared with elsewhere in Australia (Fig. 2). Gauges were situated on streams and rivers with a wide range of upstream catchment areas (6–222 674 km^2) but with most (72%) being 100–10 000 km^2 in area. The set of 830 gauges covered most of the climatic (and hence potential flow-regime)

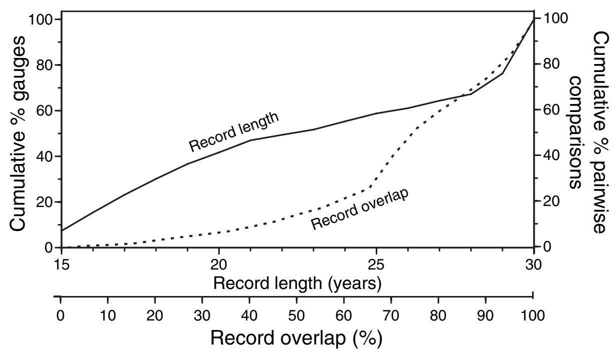


Fig. 1 Cumulative frequency distributions of gauging stations used in the analysis (n = 830) showing the length of discharge record (number of whole years, solid line) and the percentage overlap in period of record for all possible pairs of gauges (fine dashed line, n = 344 035 pairwise comparisons).

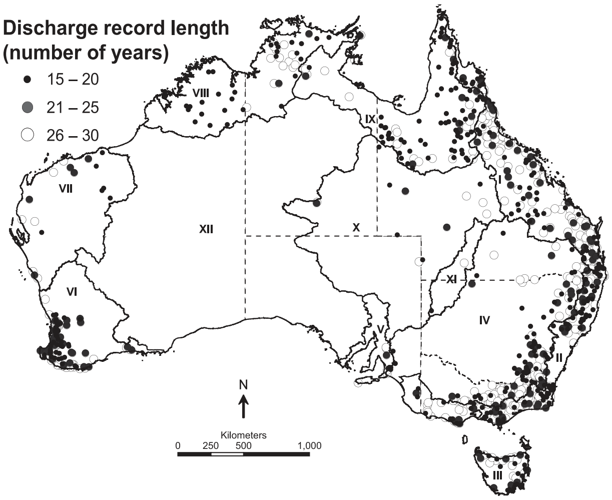


Fig. 2 Length of discharge record for each stream gauge used in the analyses. Australian drainage divisions (AWRC, 1976; coarse lines) and State and Territory borders (thin dashed lines) are also shown. Drainage divisions are: I – North-east Coast, II – South-east Coast, III – Tasmania, IV – Murray-Darling, V – South Australia Gulf, VI – South-west Coast, VII – Indian Ocean, VIII – Timor Sea, IX – Gulf of Carpentaria, X – Lake Eyre, XI – Bulloo-Bancannia, XII – Western Plateau. This figure incorporates data which are © Commonwealth of Australia (GeoScience Australia 2006).

types throughout Australia and were comparable with respect to the length and temporal period of discharge record (see Kennard *et al.*, 2009).

Hydrologic metrics. Numerous hydrologic metrics can be used to describe ecologically relevant components of the hydrologic regime in terms of the magnitude, frequency, duration and timing of discharge events, rate of change in discharge events and the temporal variability in these measures [reviewed by Olden & Poff (2003)]. Olden & Poff (2003) examined patterns of correlation among 171 hydrologic metrics and quantified their ability to describe the key ecologically relevant components of hydrologic regimes in 420 stream gauges across the continental U.S.A. They concluded that the 66 hydrologic metrics (including measures of central tendency and dispersion) calculated by the Indicators of Hydrologic Alteration (IHA) software package (Mathews & Richter, 2007) could adequately describe most of the major flow-regime components but recommended several additional metrics to describe the magnitude and frequency of high-flow events. This reduced set of minimally redundant metrics formed the basis for the selection of hydrological metrics for the present study. To these, we added metrics that describe ecologically important aspects of flow regimes in Australia, particularly those associated with the low-flow end of the hydrological spectrum. We also attempted to 'balance' the number of metrics for each major component of the flow regime to avoid one component being overrepresented in the hydrologic classification, although this was unavoidable in some instances (i.e. there are limited ways to describe rates of change in flow events compared with numerous approaches available to describe flow magnitude).

Following Olden & Poff (2003), we grouped our final set of 120 individual hydrologic metrics (see Appendix S1 for details on the method of calculation) into five major categories describing different ecologically relevant components of the flow regime. These included measures of central tendency (mean) and dispersion (variance) in the magnitude (n = 54 metrics), frequency (n = 14), duration (n = 34), timing (n = 12) and rate of change (n = 6) in flow events, where magnitudes were subsequently divided into average (n = 32), low (n = 7) and high (n = 15) categories, frequency into low (n = 6) and high (n = 8) categories, and duration into low (n = 18) and high (n = 16) categories. The extent of multicollinearity among hydrologic metrics, as evaluated by examining cross-correlations between all 120 metrics, was generally low (Kennard *et al.*, 2008). The majority (i.e. >70%) of between-metric comparisons had absolute correlation coefficients <0.5 and fewer than 5% of between-metric comparisons had absolute correlation coefficients >0.80. These observations were consistent when examining for linear (Pearson's correlation) and rank-order (Spearman's correlation) relationships among variables.

Hydrologic metrics were calculated using the Time Series Analysis module of the River Analysis Package (RAP, Marsh, Stewardson & Kennard, 2003). Hydrologic metrics describing flow magnitude were standardised to downweight their influence on subsequent classifications. Except for six metrics specifically describing runoff (i.e. discharge divided by upstream catchment area – see Appendix S1), all metrics describing flow magnitude (expressed in ML day^{-1}) for each stream gauge were standardised by dividing by the mean daily flow calculated for the entire record. Mean daily flow was used as the denominator rather than median daily flow (as has often been used in other studies) because many gauges had long-term median daily flows of zero.

Geospatial and environmental data

Geospatial and environmental data hypothesised to be important discriminators of flow-regime types were used to interpret the hydrological classification. These included variables describing the geographic location of each stream gauge (latitude and longitude) and environmental characteristics of the reach and/or catchment upstream of each gauge. Environmental variables included catchment and valley topography [n = 12 variables describing elevation, catchment area and shape (elongation ratio), catchment storage, valley confinement catchment relief, distance to source and stream network density], surficial geology and substrate (n = 11 variables describing catchment average values of soil saturated hydraulic conductivity and plant-available water-holding capacity, areal percentage of catchment overlying various bedrock lithology classes including siliciclastic and carbonate sedimentary rocks, metamorphic rock, igneous rock and unconsolidated rocks), present-day vegetative cover (n = 2 variables describing the areal proportion of the catchment covered by trees and grasses, respectively) and climate (n = 35 variables describing catchment average annual and monthly areal actual evapotranspiration, annual and monthly mean rainfall, mean rainfall in the driest, wettest, coldest and warmest quarter, catchment average annual mean solar radiation, catchment mean temperature, mean temperature in the hottest and coldest month, and catchment average rainfall erosivity). A detailed description of environmental variables and their methods of derivation and source are described in Stein *et al.* (2008).

Statistical analyses

Hydrological classification. Hydrological classification was undertaken using a fuzzy partitional method, Bayesian mixture modelling, implemented using the AutoClass C program (v 3.3.4 – Hanson, Stutz & Cheeseman, 1991; Cheeseman & Stutz, 1996). In Bayesian mixture modelling, the observed distribution of data is modelled as a mixture of a finite number of component distributions to determine the number of distributions, their parameters, and object memberships (Webb *et al.*, 2007). The approach is fully probabilistic and uncertainty is 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; i.e. the probability of the model being correct given the data (Cheeseman & Stutz, 1996; Webb *et al.*, 2007). All 120 attributes (hydrologic metrics) were $\log_{10}(x + 1)$ transformed prior to analysis and modelled as normally distributed continuous variables. Outputs from the analysis include: the probability of class membership for each object (gauge); class strength (the probability that the attribute distributions at the class level can be used to predict the class members, with strong classes tending to have tight distributions of attribute values); and the importance of the individual attributes for distinguishing each class. This is evaluated using the Kullback-Leibler distance, a measure of distance between data distributions, which accounts for the central tendency and variability of the data distribution. The summed Kullback-Leibler distances over all attributes provided an estimate of overall divergence of each class from the overall distribution of cases.

