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REGIONAL FRAMEWORKS APPLIED TO HYDROLOGY: CAN LANDSCAPE-BASED FRAMEWORKS CAPTURE THE HYDROLOGIC VARIABILITY?

R. A. MCMANAMAY,[a]* D. J. ORTH,[a] C. A. DOLLOFF[b] and E. A. FRIMPONG[a]
[a] *Department of Fisheries and Wildlife Sciences, Virginia Tech, Blacksburg, Virginia, USA*
[b] *USDA Forest Service, Department of Fisheries and Wildlife Sciences, Virginia Tech, Blacksburg, Virginia, USA*

ABSTRACT

Regional frameworks have been used extensively in recent years to aid in broad-scale management. Widely used landscape-based regional frameworks, such as hydrologic landscape regions (HLRs) and physiographic provinces, may provide predictive tools of hydrologic variability. However, hydrologic-based regional frameworks, created using only streamflow data, are also available and have been created at various scales; thus, relating frameworks that share a common purpose can be informative. In addition, identifying how the relative importance of variables change in governing streamflow with respect to scale can also be informative. The purpose of this study was to determine whether landscape-based frameworks could explain variation in streamflow classifications and in the hydrologic variables used in their creation. We also evaluated how climate and watershed-based variables govern the divergence of different flow classifications at two different scales. HLRs and physiographic provinces poorly predicted flow class affiliation within our study and for the entire USA, although physiographic provinces explained more variability. We also found that HLRs explained very little variation in individual hydrologic parameters. Using variables summarized at the watershed scale, we found that climate will play a larger role in influencing hydrology across the entire US, whereas soils may govern variation in hydrology at smaller scales. Our results suggest that predictor variables, developed at the watershed scale, may be the most appropriate at explaining hydrology and that the variables used in creating regional landscape-based frameworks may be more useful than the frameworks themselves. In addition, managers should be careful when using landscape-based regional classifications for stream management because the scale of their construction may be too broad to capture differences in flow variability. Copyright © 2011 John Wiley & Sons, Ltd.

KEY WORDS: flow classification; environmental flow standards; hydrologic landscape regions

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INTRODUCTION

The development of regional frameworks for conservation, prioritization, or broad-scale management has increased substantially in recent years (McMahon *et al.*, 2001; Snelder *et al.*, 2004; Wollock *et al.*, 2004; Sowa *et al.*, 2007). Regional frameworks inform management by relating spatial patterns to ecological and physical variables at the landscape scale. However, their utility rests upon the ability to provide spatially explicit data, predictive tools, templates for categorization and a way of relating existing datasets to geographical information. Thus, as new regional frameworks are created, it may be important to understand how these datasets are related to other frameworks to inform management. This is especially true for hydrological frameworks because water is becoming a scarce resource (Sun *et al.*, 2008; Vörösmarty *et al.*, 2010).

Hydrology varies extensively across large scales and can change substantially depending on how humans alter the landscape (Poff *et al.*, 1997; Poff *et al.*, 2006a). Because of this obvious relationship, it makes intuitive sense that regional frameworks might be developed to relate hydrology with the landscape. Hydrologic landscape regions (HLRs) were developed by the United States Geological Survey (USGS) as part of the National Water-Quality Assessment Program in order to provide a regional framework for stratifying water-quality study sites based on different hydrologic contexts (Wollock *et al.*, 2004). HLRs were developed using variables that control hydrology (Wollock *et al.*, 2004); thus, they have a potential to predict flow variability in streams. HLRs, or the specific variables that comprise them, have been used to predict or model chemical concentrations in streams (Poor *et al.*, 2008; Hoos and McMahon, 2009), baseflow levels (Santhi *et al.*, 2008) and fish assemblages (Frimpong and Angermeier, 2010). Another regional framework, physiographic provinces, was originally created by Fenneman and Johnson (1946) as regions that share common topography and geomorphological structure and history. Physiographic

*Correspondence to: R. A. McManamay, Virginia Tech, Fisheries and Wildlife Sciences, 113 Cheatham Hall, Blacksburg, Virginia 24061, USA. E-mail: rmcmanam@vt.edu

provinces have been used as a regional framework for regional channel morphology relationships (Johnson and Fecko, 2008), the importance of different variables on hydrology (Mohamoud, 2008; Morris *et al.*, 2009) and watershed classifications (Wardrop *et al.*, 2005).

Landscape-based approaches used to predict hydrology have primarily been centralized around flow-routing tools or complex hill storage models. Flow-routing tools and hydrology models can accurately predict streamflow discharge across time (Easton *et al.*, 2007; Gong *et al.*, 2009; Matonse and Kroll, 2009) with increasing accuracy as model complexity increases (Butts *et al.*, 2004). However, flow-routing tools are generally limited to small scales and individual basins (Arora *et al.*, 2001; Shaw *et al.*, 2005; Gong *et al.*, 2009). Although landscape-based approaches are widely used as predictive tools of hydrology, datasets created to evaluate spatial variation in hydrology based on stream discharge alone (e.g. flow classifications) have been conducted for individual states (Kennen *et al.*, 2007; Turton *et al.*, 2008; Kennen *et al.*, 2009), specific regions (McManamay *et al.*, 2011), the entire USA (Poff and Ward, 1989; Poff, 1996), Australia (Kennard *et al.*, 2010) and globally (Poff *et al.*, 2006b). An important clarification is that spatial flow classifications, in comparison to flow-routing tools, generally do not encompass temporal variability in streamflows. Nonetheless, within a spatial context, streamflow classifications may be useful in relating hydrologic variability to landscape-based regional frameworks over large scales. It also may be informative to understand how regional frameworks and landscape characteristics (including climate) influence the spatial variation in hydrology with respect to scale.

The overall purpose of this study was to determine if landscape-based hydrologic frameworks could explain variation in streamflow hydrology across different scales. Specifically, we wanted to understand how flow classifications, conducted at different scales, may relate to existing and widely used regional frameworks (HLRs and physiographic provinces). Poff (1996) created 10 flow classes for 806 streams across the entire USA based on hydrologic variables. In a similar study, McManamay *et al.* (2011) classified 292 streams into eight flow classes in a sub-region of the Southeast, which formed the basis for a hierarchical classification system. Therefore, we wanted to determine how well HLRs and physiographic provinces predict the affiliation of these two spatially explicit flow classifications. It is important to clarify that we do not assess the relative importance of spatial autocorrelation in the predictive capability of HLRs or physiographic provinces. Rather, our sole purpose is to compare how well these two frameworks, which should be sensitive to hydrology, predict natural flow classes. However, because there is some bias in using one classification system to 'predict' another classification system, we wanted to show how well HLRs can predict specific hydrologic variables that were used to create the US flow classes. Lastly, we wanted to determine what specific climate or watershed variables (topography, soils, etc.) govern flow variability at the sub-regional and US spatial scales.

