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A REGIONAL CLASSIFICATION OF UNREGULATED STREAM FLOWS: SPATIAL RESOLUTION AND HIERARCHICAL FRAMEWORKS

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ABSTRACT

River regulation has resulted in substantial losses in habitat connectivity, biodiversity and ecosystem services. River managers are faced with a growing need to protect the key aspects of the natural flow regime. A practical approach to providing environmental flow standards is to create a regional framework by classifying unregulated streams into groups of similar hydrologic properties, which represent natural flow regime targets. Because spatial resolution can influence the structure of regional datasets, it may be advantageous to relate datasets created at different scales in order to establish hierarchical structure and to understand how the relative importance of variables change with regard to scale. The purpose of this study was to classify unregulated streams within an eight-state region into groups in order to provide environmental flow standards for managers and to relate that dataset to frameworks created at larger scales. Using USGS daily stream gauge information, we used 66 hydrologic statistics to classify 292 streams in groups of similar hydrologic properties. We isolated six flow classes in a sub-region of the Southeastern US that ranged from extremely stable to highly variable to intermittent. We developed classification trees to reduce the number of hydrologic variables for future classifications. By comparing flow classes in our study to those of the entire US, we found that hierarchical structure did exist and that the divergence of flow classes will largely depend on the spatial resolution. Copyright © 2011 John Wiley & Sons, Ltd.

KEY WORDS: flow classification; flow standards; hydrologic alteration; regional framework

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INTRODUCTION

River regulation has resulted in substantial losses in natural flow variability, habitat integrity, and consequently, species diversity (Poff *et al.*, 1997; Vitousek *et al.*, 1997; Pringle *et al.*, 2000; Poff *et al.*, 2007). The natural flow regime (magnitude, frequency, duration, timing and rate of change in flow events) is essential for creating and maintaining habitat in river channels, transporting sediment, and connecting rivers and their floodplains (Poff *et al.*, 1997). Hydrologic disturbances create and maintain habitat heterogeneity (Trush *et al.*, 2000) and stabilize food webs (Wootton *et al.*, 1996; Cardinale *et al.*, 2005). Dams alter the frequency and duration of floodplain-inundation (Nislow *et al.*, 2002), which decreases bankfull area and lateral migration while also increasing riparian encroachment (Gordon and Meentemeyer, 2006). Substantial withdrawals have either left rivers without any water or dramatically reduced flows to the extent that river ecosystem function is lost (Poff *et al.*, 2003). The 'homogenization' of natural flow variability across geographic scales (Poff *et al.*, 2006a; Poff *et al.*, 2007) has resulted in the decline of species whose life history strategies are adapted to the natural variation in flow regimes (Bunn and Arthington, 2002; Poff *et al.*, 1997).

With over 82 000 dams in the US (USACE, 2009) and water rights battles across the country (Poff *et al.*, 2003), river managers are faced with a growing need to protect the key aspects of the natural flow regime. However, managing for the specific needs of every river and their associated biotic community is easier said than done. The interaction between social, economic, political, and finally, ecological demands results in simple and general flow rules that ignore the complexity of flow variability responsible for sustaining river systems (Arthington *et al.*, 2006). One practical approach to providing environmental flow standards is to form classes of rivers with similar hydrologic properties across regions from which standards for managing flow needs can be developed (Poff, 1996; Arthington *et al.*, 2006). Each flow class then becomes a hydrologic unit for management rather than managing for the individuality of each and every river system. The assumption is that rivers within similar hydrologic units are also similar ecologically, in terms of community composition, functional groups and responses to flow variability. Also, broad generalizations concerning the impacts of flow regulation on multiple groups of riverine biota has only recently received attention (Poff and Zimmerman, 2010); thus, a regional framework

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to evaluate biotic responses to flow regulations would be advantageous.

The other main approach to developing environmental flow standards is by using instream-flow-needs (IFN) techniques that relate flow to ecological targets. IFN approaches range from simple relations between hydrologic indices and aquatic habitats (i.e. weighted usable area) to more complex hydrodynamic models, which may or may not be linked to approaches that relate flow variability to many components of the river ecosystem (Tharme, 2003; Anderson *et al.*, 2006). PHABSIM models have been used extensively in the US and worldwide (Spence and Hickley, 2000; Tharme, 2003) and have been used with success in providing potential ecological responses to flow alterations (Gallagher and Gard, 1999). However, they are limited in that they are applicable to only the reach under study (Moir *et al.*, 2005), biased by site location (Williams, 2010), and are generally expensive in terms of time and money (Spence and Hickley, 2000). Another limitation is that PHABSIM models generally develop suitability criteria for one up to several target biota rather than the entire river community. Although holistic approaches may consider how a given flow regime may influence multiple components of a river ecosystem, Anderson *et al.* (2006) argues that these approaches generally do not incorporate process-driven ecological dynamics, especially internal feedback loops, into analyses of the influence of flow on aspects of the ecosystem. Ecological restoration should be founded upon restoring the processes responsible for maintaining ecosystems (Ward *et al.*, 2001). However, empirical information on the relationship between flow regimes and complex ecological dynamics is extremely limited (Poff and Zimmerman, 2010). Furthermore, forming environmental flow standards by evaluating all the complex ecological dynamics (population, community, spatio-temporal) and then translating that scientific information into quantitative demands to policy makers is unrealistic for every single regulated river.

Regional flow classifications based on unregulated rivers provide ecologically-relevant units, which are an organized and less-complex framework for developing environmental flow standards for management. Because flow standards are developed using the natural flow regime of unregulated rivers, prescriptions for flow regime alterations are applicable to the entire river ecosystem not just target biota. Future efforts to create sustainability boundaries (Richter, 2010) require acceptable regional flow classification. Flow classifications are also convenient in that they can produce flow prescriptions quickly without time intensive field work, developing flow-ecology relationships, and high monetary costs. Lastly, the majority of current understanding of the impacts of flow alterations on biota is case-specific knowledge (Poff and Zimmerman, 2010); thus, regional flow classifications may provide a framework to generalize patterns of disturbance as additional investigations proceed.

The classification of flows based on stream discharge alone is not unprecedented. Poff (1996) classified natural flow variability for 816 streams across the entire US into 10 flow categories using only flow records; however, because of the coarse scale of that study, only three flow classes were isolated for the area of interest of this study (GA, KY, MD, NC, SC, TN, VA, WV). Because of the variation in climate and watershed characteristics found at the scale of our study, we believe that a higher resolution classification is needed to adequately represent flow classes with distinct hydrologic properties. It is important to clarify that we are not campaigning for one classification over another. In contrast, we believe that coarse and fine resolution classifications are both essential to management and facilitate the formation of hierarchical datasets of flow variability at different scales. In addition, relating datasets to existing regional frameworks can increase our understanding of how ecosystem dynamics are governed at multiple scales. We chose to focus our classification within the Southeastern United States because of the increasing water demand from multiple sources and the need for a framework to develop sustainable water management in the Southeast (Sun *et al.*, 2008). Secondly, for the states found in this region, the practice of making environmental flow recommendations has been to apply statewide criteria, treating all classes of flow types in a similar way. Obviously, we find this inadequate for protecting the variability in flow regimes that support aquatic biodiversity.

The purpose of this study was to classify 292 unregulated streams based on hydrologic data within an eight-state region of the southeastern US in order to provide environmental flow standards for regulated rivers. Classifications are important to management in that they consolidate large amounts of information into digestible units. Because large amounts of variables can be overwhelming, we also wanted to provide a reduced set of hydrologic indices useful to managers in classifying future streams. We also wanted to compare our dataset to Poff's US flow classification to determine the potential for scale-dependent hierarchical flow classes. Specifically, our objectives were to (1) classify 292 unregulated streams within an eight-state region of the southeast into distinct flow classes important for environmental flow management, (2) provide a reduced set of hydrologic variables that can be used as foundational indices for future classifications and flow management and (3) determine the hierarchical structure in the divergence of flow classes between our study and that of the US flow classification.