Bayesian classification using AutoClass requires the user to specify measurement uncertainty for each attribute and those attributes with lower uncertainty have more influence on the final classification (Webb *et al.*, 2007). Uncertainty in the estimation of different hydrologic metrics is primarily a function of the length of discharge record used to calculate them and varies between different metrics for a given length of record (Kennard *et al.*, 2009). We specified uncertainty for each hydrologic metric using estimates of mean accuracy (i.e. the scaled mean squared error, hereafter termed sMSE) based on the minimum discharge record length (15 years) (Kennard *et al.*, 2009). We viewed the use of the 15-year sMSE as conservative but compared the classification based on the 15-year sMSE (C1) with a classification using the 30-year sMSE (C2). We also investigated the effects of including only the 334 stream gauges with ≥25 years of record (C3) and the effects of data order on clustering results. We re-ordered the data randomly 10 times, and re-ran the original classification (i.e. 15 year sMSE uncertainty for each metric). The most probable solutions for all 10 data orderings (C4–C13) were compared with the original classification (C1). Lastly, we undertook a 'hard' classification (C14) of the stream gauges in which individual objects are assigned to a single class only. We used an agglomerative hierarchical fusion technique (unweighted pairwise group arithmetic averaging) based on a Euclidean distance matrix (hydrologic metrics were range-standardised prior to analyses) and set the number of groups to equal the number produced by the most likely Bayesian solution of C1 to provide a direct comparison of the two classification results.

The different clustering results were compared using the adjusted Rand index (ARI; Hubert & Arabie 1985). The ARI has been shown to be the most desirable index for measuring cluster recovery (e.g. Steinley, 2004). The index is based on the relation of every pair of objects (gauges), and whether these relations differ between two cluster solutions. The index ranges between 0 (indicating agreement between two clustering solutions is no better than chance) and 1 (indicating perfect agreement). After assigning objects to their most probable classes (from the Bayesian classifications), we calculated the ARI comparing C1 with all other solutions (C2–C14) and tested significance values for each comparison using a randomisation approach following Steinley (2004) and the mclust (v.3) package for R (Fraley & Raftery, 2006). We also compared the relative influence of hydrologic metrics (based on Kullback-Leibler distances) on each classification (C1–C13) using Pearson's correlation to evaluate whether the classes defined in each classification were hydrologically similar. The relative influence of hydrologic metrics on the hard classification (C14) was defined by the magnitude of Kruskal–Wallis test statistics used to evaluate the ability of each hydrologic metric to discriminate among C14 classes. Graphical methods were also used to evaluate among-class variation (from C1) in a subset of key hydrologic metrics representing each of the five ecologically relevant components of the flow regime and which are commonly used in ecohydrological studies, are easily interpretable, and hence potentially amenable to management action (Poff *et al.*, this volume).

Explanation and prediction of flow-regime classes using external environmental data. We explored the mechanisms responsible for shaping broad-scale variation in flow regimes by comparing the geospatial and environmental characteristics of stream gauges across flow-regime classes. Differences in multivariate environmental characteristics among flow-regime classes were tested using an Analysis of Similarity (ANOSIM) based on the normalised Euclidian distance coefficient (PRIMER software, v. 5.2.9; Clarke & Gorley, 2001). ANOSIM compares rank similarities within *a priori* defined groups (i.e. classification groups) against rank similarities among groups and calculates a statistic, R, which is scaled to lie between −1 and +1 (Clarke & Gorley, 2001). In the context of our study, a value of 1 indicates that all gauges within flow classes are more similar to one another than any gauges from different classes, a value of 0 indicates that there is no difference among flow classes (i.e. representing the null hypothesis), and a value of −1 indicates that all gauges within classes are less similar to one another than any gauges from different classes. Statistical significance was assessed using a permutation test where group membership is randomly permutated 999 times and R calculated for each permutation. Separate ANOSIMs were conducted using different combinations of variables including: (i) geographic location; (ii) climate; (iii) catchment topography; (iv) geology, substrate and vegetative cover; and (v) combined environmental variables sets (ii)–(iv).

We also developed classification tree models (CART, Breiman *et al.*, 1984) to predict the flow-regime class membership of each stream gauge using each set of environmental data. This approach can identify those environmental variables important in discriminating among homogeneous groups of stream gauges, if indeed they do exist. Tree-based modelling provides a flexible nonparametric alternative to discriminant functions analysis for classification problems in that it can model nonlinear, non-additive relationships among mixed variable types, it is invariant to monotonic transformations of the explanatory variables and it facilitates the examination of collinear variables in the final model (De'ath & Fabricus, 2000). The splitting criterion was based on the Gini impurity index, and we selected the smallest tree within 1 standard error of the tree with the least classification error as determined using 10-fold cross-validation (Breiman *et al.*, 1984). We conducted separate analyses using the five different sets of environmental data described earlier for the ANOSIM analyses. Predictive performance of the classification trees was evaluated by calculating the percentage of stream gauges correctly allocated to their *a priori* defined flow-regime class and comparing these classification rates to the probability of correct allocation due to random expectations (9.1%, assuming all groups have equal sample size, 9.6% if proportional to group size, and 15.1% probability of being allocated to the group with the largest sample size). Cohen's κ coefficient of agreement was also used to assess the predictive performance of the classification trees compared to random expectations (Fielding & Bell, 1997). CART modelling was implemented using the rpart library of functions within S-PLUS 2000 (Statistical Sciences, 1999). Further description of variation in environmental characteristics of stream gauges within and among flow-regime classes is presented in Kennard *et al.* (2008).

Assigning new stream gauges to a flow-regime class using hydrologic metrics. We developed a decision tree to enable new stream gauges (i.e. not used in the present analyses) to be assigned to an individual flow-regime class based on their hydrological characteristics. The decision tree was constructed using a CART model in which the original 830 stream gauges were classified into groups using the 120 hydrological metrics as predictors of group membership. Predictive performance was evaluated by calculating the percentage of stream gauges correctly allocated to their *a priori* defined flow-regime class and using Cohen's κ coefficient of agreement.

Results

Hydrological classification

The most likely classification (C1) from the Bayesian clustering analysis produced 12 classes reflecting distinctive flow-regime types. The majority (91%) of stream gauges had a ≥99.9% probability of belonging to only one class (Fig. 3a). Only 12 of the 830 gauges exhibited a class membership probability of <0.990 for their most likely class and only one of these gauges had a probability (albeit low, $P = 0.002$) of belonging to more than two classes. Classes varied in their divergence (i.e. hydrologic difference) from the global distribution. Classes 1, 2 and 12 exhibited the greatest class-level divergence with respect to the global class, while the remaining nine classes had generally equivalent divergence values (Fig. 3b). Classes 2, 5 and 8 had the greatest class strength relative to the global distribution, indicating comparatively low

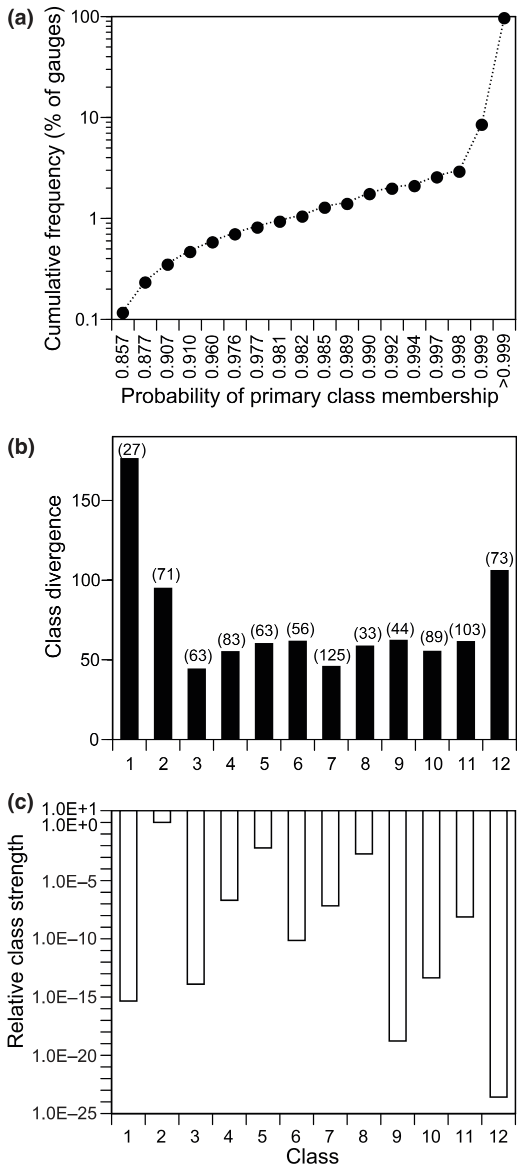


Fig. 3 Results of Bayesian classification (C1) of all 830 stream gauges showing (a) cumulative frequency distribution of the probability of each gauge belonging to its most likely class, (b) class divergence (number of stream gauges in each class shown in parentheses), (c) relative class strength.

within-class variation in hydrologic characteristics, whereas Classes 1, 9 and 12 had the lowest class strength (Fig. 3c).

