Choosing the Right Tool for the Job: Comparing Stream Channel Classification Frameworks

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ABSTRACT

Stream classification provides a means to understand the diversity and distributions of channels and floodplains occurring across a landscape while drawing linkages between geomorphic form and process. Accordingly, stream classification is frequently employed as a watershed planning tool. In practice, a variety of frameworks are available to managers for classifying rivers, yet little information exists about how frameworks compare. Specifically, the data, time, and expertise required to implement a given classification, consistency of classification results, and the subsequent geomorphic interpretation between multiple frameworks have not been discussed following data-driven framework comparisons. Here we apply four classification methods within a watershed of high conservation interest in the U.S. Columbia River Basin. We compare the results of the River Styles Framework (RSF), Natural Channel Classification (NCC), Rosgen Classification System (RCS), and channel form-based statistical classification. We find that the four frameworks generally classified reach types consistently. Where divergence in classified channel types occurred, differences could be attributed to the (a) spatial scale of input data used, (b) the requisite metrics and their order in completing a framework's decision tree and/or (c) whether the framework attempted to classify current or historic channel form. We discuss the relative effort and disciplinary expertise required to complete each classification, noting that if a framework classifies current or pre-disturbance channel form, results can provide insight on watershed disturbance. By classifying a single watershed using multiple frameworks, we are able to identify trade-offs between frameworks, discussing how each framework mechanistically differs in grouping streams and their driving processes.

1. INTRODUCTION

The physical form of a stream channel is the result of the coupled climatic, vegetative, and hydrogeomorphic processes acting upon it [*Davis*, 1899; *Schumm and Lichty*, 1965; *Buffington and Montgomery*, 2013]. As such, the classification of rivers into reach types by their physical characteristics lends insight into the relative efficacy of the formative processes that shape channels. These insights can be leveraged when assessing channel condition and/or prioritizing the management and restoration of degraded streams [*Kondolf*, 1995; *Fausch et al.*, 2002; *Roni et al.*, 2002]. Numerous frameworks for classifying streams exist, with markedly differing spatiotemporal output scales [see *Montgomery and Buffington*, 1998; *Brierley and Fryirs*, 2005; *Kondolf et al.*, 2005], but over the past two decades, there has been intense debate and criticism of the utility of particular frameworks [*Palmer et al.*, 2005; *Simon et al.*, 2007; *Roper et al.*, 2008; *Lave*, 2009; *Rosgen*, 2009].. These criticisms range from the limitations of a given framework, to criticisms of the decisions that can arise when a given classification framework is misapplied, to the fact that measurements of process rates (e.g. sediment flux, bank stability) are absent from most frameworks and process is more often inferred. An unfortunate effect of these criticisms is that stream channel classification frameworks may not be applied for what they deliver, but for perceptions of past applications. Important decisions about why stream classification is being undertaken in a watershed are often poorly defined at the outset, leading to difficulty in choosing a framework that will best achieve the intended goals and deliver the information required.

The lack of acknowledgement and understanding of the core underlying principles of each framework, and for what purpose they were designed, has been lost in a broader debate involving the relative merits of individual classification frameworks [*Tadaki et al.,* 2014]. The discussion of appropriate channel classification frameworks has been frequently subsumed in a broader conversation on stream restoration [*Wilcock*, 1997; *Lave,* 2008; *Lave,* 2009]. This debate weighs the relative merit of 'process-based' restoration approaches against others that are viewed as simpler, 'form-based' approaches. We argue that this broader debate has been ambiguously executed and often simplistically identifies any restoration that leverages channel type classification for context as 'form-based.' We do not digress into this broad restoration debate here, but instead attempt to evaluate the requirements of, and agreement between, classification frameworks that can inform such channel restoration.

The 'best' classification framework is not simply the least-criticized, nor the oldest, the most popular, or the easiest to implement. In a long and fruitful history of disagreement between proponents and detractors of particular classification frameworks, it would appear that the one tenet upon which all frameworks agree is that *geomorphic context matters* in terms of separating channel reaches [*Buffington and Montgomery*, 2013]. That is, in nearly all frameworks, metrics are used which describe the capacity of a channel to perform geomorphic work and adjust within a valley bottom (e.g. channel gradient, measures of valley setting or entrenchment, and sediment characteristics). At the same time, competing classification frameworks produce results over vastly different spatial scales and may seek to describe past or present channel condition, while also requiring disparate types and amounts of input data, analysis time, and geomorphic expertise. As such, we argue that no single framework is best suited for all classification scenarios across all stream networks, or even within a single watershed. This suggestion is similar to that made by *Buffington and Montgomery* [2013] in their recent review on the geomorphic classification of rivers. Instead the choice to employ a classification framework, and the ensuing choice of which classification to use, varies depending on the management or research objectives of a given watershed or reach-scale assessment. A secondary consideration is that the 'best' framework is the one that matches the time, data, and financial resources available to the practitioner and their level of geomorphic expertise.