METHODS

Regional frameworks

One of our goals was to compare the performance of existing regional frameworks in explaining the variation in the regional affiliation of flow classes at two scales. HLRs are small watersheds (approx. 200 km^2 each) that were categorized into one of 20 different classes of regions that differ in hydrologic conditions across the entire conterminous USA. The development of HLRs was based on factors that govern the hydrologic cycle (precipitation, evapotranspiration, infiltration, groundwater flow and overland flow) (Wollock *et al.*, 2004). Physiographic provinces, on the other hand, were originally created to map regions of common geographical structure and topography (Fenneman and Johnson, 1946), which may also explain differences in hydrology. We mapped the US flow classes and the sub-regional flow classes on HLRs and physiographic provinces in order to visually evaluate whether flow classes were geographically affiliated with different regional frameworks.

We also wanted to quantitatively determine the ability of regional frameworks to predict flow class affiliation. Fortunately, the dominant HLR within the basin of each gauge was available in the Geospatial Attributes of Gages for Evaluating Streamflow (GAGES) dataset created by Falcone *et al.* (2010). The dataset consists of 375 variables for 6785 USGS stream gauges across the USA including basin morphology, climate, topography, soils and anthropogenic disturbance factors (disturbance index, population density and land use). Each basin's dominant physiographic region, however, was not included in the dataset. Using the 'select by location' tool in ARCMAP 9.2 (ESRI, Redlands, CA, USA), we recorded the physiographic region where each gauge was located for all streams. Using the province represented by each site location rather than the basin-wide average may induce some bias in the analysis, especially in gauges that are very close to physiographic boundaries. However, our purpose is simply to evaluate, on a coarse level, the overall ability of these regional frameworks to predict flow class membership. We used r^2 values calculated from −log-likelihood tests to compare the ability of HLRs and physiographic provinces to explained variation in the grouping of flow classes. The r^2 in −log-likelihood tests

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is calculated as the proportion of variation explained by the model relative to total uncertainty where

$$-\log\text{-likehood Model} = \sum_{ij} n_{ij} \ln\left(\frac{p_{ij}}{p_j}\right)$$

$$\text{and}-\log\text{-likehood Total} = \sum_{ij} n_{ij} \ln(p_j)$$

$$\text{where} \quad p_{ij} = \frac{n_{ij}}{N} \quad \text{and} \quad p_j = \frac{N_j}{N}$$

and n_{ij} is the count for *i*th factor and *j*th response level, N_j is the total of the *j*th response level and *N* is the total sample size (SAS, 2008). Assessing the ability of regional frameworks to predict flow class grouping is biased because of a different number of flow classes and regional units. Therefore, to assess whether the number of flow classes made a difference, we used the US classification variables (13) to re-run a cluster procedure in order to create the same number of classes as regional units for each framework: HLRs ($n = 19$) and physiographic provinces ($n = 22$). We then re-ran the statistical tests to determine if there were increases in the predictive ability of the frameworks. We also compare the average proportion of gauges in all classes that were found within their dominant region.

Ability of hydrologic landscape regions to predict hydrologic variables

We hypothesized that regional frameworks, such as HLRs, may be useful in explaining the variability of hydrologic variables that make up flow classes rather than the flow classes themselves. In addition, there could be great deal of bias when using one classification system to predict another, especially considering that frameworks may be created with totally different underlying variation. Thus, we wanted to determine how much variation HLRs explained in the individual hydrologic variables that were used to form the US flow classes. We conducted one-way analysis of variance tests (ANOVA) for the hydrologic variables among different HLRs. We also conducted ANOVA tests for the 15 variables among US flow classes to compare the amount of variability explained in hydrologic variables for each regional framework. We did not conduct this analysis for physiographic provinces because the dominant province was not summarized for each gauge and the data was not readily available.

Variables that govern flow at different scales

Flow classifications conducted at different spatial scales may be governed by very different factors. It may be very informative to understand the relative importance of specific variables in predicting hydrology, which is not possible when using regional classes as predictors. Therefore, we wanted to determine what physical and climate variables at the watershed scale explained flow variability within and across regions. Watershed and climate variables for USGS gauges were also downloaded from the GAGES dataset (Falcone *et al.*, 2010). We were primarily interested in how natural climate and watershed variables (climate, basin morphology, topography and soils) could be used to classify relatively undisturbed flow classes; thus, anthropogenic disturbance variables were removed from the analysis. We also removed any categorical variables from the dataset because classification tree decisions are based upon only two outcomes. Many variables, primarily climate, were represented by a value for the entire basin or for the site where each gauge was located. We removed variables that were site-specific (at the gauge location) assuming that flow dynamics are governed by variables that account for the entire basin. The finalized dataset was reduced to 83 variables and each gauge was joined to its respective flow class. We joined our flow classes and the US classes to 83 watershed/climate variables forming two separate datasets. The joined dataset with our flow classes only had only 273 streams (rather than 292 in the original) and the joined dataset with the US flow classes had 787 streams (rather than the 816 total). Missing streams were not included in the dataset primarily because they did not have 20 years of complete-year flow records from 1950 to 2007 or did not have watersheds that could be accurately delineated (Falcone *et al.*, 2010).

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 using climate or watershed variables. The rpart package in R uses recursive partitioning, which includes some of the same ideas developed in the CART software (Salford Systems, San Diego, CA, USA) (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-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 overfitting the data. After the trees were completed, we were able to calculate a

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misclassification error to assess the accuracy to which the subset of variables could classify flow groups.

RESULTS

Regional frameworks

Patterns emerged in the spatial grouping of flow classes, which suggested that flow classes were regionally affiliated; however, individual classes were found in multiple HLRs and physiographic provinces (Figures 1 and 2). Twelve HLRs were represented in the Southeastern sub-region compared to only five physiographic provinces (Tables I and II). Perennial run-off 1 and 2 classes (PR1 and 2) were represented in over nine of the HLRs. PR 1 and stable high baseflow 1 classes (SBF 1) were represented in all five physiographic provinces. Excluding the