Specifying variable uncertainty using the 30-year sMSE values resulted in the most likely classification (C2, $n = 830$ gauges, 14 classes) being reasonably similar to C1 (ARI = 0.481). The most important hydrologic metrics responsible for group formation were also similar between the two classifications

(Pearson's $r = 0.88$ for comparison of relative importance of hydrological metrics). Variation among stream gauges in the length of discharge record appeared to make little difference to classification group structure, at least over the range of differences in record length examined. A comparison of C1 with a classification based only on the subset of stream gauges with ≥25 years of record (C3, $n = 334$ gauges, 11 classes) revealed similar classification structure (ARI = 0.632) and similar relative importance of hydrologic metrics ($r = 0.85$) between solutions. Randomly re-ordering the stream gauges in the dataset also made little difference to the classification results (C4–C13, 12–14 classes) (mean ARI = 0.505, range = 0.450–0.551, $n = 10$ comparisons) or the relative importance of hydrologic metrics contributing most to group formations ($r > 0.91$ for all comparisons). In comparison to these alternative classifications, the results of a hard clustering method (C14, 12 classes) were less similar to C1 (ARI = 0.371), and the similarity in the relative importance of hydrological metrics was lower, though still strongly correlated ($r = 0.69$).

Hydrological characteristics and geography of flow-regime classes (from C1)

The twelve flow-regime classes could be first broadly grouped into perennial (Classes 1–4) and intermittent streams and rivers (Classes 5–12). This latter intermittent group was further divided into those streams and rivers that rarely ceased to flow (Classes 5–8), those that regularly stopped flowing (Classes 9–11) and those that were extremely intermittent (Class 12) (Figs 4a & 5a). Further distinctions among classes were evident in terms of the monthly timing of discharge (Fig. 4b), flood magnitude, frequency and duration (Figs 4c & 5), and other aspects of discharge magnitude, predictability and variability (Fig. 5). The flow-regime class membership all 830 gauges is provided as supporting information in the online version.

Class 1 streams (called *stable baseflow* streams) were perennial (Figs 4a & 5a) with comparatively high baseflow contribution (mean baseflow index = 0.35; Fig. 5b), high runoff magnitude (Fig. 5c) and high constancy of monthly mean flows (Colwell's C = 0.37, Fig. 5d). This high baseflow constancy is further indicated by the generally flat slope of the flow-duration curve throughout the range of percentile flow values (Fig. 4a). These streams were highly predictable (Fig. 5e) due to baseflow constancy (Fig. 5d) but had a relatively weak seasonal signal (Fig. 5f) because discharge magnitude was relatively uniform throughout the year (Fig. 4b). Streamflows tended to be very stable within years (i.e. low variability in daily flows; Fig. 5g) and among years (data not shown), with low skewness and low rates of rise and fall (Fig. 5i–k). High-flow events (e.g. >1st percentile) were comparatively small, frequent and of short duration (Fig. 5m–o) and maximum flows generally occurred at a similar time from year to year (e.g. low variability in timing of maximum flows; Fig. 5h). *Stable baseflow* streams were generally small (median catchment area = 101 km^2) and widely distributed geographically. They occurred most frequently in the South-east Coast, Tasmania and South-west Coast drainage divisions (Fig. 6) but representatives also occurred in the eastern Timor Sea division, northern Gulf of Carpentaria, southern North-east coast and the Murray-Darling drainage divisions. These streams were minimally influenced by the prevailing climatic signal due to the high baseflow contribution to runoff (driven by significant groundwater contributions).

Streams and rivers in Class 2 (called *stable winter baseflow*) and Class 3 (called *stable summer baseflow*) were also perennial with a high baseflow contribution and high runoff magnitude (Figs 4a & 5b,c) but had lower constancy and predictability of monthly mean flows compared with Class 1 streams (Fig. 5d,e). High-flow events (e.g. >1st percentile exceedence flows) tended to be of slightly higher magnitude and longer duration, but were less frequent than in Class 1 streams (Fig. 5m–o). A strong seasonal signal of discharge (M/P) was recorded for both classes (Fig. 5f) with the majority of runoff occurring in winter in Class 2 streams and summer in Class 3 streams (Fig. 4b). Discharge in both classes tended to be very stable within and among years (low variability in daily and annual flow; e.g. Fig. 5g), with low skewness and low rates of rise and fall (Fig. 5i–k). High-flow events (e.g. >1st percentile) in Class 3 streams were of greater magnitude, less frequent and of longer duration than in Class 2 streams (Fig. 5m–o). *Stable winter baseflow* (Class 2) streams tended to be small (median catchment area = 225 km^2) and were restricted to the southern temperate half of the continent, occurring mainly in the South-east Coast,