Despite the fact that the relevance or utility of a particular classification framework may vary on a case-by-case basis [*Tadaki et al.*, 2014], few, if any, direct comparisons have been made between the application of several classification frameworks. One byproduct of this lack of a direct comparison is that practitioners and researchers alike may not understand the inherent uncertainty of the classified output and the relative resource commitment and insight provided by one framework versus another. Instead of relying on direct comparisons of the applications and trade-offs between frameworks, watershed managers may instead fall back on the framework they are most comfortable with or know best. While there is a growing body of literature with examples of how individual stream classification frameworks can be applied [*Savery et al.*, 2001; *Thomson et al.*, 2004; *Beechie and Imaki*, 2014], here we present a direct comparison of stream classification frameworks, discussing not only classification outputs, but also the process by which each classification aggregates reaches into groups that reflect geomorphic processes in their patterns.

This paper applies four classification frameworks across a watershed of high conservation interest in the Pacific Northwest, USA. Our goal is to understand the similarities and differences in their outputs. Where the frameworks differ, we attempt to ascertain the methodological differences that lead to divergence in classification. We further explore the complexity of each analysis, along with the requisite amount of time and degree of geomorphic expertise necessary for successful stream classification using each framework. Herein we focus on the ***River Styles Framework*** (RSF; *Brierley and Fryirs*, 2005), the ***Natural Channel Classification*** (NCC) method developed by *Beechie and Imaki* [2014], and the popular ***Rosgen Classification System*** **(RCS;** *Rosgen*, 1994; *Rosgen and Silvey*, 1996] approach to stream classification. We contrast these with a statistical classification approach that clusters field-measured, reach-scale data into groups based on channel form. While both the RSF and RCS are well known and commonly applied, the NCC framework as presented here uses elements of the *Montgomery and Buffington* [1997] framework, whereas the statistical classification we use is a good proxy for similar approaches commonly used in geomorphology (e.g. *Sutfin et al.*, 2014) and hydrology (e.g. *Coopersmith et al.*, 2014). This research aims to familiarize watershed scientists with select classification frameworks of the many that are available. In so doing, we anticipate that this discussion will also assist those seeking to perform stream classification in selecting a framework that addresses the geomorphic processes at work in the watershed of interest, while also matching their resources and expertise.

2. METHODS

2.1. STUDY SETTING

The Middle Fork of the John Day River (Oregon, USA) is 117 km long and drains 2051 km^2 within the broader Columbia River Basin (Figure 1). The landscape is largely composed of metamorphic and igneous rocks underlain by basalt and older extrusive rock, which have been uplifted and reworked to create a watershed marked by steep-sloped canyons, deeply dissected highlands, dissected tablelands, and rounded uplands containing broad meadows. The watershed is generally semi-arid, receiving 560 mm of annual precipitation throughout the basin on average [*PRISM Climate Group*, 2014]. However, the John Day Basin is also marked by distinct elevation-dependent precipitation boundaries: the upper 10% of elevations receive an average of 880 mm of precipitation, while the lowest 10% receive 370 mm. Average annual streamflow measured at the Ritter, Oregon gauging station (USGS #14044000, A_d = 1334 km^2; 83 years of record) is 7.36 m^3s^{-1}. This varies considerably from the spring months when snowmelt in the uplands causes peak flows that average 21.0 m^3s^{-1} to low summer base flows that average 1.1 m^3s^{-1}. Lowland vegetation is dominated by sagebrush (*Artemisia sp.*) and grasslands interspersed with juniper (*Juniperus sp.*), while uplands are comprised of forests dominated by subalpine fir (*Abies lasiocarpa*), Engelmann's spruce (*Picea engelmannii*), lodgepole pine (*Pinus contorta* spp. *latifolia*) and Douglas fir (*Pseudotsuga menziesii*). Riparian vegetation ranges from gallery cottonwood (*Populus balsamifera*) forests to alder (*Alnus spp.*) and willow (*Salix spp.*) shrublands to wetland meadows dominated by sedges (*Carex spp.*), graminoids, and forbs.

2.2. COLUMBIA HABITAT MONITORING PROGRAM

Reductions in native fish populations throughout the Columbia River Basin, including the Middle Fork John Day River, have led to large-scale aquatic habitat monitoring across the Columbia Basin. In particular, steelhead trout (*Oncorhynchus mykiss*), listed as threatened under the U.S. Endangered Species Act, have seen drastic reductions in the size of their runs [*Nehlsen* 1997], presumably as a direct effect of anthropogenic habitat degradation [*Waples et al.*, 2009]. As a result, sub-watersheds throughout the Columbia River Basin have received intensive monitoring efforts to document the status and trend of salmonid populations and habitats. For example, the U.S. Bureau of Reclamation [2008] has completed channel classification based on valley confinement [e.g. *Frissell et al.*, 1986] and associated geomorphic condition assessments for selected sediments of the mainstem Middle Fork John Day River. Additional classifications documenting the suitability of habitat for native vegetation have been performed by *Beschta and Ripple* [2005], along with assessments of morphologic variability and the presence of thermal refugia for salmonids along the mainstem [e.g. *Torgerson et al.*, 1999; *McDowell*, 2001].

