HYDROGEOMORPHIC CLASSIFICATION OF WASHINGTON STATE RIVERS TO SUPPORT EMERGING ENVIRONMENTAL FLOW MANAGEMENT STRATEGIES

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ABSTRACT

As demand for fresh water increases in tandem with human population growth and a changing climate, the need to understand the ecological tradeoffs of flow regulation gains greater importance. Environmental classification is a first step towards quantifying these tradeoffs by creating the framework necessary for analysing the effects of flow variability on riverine biota. Our study presents a spatially explicit hydrogeomorphic classification of streams and rivers in Washington State, USA and investigates how projected climate change is likely to affect flow regimes in the future. We calculated 99 hydrologic metrics from 15 years of continuous daily discharge data for 64 gauges with negligible upstream impact, which were entered into a Bayesian mixture model to classify flow regimes into seven major classes described by their dominant flow source as follows: groundwater (GW), rainfall (RF), rain-with-snow (RS), snow-and-rain (SandR), snow-with-rain (SR), snowmelt (SM) and ultra-snowmelt (US). The largest class sizes were represented by the transitional RS and SandR classes (14 and 12 gauges, respectively), which are ubiquitous in temperate, mountainous landscapes found in Washington. We used a recursive partitioning algorithm and random forests to predict flow classes on a suite of environmental and climate variables. Overall classification success was 75%, and the model was used to predict normative flow classes at the reach scale for the entire state. Application of future climate change scenarios to the model inputs indicated shifts of varying magnitude from snow-dominated to rain-dominated flow classes. Lastly, a geomorphometric classification was developed using a digital elevation model (DEM) and climatic data to assign stream segments as either dominantly able or unable to migrate, which was cross-tabulated with the flow types to produce a 14-tier hydrogeomorphic classification. The hydrogeomorphic classification provides a framework upon which empirical flow alteration–ecological response relationships can subsequently be developed using ecological information collected throughout the region. Copyright © 2011 John Wiley & Sons, Ltd.

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INTRODUCTION

Societal dependence on freshwater ecosystems is increasing worldwide as growing human populations and economies rely more heavily on water for irrigation, consumption and industry (Postel and Richter, 2003). Water conflicts manifesting on local to international scales highlight the enormous pressures on freshwater ecosystems, with these challenges projected to increase with a rapidly changing climate and geography of human need (Fitzhugh and Richter, 2004; Palmer et al., 2008). The Pacific Northwest of the USA encompasses a range of climates, topography and vegetation, ranging from semi-arid to rainforest, creating a wide range of natural flow regimes and diverse examples of competing water demands between humans and ecosystems. Moreover, rapid population growth, urbanization and intensive agriculture mapped upon an uneven distribution of freshwater has contributed to the high-profile and contentious demise of iconic Pacific salmon species throughout this region (Schindler et al., 2008). Water withdrawals, impoundments and land-use changes have resulted in extreme low flows in over a quarter of river basins in Washington State, approximately one quarter of which are ‘over-appropriated’—meaning that more water has been legally allocated than is naturally available (WA DOE, 2003). Combined with forecasted decreases in regional streamflow associated with projected climate change (Luce and Holden, 2009; Elsen et al., 2010), natural resource managers in Washington State (and beyond) are calling for new tools to reliably define ‘sustainability
boundaries’ within which the quantity and timing of flows support freshwater biodiversity and ecosystem function (Arthington et al., 2006; Richter et al., 2006).

A growing body of literature supports the notion that natural flow variability over a range of temporal scales is critical to sustaining the structure and function of riverine ecosystems (Poff et al., 1997; Bunn and Arthington, 2002; Naiman et al., 2008). In lieu of detailed, site-specific information, regionalization of streamflow patterns can be used to prescribe flows that retain natural flow variability (Arthington et al., 2006). Conventional flow management schemes in the USA, including Washington State, have focused primarily on microhabitat requirements for individual species (usually fish) and effectively ignore dynamic feedbacks among physical and biological components of the river system. These schemes range in complexity from simple discharge limits thought to maintain a desired ecological outcome, such as the Tennant (1976) and Texas (Mathews and Bao, 1991) methods, to the instream flow incremental methodology (Bovee, 1982), which explicitly accounts for the microhabitat requirements of individual species and life stages. The physical habitat simulation model (one tool in the instream flow incremental methodology) is perhaps the most widely adopted by natural resource agencies (in its original or some modified form), despite its required hydraulic and geomorphological surveys and uncertainties in defining habitat preferences for species of interest (Bovee and Milhous, 1978; Scott and Shirvell, 1987; Castleberry et al., 1996). This management process requires site-specific and basin-by-basin examination of optimal flows for each stage in the life cycle of each species of concern, leading to an absence of instream flow targets for countless data-poor rivers or for rivers managed with limited resources. These issues highlight the need for a methodology that both addresses the complexity of ecological responses to streamflow and is regionally applicable.

‘Environmental flows’ aim to balance holistic ecosystem needs and those of humans by recognizing that the natural flow regime’s key components must be mimicked, at least in part, for preservation of freshwater biodiversity and sustainability of riverine goods and services. These approaches were pioneered and gained momentum in the 1990s (Arthington et al., 1992; King and Tharme, 1994; Richter et al., 1996; Dunbar et al., 1998), several originating in South Africa and Australia where the challenge of protecting freshwater species (many with poorly understood ecological requirements) favored ecosystem-based approaches rather than species-based strategies aimed at high-profile fauna (Tharme, 2003). Recently, coupling the benefits of environmental flows with the need for regionalization in flow management has led to an internationally derived framework called the ecological limits of hydrologic alteration (ELOHA; Poff et al., 2010). ELOHA is a methodology that synthesizes existing hydrologic and ecological databases from many rivers within a region to generate flow alteration–ecological response relationships. Anchored by ecological theory and empirical data showing that ecosystems with common streamflow characteristics respond similarly to flow alteration (Poff et al., 1997; Bunn and Arthington, 2002), this methodology allows for extrapolation of limited ecological response data to rivers of similar hydrologic regimes, broadening spatial applicability and quickening the pace at which flow standards can be defined (MacDonnell, 2009). A prerequisite for using ELOHA or any other regional flow–ecology approach is the assessment of hydrologic and geomorphic similarity across the region of interest.