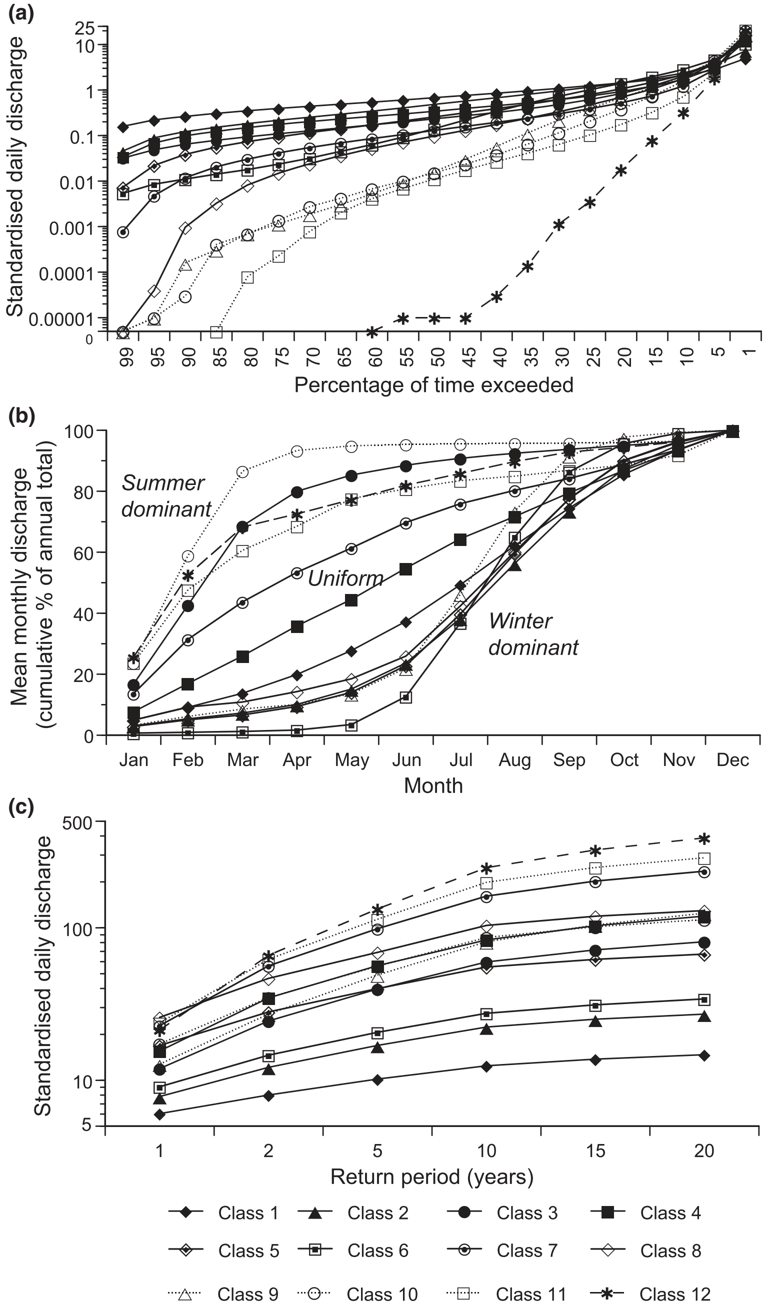
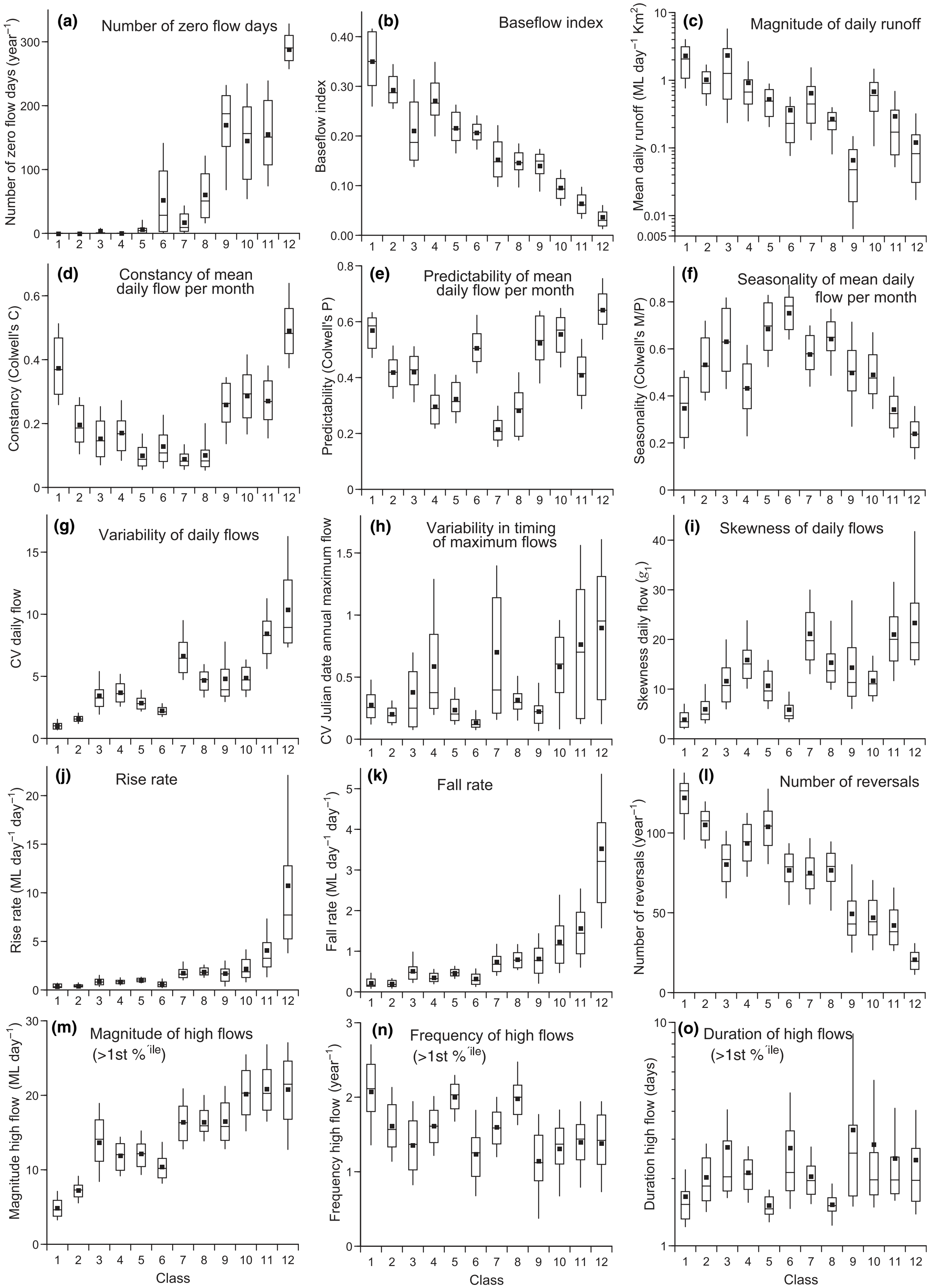


Fig. 4 (a) Average flow-duration curves for each for each flow-regime class, (b) average monthly flow for each flow-regime class, and (c) average flood frequency distributions for each flow-regime class. In (a) data are the percentage of time each daily discharge was exceeded. In (b) data are expressed as a cumulative percentage of the annual total. In (c) data are the magnitude of the 1, 2, 5, 10 and 20 year Average Recurrence Interval floods, respectively. Discharge data (y-axis) in (a) and (c) are dimensionless as they are standardised by long-term mean daily flow (see Appendix S1 for further details).

Tasmania and South-west Coast drainage divisions. *Stable summer baseflow* (Class 3) streams and rivers encompassed a wide range of catchment sizes (median catchment area = 616 km^2) and were primarily located in northern Australia occurring in the North-east Coast (particularly the Wet Tropics region), Gulf of Carpentaria and Timor Sea drainage divisions (Fig. 6).

Compared with the other perennial streams and rivers, discharge in Class 4 streams (called *unpredictable*

Fig. 5 Box plots showing variation for each flow-regime class (from C1) in selected hydrologic metrics representing each of the five ecologically relevant flow-regime components. The lines at the top, middle and bottom of each box represent the 75th percentile, median and 25th percentile of metric values, respectively. Vertical bars (whiskers) represent 90th and 10th percentiles and mean values are represented by symbols.


(a) Number of zero flow days
Number of zero flow days (year^{-1})
(b) Baseflow index
Baseflow index
(c) Magnitude of daily runoff
Mean daily runoff (ML day^{-1} Km^{2})
(d) Constancy of mean daily flow per month
Constancy (Colwell's C)
(e) Predictability of mean daily flow per month
Predictability (Colwell's P)
(f) Seasonality of mean daily flow per month
Seasonality (Colwell's M/P)
(g) Variability of daily flows
CV daily flow
(h) Variability in timing of maximum flows
CV Julian date annual maximum flow
(i) Skewness of daily flows
Skewness daily flow (g_1)
(j) Rise rate
Rise rate (ML day^{-1} day^{-1})
(k) Fall rate
Fall rate (ML day^{-1} day^{-1})
(l) Number of reversals
Number of reversals (year^{-1})
(m) Magnitude of high flows (>1st %´ile)
Magnitude high flow (ML day^{-1})
(n) Frequency of high flows (>1st %´ile)
Frequency high flow (year^{-1})
(o) Duration of high flows (>1st %´ile)
Duration high flow (days)
Class