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METHODS

We accessed the USGS Realtime Water Data for the Nation website (http://waterdata.usgs.gov) to find daily stream gauge data and to judge the extent of regulation due to impoundment or other hydrologic disturbances. Criterion for relatively undisturbed flow status was determined if the stream: (1) had at least 15 years of data, (2) had no upstream impoundments (including tributaries), (3) did not have large diurnal fluctuations due to withdrawals and (4) did not have a significant amount of its drainage area made up of urban areas, development, canals and pipelines. We used a four-step process to determine relatively undisturbed status. First, we selected gauges with at least 15 years of total data (some gage records had missing data as long as at least 15 total years were represented). Kennard *et al.* (2010a) concluded that at least 15 years of record are suitable for estimating variables that are used to detect differences in the spatial variation in stream flows, such as flow classifications. The study also concluded that discharge records should be contained within a temporal window that allows 50% overlap across records. We used the entire period of record available to capture as much of the hydrologic variability possible. However, because some records are from different time periods, have some missing data and may not sufficiently overlap, we attempted to examine any uncertainty in hydrologic metrics overwhelmed any variation in the classes that we formed. We discuss this further in the *Temporal Analysis* section. In the second step, we used USGS annual water reports to ensure that there were no impoundments upstream of the gauge (including tributaries). For stream gauges with extensive records that had at least 15 years of pre-impoundment data, we selected data within periods of time that had no regulated flow to include in our analysis as 'natural' conditions. Thirdly, we used USGS annual water reports to eliminate any gauges that had large diurnal fluctuations due to withdrawals (wording in USGS reports). Some stream gauges were selected that had slight diurnal fluctuations caused by upstream withdrawals or small mills. However, we assumed that slight diurnal fluctuations would not influence the hydrologic statistics that we used, which are influenced by trends across days and months, not within a 24 h period. We also ensured that withdrawals were not a significant proportion of daily discharge as to influence seasonal patterns and low flow conditions. To determine the extent of disturbance due to urban development and fragmentation, we used the hydrologic disturbance index created by Falcone *et al.* (2010). The dataset entails 375 variables for 6785 USGS stream gauges with at least 20 years of continuous data in the US including gauge identification and location, basin morphology, climate, topography, soils and anthropogenic disturbance factors (disturbance index, population density and land use). The disturbance index is a composite score for USGS gauged streams based on eight factors for each entire basin: major dam density, change in reservoir storage from 1950 to 2006, freshwater withdrawal, artificial paths (canals, ditches and pipelines), road density, distance to major NPDES (National Pollutant Discharge Elimination System) sites and the fragmentation of undeveloped land. Because we had eliminated streams that had upstream impoundments, we adjusted the index to only take into account the other six disturbance factors by deleting major dam density and change in impoundment storage from the composite score. We then used natural breaks (Jenks, 1966) to classify the score distribution into three categories: low (4–12), moderate (12–20) and high (20–27). We removed 18 more streams from the analysis that were in the high category leaving 292 streams that were relatively low to moderate disturbance.

Mean daily and annual peak flow data for the 292 stream gauges were downloaded from the USGS Realtime Water Data for the Nation website. Hydrologic statistics were calculated for each stream using the Hydrologic Index Tool (HIT) software available through the USGS (Hendriksen *et al.*, 2006). Daily and peak flow gauge data were imported into the HIT software, which calculates the 171 hydrologic indices reported in Olden and Poff (2003). The indices are summaries of the entire period of record. The indices are grouped into five categories of flow: magnitude ($n = 94$), frequency ($n = 14$), duration ($n = 44$), timing ($n = 10$), and rate of change ($n = 9$) with each category having low, average, and high flow subcategories (Richhter *et al.*, 1996; Olden and Poff, 2003). Because of the large amount of correlated variables, we reduced the dataset by evaluating correlation matrices among variables within each subcategory and removed variables with correlations of $r > 0.75$ and $r < -0.75$. For each pair of correlated variables, we favored variables that were one of the Index of Hydrologic Alteration indices (Richter *et al.*, 1997) or used in Poff (1996). If neither of these applied to the variables or both were favored, then variables were removed on the basis of order in the dataset, where variables listed later were removed. We then combined all subsections together to eliminate any other variables that were highly correlated across different subsections. The final dataset resulted in 66 variables. We divided any variables related to magnitude by the median daily flow in order to ensure that flow groups were based upon trends in relative flow magnitude and flow variability rather than being heavily influenced by river size. We divided all variables by their respective maximum value for all streams to standardize variables on a scale from 0 to 1. We did this to ensure that variables with a greater extent of variability did not override our analysis. All standardized variables were $\log(x + 1)$ transformed. The dataset is freely available and can be obtained by contacting the corresponding author.

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We used a K-means cluster analysis to classify streams into groups of similar hydrologic properties. K-means cluster approaches require the investigator to specify *a priori* the number of clusters, to which streams are then assigned. Because we were uncertain of the appropriate number of flow clusters, we re-ran the cluster analysis a series of iterations with a different number of clusters in order to determine the minimum number of clusters. The K-means method yields a cluster assignment for each stream but also a distance measurement of each stream to the centroid of its respective cluster (i.e. residual). We then calculated the sum-of-squares of the distances (SSD) for all streams and grouped that value against the number of clusters. The SSD will decline as the number of clusters increases. We determined the minimal number of clusters at the point where the rate of the decline in the SSD is small. High numbers of variables ($n = 66$) in relation to the sample size ($n = 292$) may increase the dimensionality of the data set, which could lead to a higher number of clusters and erroneous conclusions. Thus, to ensure that the number of clusters was stable, we produced two reduced datasets followed by iterative K-means clustering procedures. We produced the first reduced dataset by conducting a PCA on all 66 variables and isolating the first 15 principle components, which explained over 90% of the correlations. The second reduced dataset was formed by using forward stepwise variable selection in discriminant function analysis (DFA) to select 15 variables that explained the majority of variability in the clusters assigned with 66 variables.

Another potential problem of K-means procedures is that the cluster assignment can be sensitive to the order of samples (streams) in the dataset (SAS, 2008). To attempt to determine the probability of cluster assignment for each stream, we randomized the dataset and re-ran the K-means procedure for 10 more iterations. Unlike other cluster procedures, K-means clusters do not have any spatial structure (multivariate space); thus, clusters may be labeled differently and may overlap with other clusters making it difficult to compare the results following each iteration. One way to avoid confusing labeling problems is to compare average values of variables between clusters of different analyses. We compared cluster means of 10 variables, chosen using DFA, in the baseline dataset to cluster means formed by each randomized dataset. Clusters that had the smallest difference in mean values of variables were assigned to similar clusters. Based on the result of 10 iterations, streams could then be assigned a dominant cluster and a probability of cluster assignment could be calculated.

Temporal analysis and cluster assignment

To ensure that records from different time periods did not cause uncertainty in cluster assignment, we used six stream gages from different clusters with long-term records (> 68 years of record). For each stream gage, we broke up the records into 3–4 discrete 15-year time periods. We re-calculated all 66 hydrologic metrics using the HIT software for each 15-year time period. We calculated the absolute difference between 15-year metrics to metrics calculated using the entire time period (used for the classification). We then averaged all absolute differences between all 15-year time periods and the entire time period. We compared those differences to the inter-quartile range (IQR) and entire range of each stream's respective cluster. We assumed that if the difference between metrics calculated for different time periods exceeded the IQR, then cluster assignment may be influenced.