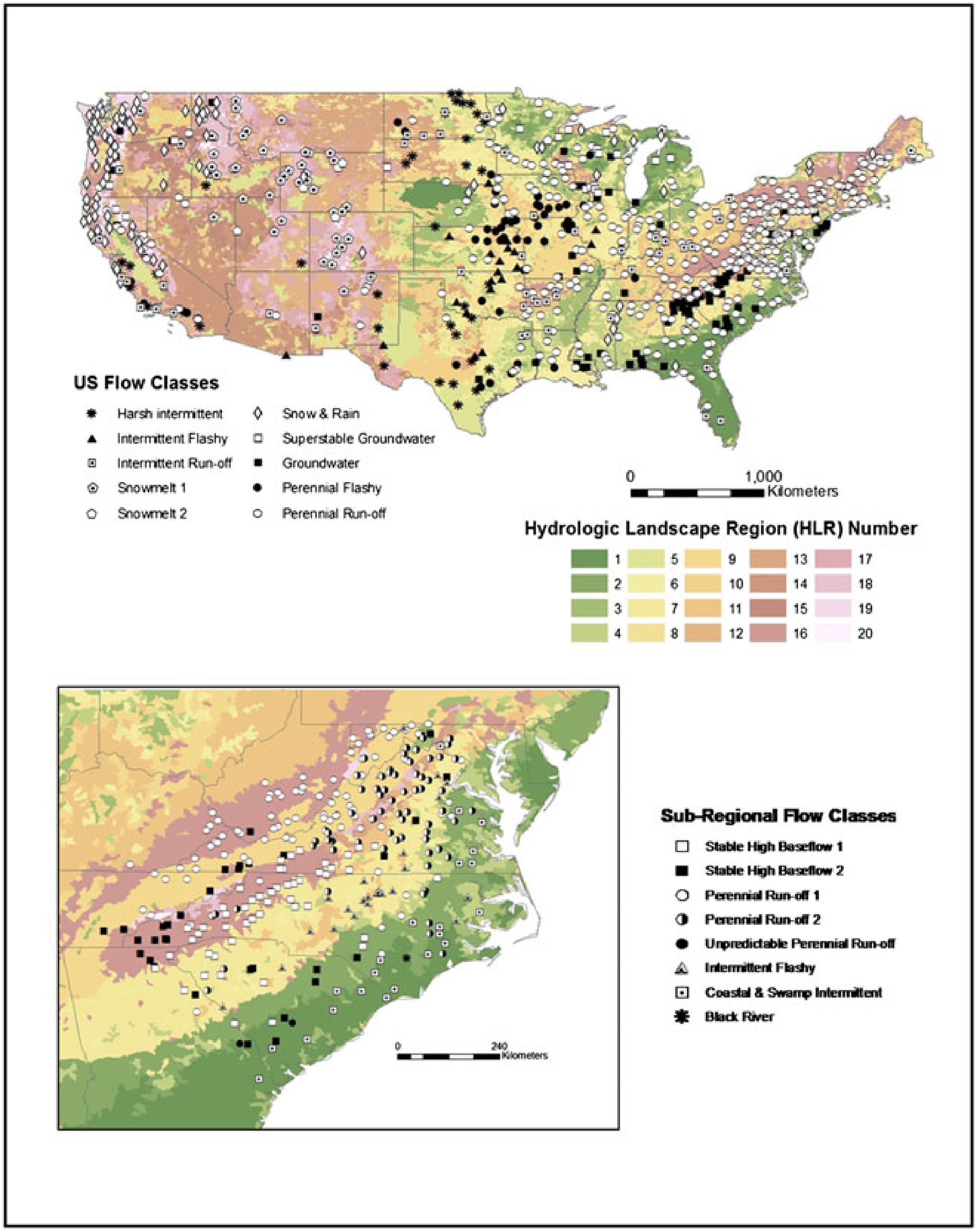

Figure 1. Geographical affiliation of flow classes for the USA and the Southeastern sub-region across hydrologic landscape regions. This figure is available in colour online at wileyonlinelibrary.com/journal/rra.

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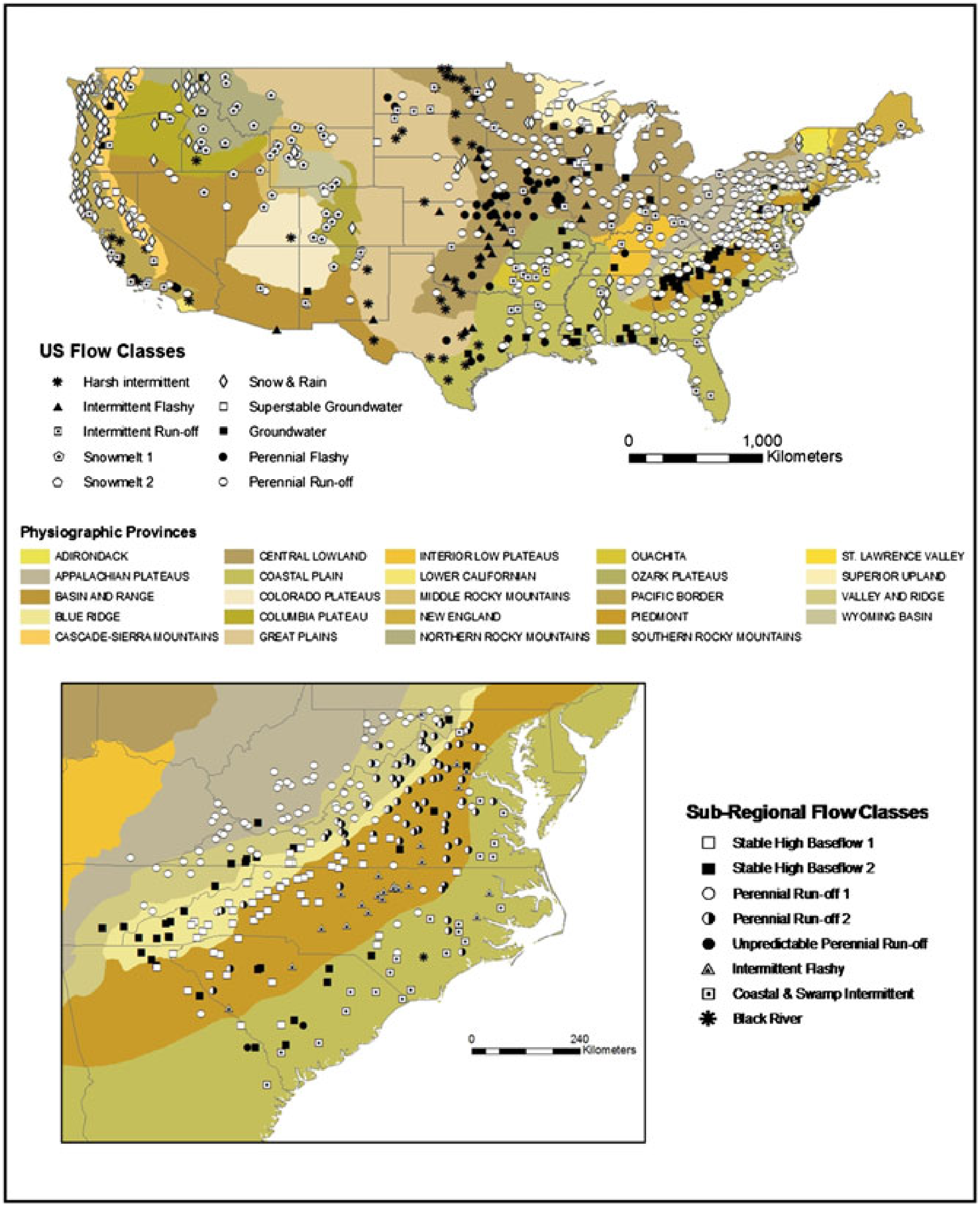

Figure 2. Geographical affiliation of flow classes for the USA and the Southeastern sub-region across physiographic provinces. This figure is available in colour online at wileyonlinelibrary.com/journal/rra.

unpredictable perennial run-off and Black River flow classes, the average percentage of gauges of each class found in their dominant region was 35% for HLRs and 62% for physiographic regions in the sub-regional area (Tables I and II).

Nineteen HLRs and 22 physiographic provinces were represented across the USA where flow classes were present (Tables III and IV). For the US classification, perennial run-off streams (PR) were found in 18 HLRs, and snow and rain and intermittent run-off streams were found in 14 HLRs. PR streams were found in 15 of the 22 provinces, whereas groundwater and snow and rain streams were found across 13 provinces. On average, for the US flow classes, the per cent of gauges in each class found in a dominant region was 31% for HLRs and 41% for provinces (Tables III and IV).