Hydrologic classification schemes provide order to inherently complex flow data by identifying flow similarities among rivers (e.g. Poff, 1996; Snelder et al., 2009a; Kennard et al., 2010b). Classification of hydrological similarity is viewed as both an organizing framework and scientific tool for river research and management as it gives an indication of the spatial structure of flow variation (Hannah et al., 2000) and can facilitate the systematic testing of ecological hypotheses (Wagener et al., 2007). Deductive approaches to hydrologic classification rely on flow metrics that describe ecologically important facets of the flow regime, including the seasonal pattern of flows; timing of extreme flows; the frequency, predictability and duration of floods, droughts and intermittent flows; daily, seasonal and annual flow magnitude and variability; and rates of change (Olden and Poff, 2003). Hydrologic classification based on spatial variation in stream hydrology plays a central role in environmental flow assessments aimed at the development of ecologically sustainable practices for water management (Richter et al., 2006). Holistic methodologies to environmental flow assessments (Tharme, 2003 for review), either implicitly or explicitly involve the hydrologic classification of rivers to varying extents. Consequently, hydrologic classifications are growing in popularity in the USA and elsewhere as a flow management tool (e.g. Seelbach et al., 1997; Kennen et al., 2007; Apse et al., 2008), allowing managers to identify groups of streams and rivers that could be managed similarly and to broadly distinguish potential ecological changes associated with flow alteration where site-specific data are lacking.

River channel and flood-plain morphology also strongly influences types and amounts of habitats available within each reach. In general, rivers that migrate across their floodplains form complex channel patterns (e.g. meandering, braided, island-braided) and contain high diversity of habitat riparian and aquatic habitat types (e.g. Kondolf et al., 2003; Beechie et al., 2006a). Channels that are either too small to migrate laterally or confined between valley
wells have lower habitat diversity and hence tend to support less complex ecosystems. Coupling classifications of hydrology and geomorphology based on these types of data can help to further distinguish potential ecological responses, improving regionalization of environmental flow efforts (Snelder and Biggs, 2002; Poff et al., 2010). Most importantly, large flood-plain rivers with complex channel patterns require flood flows to sustain geomorphic and ecological complexity, which increases the importance of peak flow considerations in flow management for these channel types. Several additional factors would also serve to distinguish ecological changes associated with flow alteration, such as stream temperature, but data scarcity precludes inclusion in regionalization efforts (Olden and Naiman, 2010).

In this paper, we present a hydrogeomorphic classification of more than 100,000 km of streams and rivers in Washington State, USA. The resolution of hydrologic and geomorphic pattern described in these classifications represents practical management units at multiple spatial scales for both regionalized and ecosystem-based flow management. Our specific aims are to present the following: (i) a statewide normative (unregulated) hydrologic classification for application in Washington State and as a template for use elsewhere; (ii) a robust predictive model for assigning hydrologic class to ungauged river segments using key climatic and physical drainage basin characteristics; (iii) a statewide geomorphic classification based on channel width and flood-plain width; and (iv) a forecast on how projected climate change will affect hydrologic class assignments in the future. Here, we use ‘normative’ to describe the flow regime under conditions prior to gross human alteration but likely not ‘pristine’ or ‘natural’ in the sense of completely free of human influence following Stanford et al. (1996). The hydrologic classification is based on ecologically relevant flow metrics, informing expectations of pattern in ecological responses when managing across hydrogeomorphic classes. By assigning flow class to ungauged or regulated rivers, we aim to fill significant data gaps on normative flows for many rivers in the state, enabling their inclusion both in analyses exploring ecological relationships across flow classes as well as in regionalized management schemes. Finally, predicting climate-induced changes in flow class will allow managers to design flow management schemes that accommodate expected ecological responses to climate change.

METHODS

Study area

We focused our study on the state of Washington (USA) to match the scale at which instream flow laws are applied. The Cascade Range divides Washington into two broad physiographic regions. Rivers in western Washington (approximately one-third of the state) drain to the Puget Sound, the Strait of Juan de Fuca, the lower Columbia River or the Pacific Ocean, whereas rivers in Eastern Washington drain to the Columbia River. Major rivers in western Washington have mountain headwaters, in some cases with glaciers, and broad lowland valleys. Much of the region was glaciated, which left unconsolidated sediments blanketing the underlying bedrock at lower elevations. Landscapes in eastern Washington reflect a range of geologic processes including basaltic lava flows, glaciation, loess deposits and scoured terrain from glacial outburst floods.

The Cascade Range also defines two major climatic regions in Washington. Western Washington has relatively warm temperatures, wet winters and dry summers, supporting dense forests of conifers and areas of temperate rainforests. Eastern Washington has a relatively dry climate with large areas of semi-arid steppe and a few arid deserts lying in the rain shadow of the Cascades. Southeast parts of the state, such as the Palouse region, were grasslands that have been mostly converted into farmland, whereas higher elevation portions of eastern Washington are forested and mountainous. Annual precipitation ranges from more than 1000 cm year\(^{-1}\) on the Olympic Peninsula in the west to less than 15 cm year\(^{-1}\) in deserts east of the Cascade Range (Widmann and Bretherton, 2000). Snowfall also spans a wide range, from 15 cm east of the Cascades to world-record depth in 1998–1999 of 29 m on Mt. Baker on the west slope of the Cascades. This broad spectrum of landscapes and climates promotes wide-ranging hydrologic regimes.