The Middle Fork John Day River is also monitored as part of the larger Columbia Habitat Monitoring Program (CHaMP; see http://www.champmonitoring.org). CHaMP data are collected at wadeable, perennial streams throughout the Columbia River Basin [*US EPA*, 2006]. Here we use survey data from the Middle Fork John Day River watershed collected during 2012 and 2013 (n = 33 sites). Discrete sampling reaches in the 2012-2013 dataset are twenty times as long as the bankfull channel width at each site and range from 120 to 360 meters in length. We use CHaMP data derived from field measurements of channel bankfull width and depth, gradient, substrate, and sinuosity.

2.3. THE RIVER STYLES FRAMEWORK

The River Styles framework seeks to provide a “coherent set of procedural guidelines with which to document the geomorphic structure and function of rivers, and appraise patterns of river types and their biophysical linkages in a catchment context” [*Brierley and Fryirs*, 2005]. In practice, the RSF offers the potential for a process-based, watershed-scale classification system for rivers, with implications for prioritizing their management and restoration. It consists of four distinct stages that progress from (1) classifying landscapes and current river form and function, to (2) assessing geomorphic river condition in context of reach evolution, to (3) understanding and forecasting trajectories of river change, and (4) prioritizing catchment management. A full description of the methods entailed in the RSF can be found in *Brierley and Fryirs* [2005]. Here we describe the application of stage one of the River Styles framework, which has been completed for the Middle Fork John Day River as part of an ongoing effort to contextualize site-specific CHaMP monitoring data in a watershed-wide framework [*O'Brien and Wheaton*, 2015]. Stage one provides a baseline assessment of current reach types (referred to as 'river styles') in a system with emphasis on longitudinal variability of stream form (i.e. longitudinal profile analyses) along the mainstem channel and tributary network.

The RSF explicitly couples channel form and watershed process, beginning with the classification of landscape units (Figure S.1). Each landscape unit has a propensity to contain a unique distribution of river styles. Within a given landscape unit, stream reaches are classified based on their valley confinement, presence or absence of floodplains, channel planform, distribution of in-channel and floodplain geomorphic units, and dominant channel substrate (Table S.1). In contrast to the other classification systems presented herein and those used among practitioners [e.g. *Rosgen,* 1994; *Montgomery and Buffington,* 1997], there is no intrinsic limit on the number of river styles that may occur in a watershed of interest. In practice, once the diversity of river styles for a particular watershed is known, a river style tree (Figures S.2 – S.4) can be constructed that allows for the classification of any stream segment from a finite list. The top-level discriminator in the RSF is valley confinement (Figures S.2 – S.4), which *Brierley and Fryirs* [2005] define as "the proportion of the channel length that abuts a confining margin on either side." Therein, *confined* channel reaches abut a confining margin along more than 90% of their length, *laterally unconfined* channel reaches abut a confining margin along less than 10% of their length, and *partly confined* channel reaches abut a confining margin along 11-89% of their length [*Fryirs and Brierley*, 2010b].

We used O'Brien and Wheaton's [2015] delineation of river styles for the MFJD where the boundaries between landscape units were defined using geospatial datasets for elevation (10 m and 1 m digital elevation models; *US Geological Survey*, 2014), slope, underlying geology [*Walker and MacLeod*, 1991], dominant vegetation [*US Department of the Interior*, 2012], and Level IV EcoRegion boundaries [*US Environmental Protection Agency*, 2013]. Following the delineation of landscape units, individual river styles were initially digitized on the National Hydrography Dataset (NHD; as polylines in ArcGIS; ESRI, Redlands, CA) using aerial photos (*US Department of Agriculture*, 2012; 1 m resolution) and elevation datasets as a guide. Field visits were conducted in the summer of 2012 and 2013 to confirm the accuracy of these delineations, refine the distinguishing characteristics of each river style and its location in the river style tree (Figures S.2 – S.4) and pinpoint boundaries between river styles.

2.4 NATURAL CHANNEL CLASSIFICATION

Beechie and Imaki [2014] constructed a probabilistic map of pre-disturbance, alluvial channel planforms observed in the Columbia River Basin, USA (drainage area 674,500 km^2). Beechie and Imaki's [2014] classes include *confined* channels and four channel patterns for unconfined reaches: *straight, meandering, island-braided,* and *braided*. These four unconfined channel patterns are commonly identified planforms for alluvial, floodplain rivers [*Leopold and Wolman,* 1957; *Schumm,* 1985; *Beechie et al.,* 2006], which have distinctly different morphology, dynamics, and ecological attributes [*Ward et al.,* 2002; *Beechie et al.,* 2006]. In NCC, confinement is considered simply as the ratio of bankfull width to valley width, and unconfined channels are those where the valley floor width is more than four times the bankfull width. Predictor variables in the model were based on known physical controls on channel pattern, including channel gradient, discharge, valley confinement, sediment supply, and sediment size [*Benda et al.*, 2004]. Channel slope, discharge, and confinement were estimated directly from digital elevation models. Relative reach slope, percent of watershed in unvegetated alpine terrain, and percent of watershed in fine-grained erosive sediments were hypothesized to be surrogates for sediment supply and size, respectively. Relative slope is the slope of a reach minus the slope of its upstream neighbor. Positive relative slope values indicate that a reach is steeper than its upstream neighbor (likely sediment supply-limited or undersupplied), and for a given slope and discharge is likely be narrower, deeper, and more armored [*Schumm*, 1985; *Dietrich et al.*, 1989], whereas negative values indicate that a reach is more likely to have low transport capacity relative to bed load supply (i.e., transport-limited or oversupplied), and will likely be wider, shallower, and finer grained or less armored.