For the sub-regional flow classes, chi-squared analysis revealed that flow class grouping was not statistically independent from HLRs and physiographic provinces

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Table I. Proportion of gauges in each flow class affiliated with each hydrologic landscape region (HLR) in the Southeastern sub-region

	Flow classes							
HLR	BKR	CSI	IF	PR 1	PR 2	SBF 1	SBF 2	UPR
1	1.00	0.24	—	0.01	—	0.03	0.04	—
2	—	0.10	—	0.03	0.04	0.06	0.06	—
4	—	0.14	—	—	0.01	0.03	0.02	—
7	—	0.14	0.37	0.10	0.17	0.09	0.10	—
9	—	0.05	0.05	0.20	0.20	0.31	0.08	1.00
11	—	0.05	0.21	0.04	0.07	0.03	0.02	—
12	—	—	—	—	—	0.03	0.02	—
15	—	0.10	—	0.16	0.01	0.03	—	—
16	—	0.14	0.26	0.27	0.40	0.19	0.52	—
18	—	—	—	0.01	0.01	—	0.04	—
19	—	—	—	0.13	0.01	0.16	0.04	—
20	—	0.05	0.11	0.05	0.06	0.03	0.04	—

Shaded boxes represent the dominant HLR for each flow class.'—' indicates that no gauges were found for that respective HLR. HLRs developed by the United States Geological Survey (Wollock *et al.*, 2004).
BKR, Black River at Tomahawk NC; CSI, coastal swamp and intermittent; IF, intermittent flashy; PR 1, perennial runoff 1; PR 2, perennial runoff 2; SBF 1, stable high baseflow 1; SBF 2, stable high baseflow 2; UPR, unpredictable perennial runoff.

($\chi^2 = 119.2$, d.f. = 55, $p < 0.0001$ and $\chi^2 = 297.8$, d.f. = 24, $p < 0.0001$). HLRs poorly predicted flow class grouping ($r^2 = 0.13$, −log-likelihood = 59.61). Similarly, physiographic provinces poorly predicted flow class grouping although it was stronger than HLRs ($r^2 = 0.30$, −log-likelihood = 148.9). Flow class grouping for the USA was also not statistically independent from HLRs and physiographic provinces ($\chi^2 = 635.7$, d.f. = 162, $p < 0.0001$ and $\chi^2 = 907.28$, d.f. = 189, $p < 0.0001$). HLRs explained more variation in flow class grouping across the USA than in the Southeastern sub-region, however the relationship was still very weak ($r^2 = 0.23$, −log-likelihood = 317.8). Again, provinces explained slightly more variation in flow classes across the USA and explained more variation in flow classes than HLRs ($r^2 = 0.33$, −log-likelihood = 317.8). Because different numbers of regions and classes may bias the analysis, we re-ran cluster analyses with the variables used in the US flow classification and specified the same number of clusters as regional units (19 HLRs and 22 provinces). Increasing the number of clusters did not substantially increase the predictive ability of the HLRs ($r^2 = 0.25$, −log-likelihood = 491.7, d.f. = 324) or the physiographic provinces ($r^2 = 0.34$, −log-likelihood = 664.3, d.f. = 441). Although not large, the per cent of gauges in each class affiliated to a dominant region did show some increase and was 43% for HLRs and 58% for provinces.

Ability of hydrologic landscape regions to predict hydrologic variables

Hydrologic landscape regions explained 7% to 39% of the variation in the hydrologic variables, whereas US flow classes explained 9% to 87% of the variation in hydrologic variables (Table V). HLRs explained more variation than the US flow

Table II. Proportion of gauges in each flow class affiliated with each physiographic province in the study area

Physiographic province	Flow class							
	BKR	CSI	IF	PR 1	PR 2	SBF 1	SBF 2	UPR
Appalachian Plateau	—	—	—	0.38		0.03	—	—
Blue Ridge	—	—	—	0.04	0.08	0.30	0.29	—
Coastal Plain	1.00	0.95	0.08	0.06	0.07	0.18	0.08	1.00
Piedmont	—	0.05	0.92	0.08	0.51	0.21	0.60	—
Valley and Ridge	—	—	—	0.44	0.33	0.27	0.04	—

Shaded boxes represent the dominant province for each flow class. '—' indicates that no gauges were found for that respective province.
BKR, Black River at Tomahawk NC; CSI, coastal swamp and intermittent; IF, intermittent flashy; PR 1, perennial runoff 1; PR 2, Perennial runoff 2; SBF 1, stable high baseflow 1; SBF 2, stable high baseflow 2; UPR, unpredictable perennial runoff

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Table III. Proportion of gauges in each of the 10 US flow classes, created by Poff (1996), that are found within 19 hydrologic landscape regions across the entire USA

HLR	US flow class (Poff, 1996)									
	GW	HI	IF	IR	PF	PR	SN1	SN2	SR	SS
1	0.04	—	—	0.06	—	0.05	0.02	—	0.02	0.14
2	0.12	—	—	—	0.02	0.02	0.02	0.09	0.03	0.23
3	—	0.03	—	0.02	—	0.03	—	—	0.01	—
4	—	—	—	0.04	0.02	0.02	—	—	0.02	—
5	—	—	—	—	—	<0.01	—	—	—	—
6	0.02	0.24	0.19	0.08	0.08	0.09	—	0.27	0.03	—
7	0.11	0.03	—	0.06	0.08	0.10	0.02	0.09	0.02	0.09
8	—	0.16	0.33	0.02	0.17	0.02	—	—	—	—
9	0.11	0.03	—	—	0.08	0.12	0.02	—	0.02	0.09
10	0.01	0.03	0.10	—	0.02	0.01	—	—	0.01	—
11	0.06	—	0.24	0.18	0.36	0.11	0.02	—	0.02	0.27
12	0.06	0.03	—	0.04	—	0.02	—	—	—	—
13	—	0.16	0.14	0.12	0.09	—	—	—	—	—
15	—	0.05	—	—	—	0.04	0.04	—	0.03	—
16	0.28	—	—	0.12	—	0.28	0.13	0.27	0.20	0.05
17	—	0.08	—	0.04	0.02	0.01	—	—	—	—
18	0.01	0.16	—	0.14	0.06	0.02	0.11	0.09	0.08	—
19	0.11	—	—	0.02	—	0.03	0.02	—	0.23	0.14
20	0.05	0.03	—	0.04	0.02	0.04	0.59	0.18	0.27	—

Shaded boxes represent the dominant hydrologic landscape region (HLR) for each flow class. '—' indicates that no gauges were found for that respective HLR. HLRs were developed by the United States Geological Survey (Wollock *et al.*, 2004).
GW, stable groundwater; HI, harsh intermittent; IF, intermittent flashy; IR, intermittent runoff; PF, perennial flashy; PR, perennial runoff; SN, snowmelt (types 1 and 2); SR, snow and rain; SS, superstable groundwater.

classes for only one variable, mean annual run-off (39% compared to 29%). For HLRs, only two variables explained more than 30% of the variation, whereas for US flow classes, six of the variables explained more than 60% of the variation.