Gauge selection

We identified 372 discharge gauging stations in Washington with at least 15 years of continuous discharge data (Figure 1); a period of record that adequately captures flow variability for hydrologic classification (Kennard et al., 2010a). From these, we identified reference gauges that were minimally influenced by upstream dams, land use or water allocations (Poff, 1996; Carlisle et al., 2009; Kennard et al., 2010b). Our objective was to maximize the number and spatial coverage of gauges available for subsequent analyses while ensuring that stream gauges were comparable in terms of data quality and quantity. We delineated upstream catchment area and accumulated hydrologic effects according to the NHDPlus hydrography (USEPA, 2006). Our criteria consisted of the following: (i) no more than one dam that regulates ≤5% mean annual discharge (MAD); (2) ≤10% urban or agricultural land use in the contributing watershed; and (3) ≤20% of water allocated in rights and permits (see Table 1 for data sources). A lack of water allocation estimates in Canada precluded the
calculation for two gauges on the Kettle River, but low urban and agricultural land use and population density suggested minimal allocation. Limitations of our filtering process included that the land cover data (Homer et al., 2004) do not necessarily represent current status, as many parts of Washington have undergone modest to significant land-use changes in the last decade that would affect a gauge’s candidacy for ‘reference’. Also, the water allocation...
data represent the best georeferenced data available, but have limited spatial scope and resolution, and may not represent actual water use. Despite these shortcomings, the data used represent the best available.

We calculated 99 hydrologic metrics (Appendix 1) for the reference gauges using the time series analysis module of the River Analysis Package (Marsh et al., 2003). Metrics accounted for magnitude \( (n = 59) \), timing \( (n = 10) \), frequency \( (n = 8) \), duration \( (n = 20) \) and rate of change of flow \( (n = 2) \) and were chosen based on previous analyses of redundancy and ecological relevance (Olden and Poff, 2003), as well as appropriateness of Washington’s climate and physiography (e.g. metrics used to describe a tropical flow regime in Australia could lack descriptive ability for Washington flow regimes). All magnitude metrics were standardized by MAD in order to minimize the effect of flow magnitude on the hydrologic classification.

We selected a subset of 9 ‘sentinel’ gauges without any measurable upstream impacts and greater than 50 years of continuous discharge data (Figure 1) to validate our selection of minimum record length of 15 years and assess any influence of climatic trends over time. First, following Kennard et al. (2010a), we quantified changes in bias, precision and accuracy in all hydrologic metrics, from 1 to 30 years of continuous data. We identified 15 years as a threshold beyond which there is negligible improvement in bias, precision and overall accuracy for each additional year of discharge record used in the estimation of all hydrologic metrics, confirming the findings of Kennard et al. (2010a).

For example, estimated values for the base flow index, predictability of monthly mean daily flows and median annual flow were within 10% of the true values (bias) and had high precision at 15 years. Second, we evaluated the influence of major climatic shifts on hydrologic metrics by evaluating the difference in mean monthly flow calculations within a moving window of 5 years between 1946 and 1995. Graphical results confirmed an influence of the 1977 shift from cool to warm Pacific Decadal Oscillation, consistent with regional climate literature (Hamlet and Lettenmaier, 2007). In order to maintain climatic uniformity among gauges, we required that discharge data for all selected gauges overlap this 1977 PDO shift (Appendix 2). To assess potential weakness in our final classification arising from minimal overlap of 1977 by several gauges, we compared the hydrologic classification for pre-1977 and post-1977 data using the adjusted Rand index (an index ranging between 0 and 1 that is based on whether the relation of every pair of objects (gauges) differs between two cluster solutions; Hubert and Arabie, 1985) and found temporal windows to be similar (0.525; Santos and Embrechts, 2009), indicating robustness to climatic influence.

Lastly, we aimed to capture flow regimes representative of all major landscapes and climatic zones and presumably all flow regime types, in Washington State. Gauges on the Columbia Plateau and other underrepresented areas did not pass our filters for length of record, climatic window or upstream impact (consistent with previous studies; Carlisle et al., 2009). In order to include gauges in these regions, we relaxed certain criteria and gained 14 gauges, allowing for the following: as few as 14 years of continuous data encompassing any year in the 1970s; up to five upstream dams regulating a total of not more than 1% MAD; up to 20% of agricultural land use; and up to 50% of water in allocation. As a final indication of robust site coverage, we ensured that our final selection of 64 reference gauges (Figure 1; Appendix 3) encompass all ecological drainage units delineated for the state (Skidmore, 2006). Drainage areas of the final selection of reference gauges range in size from 6 to 9841 km\(^2\) \( (n = 64; \text{mean} = 765.6; \text{SD} = 1750.3; \text{Appendix 3}) \).

### Hydrologic classification

Hydrologic classification was undertaken using Bayesian mixture modelling, implemented using the AUTOCLASS C programme (NASA, Washington, DC, USA) (v 3.3.4; Cheeseman et al., 1988), in which the observed distribution of data is modelled as a mixture of a finite number of component distributions to determine the number of distributions, their parameters and object memberships (Hanson et al., 1991; Cheeseman and Stutz, 1996). The approach is fully probabilistic and uncertainty is explicitly reported in terms of data specification, class specification and the final classification. Multiple plausible classifications are produced, which are then ranked on their estimated marginal likelihoods to select the most parsimonious classification that is guaranteed to have the highest posterior probability of being correct given the data (Webb et al., 2007). Prior to the analysis, we log \(- 10(x + 1)\) transformed all hydrologic metrics and modelled them as normally distributed continuous variables, but we recognize that the choice of data transformation may influence the outcome of clustering (Snelder et al., 2009b). Outputs from the analysis include the probability of class membership for each gauge; class strength (the probability that the attribute distributions at the class level can be used to predict the class members) and the importance of the hydrologic metrics for distinguishing each class. We identified the most influential metrics as those where the class-level mean was greater than three standard deviations from the global mean.

Bayesian classification using AUTOCLASS requires the user to specify measurement uncertainty for each attribute and those attributes with lower uncertainty have more influence on the final classification (Webb et al., 2007). Uncertainty in the estimation of different hydrologic metrics is primarily a function of the length of discharge record used.
to calculate them and varies between different metrics for a given length of record (Kennard et al., 2010a). We specified uncertainty for each hydrologic index using estimates of mean accuracy (i.e. the scaled mean squared error; sMSE) based on the minimum discharge record length (15 years). Graphical methods were also used to evaluate among-class variation in a subset of key hydrologic metrics representing each of the five ecologically relevant components of the flow regime and which are commonly used in ecohydrological studies, are easily interpretable and hence are potentially amenable to management action.