Assessment of hydrologic properties

We isolated nine hydrologic indices supported by literature that are known to influence various life stages and occurrences of macroinvertebrates, fish and riparian vegetation. We compared the average values and variation of the hydrologic indices among the different clusters in order to assign clusters ecologically meaningful class names, which would be important for management. We also plotted each stream by its respective cluster on a map of the southeastern US with physiographic provinces in ARCmap 9.2. Physiographic provinces, originally mapped by Fenneman and Johnson (1946) were downloaded from the USGS website and used for mapping because of simplicity (only 5 provinces in our study area) and less ambiguity in representation.

Hydrologic classification tree

Our goals in developing a hydrologic tree was to provide a subset of key variables responsible for the divergence of natural flow classes that can be used as an initial foundation for environmental flow managers and a useful tool for classifying streams in the future without having to use a large suite of hydrologic indices. We used the rpart package in the program R to develop classification trees that can be used to classify a stream into a flow class. All 66 hydrologic variables along with their respective flow classes were imported into R. The rpart package in R uses recursive partitioning, which includes some of the same ideas developed in the CART software (Therneau *et al.*, 2010). Trees are built in a two-step procedure. The first step involves splitting the data on the initial node using the 'best' variable that minimizes the risk of misclassification. This procedure continues throughout subsequent nodes until the subgroups reach a specified minimal size or no further splits can be made (Therneau *et al.*, 2010). Because trees can become very complex, the second step involves a pruning procedure that minimizes the number of nodes, the cost

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complexity factor and the cross validation error. The cost complexity factor takes into account minimizing misclassification while also increasing the complexity of the tree. We then evaluated the cross validation versus tree size plot to determine how to prune the tree. The tree is pruned at the number of nodes that minimize the cross validation error to avoid over-fitting the data. After the trees were completed, we were able to calculate a misclassification error to assess the accuracy to which the subset of variables could classify flow groups.

Hierarchical structure

One way to determine if there was a hierarchy among flow classifications created at different scales was to compare our clusters to those created for the entire US by Poff (1996). We obtained the US classification dataset through direct communication with Leroy Poff. The dataset contains 816 stream gauges, their respective flow classes, GPS locations and the variables used to create the clusters. We isolated common gauges between the two datasets using the USGS gauge number. Because of differences in the number of total clusters represented and cluster sample sizes, using a statistical procedure to directly compare datasets 'as is' would be uninformative. We decided to compare the datasets in two ways. First, we assumed that different classes that share similar hydrologic properties at the scale of our study may cluster together when the overall variability of the dataset increases (e.g. larger scales). Thus, we clumped similar flow classes in our study together and compared to the US classes by evaluating the percentage of streams misclassified. We also plotted our clumped classes on a map along as well as the US classes to visually evaluate similar geographical affiliation. The second way we wanted to compare datasets was to determine how well variables used in the US classification could predict the US flow classes relative to our classes using discriminant function analysis (linear, common covariance method). We assume that the datasets may share similar structure if variables used in US classification accurately predict our flow classes. We then used a plotted the first two canonical scores of streams to understand how our clusters may be embedded in the clusters created for the entire US in multivariate space. We also show the biplot rays of the direction of variables in canonical space to show how the hierarchical relationship was governed by the hydrologic variables.

RESULTS

All together, 292 gages were used in our flow classification. Over 80% of our gages had records that spanned from 1969–2009 (40 years). After accounting for any missing data, 86% of the streams had 30 or more years of data and 60% had 50 or more years of record for the entire dataset. Less than 8% of the gauges had chunks of missing data that comprised more than 30% of the entire record. Thirty-four of the 292 gages had pre-impoundment data that we used in the analysis. Of these, 24 gages had over 30 years of data.

Cluster analysis

We found that for the original 66-variable datasets, the SSD minimized at 8 clusters (Figure 1). We reduced the variables in the dataset using PCA and forward stepwise DFA. The first 15 PCs isolated explained over 90% of the total variation in the dataset. The 15 variables isolating using stepwise DFA had a misclassification error of 7.6% (22/292 misclassified), which suggests that the variables were fairly accurate in explaining the majority of variability in clusters

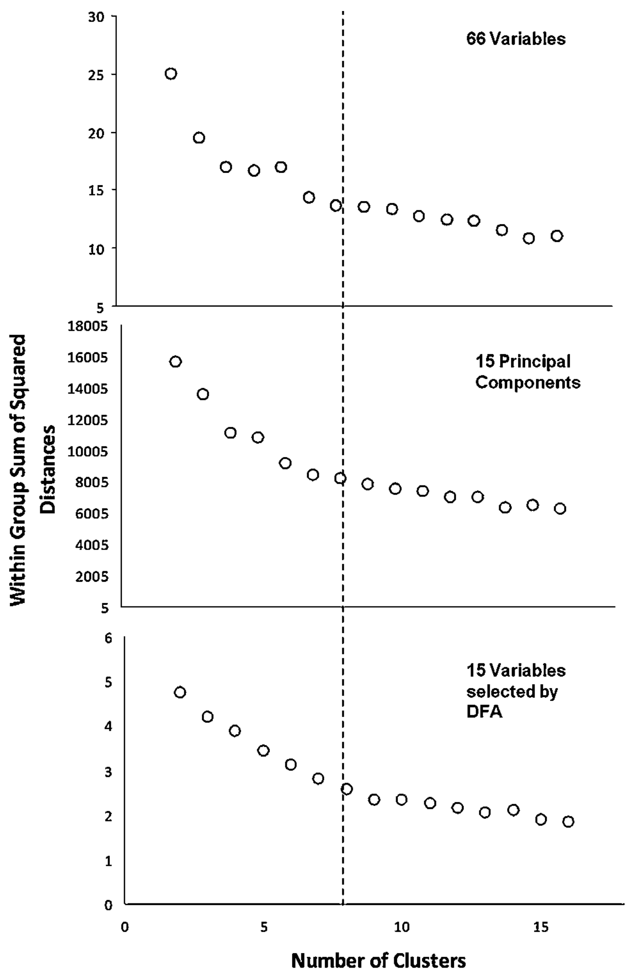

Figure 1. Comparisons of the sum-of-squared distances within groups relative to the number of clusters following iterative K-means clustering procedures to determine the appropriate number of clusters and whether variable number increased the dimensionality of the data set. Cluster analysis was conducted for all 66 variables, 15 principle components and 15 variables selected using forward stepwise procedure in discriminant function analysis

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formed using all 66 variables. Interestingly, for both reduced datasets, the SSD minimized around 8 clusters, which was very similar to the analysis conducted with 66 variables (Figure 1). Thus, we assumed that the 66 variables did not erroneously create 'new' clusters but actually did a better job of describing and assigning streams to their appropriate flow group.

After randomizing the dataset and re-running the K-means procedure, we found that only 11 out of the 292 gauges (3.8% error rate) were assigned to a different class than the baseline K-means procedure. Six of the eight classes had greater than 22 streams (Figure 2). Class B had only 2 streams and class D only had 1 stream. Thus, for all practical purposes, these 3 streams could be lumped into similar classes. Seven of the eight classes had mean probability of class membership greater than 85%; however, flow class A had a mean class membership of 71%. Over 80% of all gauges had greater than a 0.8 mean probability of class membership, suggesting that most gauges had a fairly strong affinity for their assigned flow class (Figure 2).