Variables that govern flow at different scales

For the sub-regional flow classes, the watershed cross-validation plot minimized at seven branches, with a $cp = 0.028$; however, this caused some overfitting because there were only six classes (Figure 3). Thus, we pruned the tree at six branches, with a $cp = 0.0525$. Five primary splitting variables along with their corresponding competing variables were isolated that accurately assigned 74% of the streams to their actual classes (Figure 4). Soil and infiltration variables explained a great deal of the variation in the model, along with some variation explained by precipitation. PR 1 streams were separated from the other streams primarily based on lower amounts of finer-sized soils and having shallower soils. PR 2 streams were separated on the basis of northern latitude. Stable high baseflow streams were separated from coastal swamp and intermittent (CSI) and intermittent flashy (IF) streams by the subsurface flow contact time index, which is an estimation of the days infiltrated water resides in the saturated zone before being discharged into the stream and is calculated using topography and soil properties (Falcone *et al.*, 2010). CSI and IF streams were separated from one another on the basis of soil size (permeability). SFB 1 differed from SFB 2 streams in terms of higher soil bulk densities, soil components and precipitation seasonality.

For the US flow classes, the watershed cross-validation plot minimized around a $cp = 0.025$, or six branches (Figure 3). Because six branches would have excluded four of the US flow classes, we pruned the tree to a $cp = 0.015$, which we felt was a compromise between overfitting the data and pruning the tree back to its barest form (Figure 5). Because of the size of the tree, we do not display competing variables along with the primary splitting variables. However, we do compare the results of the two pruning procedures (Nodes 1–5 indicate variables used in the barest tree). The six-branch tree accurately assigned 62% of the streams to their actual class. Increasing the tree size did not substantially increase accuracy, which was 70% of the streams to their actual flow class. The majority of variation was explained by climate variables with only a small portion of the variation explained by soils. The six-branch tree was completely composed of climate variables.

DISCUSSION

Although there was some regional affiliation of flow classes, HLRs and physiographic provinces did not explain a great deal of the variation in the grouping of flow classes

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Table IV. Proportion of gauges in each of the 10 US flow classes, created by Poff (1996), that are found within 22 physiographic provinces across the entire USA

Physiographic province	US flow class (Poff, 1996)									
	GW	HI	IF	IR	PF	PR	SN1	SN2	SR	SS
Adirondack	—	—	—	—	—	—	—	—	0.02	—
Appalachian Plateaus	—	0.03	—	0.06	—	0.18	—	—	—	0.05
Basin and Range	—	0.03	0.05	0.04	—	0.01	0.04	0.09	0.01	—
Blue Ridge	0.19	—	—	—	—	0.03	—	—	—	—
Cascade-Sierra Mountains	0.04	0.03	—	0.06	0.02	0.03	0.02	0.09	0.24	0.09
Central Lowland	0.10	0.42	0.76	0.18	0.66	0.18	0.02	0.36	0.09	0.50
Coastal Plain	0.31	0.11	—	0.18	0.13	0.15	—	—	0.05	0.05
Colorado Plateaus	0.01	0.03	—	—	—	—	0.07	—	—	—
Columbia Plateau	0.01	0.03	—	—	—	—	0.02	—	0.04	0.05
Great Plains	—	0.18	0.19	0.12	0.08	0.03	0.02	0.09	0.01	0.05
Interior Lowland Plateaus	0.01	—	—	0.06	0.04	0.02	—	—	—	—
Middle Rocky Mountains	—	—	—	—	—	—	0.28	0.09	0.01	—
New England	0.02	—	—	—	—	0.09	0.04	—	0.02	—
Northern Rocky Mountains	0.01	—	—	—	—	—	0.28	—	0.09	—
Ouachita	—	—	—	0.12	—	0.01	—	—	—	—
Ozark Plateaus	0.05	—	—	0.02	—	0.03	—	—	—	—
Pacific Border	0.01	0.16	—	0.14	0.08	0.02	—	—	0.39	0.05
Piedmont	0.19	—	—	—	—	0.11	—	—	—	—
Southern Rocky Mountains	—	—	—	—	—	—	0.13	—	0.01	—
Superior Upland	—	—	—	—	—	0.01	—	0.09	0.02	0.18
Valley and Ridge	0.05	—	—	—	—	0.09	—	—	—	—
Wyoming Basin	—	—	—	—	—	—	0.07	0.18	—	—

Physiographic provinces were originally created by Fenneman and Johnson (1946) and later digitized by United States Geological Survey for geographic information system analysis. Shaded boxes represent the dominant hydrologic landscape region (HLR) for each flow class. '—' indicates that no gauges were found for that respective HLR.
GW, stable groundwater; HI, harsh intermittent; IF, intermittent flashy; IR, intermittent runoff; PF, perennial flashy; PR, perennial runoff; SN, snowmelt (types 1 and 2); SR, snow and rain; SS, superstable groundwater.

to different regions. Some of our analyses were biased in that we used one set of classes, which were produced using landscape-based variables, to predict another set of classes, which were produced using only hydrologic variables. Thus, we hypothesized that a regional framework, such as HLRs, may explain more variation in the hydrologic variables that make up flow classes, rather than the flow classes themselves. However, we found that for the majority of hydrologic variables, HLRs explained less than 30% of the overall variability. We also found that, depending on scale, different variables will govern flow variability. Altogether, our results suggest that landscape-based regional frameworks (i.e. landscape classifications) should not be used to predict hydrology unless the relative importance of variables that comprise them is allowed to change with scale (Buttle, 2006).

Regional frameworks

Regional frameworks have increasingly been used in the development of predictive tools to aid in conservation (McMahon *et al.*, 2001; Snelder *et al.*, 2004; Wollock *et al.*, 2004; Sowa *et al.*, 2007; Frimpong and Angermeier, 2010). We used two landscape-based frameworks to predict hydrologic variability at two spatial scales in order to understand how scale can influence a framework's predictive ability and to discuss the applicability of using regional frameworks given their underlying structure. Although HLRs were developed with variables that govern hydrology and have the potential to predict flow variability in streams, they were not necessarily created as a predictive tool. Poor *et al.* (2008) found that HLRs did not improve predictions of nitrate concentrations beyond commonly used metrics. However, Hoos and McMahon (2009) found that the incorporation of HLRs into their analysis gave their models spatial structure and improved the estimation of nitrogen loading. Frimpong and Angermeier (2010) found that HLRs did a poor job of explaining fish assemblages alone but explained significant additional variation when nested in other frameworks.