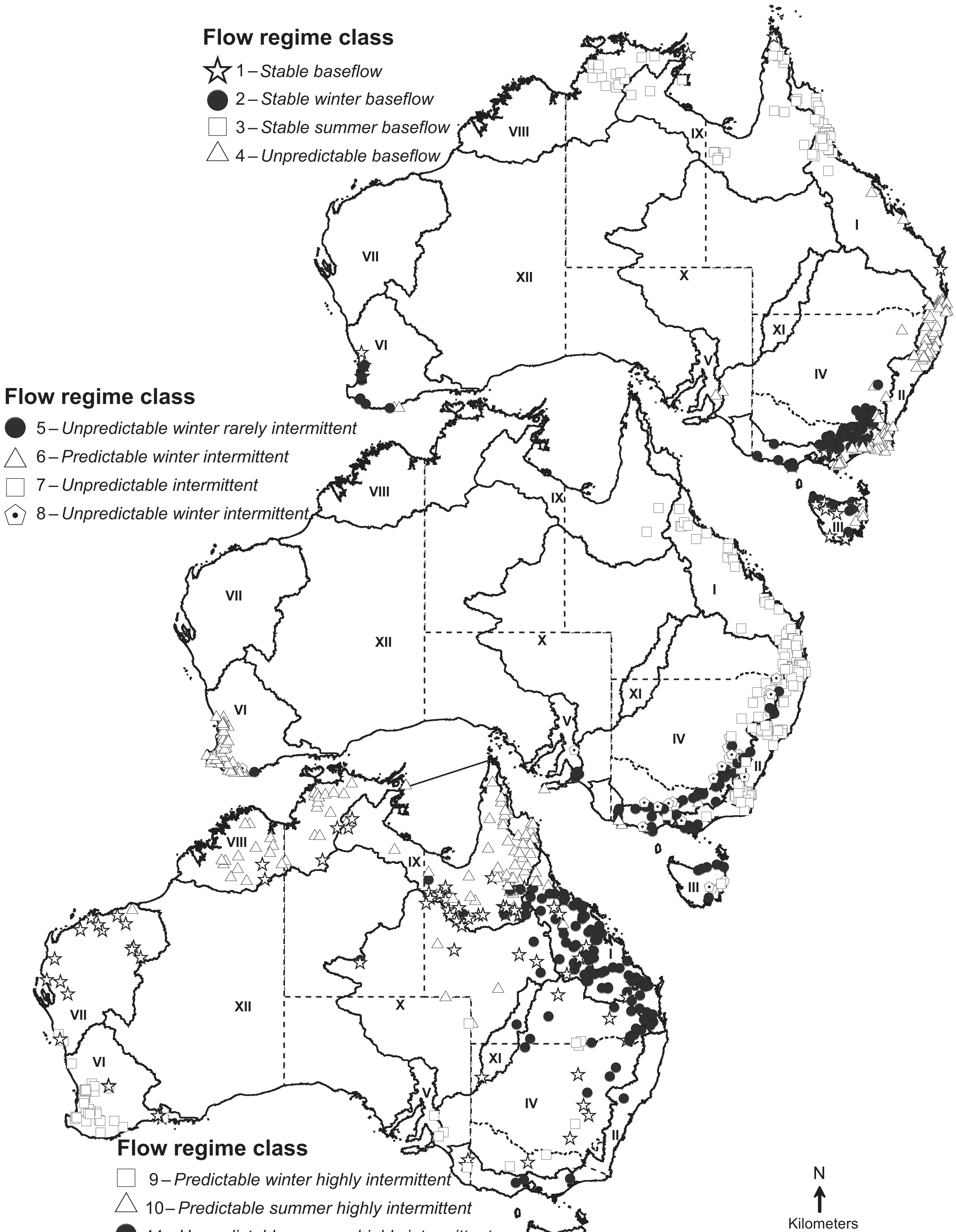


Fig. 6 Geographical variation in flow-regime class (C1) membership of 830 stream gauges in Australia. Australian drainage divisions (thick lines) and State and Territory borders (dashed lines) are also shown. This figure incorporates data which are © Commonwealth of Australia (GeoScience Australia, 2006).

baseflow) was less predictable (Fig. 5e) and had a relatively weak seasonal signal (Figs 4b & 5f). Streamflows also tended to be less stable within and among years (slightly higher variability in daily and annual flow; e.g. Fig. 5g), had higher skewness (Fig. 5i), and the timing of maximum flows was more variable (Fig. 5h). The relative magnitude of floods of various annual return intervals was also higher than in other perennial streams (Fig. 4c). Such streams tended to be small (median catchment area = 224 km^2) and were widely distributed across southern and eastern Australia (Fig. 6).

Streams and rivers in Classes 5–8 were intermittent (Figs 4a & 5a) and had low constancy of flows (Fig. 5d), intermediate baseflow contributions (Fig. 5b) and intermediate runoff magnitudes (Fig. 5c). Classes 5 and 6 were dominated by winter runoff (Fig. 4b) but Class 5 streams ceased to flow less often than those in Class 6 (mean of 5 days versus 60 days per annum, respectively; Fig. 5d) and were less predictable (Fig. 5e). Streams in Class 5 (called *unpredictable winter rarely intermittent*) were small (median catchment area = 168 km^2) and occurred mostly in south-eastern Australian coastal streams and the smaller headwater streams of the south-eastern Murray-Darling drainage division. Class 6 streams and rivers (called *predictable winter intermittent*) approximated the classic Mediterranean flow regime and were larger than Class 5 streams (median catchment area = 375 km^2). They were primarily located in south-western Australia and to a lesser extent the western portion of south-eastern Australia (Fig. 6). Discharge patterns in Class 7 (called *unpredictable intermittent*) and Class 8 (called *unpredictable winter intermittent*) streams and rivers were of very low predictability, more variable and had relatively high skewness compared with Classes 5 and 6. Streams and rivers in Classes 7 and 8 differed from one another in that those in Class 7 had more uniform runoff throughout the year (Fig. 4b) and fewer zero flow days than those in Class 8 (which were winter-dominated and much more intermittent). Discharge in Class 7 streams also tended to be less stable within and among years (higher variability in daily and annual flow; e.g. Fig. 5g), had higher skewness (Fig. 5i), and the timing of maximum flows was more variable (Fig. 5h). High flows were of a similar magnitude for both classes, but occurred more frequently and for a shorter duration in Class 8 streams. *Unpredictable intermittent* (Class 7) streams and rivers (median catchment area = 299 km^2) were widely distributed on the eastern coastal fringe of the continent, especially at the junction of drainage divisions I and II where the climate is transitional between temperate and subtropical. They also occurred in the eastern upper headwaters of the Murray-Darling drainage division and in north-eastern Australia. *Unpredictable winter intermittent* (Class 8) streams (median catchment area = 212 km^2) were limited to the eastern upper headwaters of the Murray-Darling drainage division and south-eastern Tasmania (Fig. 6).

Streams and rivers in Classes 9–11 were highly intermittent (usually 100–200 zero-flow days per year; Fig. 5a) which led to comparatively high constancy of flow (Fig. 5d). When they did flow, Class 9 streams and rivers were dominated by winter runoff and those in Class 10 were dominated by summer runoff (Fig. 4b). The strong seasonality of flows contributed to high predictability in both classes (Fig. 5e,f) but Class 9 streams and rivers had much lower runoff and the timing of annual maximum flows was much less variable than in Class 10. Class 9 streams and rivers (called *predictable winter highly intermittent*) encompassed a range of catchment sizes (median catchment area = 241 km^2) and were characteristic of inland areas in the South-west Coast and Murray-Darling drainage divisions. Class 10 streams and rivers (called *predictable summer highly intermittent*) occurred almost exclusively in the Timor Sea and Gulf of Carpentaria and typically consisted of large rivers (median catchment area = 1597 km^2). Class 11 streams and rivers (called *unpredictable summer highly intermittent*) differed from other highly intermittent streams in that minimum and especially maximum monthly flows were less predictable and exhibited weaker seasonality, and although still summer-dominated, the higher variability in Julian date of maximum flow suggests that high flows could occur at any time during the summer. Class 11 streams also had much higher flow variability, skewness, rates of rise and fall and the relative magnitude of floods of various annual return intervals was also higher. Such streams were almost exclusively restricted to the North-east drainage division and typically consisted of large rivers (median catchment area = 863 km^2).

Class 12 streams and rivers (called *variable summer extremely intermittent*) were extremely intermittent (>250 zero-flow days per year) resulting in high

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constancy of flow and hence high predictability. Although summer-dominated (Fig. 4b), the seasonality of flows was very weak (Fig. 5f). These streams and rivers were dominated by infrequent large floods which, while of similar magnitude from year to year (resulting in high predictability of maximum flows), could occur at any time of year (e.g. high variability in Julian date of maximum flows). They were also characterised by very high daily flow variability, skewness and rates of rise and fall. They encompassed a range of catchment sizes (median catchment area = 759 km^2) and are characteristic of arid and semi-arid regions, occurring in the Indian Ocean, Lake Eyre, Murray-Darling and southern Gulf of Carpentaria drainage divisions (Fig. 6).