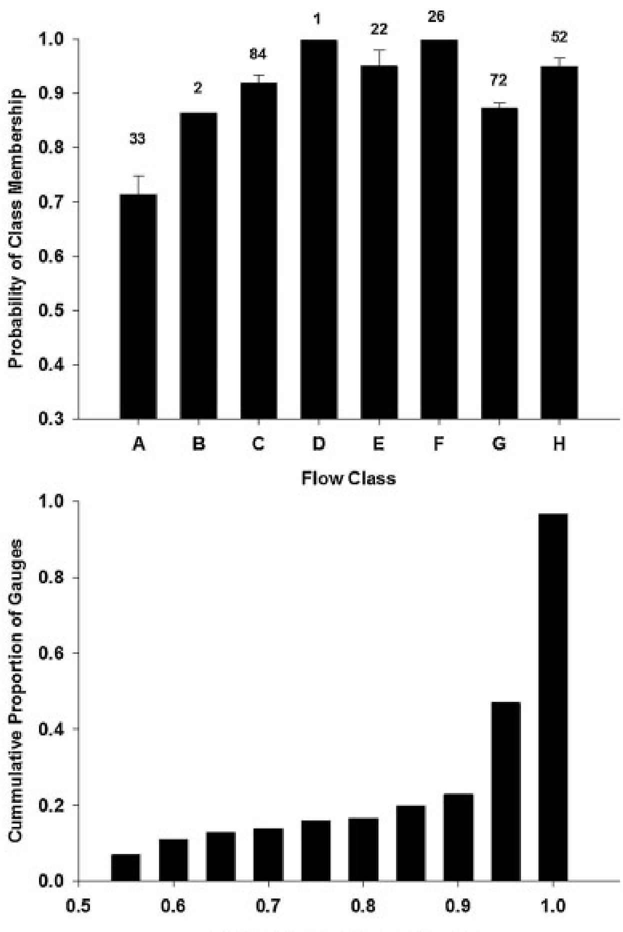

Figure 2. The mean probability of class membership for each flow class (cluster) and the cumulative proportion of gauges under various class membership probabilities. Numbers indicate the sample size in each flow class. Letters for each flow class are assigned ecologically relevant names, as indicated in Figure 3

Temporal analysis and cluster assignment

We compared the inter-quartile range (IQR) and entire ranges of 15-year time periods of 6 streams to that of each stream's respective cluster. We found that, on average, the IQR for each cluster was 18 times the absolute difference between 15-year metrics and metrics calculated for the entire time period. On average, less than 5 metrics per stream had differences in values that exceeded the IQR of the respective cluster. On average, the entire range for each cluster was 140 times that of the absolute difference between 15-year metrics and metrics for the entire time period. Only one hydrologic index (RA6) in one stream had an average absolute difference that was greater than the range of its respective cluster, which was primarily due to its extremely low average value for the cluster (mean RA6 = 0.114).

Assessment of hydrologic properties

We assigned classes ecologically relevant names by qualitatively evaluating differences in nine key hydrologic variables (Table I, Figure 3). Two of the eight flow classes only had 1–2 streams. Thus, for management purposes, we would recommend incorporating those classes into a similar larger cluster. However, for statistical purposes, we show all eight classes. The eight flow classes differed in terms of the magnitude and variability in low flows, the frequency of high flow events, the duration of flow events, the predictability and constancy of flows, and the rate of change in flow (Figure 3). Intermittent flashy (IF) streams had a high number of zero flow days per year, high variability, high frequency of high flow events, low predictability and fast rise rates. The coastal/swamp intermittent (CSI) flow class is characterized by some intermittency with 6 of the streams having a high number of zero flow days (mostly swamps). The majority of the class, however, has no zero flow days, has low variability, low frequency of high flow events, high duration of high flow events and very low rise rates. The Black River (BKR) near Tomahawk, NC (USGS guage 02106500) has a very high seasonal predictability of non-flooding (not shown) or a very high proportion of each year consists of flows greater in magnitude than the 5-year low flow magnitude. Otherwise, the BKR is similar to CSI streams in all other respects. Perennial runoff streams (PR 1 and 2) had moderate variability in daily flows, low to moderate baseflow levels, low duration of high flows, moderate predictability and moderate rise rates. Unpredictable perennial runoff streams (UPR) were similar to PR streams except that they had a large range in monthly flows and had low predictability.

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Table I. Class ID's, class names, drainage areas and standard deviation for flow classes found in this study and those of Poff (1996) found in our study region

Class ID	*n*	Class name	Drainage area (km^2)	SD
BKR	1	Black River near Tomahawk, NC	1751	–
CSI	22	Coastal, Swamp and Intermittent	2307	2334
IF	26	Intermittent Flashy	228	285
PR1	84	Perennial Runoff 1	2547	5081
PR2	72	Perennial Runoff 2	673	906
SBF1	33	Stable High Baseflow 1	1500	3010
SBF2	52	Stable High Baseflow 2	1701	3755
UPR	2	Unpredictable Perennial Runoff	70	14
US flow classes (Poff, 1996) found in current study region				
GW	22	Groundwater	775	968
IR	1	Intermittent Runoff	751	–
PR	62	Perennial Runoff	885	1040

Stable high baseflow streams (SBF 1 and 2) had low variability in daily flows, higher baseflows and minimum flows, moderate frequency of high flow events, high predictability and moderate rise rates. SFB2 differs from SFB1 in that it has a lower duration of high flow events (Figures 4 and 5).

Hydrologic classification tree

We evaluated the cross validation plots to determine the appropriate size of the hydrologic and watershed classification tree. For the hydrologic tree, the cross validation minimized around 6 nodes (branches), or around a cp (cost