Physiographic provinces have not been tested as predictive tools to the extent of HLRs. Provinces were created for visual rather than predictive purposes; however, they have been used as a spatial framework in the development of other relationships. For example, Johnson and Fecko (2008) showed that the majority of

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Table V. Results of one-way analysis of variance for 15 hydrologic variables among 19 different hydrologic landscape regions and 10 US flow classes, created by (Poff, 1996)

Hydrologic variables	Hydrologic landscape regions			US flow classes		
	F	r^2	r^2 adj.	F	r^2	r^2 adj.
Daily mean discharge	4.33	0.09	0.07	9.79	0.10	0.09
Mean annual runoff	28.87	0.40	0.39	37.20	0.30	0.29
Daily flow variability (CV)	27.13	0.39	0.37	163.88	0.65	0.65
Predictability of flow	21.54	0.34	0.32	141.65	0.62	0.62
Flood variability	8.42	0.16	0.15	16.22	0.16	0.15
Flood frequency	5.09	0.11	0.09	12.85	0.13	0.12
Flood duration	13.40	0.24	0.22	56.35	0.39	0.39
Seasonal predictability of flooding	11.32	0.21	0.19	131.68	0.60	0.60
Timing of flooding	5.99	0.12	0.10	18.36	0.18	0.17
Seasonal predictability of non-flooding	14.50	0.25	0.24	132.40	0.61	0.60
Number of zero flow days	8.10	0.16	0.14	562.65	0.87	0.87
Baseflow index	8.34	0.16	0.14	164.98	0.65	0.65
Seasonal predictability of low flow	13.14	0.24	0.22	41.23	0.32	0.32
Timing of low flow	6.28	0.13	0.11	31.38	0.26	0.26
Seasonal predictability of non-low flow	17.40	0.29	0.27	63.42	0.47	0.47

Hydrologic variables used in the clustering procedure of the 10 US flow classes (Poff, 1996). All one-way comparisons were significant ($p < 0.0001$).

regional curves for channel morphology relationships are similar within physiographic provinces. Physiographic provinces have been shown to govern how different variables control hydrology (Mohamoud, 2008; Morris *et al.*, 2009). In addition, Frimpong and Angermeier (2010) found that physiographic provinces explained more variation in fish assemblages than HLRs.

Because HLRs and physiographic provinces both are composed of factors that may influence flow in streams, we wanted to determine if these regional frameworks could explain the variability in the affiliations of flow classes, especially in relation to our watershed/climate trees. We assumed that the scale at which datasets are created will largely influence their predictive abilities depending on the scale of the response dataset. HLRs and physiographic provinces explained only 13% and 30% of the variation in the sub-region flow class affiliation, respectively, and explained 22% and 33% of the variation in US flow class affiliation, respectively. As an accuracy assessment, we wanted to determine how many streams within a given flow class were affiliated with one dominant HLR or province. We found that within the sub-region flow classes, 35% to 62% of the streams, on average, were affiliated with only one dominant HLR or province, respectively. Interestingly, within each of the US flow classes, 31% to 41% of the streams, on average, were affiliated with only one dominant HLR or province, respectively. Because, the number of clusters relative to the number of regional units may create some bias, we repeated a k-means procedure in order to create as many US flow classes as regional units. However, we found that there was not a substantial increase in the percentage of streams within a dominant flow class affiliated with only one dominant HLR or province (43% to 53%, respectively).

Variables that govern flow at different scales

Isolating key physical and climate variables that are responsible for the divergence in flow classes can be useful by providing a conceptual model that shows how flow dynamics are regulated at the watershed scale and by providing a means for classifying disturbed streams that lack sufficient pre-disturbance hydrologic data. Predicting hydrologic regimes from the landscape has become a reality in water resource management (Wollock *et al.*, 2004); thus, it may be advantageous to understand how variables that govern flow dynamics change with spatial resolution. We show that at smaller spatial scales, soils and factors that influence infiltration may govern flow dynamics whereas at the scale of the entire USA, climate may be responsible for governing flow variability.

For the sub-regional flow classes, we isolated five primary splitting variables along with their corresponding competing variables that accurately assigned 74% of the streams to their actual classes (Figure 4). Soil properties, such as particle size, soil thickness and the amount of soils in various hydrologic groups, influence permeability, infiltration capacity and the response of watershed to precipitation events (Hewlitt and Hibbert, 1963). In humid areas, the vast majority of the precipitation is yielded as subsurface flow, which is primarily influenced by soil and catchment properties (Hewlitt and Hibbert, 1963). Climate played a smaller role in discriminating among flow classes;

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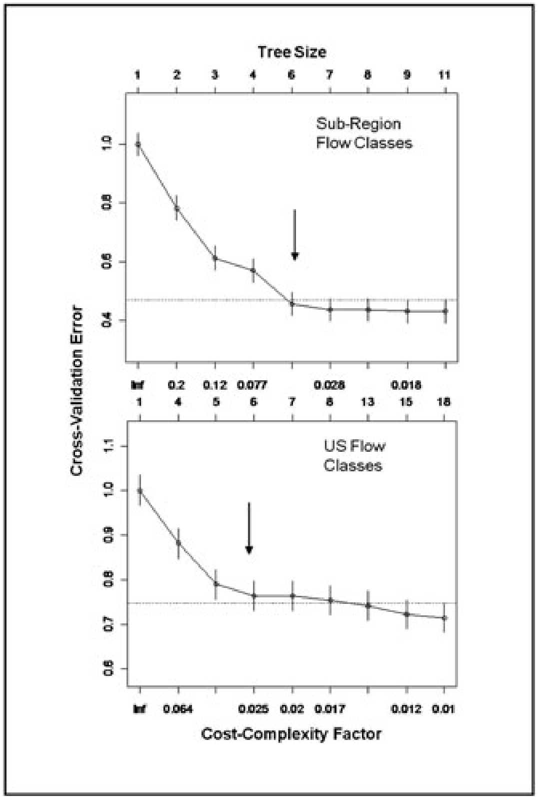

Figure 3. Plots for the hydrologic and watershed classification trees comparing the cross-validation error to the tree size (number of nodes) in order to determine where the tree should be pruned. Trees are generally pruned at the cost-complexity factor that minimizes the number of nodes and the cross-validation error. Arrows indicate the tree size that we plotted.

however, PR 2 streams were separated on the basis of northern latitude, which certainly is related to climate, as indicated by the monthly precipitation competing variables, and also to potential evapotranspiration.

Stable high baseflow streams had a lower subsurface flow contact time than CSI or IF streams. Subsurface contact time is an estimate of the time that infiltrated water remains in contact with 'saturated' soil before discharging into the stream. Initially, this seems contradictory considering that stable baseflow streams are sustained by slow draining soils, which suggests that saturated conditions would be extensive. However, humid mountain catchments, at least in western North Carolina, are characterized by deep soils with saturated areas primarily confined to aquifers along channels and saturated flow occurring only for short periods of time following precipitation events (Hewlitt and Hibbert, 1963). In these areas, high baseflows and stability in SBF streams are most likely sustained because of deep soils with properties conducive to the slow migration of moisture downslope and extended drainage times (Hewlitt and Hibbert, 1963). SBF 1 and 2 streams were separated from one another by bulk density as the primary variable, which again, would influence soil permeability and infiltration rates and, in turn, flow variability. Because IF streams were separated from CSI streams on the basis of soil size (related to permeability), we conjecture that small drainage basins originating in piedmont soils may induce flashiness in flow dynamics.

For the US classification, climate variables explained the majority of variation in flow classes (Figure 5). The pruned tree isolated five climate variables that accurately classified 62% of the streams to their respective flow classes. The partially pruned tree accurately classified 70% of the streams, in which eight of the 12 variables were climate variables. In a similar continental scale analysis, Kennard *et al.* (2010) developed a classification tree using geographic and environmental variables to discriminate among 12 flow classes across Australia. The best model included catchment, soils, vegetation and climate variables and accurately classified 62% of the streams in the study; however, climate was the dominant variable in the model and when used alone, it accurately assigned 58% of the streams to their respective flow class.