Predicting hydrologic class for ungauged rivers

We used classification and regression trees or CART (Breiman et al., 1984) and a random forest classifier (Cutler et al., 2007) to first explore and then predict normative hydrologic class (i.e. in the absence of flow data; either ungauged or regulated reaches) as a function of climatic and physical drainage basin characteristics for rivers throughout Washington State. In the Pacific Northwest, various processes control streamflow across multiple scales, hydroclimatic regions and elevation gradients. We computed the upstream average values of eight climatological variables and seven physical basin attributes (Table I) for 55,625 flow lines in NHDPlus (Horizon Systems, Herndon, VA, USA) that represent most streams and rivers (excluding canals, ditches or artificial paths, as well as flow lines with upstream catchment areas too small for accumulation analyses). We chose variables based on those shown to be most influential in previous modelling efforts for the region (e.g. Sanborn and Bledsoe, 2006). Climatological variables included measures of precipitation, temperature, evapotranspiration, snowfall and solar radiation. Snowfall and solar radiation data were not available for the Canadian portion of our study area, and so we used regression-based extrapolation methods to estimate those values. Physical attributes of the basin included elevation, slope, drainage density, land use and surface geology. To capture the greatest relevance to runoff processes, we used the forested and urbanized per cent of upstream catchment areas to produce predictions of hydrologic class across Washington. We used CART to repeatedly partition the data set according to the explanatory variables (i.e. climate and physical factors) into a nested series of mutually exclusive groups, each as homogeneous as possible with respect to the response variable (i.e. hydrologic class). The branching topology of the resulting decision tree reveals non-additive variable effects, where the primary splitting variables and the best competitors (called surrogate splits) are indicated. We used the Gini impurity criterion to determine the optimal variable splits (minimum parent node size: \( n = 5 \); minimal terminal node size: \( n = 2 \)), and we determined the optimal size of the decision tree by constructing a series of cross-validated trees and selecting the smallest tree based on the one-standard-error rule (De'ath and Fabricus, 2000). Cohen's \( \kappa \) coefficient of agreement was used to assess the predictive performance of the classification tree compared with random expectations.

Whereas CART provided an explanatory model to understand the main drivers of hydrologic class membership, we used a random forest classifier (Cutler et al., 2007) to generate predictions of hydrologic class across Washington. Random forest classifiers are a model-averaging or ensemble-based approach in which multiple classification or regression tree models are built using random subsets of the data and predictor variables. The model predictions are then combined to produce one prediction for each observation. We grew a forest of 1000 classification trees by sampling (with replacement) \( \sqrt{n} \) randomized subsets of the original observations and four random predictor variables.

Geomorphic classification

The degree to which a channel can migrate and create a dynamic floodplain represents one influence on key instream and riparian ecological processes, including flow regime, habitat formation and nutrient availability (Ward et al., 2002). As a binary metric, whether a channel is able to migrate or not offers the most refinement of hydrologic classes possible given available data at the state scale. We identified stream segments as either largely able or unable to migrate using a two-step process. It has been shown that channels that do not meet certain minimum bankfull width thresholds are not likely to migrate (e.g. Beechie et al., 2006a) and thus were classified as non-migrating. We thus first screened for channels meeting a bankfull width threshold of 15 m for western and coastal WA and 8 m for the Columbia River basin, based on the research of Beechie et al. (2006a) and Hall et al. (2007). Channels narrower than these thresholds were classified as non-migrating. Second, for all channels above the minimum bankfull widths, we classified stream reaches as migrating or non-migrating according to a cutoff confinement ratio (floodplain to bankfull width) of 4.0. This ratio represents a flood-plain width above which channels can develop sinuous or multi-thread channel patterns (Beechie et al., 2006a).

We estimated bankfull width from drainage area and precipitation according to spatially explicit relationships derived for the region. These relationships were strong for the Columbia River basin with \( r^2 > 0.8 \) (Imaki and Beechie, NOAA Fisheries, Seattle, WA, unpublished results) and moderately strong for western Washington (0.45 < \( r^2 < 0.54 \); Faustini et al., 2009). We converted these bankfull widths to bankfull depth estimates following Hall et al. (2007). Floodplain widths were estimated from a 10-m digital elevation model (DEM) by projecting 10 transects across each valley segment and averaging the width estimates. Bankfull channel widths were estimated according to a regression model using field measured data and confinement ratios calculated (confinement ratio = valley width / bankfull channel width). High resolution hydrography allowed us to classify stream segments at 200-m intervals for the Columbia River basin, whereas we were limited to the resolution of NHDPlus hydrography (on average 2-km river segments) for western and coastal Washington. Assigned classes represent the dominance of either migrating or non-migrating channel type. Finally, we cross-tabulated the geomorphic and hydrologic classifications to produce a 14-tier hydrogeomorphic classification.

**Forecasting climate-driven changes in hydrologic class**

Washington State hydrology is considered particularly sensitive to climate change because of mountain snowpack’s influence on streamflow (Elsner et al., 2010). An assessment of how the frequency and distribution of hydrologic classes may change in the future will facilitate the design of flow management schemes that accommodate expected ecological responses to climate change. Shifts in hydrologic class were predicted according to two scenarios of projected temperature, precipitation and snowfall conditions (Mote and Salathe, 2009). Projected data for air temperature and precipitation represent monthly changes (i.e. deltas) between a 30-year contemporary period (1970–1999) and projected future climate in a future 30-year period (2030–2059). The data represent regionally averaged monthly deltas from an ensemble of 19 global circulation models (GCMs) produced through the Intergovernmental Panel on Climate Change (IPCC, 2007), encompassing the Pacific Northwest region (Washington, Oregon, Idaho, western Montana and small sections of neighbouring states and British Columbia) and according to two different emission scenarios (A1B and B1). Of the more than 40 greenhouse gas and sulphate aerosol emission scenarios produced through the IPCC, scenarios A1B and B1 are two of the three most commonly chosen to force GCMs and to capture the ‘high’ and ‘low’ ranges, respectively, of the emission spectrum for the Pacific Northwest. The regional averaging approach of the 19 GCMs allows the inclusion of information from all models while still accounting for major discrepancies between GCM outputs across the region (Mote and Salathe, 2009). While recognizing uncertainty inherent to climate predictions, these data represent the most in-depth and comprehensive regional forecasts available. Mean annual snowfall forecasts were subsequently estimated using a multiple linear regression model built from the observed monthly snowfall, temperature, precipitation and elevation data described in Table 1 (\( R^2 > 0.8 \); \( F_{16,55068} = 9762; p<0.00001 \)). Lastly, projected temperature, precipitation and snowfall were input into the random forest classifier, and future statewide hydrologic classifications were produced for A1B and B1 scenarios.