For all channel segments with bankfull width > 8 m, attributes were assigned to each 200-m long reach in the study area (> 2,000,000 reaches) based on available geospatial data, and adjacent reaches with similar characteristics were then aggregated into sets of geomorphically meaningful reaches. A sample of more than 30 relatively natural reaches of each channel pattern was selected as the training data set (i.e., the natural channel pattern was not obscured by contemporary land use or dams); hence, the model should predict channel patterns expected in the absence of human impacts, rather than current channel form. A support vector machine

(SVM) classifier was used to relate all 63 possible combinations of reach attributes to channel pattern using a total training data set of 147 reaches. The multiple models were evaluated using cross-validation (classification accuracy), and the most accurate SVM model was then used to predict channel pattern for all reaches in the study area. Bootstrapping of the final model created 1000 separate predictions of channel pattern for each reach, and the consistency of predictions can be used as an indicator of model uncertainty for each reach. For example, if 85% of the predictions for a reach were 'braided,' we considered that reach to have a high likelihood of having a braided channel pattern. This statistical approach produces maps of (1) the most likely channel pattern for each reach in the Columbia River Basin, and (2) uncertainty in the channel pattern prediction. For channels with bankfull width < 8 m, reaches were classified as pool-riffle, plane-bed, step-pool or cascade based on channel gradient [*Montgomery and Buffington*, 1997].

2.5. *ROSGEN CLASSIFICATION SYSTEM*

The Rosgen Classification System (RCS; *Rosgen*, 1994; *Rosgen*, 2011) is widely used to assess channel condition and in the design of reach-scale stream restoration projects, providing a standardized workflow for river classification based on a field survey of the geomorphic characteristics of a particular stream reach. RCS consists of four hierarchical stages of classification moving from coarse to fine spatial scales [*Rosgen*, 2009]. In Level I, the system uses spatial data describing valley confinement, channel planform, local soil types, hydrologic regime, and watershed physiography to establish a broad geomorphic characterization of river reaches. In Level II, the geomorphic characteristics of a site (e.g. entrenchment ratio, width/depth ratio, sinuosity, median grain size, and gradient) are assessed and a particular stream type is assigned to the reach using the decision tree first presented by *Rosgen* [1994]. Like the RSF and

NCC, in Level II the RCS emphasizes valley setting and confinement early in the process. RCS uses a field-measured entrenchment ratio (channel wetted width at two times bankfull depth divided by the bankfull width), which is analogous to the bankfull to valley width ratio that NCC uses as a proxy for confinement. In Level III, the stream's condition is assessed based on channel planform, bed and bank stability, occurrence and type of riparian vegetation, and any alterations in flow regime. Finally, stream types delineated in Levels II and III are field-checked by direct measurements of sediment transport and size, flow, bed/bank stability, and rates of bank erosion to ensure a valid stream type classification has been made (Level IV).

We classified the 33 CHaMP reaches in the Middle Fork John Day watershed (Figure 1) using Levels I and II of the RCS. Channel form data used to complete RCS classification were collected during the summers of 2012 and 2013. We used digital elevation models, aerial imagery, and ground-based assessments to infer the Level I valley types surrounding each CHaMP reach. Delineation of bankfull elevation was completed by trained technicians in the field and surveyed as part of the CHaMP topographic survey. Calculations of width-to-depth ratio, channel sinuosity, entrenchment ratio, and channel gradient were derived from CHaMP topographic survey DEMs (0.1 m grid resolution) using the River Bathymetry Toolkit (RBT; *McKean et al.*, 2009). A bankfull water surface was derived by detrending a DEM and best-fitting a water stage through the measured bankfull points and examining inflections in the hydraulic geometry using the CHaMP Topo Toolbar (https://sites.google.com/a/northarrowresearch.com/champtools/). Measurements that typically are derived from cross sections using RCS were derived from averages of 100+ of cross sections spaced at 1-meter intervals at every CHaMP site and processed using the River Bathymetry

Toolkit. These metrics allowed us to categorize each CHaMP reach into broad level RCS stream types (A-G). By combining broad RCS stream types with median grain size data (D_{50}) collected during CHaMP surveys, we classified each site into a final channel type according to the RCS classification. Although we did not explicitly validate our reach type delineations in the field (e.g. Level IV as described above), the wealth of on-the-ground photographs and high-resolution topographic data (0.1 m-resolution DEMs) collected as part of CHaMP surveys were used to ensure the validity of classified reaches.