Can landscape-based frameworks capture the hydrologic variability?

Ultimately, our results suggest that two widely used, landscape-based classifications poorly predicted streamflow variability across the entire USA and within a sub-region of the USA. We find this highly significant because landscape-based frameworks have currently been used to predict the natural flow regimes of rivers and to inform management (Carlisle *et al.*, 2010). The poor performance of both frameworks most likely stems from the purpose and scale of their creation, the underlying variability of their classification and the structure of their framework. Large-scale regional frameworks are currently being used to organize river conservation measures (McMahon *et al.*, 2001, Snelder *et al.*, 2004, Wollock *et al.*, 2004, Sowa *et al.*, 2007). In light of this, we wanted to provide some broadly applicable considerations for management. We provide three main reasons for the inability of the landscape-based classifications used in this study to accurately predict streamflow variability:

(1) *The spatial resolution of continental-wide, landscape-based classifications is too coarse for predicting the flow variability of geographically close river systems.* The ability of a regional dataset to predict hydrology is largely an artifact of the number and size of the regions represented and differences in variability between datasets. Fewer and larger physiographic provinces most likely allowed more clustering of streams within the region's boundaries as compared to HLRs. However, we found that arbitrarily increasing the number of classes

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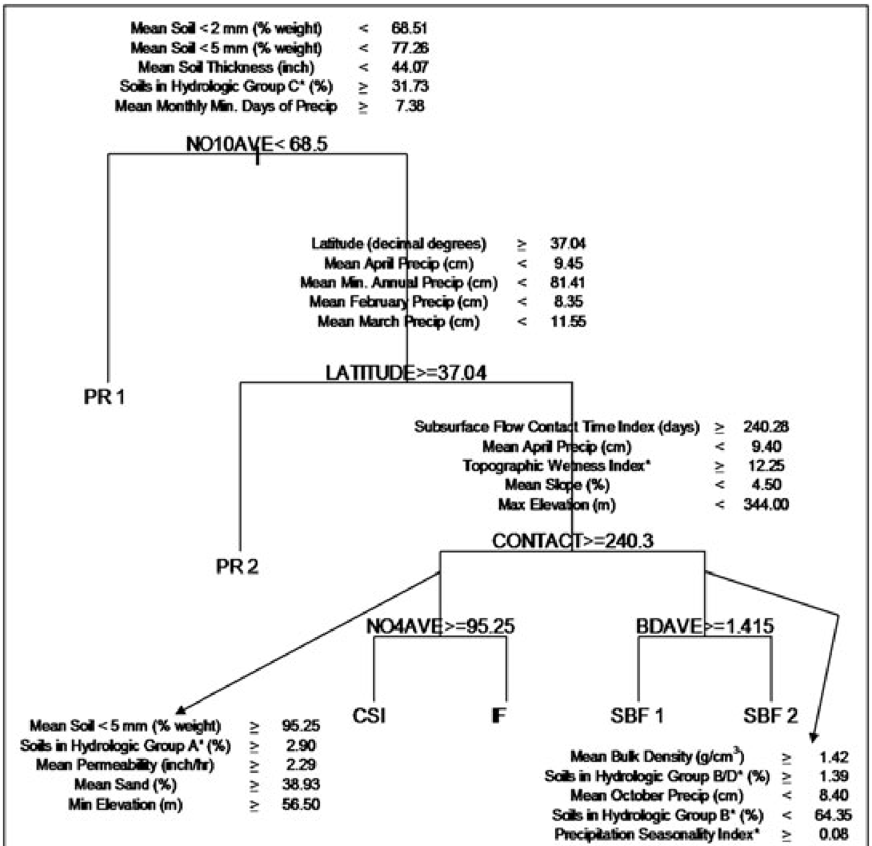

Actual Classification

Tree Assignment	BKR	CSI	IF	PR 1	PR 2	SBF I	SBF 2	UPR
n	1	21	19	79	70	32	48	2
CSI	1.00	0.81	0.05	--	0.13	--	–	0.50
IF	–	0.05	0.74	0.08	–	--	0.02	–
PR 1	–	--	0.05	0.78	0.10	0.03	–	–
PR 2	–	0.14	0.16	0.05	0.71	0.09	0.02	–
SBF I	–	--	--	0.01	0.01	0.59	0.13	0.50
SBF 2	–	--	--	0.08	0.04	0.28	0.83	–

Figure 4. Classification tree using five climate/watershed metrics as primary splitting variables along with the four corresponding competing variables to classify six of the eight flow classes in this study. 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 grey boxes. For class codes, see Figures 1 and 2.

(via cluster analysis) for the entire USA did not substantially increase the predictive capability of either framework. All spatial frameworks are subject to spatial autocorrelation (Frimpong and Angermeier, 2010). Obviously, physiographic provinces explained more variation in flow class affiliation because provinces are spatially contiguous whereas HLRs are not. However, our purpose was not to test how much spatial autocorrelation is explained by various regional frameworks. In contrast, we simply wanted to determine how much variation in flow class affiliation each of these frameworks explain, because they were constructed using variables that influence hydrology.

We believe that the scale of HLRs and physiographic provinces was unable to accurately assess flow variability for three main reasons: Firstly, flow at a given gauge represents the culmination of watershed processes from that point upstream regardless of the geographical location of the gauge. In the case of large river systems, this may include areas across multiple regions. Although this may be an obvious fact, most ecologists would agree that a stream in the lower piedmont looks quite different than a stream in a mountainous environment. The tendency is to assume that because gradient, substrate and channel geometry are far different, flow characteristics should follow suit. However, flow metrics are

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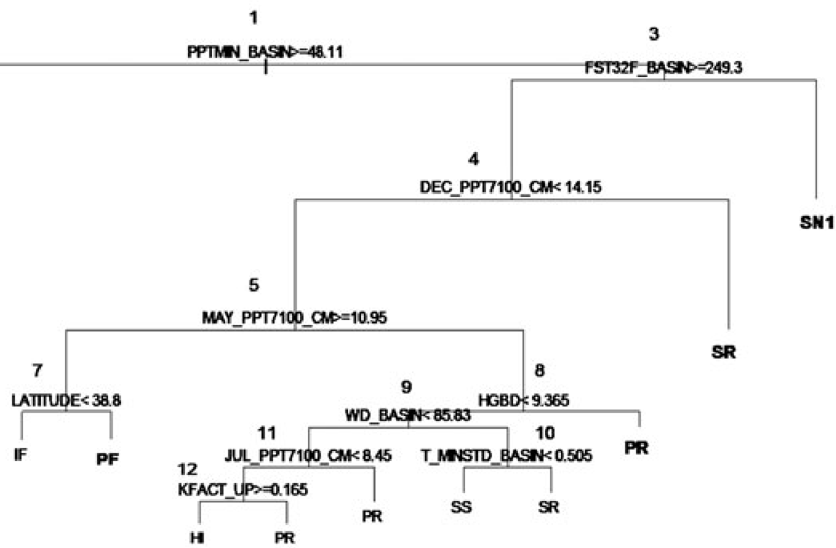