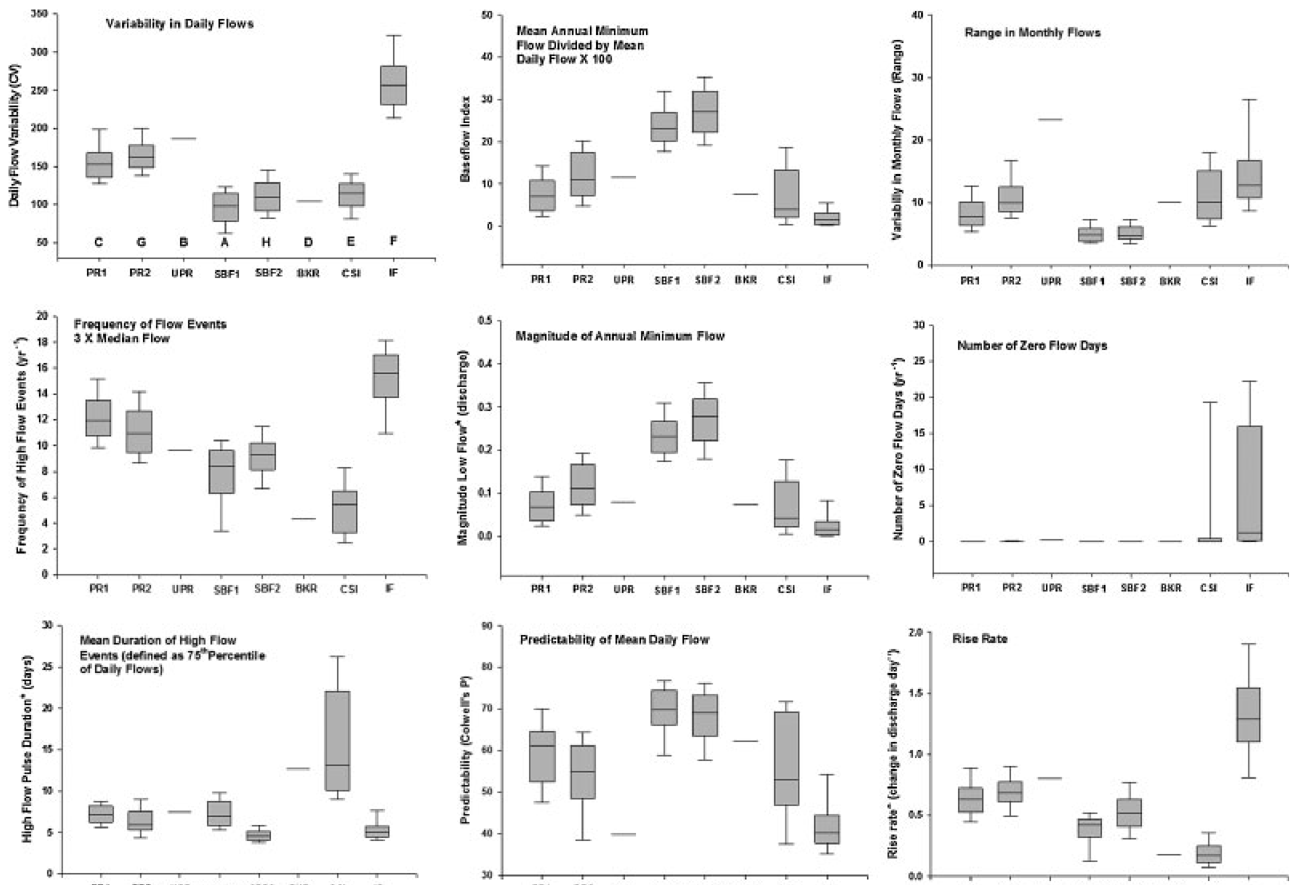

Figure 3. Comparisons of 9 ecologically relevant variables among different flow classes. Letters in the first box and whisker plot are given in order to compare letters in Figure 2 with the flow-class names. * indicates that variable was standardized by dividing by median daily flow. For class codes, see Table I

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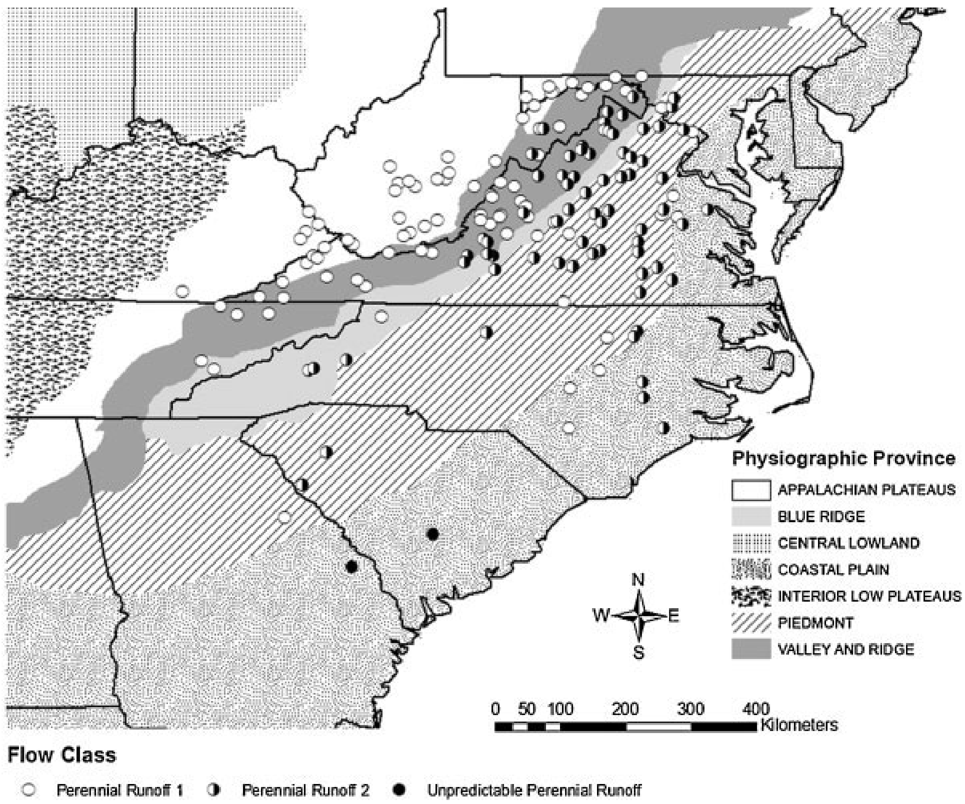

Figure 4. Geographic distribution of three of the eight flow classes across physiographic provinces in the eight-state region. Physiographic provinces created by Fenneman and Johnson (1946)

complexity factor) of 0.05 (Figure 6). The tree was pruned to that value and represented six of the eight flow classes (Figure 7). The BKR and UPR classes were not represented because the cost of representing 1 and 2 streams, respectively, was too high compared to the gain in variation explained. The hydrologic classification tree isolated five primary variables that accurately classified 85% of the gauges to their assigned flow class. The first four competing variables are also listed in order of accuracy under each primary splitting variable. Most classes were accurately assigned to their respective flow class ($\sim$ 80% or higher) except the SFB1 class, which only had 66% of gauges accurately assigned.

The vertical distance of the tree branches are an indication of the amount of variability explained by each variables. Thus, the first two primary variables, mean September flows and minimum July flows explained a great deal of variation in the entire dataset. Lower September flows separated PR1 from the rest of the dataset and re-emerged as a primary splitting variable separating SBF 1 and 2 stream classes. Higher minimum July flows separated SBF 1 and 2 classes from the remainder of the dataset. Maximum November flows separated CSI streams from IF and PR 2 streams, which were separated by daily flow variability.

Hierarchical structure

Eighty-five streams were found in both our dataset and that of the US classification. Six of our eight flow classes were represented in the dataset, excluding UPR and BKR flow classes. Three flow classes were represented in the US classification dataset: groundwater streams (GW), perennial runoff streams (PR), and one intermittent-runoff stream (IR). By comparing the grouping between our dataset with the US classification, we found that SBF1 and SBF2 streams tended to primarily be classified as GW streams while PR1, PR 2, IF and CSI streams tended to classify with the PR streams (Table II). The one IR class grouped with the CSI streams. Initially, we combined the SBF1 and SBF2 classes into a ‘GW’ class and combined the PR1 and PR2 classes together into a ‘PR’ class while leaving the IF and CSI classes separate. After comparing the combined classes to the US classification, we found that 75% of the streams were grouped similarly, with 11% of the error coming from the CSI and IF classes. We then combined the CSI and IF classes with the PR class and compared the new classes to the US classification and found that 86% of the streams were grouped similarly. The map of our new flow classes and the US flow classes showed similar geographical affiliation of classes with similar hydrology (Figure 8).

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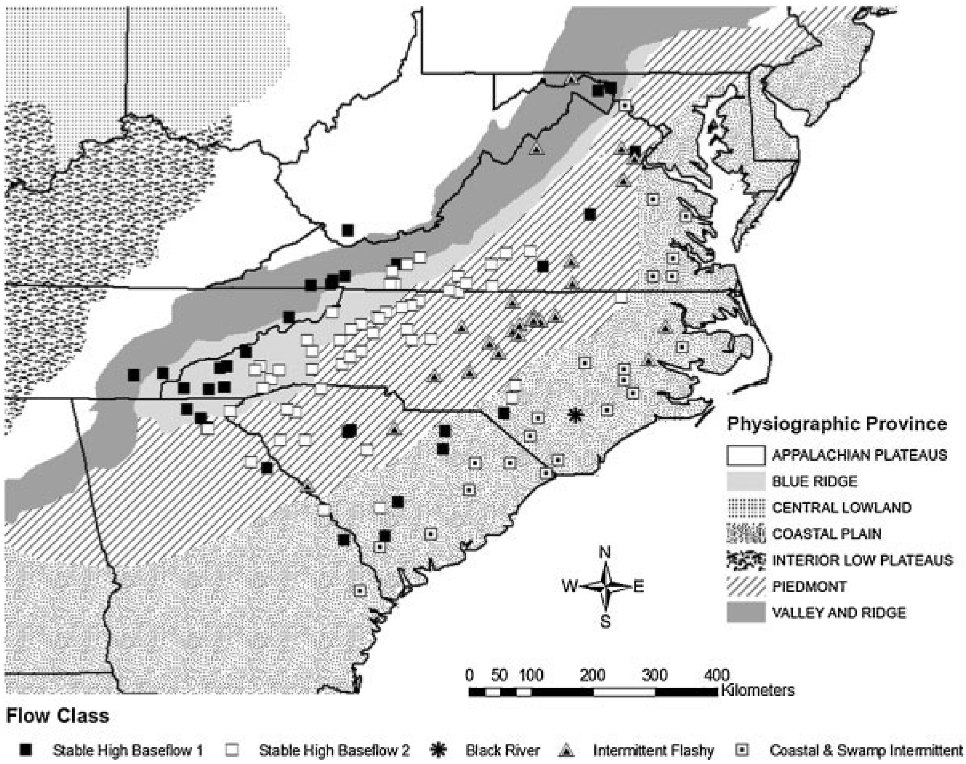