2.6 STATISTICAL CLASSIFICATION

We classified the 33 CHaMP reaches in the Middle Fork John Day Watershed by clustering reaches on their multiple instream geomorphic attributes: bankfull width, wetted width, site sinuosity, stream gradient, bankfull width to depth ratio, and D_{16}, D_{50}, and D_{84} particle size. CHaMP metrics that reflect sediment size and channel form were selected in order to maintain consistency with data used in the classifications presented in Sections 2.3, 2.4, and 2.5. We selected a partitioning around medoids clustering algorithm to identify clusters of distinct reach types, testing for differences in stream attributes between reach clusters using PERMANOVA [*Anderson*, 2001]. We plotted the cluster solution within a principal components analysis (PCA) of the same stream channel attributes, visually comparing the classification of CHaMP reaches between each method. Full clustering methods and results are presented in the supporting information.

2.7. SPATIOTEMPORAL SCALES OF CLASSIFICATION FRAMEWORKS

Each of the four classification frameworks discussed here requires data from, and produces outputs at, different spatial scales and points in time. Both the requisite scale of input data and the scale of output channel classifications are important when considering which framework is appropriate for a particular application. The data requirements and outputs of each framework are shown in Table 1. We discuss only the spatiotemporal scales of input/outputs used for the stage(s) of each framework completed here. The River Styles framework requires information at the watershed scale, including data describing land cover, climate, and bedrock/surficial geology (particularly for the delineation of landscape units). It requires reach-scale information describing channel confinement and the distribution of in-channel and floodplain geomorphic units, ultimately classifying current channel types continuously at the network scale, which in turn require site-level visits for validation of stream types and confirmation of the location of reach breaks.

Natural Channel Classification uses regional-scale input data describing slope, bedrock and surficial geology, and vegetation cover to derive a continuous prediction of background (e.g. pre-disturbance) channel types across a large land area (here, the Columbia River Basin). The Rosgen Classification System requires field-based, reach-scale measurements of channel and floodplain geometry and physical characteristics (e.g. sediment size, channel gradient) to classify current reach types at the site scale. Finally, statistical clustering employs similar site-scale data of the user's choosing to classify current channel types at the reach scale. Here we employed metrics for clustering reaches most similar to those used in the other frameworks described (see Section 2.6). Note that while the RSF and NCC may be downsampled to derive discrete site-scale reach types from the continuous network-scale classification, it is difficult to upscale the reach types classified by the RCS and statistical clustering to produce a continuous, network-scale classification of past or present channel types.

2.8 ASSESSING CLASSIFICATION FRAMEWORK AGREEMENT

To compare the level of agreement between each classification framework at the 33 CHaMP sites discussed in Section 2.2, we compared classifications by approximating analogous reach types between each classification framework. We began by using the eight reach types identified by Natural Channel Classification, as these descriptors provided intuitive and widely-known examples of channel planforms and associated physical characteristics. For each NCC reach type, we identified the most closely related reach types from the RSF, the RCS (using top-level channel types A-G), and statistical clustering. Where available (RSF, RCS), decision trees were used to select those reach types that best approximated each NCC type based on common geomorphic metrics (gradient, geomorphic units present, planform). In the case of statistical clustering, the geomorphic attributes inherent to each of the four clusters (Figure 4) were used to approximate the corresponding NCC reach type. Those RSF, RCS, and statistical clustering reach types that were most closely related to each NCC type were classified as being in "good" agreement (e.g. all geomorphic attributes of the reach type could conceivably be present in the associated NCC channel class), while those which were only marginally related to each NCC class (that is, some aspects of the reach types fit with an NCC class while others did not) were classified as having "moderate" agreement (Table 3). RSF, RCS, and clustering reach types with no characteristics in common with NCC classes were classified as having "poor" agreement. While this method is inherently qualitative, we attempted to take an inclusive approach when determining agreement among reach types between frameworks, as considerable geomorphic variability can exist across each reach type within a given framework [*Rosgen*, 1996*; Brierley and Fryirs*, 2005].

3. RESULTS

3.1. THE RIVER STYLES FRAMEWORK

In total, 14 distinct river styles were classified across the MFJD Watershed. To begin, landscape units were classified across the watershed (Figure S.1). The river styles trees showing the characteristics of each river style are shown in Figures S.2 - S.4, and the distribution of river styles within the MFJD Watershed is shown in Figure 2.1, with distinctions made based on valley confinement (confined, partly confined, laterally unconfined; Fryirs and Brierley, 2010). Overall, confined valley channels were the most common river styles across the MFJD Watershed (86% of total stream length), whereas channels in partly confined valley (8%) and laterally unconfined valleys (6%) were far less common although they comprise the majority of the mainstem (Figure 3.1). Small, low-order, confined channels (boulder bed and steep ephemeral hillslope river styles) comprised the majority of total stream length within the watershed (68%, Table 2). Regarding the most common classifications of CHaMP sites, 33% of sites were classified as partly-confined valley with low-moderate sinuosity planform-controlled discontinuous floodplain reach types, 15% were classified as confined valley with occasional floodplain pockets, and 12% each were classified as partly-confined valley with meandering planform-controlled discontinuous floodplain and bedrock-controlled elongate discontinuous floodplain reach types (Figure 3.1). Classification of all channels (approximately 4100 km total length) across the MFJD Watershed required roughly three to four months to complete using desktop based reach delineation and field work.