Node	Variable Description
1	Mean Min Monthly Precip (cm)
2	Mean February Precip (cm)
3	Mean Day of First Freeze (1-365)
4	Mean December Precip (cm)
5	Mean May Precip (cm)
6	Latitude (decimal degrees)
7	Latitude (decimal degrees)
8	Percentage of Soils in Hydrologic Group B/D*
9	Mean Annual No. of Days of Measurable Precip (days)
10	SD of Min Monthly Air Temp
11	Mean July Precip (cm)
12	Mean K Factor of Upper Soil Horizon*

Actual Classification

Tree Assignment	GW	HI	IF	IR	PF	PR	SN1	SN2	SR	SS
n	81	38	21	49	53	373	46	11	93	22
GW	0.25	--	--	--	0.02	0.02	--	--	--	--
HI	0.01	0.76	0.14	0.33	0.13	0.02	0.02	--	0.02	--
IF	0.02	0.16	0.57	0.02	0.06	0.01	--	--	--	--
PF	--	--	0.10	0.04	0.55	0.01	--	--	--	--
PR	0.59	0.08	0.14	0.57	0.21	0.89	0.07	0.36	0.14	0.09
SN1	0.01	--	--	--	--	--	0.85	0.18	0.04	0.05
SR	0.06	--	--	0.04	0.02	0.04	0.04	0.27	0.76	0.18
SS	0.05	--	0.05	--	0.02	0.01	0.02	0.18	0.03	0.68

Figure 5. Classification tree using five climate/watershed metrics as primary splitting variables along with the four corresponding competing variables to classify eight of the 10 US flow classes (Poff, 1996). Tree shown has been pruned to a $cp = 0.015$. The first five nodes and the classes in larger, bold letters indicate that the tree has been pruned to a $cp = 0.025$ (see METHODS section). 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 grey boxes. For class codes, see Figures 1 and 2.

calculated from discharge, which is the volume of water per time, and not just velocity, depth and channel profile alone. Thus, there is a tendency of a river to have ‘flow inertia’, that is the tendency to retain flow characteristics from upstream areas despite geographical location and reach characteristics. Secondly, smaller streams, whose watershed may be entirely contained within the given province, may be located in close proximity to larger rivers, whose watershed may span multiple provinces. Thirdly, a river’s flow regime is largely dictated by watershed characteristics and climate patterns, which may vary extensively within the same physiographic province. This suggests that flow regime should be related to watershed characteristics and not just geographical location alone.

(2) *Landscape-based classifications may not incorporate layers of information or hierarchical structure*. Classifications are generally a way of consolidating variability. However, the construction of one framework may poorly predict another regional framework, if the underlying variability between the two datasets is very different. Using continuous variable descriptors rather than discrete classes will allow for flexibility in the relative importance of some variables in comparison to others. Also, allowing for hierarchical structure, such as nesting classes, may be informative and increase accuracy. For example, our watershed/climate trees suggest that at various scales, the relative importance of variables may change; therefore, static classifications conducted at one scale may be inappropriate for applications of finer resolution.

Buttle (2006) argues that one limitation of HLRs is that they do not identify the relative importance of different controls on hydrology nor do they indicate how the importance of those controls change depending on scale. Interestingly, Santhi *et al.* (2008) found that the variables used in the construction of HLRs could be used to accurately define groundwater flow.

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Variables used in the construction of HLRs are publicly available for each of the 43 931 small watersheds (approx. 200 km^2). We only used 19 HLRs as predictors; however, we imagine that if we had isolated variables used in the construction of HLRs across each of our watersheds, they could have explained a great deal of variability in flow classes. This suggests that, depending on the application, the variables that comprise regional frameworks may be more useful for predicting flow variability than the regional framework itself.

(3) *The watershed is the appropriate scale to relate landscape characteristics to flow variability*. The spatial scale of frameworks will largely influence their ability to accurately predict some response variable. For example, although we used the dominant HLR in each watershed, watersheds that were delineated at each gauge location may have been composed of many different HLRs. Our watershed/climate trees accurately assigned 70–74% of streams to their appropriate flow class compared to an average of 31–35% and 41–62% of streams affiliated with a dominant HLR or province, respectively. Although this comparison is somewhat biased because of key structural differences, we wanted to make a very obvious point: regional frameworks created as classes are mutually exclusive whereas watersheds are not. Our watershed/climate trees were created with variables that were summarized at the watershed scale. HLRs and provinces, on the other hand, span extensive areas and may not relate to the scale at which flow is measured. Carlisle *et al.* (2010) found that HLRs poorly predicted 13 streamflow indices and concluded that local basin-scale factors in addition to regional factors must be included in models used to predict natural flow variability. Because flow in rivers is the result of a culmination of hydrologic processes within a watershed, the watershed scale (delineated at the point where hydrology is measured) is the most appropriate at linking the landscape to flow dynamics. Furthermore, this scale continuously changes with drainage area.

CONCLUSION

Landscape-based regional frameworks (at least classes) should be used with caution as independent predictive entities of hydrology, depending on their purpose, the scale at which they were produced and the underlying variability of their classification. We believe that the classification of flow regimes based on hydrological data alone is important in the broader management context of river conservation. A general trend in current conservation management is developing regional frameworks to organize and prioritize conservation objectives (McMahon *et al.*, 2001, Snelder *et al.*, 2004, Wollock *et al.*, 2004, Sowa *et al.*, 2007). In addition, current conservation strategies have and will continue to require landscape-based models to predict streamflow variability when sufficient hydrologic information is not available (Carlisle *et al.*, 2010). The development of many regional frameworks operates under the assumption that similar patterns in landscape-scale factors will be represented in either physical responses (i.e. hydrology) or biotic responses. We find this highly appropriate and very useful; however, we suggest that managers should be careful in selecting what variables to use in river classification. The scale of regional frameworks may not explain ecological differences in geographically close river systems (Snelder *et al.*, 2004). Our data suggest that flow regimes can be quite different for streams occurring in the same physiographic province or HLR and gross classes may override important differences in the hydrologic regime of rivers. If landscape-based approaches are to be used to predict hydrology, we suggest that their structure incorporate models to predict existing (although limiting) hydrologic information. Because flow classes consolidate variability, landscape-based frameworks may explain more variation when predicting flow classes rather than predicting individual hydrologic indices. In this case, hydrologic classifications should be conducted prior to developing predictive landscape-based frameworks. Furthermore, similar to Poff *et al.* (2006b), we suggest that a hierarchical approach is appropriate when applying flow variability to a geomorphic context across multiple scales. Additionally, we suggest that managers use layers of information either by nesting classes or using the underlying variables of frameworks rather than classes. Also, we suggest that the appropriate scale for attributing flow dynamics to the landscape is the watershed.

We also suggest that regional framework datasets, including variables used in their construction, should be publicly available (Frimpong and Angermeier, 2010). Much of the comparisons in this study were possible because datasets were available through USGS (Wollock *et al.*, 2004), Ecological Archives (Falcone *et al.*, 2010) and direct communication with an author (Poff, 1996). The utility of regional frameworks is their ability to relate to other datasets. Obviously, the utility of those frameworks cannot be tested if they have limited access.

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