Figure 5. Geographic distribution of five of the eight flow classes across different physiographic provinces in the eight state region. Physiographic provinces created by Fenneman and Johnson (1946)

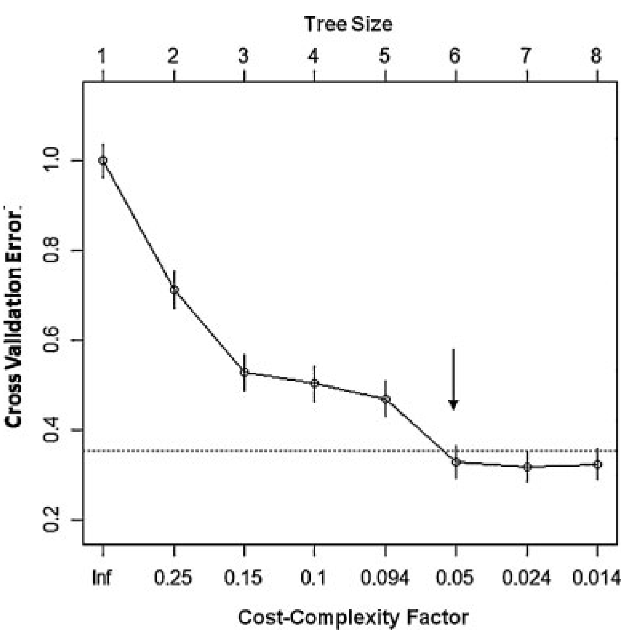

Figure 6. Cost-complexity plot for the hydrologic classification tree comparing the cross validation error to the tree size (number of nodes) in order to determine where the tree should be pruned. Trees are generally pruned at the cost-complexity factor where at the minimum number of nodes that also minimize the cross validation error (indicated by arrow)

Discriminant function analysis showed that the 13 variables used in the US classification misclassified 4.76% of streams to their actual US flow classes. The 13 variables misclassified 3.57% of their streams to our six flow classes. The biplot of canonical scores showed that our six flow classes were embedded in multivariate space of their compatible US flow classes, suggesting hierarchical structure (Figure 9). For example, SBF1 and SBF2 classes were centralized around the GW class where PR1, PR2, IF and CSI classes were centralized around the PR class. Our six flow classes also tended to capture a greater extent of the dimensionality of the dataset than the US classes at the scale of this analysis (85 streams). We show 7 of the 13 variables with the strongest loadings. The biplot rays showed that the SBF streams had a higher baseflow index but SBF2 streams had a lower low flow predictability (Figure 9). IF streams diverged from PR streams based on daily variability whereas PR streams diverged from one another based on low flow and daily predictability. CSI streams diverged from PR streams based on flood duration and the number of zero days.

DISCUSSION

We isolated six flow classes (eight statistically) in the eight-state region that differ in the magnitude, frequency, duration,

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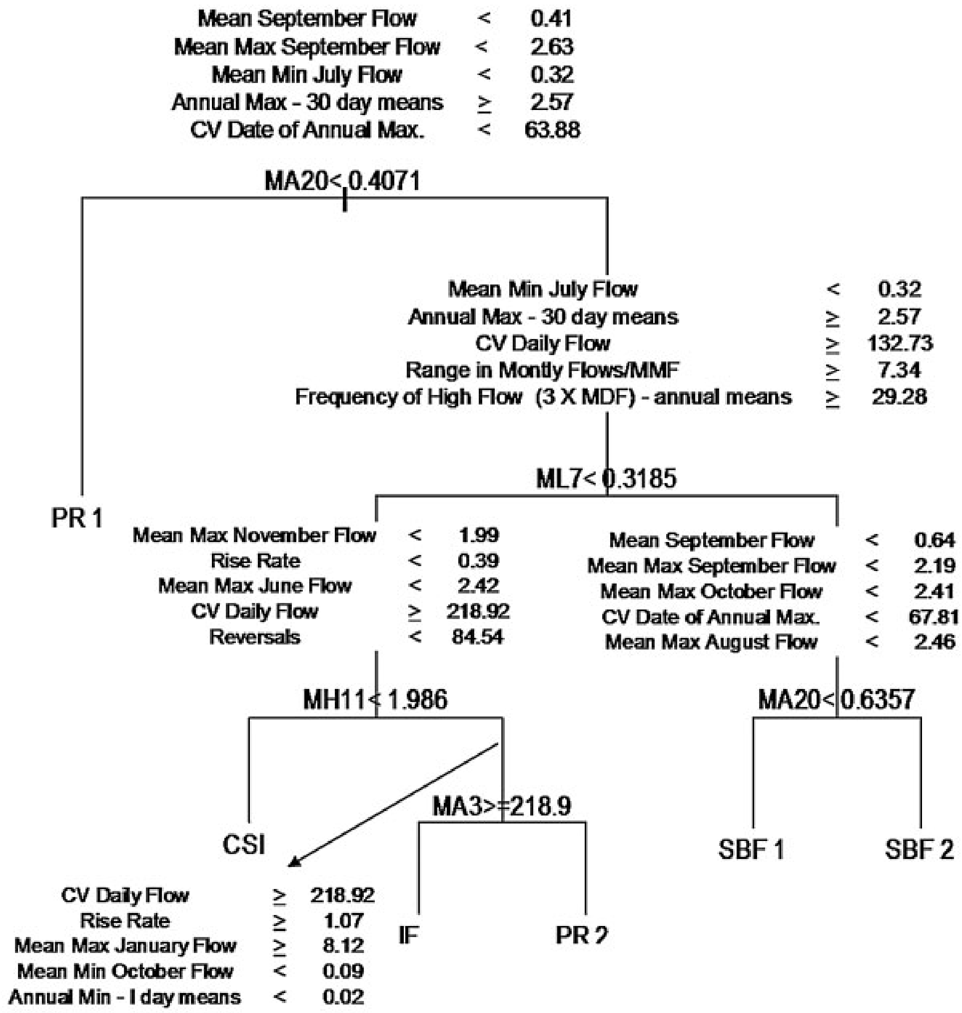

Actual Classification

Tree Assignment	BKR	CSI	IF	PR 1	PR 2	SBF I	SBF 2	UPR
n	1	22	24	84	72	33	52	2
CSI	1.00	0.95	–	0.02	–	0.06	–	0.50
IF	–	–	0.79	–	0.01	–	0.02	–
PR 1	–	–	0.13	0.86	0.01	0.09	–	0.50
PR 2	–	–	0.08	0.12	0.92	0.03	0.06	–
SBF I	–	–	–	–	0.03	0.66	–	–
SBF 2	–	0.05	–	–	0.03	0.15	0.92	–

Figure 7. Classification tree using 5 hydrologic metrics as primary splitting variables along with the 4 corresponding competing variables to classify six of the eight flow classes. The left branch meets the conditions of the equation on each node. The matrix below the tree shows the proportion of gauges in the actual flow class (columns) classified to each flow class using the tree (rows). The proportion of each actual flow class accurately assigned by the tree is shown in gray boxes. For class codes, see Table I

timing and rate of change in flow and provide a reduced set of hydrologic indices to use in future classifications. Secondly, we show that datasets created at different scales can be related and may exhibit hierarchical structure. Thus, the divergence of flow classes may be relevant to the scale of management.