3.2 NATURAL CHANNEL CLASSIFICATION

Natural Channel Classification derived nine channel patterns across the Columbia River Basin [*Beechie and Imaki*, 2014], eight of which were predicted within the MFJD Watershed (Figure 2.2). By total stream length, the majority of reaches (83%) were small channels with bankfull width < 8 m. Across the MFJD, 35% of the total reach length was classified as step-pool channels, and 25% classified as plane-bed channels [*Montgomery and Buffington*, 1997]. For channels > 8 m bankfull width, 8% of the total reach length was classified as having a straight planform, 3% of channels classified as island-braided, and 2% classified as meandering (Figure 3.2; Table 2). The remaining reaches > 8 m were classified as confined channels because valley width was less than four times bankfull channel width [*Beechie and Imaki*, 2014]. With regard to the most common classifications of CHaMP sites, 25% of sites each were classified as straight or plane bed reaches, with an additional 15% of sites classified as pool riffle (Figure 3.2). Classification was completed for all channels > 3 m bankfull width over the entirety of the Columbia River Basin. Model development, including data collection and pre-processing - projecting to a common coordinate system, mosaicking of individual raster tiles - and subsequent analysis required roughly two months to complete. Once data were collected and pre-processed, actual model run time was approximately two days.

3.3 ROSGEN CLASSIFICATION SYSTEM

We classified 11 RCS stream types within 33 CHaMP surveyed reaches in the MFJD Watershed (Figure 2.3). The most common stream types, each containing 24% of the CHaMP reaches, were B4 (stable plane bed with occasional pools) and C4b (low gradient, meandering, riffle/pool sequences; Figure 3.3). In total, 50% of the reaches were B stream types, all of which were within valley type II (colluvial, moderately steep and confined), with a single exception. C stream types (sinuous, wide and low-gradient) were the next most common (27%) and E (highly sinuous, coarse-fine bed), F (entrenched, wide, moderately sinuous, low gradient), and G (entrenched, low-gradient, low width:depth ratio) types were the least common (3% each). Only one CHaMP site had a substantial length of side channels (24%), however the other metrics did not fit a D stream type. Therefore, we did not delineate any multi-threaded channels (RCS stream type D). Surveying of individual CHaMP sites required approximately eight hours of crew time (typically 2-4 individuals), although some of this time was spent collecting data not used in the classifications here. Subsequent manual RCS classification of all 33 CHaMP sites required about two weeks.

3.4 STATISTICAL CLASSIFICATION

Because statistical clustering does not have an *a priori* set of outcomes, we compared multiple classification results (two to ten groups of channels) from the partitioning around medoids algorithm. We selected a four cluster final solution based on cluster fidelity, minimizing overlap between cluster groups (Figure 4; Tables S.2. – S.4.). After plotting the final cluster solution within a principal component analysis, the clustered stream channel attributes showed that each group differed based on multiple channel form attributes. Accordingly, each cluster was named based on the dominant attributes that differentiated clusters from one another. The four final groups consisted of (1) narrow, sinuous, high-gradient reaches (n=7), (2) wide, low-gradient, coarse substrate reaches with high width to depth ratios (n=5), (3) high-gradient, narrow reaches with moderate-sized substrates (n=16), and (4) moderate gradient, wide and sinuous, coarse-substrate reaches (n=5; Figure 4). The number of CHaMP sites assigned into each cluster are shown in Figure 3.4. Channel clusters were significantly different from one another (PERMANOVA; $p < 0.05$), and particle D_{16}, D_{50}, and D_{84} were the attributes that were most strongly correlated to the principal component analysis (Tables S.2. – S.4.). Clusters in the final four cluster solution were distinct (silhouette widths 0.24-0.60; mean width 0.41; Figure 4). The cluster group assigned to each CHaMP site is shown in Figure 2.4 and Figure S.7. Because the same CHaMP sites were classified using statistical clustering and RCS, the time spent on data collection is identical to RCS classification detailed above. Actual run time of clustering algorithms was less than one minute.

4. SYNTHESIS

4.1. COMPARING OUTPUTS BETWEEN CLASSIFICATION FRAMEWORKS

Stream channel classification often relies on multiple landscape, watershed, and reach-scale attributes to create pattern-based groups of reaches that reflect hydrologic, geomorphic, and often, ecological processes. Here we classified 33 individual reaches into river styles, Natural Channel Classification planform types, Rosgen Classification System classes, and statistically clustered groups of reaches. We followed each classification framework's data requirements (Table 1) in this process, relying on a mix of remotely-sensed landscape data and field-collected stream channel data.