**RESULTS**

**Hydrologic classification**

The most likely classification from the Bayesian clustering analysis produced seven hydrologic classes reflecting a mosaic of distinct flow regime types across Washington State [Figure 2(A)]. Probability of class membership exceeded 99% for all reference gauges, suggesting strong support for the seven-tier classification. Additionally, results from an eightfold cross-validation (i.e. holding out eight of the total 64 gauges, each in turn, and performing a cluster analysis) indicate the classification’s robustness, with adjusted Rand indices between classification memberships ranging from 0.62 to 0.93 (mean = 0.73). The shape of the annual hydrographs was markedly different among the hydrologic classes [Figure 2(B)], with classes characterized by their dominant flow source and referred to as follows: groundwater (GW), rainfall (RF), rain-with-snow (RS), snow-and-rain (SandR), snow-with-rain (SR), snowmelt (SM) and ultra-snowmelt (US) (Figure 2). The geographic distribution of hydrologic classes showed noticeable spatial clustering consistent with a strong orographic influence of the Cascade Range, with each of the seven classes predominantly (although not exclusively) represented on just one or other side of the divide [Figure 2(A)]. US and SM sites are dominated by a strong spring snowmelt signals of differing duration and peak timing compared with RF sites that are controlled by winter rains with negligible influence of snow. The transition classes reflect a hybrid hydrograph containing a mixture of the spring snowmelt and winter rain, either in relatively equal contributions (SandR) or with great contributions of snow (SR) or rain (RS). GW sites are characterized by relatively uniform monthly mean discharge, highlighting a negligible role of precipitation or snowfall on flow patterns within the class [Figure 2(B)].

The GW group is distinguished by its high constancy, predictability and annual minimum and base flow values
relative to other classes (Table II), exhibiting a slight snowmelt signature with no noticeable winter rain signal (Figures 2 and 3). This is consistent with the low precipitation of the Columbia Plateau and basalt-dominated regions of the state. Despite uncertainty associated with having only three reference gauges defining the GW class, the addition of this class (versus a six-class solution in which these sites are classified as RF or transitional) is necessary to characterize much of the Columbia Plateau.

RF sites follow a clear unimodal pattern of high flows in the winter rainy season and low flows during the arid summer, with relatively fast fall rates and low constancy (Figure 3). Winter peak flow variables were most influential in distinguishing this class, specifically mean maximum December and January flows (Table II). These sites follow spatial patterns of strong orographic precipitation, covering the western lowlands of the Coast or Cascade ranges, with additional representation in the lowlands west of the Blue Mountains in southeast Washington.

The three transitional classes (RS, SandR and SR) are all bimodal, differentiated by the relative influence of rain and snow, with RS sites experiencing higher winter than spring flows and the remaining two groups showing higher snowmelt-driven spring flows [Figure 2(B)]. All three groups sustain relatively high base flows, indicative of some combined influence of rain and snow, but higher frequencies and lower durations of high pulse flows in the RS and SandR groups clearly demonstrate a dominant or equal rain influence relative to snowmelt (Figure 3). Similar to the unimodal rainfall signal seen in the RF group, winter flow variables proved most influential in delineating the RS class, whereas the remaining two transitional classes with greater snow influence were distinguished more by variability metrics (Table II), consistent with snowmelt signals. Spatial distribution of the three transitional groups highlights strong orographic effects of the state’s mountain ranges, with RS and SandR sites falling on the wet west side of the Cascades and SR sites on the arid east side of the state.
and the rain shadow along the northeast slope of the Olympic Mountains.

Both SM and US groups are found east of the Cascade divide and can be described by high snowmelt-driven spring flows and little discernible winter rain influence. US separates out the high-elevation and glacier-fed snowmelt systems from the larger SM class, with a later spring melt signal than SM and even more negligible winter rain influence (Figure 2), demonstrated by the degree of deviation of hydrologic metrics describing these influences from the global means (e.g. greater than six deviations below the global mean for mean maximum February flows; Table II) and consistent with small high-elevation streams. Many of the same hydrologic metrics distinguished SM

<table>
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<th>Attribute</th>
<th>Description</th>
<th>Groundwater (GW) (n = 3)</th>
<th>Rainfall (RF) (n = 10)</th>
<th>Rain–snow (RS) (n = 14)</th>
<th>Snow–rain (SandR) (n = 12)</th>
<th>Snow–rain (SR) (n = 9)</th>
<th>Snowmelt (SM) (n = 10)</th>
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<tr>
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<td>ML8</td>
<td>Mean minimum Aug flows</td>
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<td>ML10</td>
<td>Mean minimum Oct flows</td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<td>3.69</td>
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<tr>
<td>ML11</td>
<td>Mean minimum Nov flows</td>
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<td>4.29</td>
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<td>Base flow index</td>
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<tr>
<td>MKML3</td>
<td>Low flow discharge</td>
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<td>MH1</td>
<td>Mean maximum Jan flows</td>
<td>5.02</td>
<td>3.8</td>
<td></td>
<td>-3.58</td>
<td>-3.38</td>
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<td>-3.38</td>
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<td>Mean maximum May flows</td>
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<td>TA1</td>
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<td>3.99</td>
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<td>TL2</td>
<td>Variability in Julian date of annual minimum</td>
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<tr>
<td>TH0</td>
<td>Constancy ((C)) of max daily flow (month)</td>
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<tr>
<td>MKTH2</td>
<td>Predictability ((P = C + M)) of maximum instantaneous flow (month)</td>
<td>4.22</td>
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</table>

Filled cells in the table include the variables for each class in which \(SD > 3\). The figure indicates the number of class-level standard deviations separating the class-level mean from the global mean, with ‘+’ indicating that the class-level distribution is on average greater than the global distribution, whereas ‘−’ implies the opposite. Attributes that were not influential for any class are not included. The relative strength and class divergence for each class are also shown.
sites, but to lesser degrees (Table II). These two snow-dominated groups emerge in the Cascades, northern Rockies and Blue Mountains, but not the Olympics where high elevations receive larger proportions of precipitation as rainfall.