Explanation and prediction of flow-regime classes using external environmental data

Analysis of Similarity revealed there were significant differences among flow-regime classes (from C1) in terms of the geographical location of stream gauges and their catchment topography, geology, vegetative cover and climate (Table 1). A strong geographic signal to flow-regime types was evident when using stream gauge latitude and longitude to distinguish flow regime classes ($R_{ANOSIM} = 0.558$, $P < 0.001$). Geographic variation in climate characteristics no doubt contributed to this strong discriminatory power as climate variables were similarly able to distinguish flow-regime classes ($R_{ANOSIM} = 0.587$, $P < 0.001$). Catchment topographic variables ($R_{ANOSIM} = 0.172$, $P < 0.001$) and geology, substrate and vegetative cover variables ($R_{ANOSIM} = 0.155$, $P < 0.001$), although significant, showed considerably lower discriminatory power compared to other environmental variables. ANOSIM using all catchment topography, geology, vegetative cover and climate variables strongly discriminated among flow-regime classes ($R_{ANOSIM} = 0.451$, $P < 0.001$).

Classification tree (CART) model accuracy (percentage of gauges correctly allocated to their *a priori*

Table 1 Results of analysis of similarity (ANOSIM) and classification tree (CART) analyses using various sets of geographic and environmental variables to discriminate among flow-regime classes (from C1). For each set of variables, the ANOSIM Global R, classification tree predictive accuracy (overall % correct classification rate, Cohen's κ) and the variables used to construct the tree (ranked in decreasing order of importance) are given. All ANOSIM results were significant at $P < 0.001$. Predictive accuracy of the classification tree models compares with random expectations of 9.1% (assuming all groups have equal sample size), 9.6% (if proportional to group size) and 15.1% (probability of being allocated to the group with the largest sample size). Significance values for Cohen's κ are listed in parentheses

Variable set	ANOSIM Global R	CART model Accuracy (%)	Cohen's κ	Predictor variables
1. Geographic location	0.558	47.7	0.413 ($P < 0.001$)	(1) Latitude, (2) Longitude
2. Climate	0.587	57.8	0.534 ($P < 0.001$)	(1) Annual mean solar radiation, (2) Mean February rainfall, (3) Mean August rainfall, (4) Mean April rainfall, (5) Mean annual rainfall, (6) Mean March rainfall, (7) Mean February actual evapotranspiration
3. Catchment topography	0.172	38.4	0.315 ($P < 0.01$)	(1) Catchment slope, (2) Catchment relief, (3) Stream density, (4) Maximum upstream elevation, (5) Catchment relief ratio, (6) Catchment area, (7) Reach elevation
4. Geology, substrate and vegetation	0.155	37.2	0.290 ($P < 0.01$)	(1) Old bedrock, (2) Solum plant available water holding capacity, (3) Unconsolidated material (regolith), (4) Present day tree cover
5. Catchment + substrate + vegetation + climate	0.451	62.1	0.579 ($P < 0.001$)	(1) Mean rainfall in coldest quarter, (2) Mean rainfall in driest quarter, (3) Mean August rainfall, (4) Mean March areal actual evapotranspiration, (5) Mean January areal actual evapotranspiration, (6) Mean March rainfall, (7) Mean June areal actual evapotranspiration, (8) Mean November rainfall (9) Mean August rainfall, (10) Mean rainfall in warmest quarter

flow-regime class from C1) was substantially greater than would be expected by chance for each model, with classification success rates ranging from 37.2% ($\kappa = 0.290$, $P < 0.01$) to 62.1% ($\kappa = 0.579$, $P < 0.001$) (Table 1). The outcomes of CART modelling were similar to the results of ANOSIM analyses in that models using geographical location and climate predictor variables could more accurately discriminate flow-regime classes than those using catchment topography or substrate and vegetation variables alone (Table 1). The best model, based on a combination of catchment, substrate, vegetation and climate variables, correctly classified 62.1% of stream gauges into their *a priori* flow-regime class (Table 1, Fig. 7). The primary and competing splitting variables mostly described temporal variation in catchment average rainfall, areal actual evapotranspiration, annual mean air temperature and rainfall erosivity. Topographic variables describing catchment slope and catchment relief were occasionally selected as competing splitting variables, but no geology or vegetation variables were selected in the final tree. The primary splitting variable in the CART model split stream gauges dominated by summer runoff (Classes 10–12) from all others on the basis of comparatively low total rainfall in the coldest quarter (Fig. 7). Competing splitting variables indicated that these stream gauges also had high solar radiation, low rainfall in August and high annual temperatures. On the right side of the tree, two major groups of gauges were distinguished on the basis of whether their catchments experienced low or high August rainfall (competing variables described high rainfall earlier in the year). Streams in catchments receiving high rainfall in August were rarely intermittent or were perennial, whereas streams with catchments receiving little rain at this time tended to

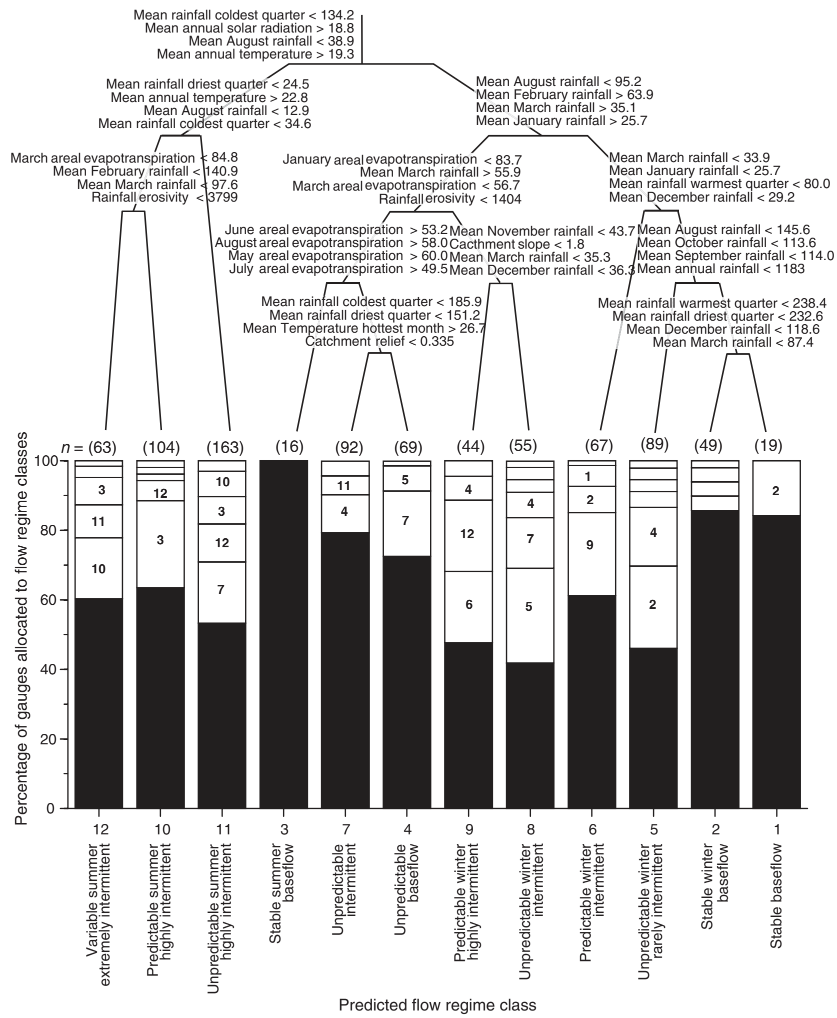

Fig. 7 Classification tree for predicting flow-regime class (C1) membership of each stream gauge using a combination of environmental variables describing catchment topography and climate. The environmental variables used in forming the tree (primary splitting variables shown first, followed by the three most important competing variables) and their critical values for determining the splits are shown above each split. Gauges that met each splitting criteria are split off to the left branch. The number of gauges (*N*) within each classification tree group is given at the base of the tree. The stacked bar chart shows the percentage of gauges belonging to each tree group. The predicted flow-regime class of each tree group is determined by the highest proportion of gauges belonging to a particular group (shown as closed bars), with misclassified gauges shown as open bars and numbered according to their actual flow-regime class membership (for those with misclassification rates ≥5%).

be intermittent or unpredictable. Class 3 streams (*stable summer baseflow*) were an exception. This group, limited to northern Australia, was grouped separately from other summer-dominated streams due to relatively high rainfall occurring outside the summer wet season period. Misclassifications (i.e. compared with *a priori* defined flow-regime classes) usually occurred among flow-regime classes that were in close geographic proximity to one another and hence presumably shared regional climatic conditions. For example, *variable summer extremely intermittent* gauges (Class 12) frequently grouped with other summer dominated flow-regime classes (i.e. Classes 10, 11 and 3) and *vice versa*. Stream gauges from these classes were generally situated across tropical northern Australia (Fig. 6). The CART model had particular difficulty correctly classifying *stable summer baseflow* (Class 3) streams that were not situated in the central core of the Wet Tropics region (Fig. 6). These streams had relatively high baseflows throughout the year due to groundwater contributions from the Tindall aquifer, rather than the more constant rainfall and runoff experienced in the Wet Tropics region.