The analysis of agreement between reach types of each framework used here (Section 2.8; Table 3) generally indicates that more often than not, frameworks produced reach type classifications that were congruent with one another. When comparing the level of agreement between NCC and each of the other three frameworks at 33 CHaMP sites (for a total of 99 comparisons), we found "good" agreement at 60 sites (61%), "moderate" agreement at 19 sites (19%), and "poor" agreement at 20 sites (Table 4). Thus, reasonable agreement was found at 80% of sites. The reasons that the reach classification of each framework does (or does not) agree with those of the other frameworks may be the result of the spatial scale of the requisite input data, the timeframe (e.g. current or historic) that each framework attempts to classify or alternatively may arise as a result of differences in the workflow of each framework. To illustrate this, here we discuss four cases exhibiting a range of agreement between frameworks (Figure 5).

At a confined valley reach on the Middle Fork John Day River (CHaMP site: CBW05583-004682), we found a B4c RCS type, wide, low-gradient statistical cluster, island-braided NCC, and entrenched bedrock canyon river style (Figure 5). The statistical classification matched the definition of a wide, low-gradient, B4c RCS channel type. While it is plausible that a B4c RCS channel type and an entrenched bedrock canyon river style could be applied to the same reach, the island-braided NCC classification is deserving of further exploration as it may hint at a departure from historic channel condition, which NCC attempts to predict. Subsequent field visits by *O'Brien* [Personal Communication] note that numerous deposits of legacy sediment [e.g. *Walter and Merritts*, 2008] above the active channel at this site, along with the wide valley bottom allowing a high capacity for channel adjustment, may imply that the system was overwhelmed by sediment during the early Holocene. As such, the pre-disturbance classification of an island-braided channel using NCC may be appropriate in this case, and could hint at the background morphology of the channel. Thus, the divergence in classified reach types at this site may arise as a result of NCC's attempting to discern the background, pre-disturbance channel planform, while the other frameworks classify present channel condition.

In contrast, we found good agreement between all classification frameworks at two example reaches. The first is a laterally unconfined reach on the Middle Fork John Day River (Figure 5; CHaMP site: CBW05583-003826) classified as a G4c RCS type, narrow sinuous statistical cluster, pool-riffle NCC, and meandering gravel bed river style. The second site is a partly confined reach on Slide Creek (Figure 5; CHaMP site: CWB05583-144394), classified as a meandering planform-controlled discontinuous floodplain river style. This site was further classified as an E4 RCS reach, pool riffle RCC type, and narrow, sinuous statistical cluster. At these locations, the combination of geomorphic characteristics produced a reach classification that was highly similar in terms of valley setting, planform, and assemblage of geomorphic units between all four frameworks. In the case of the former site, the reach occurs within a broader ~10 km reach of the Middle Fork John Day that exhibits a sinuous planform in an unconfined valley. The latter site also occurs in a ~5 km segment of Slide Creek that exhibits a consistent meandering planform. These more longitudinally-continuous reaches are undoubtedly helpful for agreement in classification among continuous frameworks (e.g. RSF and NCC) that may use disparate spatial scales of data (e.g. NHD+ and field-based validation versus NHD and basin-scale 10 m DEMs, respectively) and derive classifications remotely prior to field-based verification.

An example moderate agreement site was found in a partly confined valley setting on Slide Creek (Figure 5; CHaMP Site CBW05583-013322). This reach showed different, but plausible combinations of channel types. The reach was classified as a partly-confined valley with meandering planform-controlled discontinuous floodplain river style - whose in-channel geomorphic unit assemblage is essentially repeating pool-riffle sequences - and pool-riffle in NCC, but was classified as a B4 RCS and steep, narrow statistical cluster. Reaches such as this one that exhibit mixed agreement between classification frameworks highlight that subtle differences in channel form, such as channel gradient and sinuosity, can lead to significant differences in the classification of an individual reach. These differences arise as a result of the hierarchical and statistical clustering classifications used here, as the order of appearance of geomorphic metrics in a decision tree can vary between frameworks and subsequently affect classification output.

Individual reaches classified into groups of similar morphologies within one framework sometimes failed to align with a comparable group under another classification framework (Table 4). This pattern was most apparent in confined reach types that did not aggregate into consistent groups across statistical clusters, Rosgen Classification System types, and natural channel classes. For example, River Styles' confined valley with occasional floodplain pockets were classified as all four statistical clusters, five different RCS reaches, and three NCC classes (Table 4). In contrast, partly confined channel types were more likely to be grouped into only one or two channel types from other classifications. For example, River Styles' partly confined low-moderate sinuosity, planform-controlled discontinuous floodplain grouped into RCS types of C4b and B4, and NCC classes of plane bed or straight planform, and steep/narrow and narrow/sinuous statistical clustering classes. Additionally, the partly confined low-sinuosity planform-controlled anabranching river style occurred exclusively as B4 RCS classes, straight, narrow statistical cluster, and straight NCC. The partly confined bedrock-controlled elongate discontinuous floodplain river style classified as slightly to moderately entrenched, moderate sinuosity RCS types (C, B channels), and wide, low-gradient clusters, but was less consistently grouped by NCC (straight, confined, and island braided). While strict fidelity between groups within each classification did not occur, partly confined River Styles grouped well with the other classifications based on their component inputs.