**Predicting hydrologic class for ungauged rivers**

The classification tree indicates that climate factors are the principle discriminators of the hydrologic groups. With the exception of elevation, physical basin attributes (e.g. slope, drainage density, soil porosity, land use) had little importance in the modelling process and were not selected as primary or surrogate splits. Spring (March) precipitation was the primary splitting variable, differentiating between classes dominated by rainfall at lower elevations (left branches: Figure 4) or predominantly rainfall at higher elevations (RS) from the remaining five classes. An intermediate level of annual spring precipitation (between 185.6 and 261.7 mm year$^{-1}$ for March) was predictive of

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Figure 3. Box plots showing variation in selected hydrologic metrics for each flow class. Metrics were selected to capture magnitude, duration, frequency and timing attributes. Codes refer to those proposed in Olden and Poff (2003) with the exception of those marked by *. The lines at the top, middle and bottom of each box represent the 75th percentile, median and 25th percentile of metric values, respectively. Vertical bars (whiskers) represent 90th and 10th percentiles and outliers are represented by symbols.
sites reflecting the snow-and-rain (SandR) hydrograph. For the remaining four classes, annual January (with December and February temperature as competitive surrogates) air temperatures below −5 °C were indicative of snowmelt-driven classes, where more extreme minimum winter temperatures (<−7.7 °C) defined US from SM. SR classes were classified as those sites with relatively warmer January temperatures in basins with annual snowpack exceeding 1741 mm in depth (with April and May temperature as competitive surrogates); the remaining sites were classified as GW.

Based on the random forest classifier, over 75% of class assignments were accurately predicted (calculated based on out-of-bag samples) for reference gauges ($\kappa = 0.70$, $Z = 12.36$, $p < 0.001$). The model achieved highest classification accuracy (87%) for the class with most training data points—RS ($n = 14$). The lowest classification accuracy was 33% for GW sites, of which there are only three training data points, with two misclassified as SandR and SR. The model misclassified at least one gauge into every class except for GW, over-predicting SandR and SM the most (five and four misclassifications, respectively). Variable importance from the random forest classifier was largely similar to the explanatory classification tree presented in Figure 4. Winter temperature variables emerged as the most important, with minimum winter and January temperatures ranking first and second, respectively. October temperature, elevation and March precipitation followed, with a mix of spring, winter and fall temperature variables ranking fifth through tenth in importance. This indicates a ubiquitous but variable predictive effect of temperature. With the exception of elevation, physical basin attributes (e.g. slope, drainage density, soil porosity, land use) had little overall importance as predictors in the random forest model.

Overall, the predicted distribution of normative hydrologic classes across the state corresponded to what could be expected given known physiography, associated orographic effects and climatic zones (Figure 5). Most basins with mountain headwaters demonstrated a logical downstream progression from US or SM, through transition classes, to RF lowlands, illustrating the attenuating signal of snowmelt and increasing role of precipitation as elevation decreases. The mainstem of the Columbia River, however, constitutes an exception in which the high proportion of basin area with both low annual rainfall and winter temperatures (much outside of Washington State) drive its classification as SM, even though it receives a number of large tributaries classified as GW, SR or RF. The predictions highlight the limitations of having found only two suitable reference gauges in the Columbia Plateau, resulting in a broad GW
classification of the region despite other known flow regimes, including RF. This same limitation affects the GW class overall, as there are known GW systems west of the Cascades that the model cannot predict with limited training data.

**Geomorphic classification**

Approximately seven times more channel distance was classified as non-migrating (~85,000 km) versus migrating (~12,000 km), with some 3000 km of river unclassified due to lack of underlying data (DEM) resolution (Figure 5). The ratio of non-migrating to migrating channels did not differ between east and west sides of the Cascade divide. The model generally mapped non-migrating channels at higher elevations (mean elevation = 718 m; SD = 426 m) and lower stream orders than migrating channels (mean elevation = 362 m; SD = 281 m). This lack of channel migration at upper elevations is consistent with previous regional studies (Beechie et al., 2006a) and highlights the density of low-order headwater and steep tributary streams draining the multiple mountain ranges present in Washington State.

Coupling of the binary geomorphic classification with the hydrologic classes produced a 14-tier hydrogeomorphic classification. All 14 classes are present in Washington State. However, migrating US channels are only negligibly represented (~150 km) because US hydrographs tend to occur in high-elevation headwater streams, whereas migrating channels are predominantly associated with low-elevation rivers. The greatest proportion of total river distance was estimated as non-migrating GW channels (~27,000 km), more than double the next most prevalent classes, non-migrating SR and non-migrating RF (each with ~12,800 km). Overall, migrating channels were most represented in the RF class and least in the US class, decreasing in stepwise order from greatest to least rainfall influence. We illustrate the hydrogeomorphic classification for the Skagit River basin in western Washington (Figure 6). The basin has a drainage area of 8106 km$^2$. Its headwaters are in the North Cascade Mountains, and the river flows westward into the Puget Sound. The climate is temperate maritime, although temperature varies widely from mountain to lowland subbasins. Eleven hydrogeomorphic classes are found in the Skagit (although only 10 are visible in Figure 6), and patterns of migration ability typify the rest of Washington State, with the highest elevation segments of each flow class being non-migrating, opening to migrating at lower elevations.

**Forecasting climate-driven changes in hydrologic class**

While recognizing uncertainties in the GCMs, results according to both greenhouse gas emission scenarios indicate large-scale shifts from streams characterized by snowmelt signatures to more rainfall-dominated hydrographs (Figure 7; results for A1B only shown). These changes were more pronounced under the A1B scenario compared with the B1 scenario. Shifts are not limited to stepwise changes between classes (e.g. US to SM or SM to SR) but often represent multi-class changes in the proportion of rainfall influence, such as gross transitions from US and SM to RF classes. According to the A1B scenario, the total river distance belonging to all snow-influenced classes showed losses, with US showing the largest overall percentage loss (~86%), followed by RS (~62%) and SR (~55%). By contrast, the spatial distribution of the RF class increased over 125% (Figure 7). The proportion of GW channels is not estimated to change, reasonably because of their independence of precipitation influence. However, our modelling does not account for groundwater recharge processes that would affect classification of GW sites.