Predicting flow-regime class membership using hydrologic metrics

A CART model using only 12 of the original 120 hydrologic metrics as primary splitting variables was able to correctly classify 81.2% of the 830 stream gauges into their *a priori* flow-regime class ($\kappa = 0.790$; Fig. 8). The 12 hydrologic metrics described low-flow

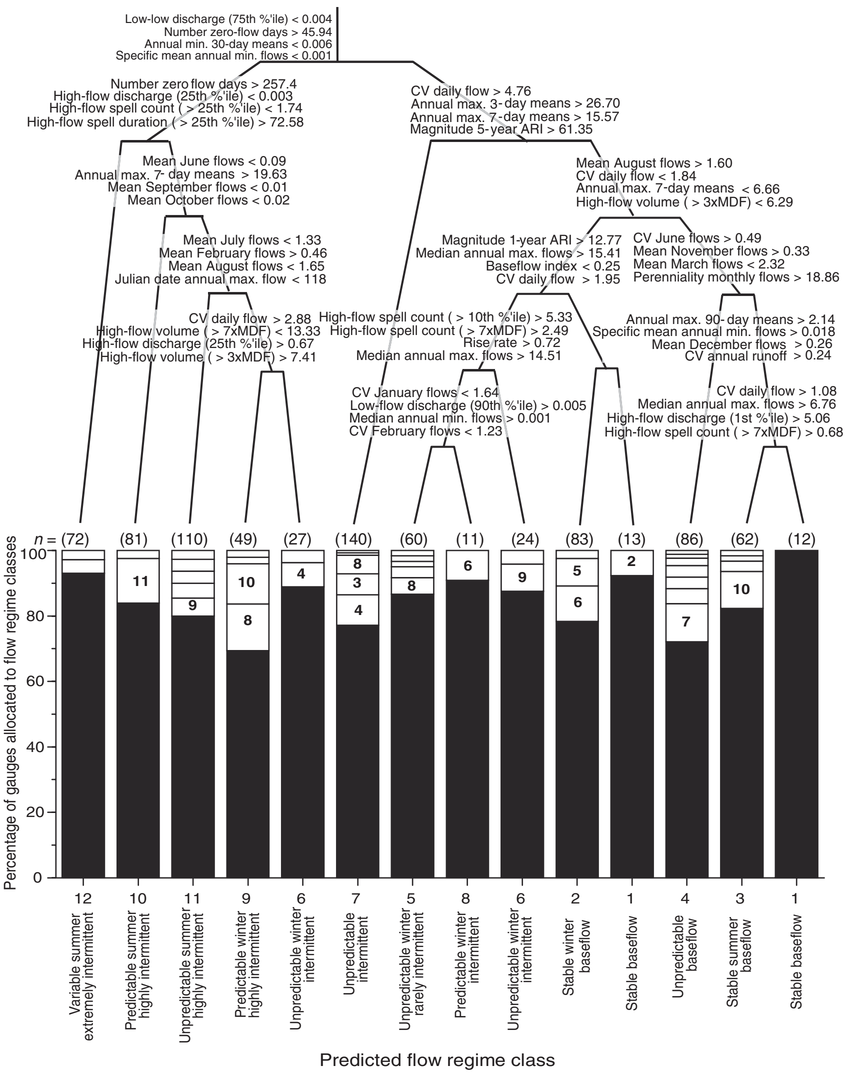

Fig. 8 Classification tree for assigning new stream gauges to a flow-regime class (C1) using hydrologic metrics. The subset of hydrologic metrics used in forming the tree (primary splitting variables shown first, followed by the three most important competing variables) and their critical values for determining the splits are shown above each split. Gauges that met each splitting criteria are split off to the left branch. The number of gauges (*N*) within each classification tree group is given at the base of the tree. The stacked bar chart shows the percentage of gauges belonging to each tree group. The predicted flow-regime class of each tree group is determined by the highest proportion of gauges belonging to a particular group (shown as closed bars), with misclassified gauges shown as open bars and numbered according to their actual flow-regime class membership (for those with misclassification rates ≥5%).

magnitude and duration, daily flow variability, the magnitude and variability of flows in particular months, and high-flow magnitude and frequency. To determine the most likely flow-regime class for a new stream gauge (i.e. one not used in the present analyses), the CART decision tree (Fig. 8) can be used to assign the gauge to an individual flow-regime class provided that data for the 12 hydrologic metrics (or for the competing splitting variables) are available.

Discussion

Hydrologic classification

Our study represents the first continental-scale classification of Australian streams and rivers based on ecologically relevant hydrologic characteristics. Our classification analysis necessarily involved the forced imposition of a grouped structure to rivers and streams, whereas in reality the extent to which such discrete groupings exist is uncertain. However, we were able to explicitly quantify this uncertainty in terms of data specification, class specification and the final classification chosen using a fully probabilistic Bayesian clustering approach. We identified 12 distinctive flow-regime classes that broadly differed in the degree of flow predictability and variability, the seasonal discharge pattern, flow permanence (i.e. perennial versus varying degrees of intermittency) and variations in the magnitude and frequency of extreme events (i.e. floods and low-flow spells).

Our analyses revealed that geographic, climatic and some topographic factors were generally strong discriminators of flow-regime classes (e.g. Table 1, Fig. 7) supporting the view that spatial variation in hydrology is determined by interactions among climate, geology, topography and vegetation at multiple spatial and temporal scales (Snelder *et al.*, 2005; Poff *et al.*, 2006; Sanborn & Bledsoe, 2006). However, some aspects of the hydrograph were poorly explained using the independent environmental datasets. For example, the CART model had particular difficulty correctly classifying *stable summer baseflow* (Class 3) streams that were not situated in the central core of the Wet Tropics region (Fig. 6). Many of these misclassified streams had relatively high baseflows throughout the year due to significant groundwater contributions from the widespread Tindall aquifer, rather than the more constant rainfall and runoff experienced in the Wet Tropics region. This difficulty in correctly predicting flow-regime characteristics is not surprising for these streams given the dominance of climatic variables as predictors and the relative coarseness of the geology variables available to us for modelling (and which were not selected by the CART models). Our ability to capture the critical landscape controls on stream hydrology will require a greater investment in research. In particular, it will be important to address shortcomings in the methods available to characterise the influence of catchment geology and the geological mapping on which it is based (see also Stein *et al.*, 2008). Further improvements in our ability to explain and predict hydrologic characteristics using independent environmental descriptors may also be achieved by undertaking these analyses at finer spatial scales of resolution (i.e. to explain within-class hydrological variation), as has been shown by Sanborn & Bledsoe (2006).

An important result of our study was that the geographical distribution of flow-regime classes showed varying degrees of spatial cohesion (Fig. 6), with stream gauges from certain flow-regime classes often being non-contiguously distributed across the continent. This was particularly pronounced for flow-regime classes described as *stable baseflow* (Class 1), *predictable winter highly intermittent* (Class 9) and *variable summer highly intermittent* (Class 12). As a consequence, caution should be used if extrapolating flow-regime characteristics from individual gauges to ungauged areas, even those within relatively close proximity. As suggested by Poff *et al.* (2006), this represents a serious constraint in terms of mapping hydrologic landscapes simply from available gauges used in an empirical classification analysis. In this context, deductively based classification of key environmental attributes assumed to broadly shape patterns of flow regimes at large spatial and temporal scales (hydrologic landscapes, *sensu* Winter, 2001) can provide additional useful information as it is not reliant on an extensive spatial coverage of measured flow data to characterise river flow regimes (e.g. Wolock, Winter & McMahon, 2004; Snelder *et al.*, 2005; Stein *et al.*, 2008).