One of the challenges in managing for flow diversity is the inherent complexity and the variability of river systems (Poff *et al.*, 2003; Arthington *et al.*, 2006). Our purpose is to not undermine the importance in the individuality of river systems. On the contrary, flow classifications should reduce the complexity of 'managing' by providing a starting

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Table II. Comparison of the proportion of streams within each of the flow classes created in this study compared to classes created for the entire US. Classes for US found in Poff (1996). *n* refers to number of streams within each flow class in this study. For class codes, see Table I

US classes	Flow classes (this study)					
	CSI	IF	PR1	PR2	SBF1	SBF2
n	9	3	21	25	12	15
GW	0.22	—	—	0.04	0.66	0.73
IR	0.11	—	—	—	—	—
PR	0.66	1.00	1.00	0.96	0.33	0.26

baseline from which regional flow standards and criteria can be developed. Flow classes provide ecologically-relevant management units that reduce the complexity of managing for the natural flow regime of every individual river while also protecting the key elements that make river flow distinct (Arthington *et al.*, 2006). We also believe that using this framework sets the stage for adaptive management. For example, after flow standards and criteria are developed and implemented based on 'natural' flow classes, they also should be able to be modified based on the individual needs of each river system. Therefore, treating river flows as ecosystem-scale experiments is a necessary aspect of river management (Poff *et al.*, 2003) and a less-explored area of ecology (Palmer and Bernhardt, 2006; Poff and Zimmerman, 2010).

We found that 8% of stream gauges had probabilities of class membership greater than 0.8, which suggests that most gauges had a relatively strong affiliation to their respective flow class. Also, results of the three different clustering procedures indicated that the number of flow classes (8) was fairly stable. Considering that 80% of our gauges spanned the last four decades (i.e. substantial overlap), we believe that assessing the uncertainty in using 15-year records is a worst-case scenario. Regardless, the time period assessment revealed that 15-year records of different time periods had substantially lower differences compared to the inter-quartile range and entire range of their respective clusters.

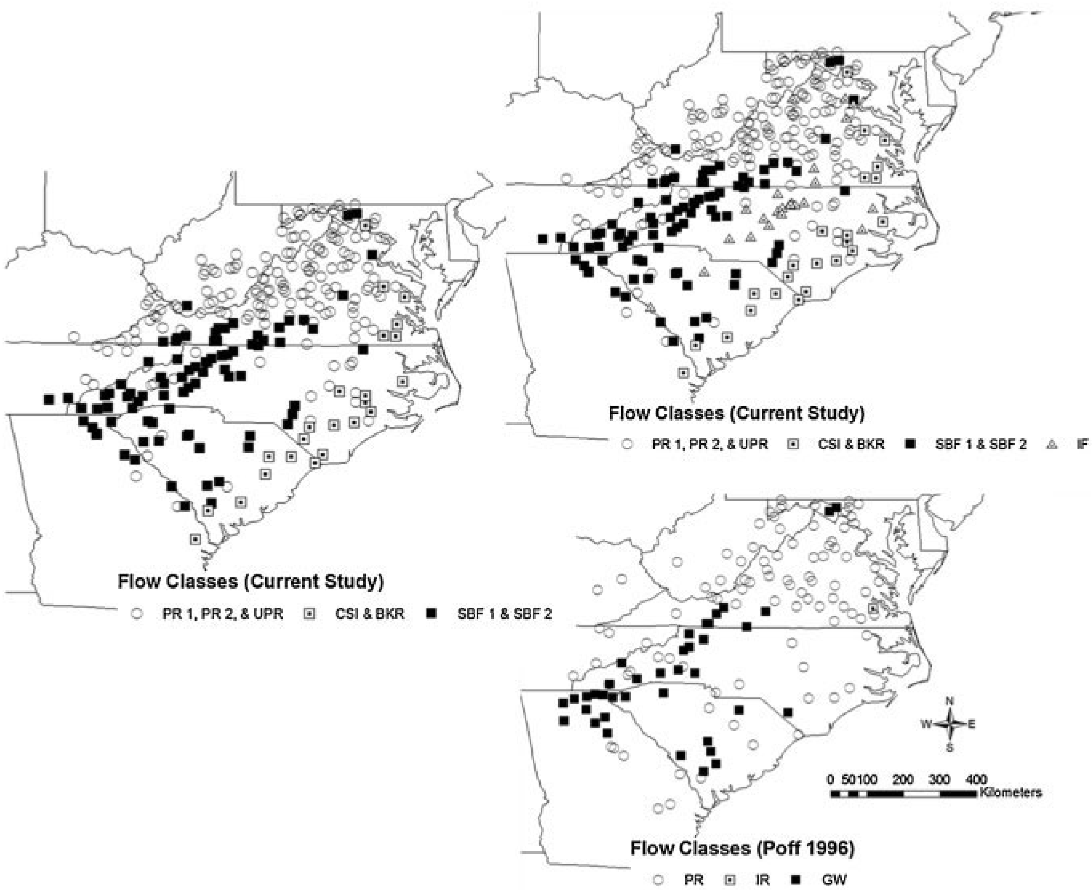

Figure 8. Geographic distribution of our combined flow classes and the US flow classes (Poff, 1996) found within the eight state region. For class codes see Table I