**DISCUSSION**

The hydrogeomorphic classification presented here provides the quantitative foundation necessary to understand flow variability in the Pacific Northwest (USA) and to develop regional environmental flow management plans that balance human and ecosystem demand for freshwater. Our study reveals seven distinct hydrologic classes in Washington State that capture the varying degrees of rain versus snow influence on flow pattern across the state’s landscapes. Classes dominated by either rain or snow—RF, SM and US—exhibit largely unimodal annual hydrographs with a single precipitation form contributing to peak flows. The orographic effect of the Cascade Range is highlighted by disproportionate representation of RF sites on the west side and of US and SM sites on the east side of the mountains. The bimodal hydrographs of the three transitional classes—RS, SandR and SR—illustrate varying degrees of shared rain and snow influence on flow pattern. These sites are found across the state in upper mountain elevations, including the Olympic, Cascade and Blue mountains, but the most snow-influenced of these classes (SR) is largely limited to the east side of the state consistent with the distribution of SM and US sites, and again reflecting the climatic zonation caused by the Cascade Range. A relative insensitivity to precipitation patterns is depicted in the annual uniform flow pattern of the GW sites. The spatial distribution of GW sites is consistent with the national classification of Poff (1996), spanning much of the Columbia Plateau and portions of the San Juan Islands that

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1Available for download at http://www.fish.washington.edu/research/old-enlab/outreach/waeflows.html.
are on the leeside of the Cascade and Olympic ranges, respectively, where steady groundwater inflow is a significant driver of streamflow relative to snowmelt and rainfall.

Although Washington streams fall along a gradient of snow-to-rain source, the evidence for distinct classes is readily seen in several hydrologic metrics. For example, discharge varied least in the class most equally influenced

Figure 5. Predicted normative hydrologic classes for streams and rivers of Washington State according to the random forest classifier (A) and map of geomorphic classification (migrating or non-migrating; B). Diamonds represent the 64 reference gauges and are coloured according to flow class as determined by the Bayesian mixture model (see Figure 2). It is important to note that groundwater predictions are limited by the scarcity of reference gauges in this class \((n = 3)\). This figure is available in colour online at wileyonlinelibrary.com/journal/rra.
by rain and snow, SandR, with variability increasing bi-directionally in a stepwise pattern through the classes towards dominance by either rain or snow (RF or US). This bi-directional pattern of gradient from the dominance of one precipitation form or another, converging on SandR, is seen in metrics of magnitude, timing, frequency, duration and rate of change, but is most strongly evident in the magnitude metrics (e.g. ML16, ML17, MA3). The distinction of flow class along this gradient is important for distinguishing climate change’s more subtle effects on the position of streams along this continuum.

Our analyses revealed that climatic and some topographic factors were strong predictors of hydrologic class, supporting the view that spatial variation in hydrology is determined by interactions among these factors at multiple spatial and temporal scales (Snelder et al., 2005; Poff et al., 2006; Sanborn and Bledsoe, 2006; Kennard et al., 2010b). In particular, the emergence of precipitation variables and elevation as optimal splits in the classification tree implies their role as interactive determinants, with snowpack typically melting later in the season at higher elevations, of the most influential hydrologic metrics in class distinction—timing and magnitude of high flows. The lack of importance of physical basin attributes other than elevation in predicting flow class contrasts other studies (e.g. Snelder et al., 2009a; Kennard et al., 2010b) in which variables such as vegetation and substrate contributed significantly to model performance. This highlights the overarching importance of climatic signal on Washington flow regimes relative to other regions and holds strong management implications including climate change preparedness. Given the broad scale (Washington State) and resolution (flow segment) of this study, this lack of physical basin attribute influence is also consistent with conventional hierarchical topologies that place climate as a first-order driver of flow regime, with basin attributes affecting more localized flow patterns.

Predicting normative flow class to ungauged or regulated rivers presented certain challenges with respect to data availability. As land use and flow regulation increased heavily in the latter half of the 20th century, it is now difficult to find suitable reference gauges in the eastern part of the state and specifically on the Columbia Plateau. The small number of Columbia Plateau sites that met our reference site criteria limited our training dataset and thus our flow class model’s predictive accuracy, particularly for the GW class. Developing a model that reconstructs daily time series of groundwater flow regimes using detailed climatic, geologic and topographic data from additional groundwater-driven gauged sites in the Pacific Northwest.
may provide a solution to this problem but was beyond the scope of this project. Indeed, Kennard et al. (2010b) faced similar challenges with predicting groundwater streams in Australia and identified geologic data quality as a limiting factor. As such, it is important to acknowledge likely over-prediction of groundwater-dominated streams, particularly on the Columbia Plateau.

The high proportion of non-migrating GW channel distance captured by our hydrogeomorphic classification may be attributed to several factors, mainly that GW channels in the Columbia River basin are typically small channels less than 8m wide because of the region’s aridity, precluding their classification as migrating. Other possible factors include that lower elevations dominated by
GW channels were typically not glaciated (i.e., did not form glacial outwash valleys) and thus not prone to erodibility; are often of young, un-erodible basalt surface geology; or that GW systems lack the stream power needed for channel migration and development of flood-plain channels. The increase in proportion of migrating channels as rivers transition from US to RF sites reflects both the increases in streamflow (typically small in high elevation headwater streams classified as SM and US) and increases in valley width. Moreover, lower elevation streams are more likely found in broad valleys formed in part by glaciation, which is spatially coincident with the predominance of RF regimes in the state’s broad lowland valleys. An exception to this rationale, the ~150 km of migrating US channels, likely represents channels in high alpine areas where small headwater streams meander across alpine meadows and have unconfined valleys.