Flow-ecology relationships

The hydrologic metrics underlying the classification represent ecologically relevant components of the hydrologic regime, and consequently, streams and rivers that cluster together presumably share certain ecological features (Resh *et al.*, 1988; Poff & Ward, 1989; Poff, 1996). Several studies relating spatial patterns in assemblage composition, species' ecological traits and community function to regional variation in hydrology exist globally (e.g. Poff & Allan, 1995; Monk *et al.*, 2006; Konrad, Brasher & May, 2008) but relatively few examples are available for Australia. Pusey, Arthington & Kennard (2004) showed that regional variation in fish species richness in north-eastern Australian rivers was strongly related to variations in aspects of discharge magnitude and perenniality. Pusey, Kennard & Arthington (2000) attributed differences in fish species richness, species' abundances and relationships with habitat structure observed between rivers of north-eastern and south-eastern Queensland to differences in discharge predictability and constancy between these regions. Finally, Kennard *et al.* (2007) reported that hydro-ecological predictive models of fish assemblage composition, abundance and biomass developed for a south-eastern Queensland river varied in their ability to predict spatial and temporal variation in these assemblage properties in a nearby river that differed hydrologically (particularly with respect to flow predictability, runoff magnitude and variability and the frequency of extreme low flows).

These studies collectively support the view that relationships between hydrology and ecological responses differ within and among particular regions and that this may be driven largely by variation in flow-regime characteristics, however they are limited to a relatively small portion of Australia. The improved understanding of geographic patterns in natural flow-regime characteristics in Australia provided by our study provides a framework for designing field research aimed at investigating flow-ecology relationships in more detail. For example, the classification could facilitate comparison of ecological characteristics among flow-regime classes and along gradients of hydrologic variability within classes. It can also provide a rational basis for extrapolation of site-specific data and flow-ecology models to unsampled areas with similar hydrology. This knowledge is particularly required for large areas of tropical northern Australia where riverine flow regimes are still relatively undisturbed but where human impacts on riverine landscapes are predicted to increase.

It is important to note that the hydrologic descriptors used in our analysis described the long-term statistical pattern of the hydrologic regime, not the short-term history of hydrological events. Thus scientific studies aimed at explaining spatial and temporal variation in ecological attributes and their relationships with hydrology should account for site-specific hydrological history (Poff, 1996), particularly if concerned with explaining ecological variables that fluctuate directly in response to short-term hydrologic events (e.g. recruitment-driven variations in abundance; Kennard *et al.*, 2007) rather than for ecological variables that represent long-term adjustments to hydrological regimes (e.g. species pools and ecological traits; Poff & Allan, 1995; Tedesco *et al.*, 2008).

Environmental flow management

The need to recognise hydrologic variation at multiple spatial scales is an important first step to setting regional-scale environmental flow management strategies (e.g. Arthington *et al.*, 2006; Poff *et al.*, this volume). An explicit spatial context such as is provided by the hydrological classification presented here should allow researchers to develop meaningful generalisations about the interaction between hydrology and ecology in Australia, and provide the benchmark against which the response of biological communities to hydrological alteration can be assessed. Our results showed that 12 distinctive flow-regime types exist for Australia, at least for the stream gauges included in our analyses. This implies that attempts to manage rivers in an environmental flow context should proceed from the perspective that ecological responses to natural flow-regime characteristics are likely to vary among these flow-regime types. Further stratification of rivers within flow-regime types (e.g. using channel geomorphic characteristics) may also be desirable to account for the role that other environmental factors play in shaping ecological patterns in streams and rivers (Poff *et al.*, this volume).

Our flow-regime classification represents a first step to defining 'practical management units' (Arthington *et al.*, 2006) that can be used by state or national water resource management agencies to plan and implement environmental flow management strategies and aid in setting targets for flow restoration (Arthington & Pusey, 2003). The flow-regime classification also provides an initial hydrologic basis to predict the ecological impacts of future flow alteration (e.g. due to climate change or planned water resource developments). When combined with projections of local climatic responses to global climate change, the CART model provides a means to determine whether future changes in hydrology are likely to re-classify the river in question from one regime type to another and presumably incur some environmental degradation or change. Similarly, the development of the decision tree allowing the designation of a river to a flow-regime class based on a small number of flow metrics could assist in assessing the likely outcomes of dam construction, and water resource harvesting as well as the likely benefits of mitigating environmental flow scenarios.

Conservation of aquatic ecosystems

Our study has broad-scale ecological implications that are directly applicable to conservation of aquatic and riparian ecosystems in Australia. With an increasingly large and thirsty human population and projected future climate change, there is growing need for preservation of remaining intact systems and deliberate and strategic design of resilient ecosystems (Palmer *et al.*, 2004; Poff *et al.*, 2007). By identifying streams and rivers that exhibit distinct or representative flow regimes that are currently not altered by human activities, our results can aid in the selection of those river systems that may contribute to dynamic conservation reserves to support ecosystem resilience and maintenance of biodiversity (e.g. Higgins *et al.*, 2005; Nel *et al.*, 2007; Snelder *et al.*, 2007). In light of the increasing degradation of Australia's freshwater ecosystems, recent efforts have emphasised the need for conservation protection in the form of comprehensive, adequate and representative freshwater reserves (Dunn, 2003; Fitzsimons & Robertson, 2005). Only about 2% of the 1400 named rivers in Australia are under protection by virtue of flowing through a few large terrestrial protected areas (Nevill, 2007). Although conservation of entire river basins offers the best chance of protecting aquatic biodiversity (Kingsford *et al.*, 2005), unfortunately many of these protected waters are small streams that are intermittent or ephemeral, or are major river reaches without protection upstream or downstream (Nevill, 2007). These areas are therefore likely to support only a small fraction of the native freshwater fish diversity in Australia. We believe that the selection of freshwater reserves and the success of conservation planning will benefit from a detailed understanding of spatial patterns of natural flow variability provided by our study.

Aquatic habitats and biota are threatened by many processes, especially hydrologic changes due to human land-use, water extraction and from projected climate change (Bunn & Arthington, 2002; Dudgeon *et al.*, 2006). Environmental water allocation, scenario testing and risk analysis of various management options, and planning for the impacts of global climate change all need to be based on predicted changes in the hydrologic regime (Poff *et al.*, 2003; Stewardson & Gippel, 2003; Richter *et al.*, 2006). The ability to do so is constrained unless we understand how much flow regimes vary among rivers and regions and the extent to which such variation results in natural changes to riverine ecology. Our study identified 12 distinctive flow-regime classes that broadly differed in the degree of flow predictability and variability, the seasonal discharge pattern, flow permanence (i.e. perennial versus varying degrees of intermittency) and variations in the magnitude and frequency of extreme events (i.e. floods and low-flow spells). The examination of environmental characteristics discriminating flow-regime classes strongly suggested that spatial variation in hydrology is determined by interactions among climate, geology, topography and vegetation at multiple spatial and temporal scales. The decision trees we developed provide the ability to determine the natural flow-regime class membership of new stream gauges based on their key environmental and/or hydrological characteristics. Classification schemes are an important step in developing generalisations describing how natural systems or landscapes respond to changing global phenomena or natural resource management options (Higgins *et al.*, 2005). The classification of ecologically important characteristics of the natural flow regime presented here provides scientists and managers with knowledge that can support ecologically sustainable management, restoration and conservation of freshwater ecosystems in Australia.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Description of the 120 hydrologic metrics used in the study. Hydrologic metrics used as primary and competing splitting variables in the classification tree (Fig. 8) are indicated by *. Abbreviations used are: MDF, mean daily flow; MADF, mean annual daily flow; CV, coefficient of variation; ARI, Average Recurrence Interval. Also listed are characteristics of each stream gauge used in the analyses in terms of geographic location, discharge record period, upstream catchment area and flow-regime class membership (from C1).

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