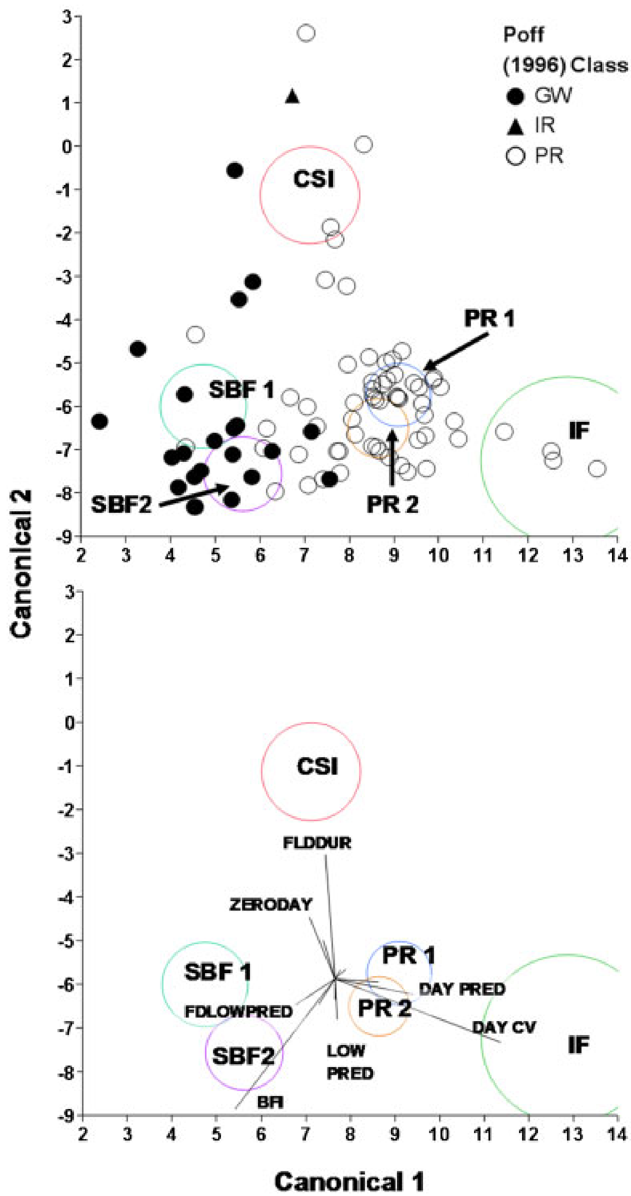

Figure 9. Canonical plot of the streams found in both our study and that of the US flow classification (Poff, 1996). Plot is based on the 13 variables used in Poff (1996) to discriminate amongst the flow classes created in this study. Ellipses represent flow classes from this study and were created using the linear, common covariance discriminant method and show the 95% confidence region. Point markers represent US flow classes. Biplot rays show seven variables that exlain the most variability in flow classes (see Poff (1996) for variable names). For class codes see Table I. This figure is available in colour online at wileyonlinelibrary.com/journal/rra

Comparisons of hydrologic variables showed a great deal of divergence among different flow classes. Thus, overgeneralized, static flow rules are inappropriate for managing for the variability in flow of these ecosystems (Arthington *et al.*, 2006). Because we observed strong divergence in flow classes, state agencies should re-consider existing approaches for recommending environmental flows in the permitting process. Management strategies for protecting environmental flows will require policy reform, which abandons static allocations to ranges of numbers that protect the inherent variability in river flows (Richter *et al.*, 1997). Ultimately, managers and stakeholders must move away from 'water-allocation' strategies and adopt 'sustainable-boundary' approaches, which are viewed similar to water quality protection in that they provide social goods and services and create a sustainable, long-lasting resource (Richter, 2010).

Classifying streams with similar hydrologic properties has progressively received more attention in peer-reviewed literature. Stream classification has been conducted across the entire US (Poff and Ward, 1989; Poff 1996), Australia (Kennard *et al.*, 2010b) and even at global scales (Poff *et al.*, 2006b). Classifications have not just been limited to theoretical frameworks but have been implemented in management and flow policies. For example, with the recent advent of state-wide water use management plans, flow classifications have been developed for New Jersey, Missouri and Oklahoma as standards for implementing flow rules (Kennen *et al.*, 2007; Kennen *et al.*, 2009; Turton *et al.*, 2008). One area of needed research is to determine if rivers within similar flow classes respond to regulation similarly (Arthington *et al.*, 2006).

Assessment of hydrologic properties

To provide names for flow classes, we chose a set of ecologically relevant hydrologic variables that would allow us to easily distinguish groups and that would make intuitive sense to managers. Flows classes showed a great deal of divergence among the hydrologic variables. Stable high baseflow streams (SBF 1 and SBF 2) had characteristics of stable flow (low variability, high predictability and higher baseflows). However, they differed from one another in terms of high flow duration. Intermittent –flashy streams (IF) were primarily classified based on the high number of zero-flow days (intermittency) and highly variable flows (flashy). Coastal/swamp intermittent (CSI) streams were stable and unresponsive (opposite of flashy), similar to SBF streams, but differed in that they had sustained lower flows. Of the CSI streams, swamps were the only water bodies showing intermittency. Swamps may be highly sensitive to drought conditions making them intermittent yet can be stable in all other aspects. Most intermittent flashy (IF) streams were located in the piedmont and had small drainage areas, which suggests that small watersheds in combination with piedmont type soils may result in flashy, highly variable flows. The values of hydrologic variables of perennial runoff streams (PR 1–2) generally were moderate in comparison to the stable and highly variable extremes. For example, PR streams had higher variability and lower baseflow than

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stable streams yet had lower variability and higher baseflows than PF and IF streams. PR streams also had moderate predictability, constancy and frequency of high flow events relative to the other classes. PR streams had broad geographical ranges across the five provinces. Interestingly, we found a higher density of PR streams in the northern section of the region. This suggests that climate, evapotranspiration and soil type may vary considerably with latitude within the same physiographic province and lead to differences in flow regimes.

Hydrologic classification tree

Providing flow rules from a large suite of hydrologic indices can be overwhelming. Thus, we wanted to provide a reduced set of hydrologic variables to provide managers with two useful tools: (1) a set of variables to classify future streams into one of the eight flow classes and (2) a foundation of key indices to develop environmental flow standards. The classification tree produced five variables that were able to correctly classify 85% of the gauges in this study.

Interestingly, monthly flows dominated the primary splitting variables in the hydrologic classification tree. However, in general, the tree supported the results of our qualitative assessment using hydrologic variables alone to describe flow classes. For example, stable high baseflow streams (SBF 1 and 2) were separated from the other classes based on higher summer flows (minimum July flows). Although IF streams and PR 2 streams were isolated from CSI streams primarily based on maximum November flows, rise rate (responsiveness) and variability were represented as competing variables that could separate the classes. Also, IF streams were separated from PR 2 streams on the basis of variability, which makes intuitive sense. The error assessment also suggested that there was some overlap among flow classes (Figure 7). For example, the SFB 1 class was misclassified primarily as SFB 2 streams but also misclassified to some degree in the other classes, except IF streams. In general, this suggests that flow classes, in some cases, may share some attributes of other classes, which would make clear partitioning in a tree prone to error. Thus, flow classes should not be viewed by their mean value but the range of variability that they represent.

Hierarchical structure

The spatial scale at which flow regimes are evaluated greatly influences the resolution to which ecologically relevant differences can be isolated and then used in management. Poff and Ward (1989) and Poff (1996) conducted a flow classification of the entire US; however, only three flow classes were isolated in the region of interest. Our flow classes formed 'sub-classes' within the US classes suggesting there was a hierarchical structure to flow variability. Furthermore, our flow classes encompassed more of the dimensionality of the dataset suggesting that as the spatial resolution under consideration increases, the divergence of more classes may be needed to adequately represent variability at that scale.

The number of flow classes (e.g. clusters) is largely a statistical artifact and a balance between sample size and the variability of the entire dataset. In a clustering procedure, a stream that is found in the margins of a cluster boundary will obviously be more likely to join a different cluster if more streams of a similar flow regime are included in the dataset. Oppositely, if the variability of the entire dataset is substantially increased (e.g. expanding the spatial scale across multiple regions), then classes at smaller scales may be lost. Thus, classifying flow regimes at various spatial scales can be useful in forming hierarchical classification systems (Poff *et al.*, 2006b). The hierarchical classes may be advantageous in that managers can then prioritize management strategies based on the strengths of class divergence and the specific application. For example, flow classes that are divergent over large spatial scales should never be managed similarly whereas flow classes that are divergent at finer scales may or may not be managed similarly depending on the whether management is conducted over inter or intra-regional scales.

CONCLUSION

We classified 292 streams of an eight-state region of the Southeast into six distinct flow classes that represent unique flow regimes and differ in terms of the magnitude, variability, frequency, duration and rate of change in flow events. We believe that these flow classes can be used as management units to develop environmental flow standards that can be used setting regional flow standards and criteria, providing guidelines for relicencing agreements and withdrawal permitting, while also setting the stage for adaptive management of flow restoration. We also provide a subset of hydrologic variables that can be used to classify streams in this region while also providing a reduced set of relevant indices that are building blocks in developing flow standards. We show that classifications conducted at different spatial resolutions display hierarchical structure and if underlying variables are available for analysis, hierarchical analyses can be informative and useful for management.

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