Results from our climate change analysis consistently predict a shift from snow to rain influence among all classes except GW and RF. This general pattern follows that projected by others for the region (e.g., Elsner et al., 2010), and the spatial resolution of our predictions now allows for management planning at the scale of river segment. The affected transitional and snow-influenced classes represent significant total river distance (approximately one-third of the state’s total), and thus changes in their flow regimes will have large effects on timing (and to a lesser extent, amount) of water availability for both humans and ecosystems, including implications for management of dams and diversions designed to capture this water. Our results suggest that less streamflow will be stored as snow for summer release to reservoirs, potentially exacerbating water stress in several regions. Implications for riverine biota include loss of refugia during summer low flows as snowmelt decreases and declines in salmon life-history diversity as the spatial extent of snow-dominated classes (SR, SM and US) is reduced (Beechie et al., 2006b). For example, predicted shifts toward rainfall-dominated hydrologic regimes in Puget Sound imply a significant loss of habitats suitable for the already rare stream-type (which have a longer freshwater residency than ocean-type) Chinook salmon Oncorhynchus tshawytscha. Hence, climate change may restrict our ability to conserve diverse salmon life histories over the long term, as the stream-type life history is dependent upon a diminishing habitat.

Management options can be prioritized (see Palmer et al., 2008) as ecological changes associated with climate change scenarios are predicted for each flow class. Understanding how hydrogeomorphic classes may shift with respect to such scenarios will enhance the efficacy of management actions. For example, physical and ecological functions of complex flood-plain channels may benefit more from higher flows to maintain rearing habitats in secondary channels and to sustain channel migration rates necessary to sustain the physical complexity through time. The high flows may have less ‘functional value’ in smaller non-migrating channels.

The classifications presented here provide several important contributions to flow management in Washington State and represent a template for use elsewhere. First, at the river segment scale, this is the most spatially explicit hydrologic classification in Washington State to date. Second, these are the first coupled hydrologic and geomorphic classifications for any US state to our knowledge. The geomorphic component addresses cases in which, for example, instream flow needs of non-migrating and migrating RS channels may differ enough to warrant distinct environmental flow prescriptions. The coupled hydrogeomorphic classification provides greater opportunity to capture the heterogeneity of flow types and related ecological responses inherent to a landscape as diverse as Washington than just a hydrologic classification, for effective use in environmental flow management. Third, the specification of uncertainty in our final hydrologic classification provided by our use of a Bayesian clustering approach represents a novel approach to flow classifications done in the USA to date. Additionally, as ecological responses to flow are expected to vary by flow class (Arthington et al., 2006; Poff et al., 2010), the list of most influential metrics in the classification presents a distillation of the full suite of metrics down to those that may hold the most ecological relevance. This list can inform selection of focal metrics for future hydro-ecological analyses in the region, such as additional classifications at finer spatial resolutions.

**IMPLICATIONS FOR SETTING ENVIRONMENTAL FLOW STANDARDS**

Regional flow classifications are recognized as a critical step towards efficiently addressing instream flow needs at regional scales (Arthington et al., 2006; Poff et al., 2010). For example, ELOHA lays out a step-by-step process for developing flow–ecology relationships specifically at the scale of regional flow class, with the premise that working at this scale is both reasonable for categorizing ecological response and expeditious of the entire process, enabling swift rule setting for large regions. Following this rationale, regional flow classifications have informed environmental flow setting in several cases. For example, Colorado has developed a watershed flow evaluation tool for predicting ecological risk to several communities (e.g., riparian vegetation, cold and warm water fishes, macroinvertebrates) according to three coarse flow classes (Wilding and Poff, 2009). In Michigan, flow–ecology relationships were modelled for six distinct flow types in the context of a
landscape classification and allowable streamflow withdrawals proposed for various changes in ecological condition for each class (Seelbach et al., 1997). More recently, basins in Michigan were grouped into 11 different classes based on basin size and July temperature and relationships with fish assemblage composition developed for each class (Zorn et al., 2008). Several additional regional flow-related classifications have been completed (for an exhaustive review, see ELOHA Tool box, Public Communication, available at http://conserveonline.org/workspaces/ehlo/documents/bibliography, accessed February 2011), including for all or parts of Pennsylvania, Texas, New Jersey, Missouri and Massachusetts. The underlying data used in the classifications vary from pre-impact observed discharge data (in limited cases) to modelled time series or even inferences from geologic and topographic maps (the latter two situations more common).

The hydrologic classification presented here for Washington provides a high degree of ecological relevance in terms of regional environmental flow management in that it is rooted in robust statistical analysis of observed, pre-impact discharge data, described by ecologically relevant hydrologic metrics, and covers the entire jurisdictional boundary of the state. As in the case studies discussed above, it is hypothesized that the ranges of variation of ecological responses will differ among hydrogeomorphic classes produced here. These distinct ranges of expected response will provide managers with the ability to consider likely ecological outcomes of flow management scenarios, from segment to basin scales.

This study has implications for dam operation, allocation of water rights, regulations associated with species protection and climate change preparedness—all of which are pressing issues in Washington State. For example, Washington populations of five Pacific Northwest salmon and steelhead species (Onchorhyncus spp.) are currently listed as Endangered or Threatened under the Endangered Species Act, with flow alteration cited as major threat in need of mitigation (Crawford and Rumsey, 2009). The ability to predict threats to these populations associated with various flow management scenarios may be critical to their survival. As well, growing numbers of permit exempt wells are being drilled across Washington State as land use shifts rapidly from rural to urban and industrial in tandem with population growth. Current knowledge related to the effects of pumping on streamflow, and whether certain flow regimes are more sensitive than others, is lacking. Rapid proliferation of these wells drives an urgent need to expedite regulation of these allocations based on sound understanding of the ecological tradeoffs so that managers can better mitigate effects of climate-induced decreases in streamflow.

With flow regulation recognized as a leading threat to global freshwater biodiversity (Dudgeon et al., 2006) and population growth leading to ever increasing exploitation of freshwater resources (Alcamo et al., 2005), expeditious and efficient means of determining and protecting environmental flow needs are urgently needed worldwide. This project’s approach provides a template for use well beyond Washington State as the hydrologic and geomorphic classifications and forecasts of class shift according to climate change scenarios can be replicated with other regional data. Once such classifications are complete, environmental flow needs can be quantified (Poff et al., 2010) for immediate incorporation into regional instream flow management and policy.

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