4.2 WHY DO CLASSIFICATION FRAMEWORKS DIFFER?

Differences in the output of classification frameworks ultimately arise because each framework emphasizes physical variables differently throughout the classification process. Although the data requirements between classification frameworks are similar, including channel planform metrics, substrate, and the ability of a channel to migrate and access sediment sources (Table S.1), the order in which these attributes appear within a particular framework's decision tree may vary markedly (see Supporting Information). For example, at the broad planform scale, the first step in the differentiation of reach types within the RCS is to distinguish between single- and multi-thread channels. In contrast, this characterization of channel planform is completed several steps later in the River Styles framework, which instead places the greatest importance on the degree of valley confinement. Both RCS and River Styles, however, make their final differentiation between stream types based on the bed material texture within a reach.

Natural Channel Classification and statistical clustering, as employed here, both use field-measured or remotely-sensed channel data to classify and group reaches based on their physical similarity. Using gradient, discharge, valley confinement, sediment supply, and sediment caliber estimated from GIS data, NCC classified historic reach types in a 147-reach training data set before classifying an entire stream network. Each reach type was probabilistically assessed through resampling procedures to provide a measure of error (uncertainty). Here, statistical clustering was used with unweighted variables that estimate channel width, gradient, sediment size, and ability to move laterally (sinuosity). These workflows and their predictor variables, while similar to RCS and RSF in that they require reach-level data from which they fit groups, differ markedly in how they group channels. A key difference between the statistical methods (NCC and statistical clustering) and RCS or RSF is that while RCS and RSF explicitly incorporate channel form (e.g. number of channels, sinuosity, entrenchment) into the classification system, the statistical methods use variables that can be expected to predict channel form (e.g. sediment size, channel dimensions, basin lithology, landscape cover).

When considering statistical approaches such as NCC and clustering as employed here, all physical attributes are used in the grouping algorithm, and true hierarchical decision trees are foregone. Because most statistical classification techniques computationally determine which of the input variables are most important in differentiating stream types, ranking them accordingly, *a priori* importance is not placed upon a given variable. While variables can be weighted in clustering and machine-learning algorithms to emphasize the importance of specific processes, many classifications, like NCC's support vector machine, instead use training data to fit algorithms before computing classes for a data set. This approach is limited not by what variable is perceived to be most important, but rather, what training data are available from which to build a model. Similar constraints exist on clustering, which can only group reaches that have data available. In building representative statistical classifications, having spatially-balanced, randomized sampling is ideal [*Stevens and Olsen*, 2004]. Another key methodological consideration in using statistical classification approaches is that the number of classes is often determined by the strength of the fit between data and algorithm, and must be validated by expert judgment of the classified statistical groups and their geomorphic likelihood. Relatively strong clustering was observed here with a relatively small number of classes (four), whereas the other three classification schemes had between eight and eleven classes. Accordingly, parameter and algorithm selection, data transformation or standardization can all influence how well data fits a given clustering algorithm, with consequences on whether geomorphically meaningful groups are lumped or split.

More generally, the difference in the relative importance of each physical variable within a particular classification framework points to the form-process interactions that each classification method attempts to document or explain. Distinct differences are also evident when the original intent of the classification framework is considered. Some frameworks produce analyses of current reach type (e.g. RSF, RCS, statistical clustering), while others predict pre-disturbance or natural channel morphology (e.g. NCC). Differences in the temporal output of each framework may not be intuitive, but provide a critical context for interpreting and using the outputs derived [*Grabowski et al.*, 2014].

Likewise, in stage one, River Styles attempts to aggregate channels into current groups regardless of their condition; an assessment of channel disturbance is made in later stages, and as such there can be significant variability in the geomorphic characteristics of a single stream type. Thus, the divergent temporal scales of classification necessitates the use of different datasets between these classifications (Sections 2.2 through and 2.4), and as a result channel reaches are classified quite differently when comparing the two frameworks depending on whether current or background channel form/condition is taken into account (Figure 2). The River Styles framework, while also providing a reach-scale classification, places a large degree of importance on landscape-scale controls and patterns of reaches in driving channel dynamics, and thus requires the integration of watershed-scale data (e.g. landscape unit delineation, Section 2.2) in concert with local valley confinement classifications. Taken to the extreme, the results of the statistical clustering approach (Section 2.5) are *entirely* dependent on user-defined data inputs, and variability in the results of this classification framework can be largely ascribed to the choice of metrics fed into the classifier.

5. DISCUSSION

A useful classification framework is one that aggregates channels into geomorphically - and often ecologically - meaningful groups within a watershed that match the purposes of the application at hand. This aggregation into groups may reflect current or historic channel conditions, and should reflect geomorphic processes that control channel form and condition. Our comparison of four distinct classification frameworks demonstrates that there is significant overlap and agreement between the workflows in terms of basin-wide channel classification. The most common classification in all four frameworks was some variant of moderate-high gradient channel with coarse substrate, reflecting the high relief nature of the Middle Fork John Day Basin resulting from resistant igneous and metamorphic lithologies (Figure 2, Table 2). Similarly, the least common channel types in all four frameworks were those variants corresponding to wide, freely meandering, low-gradient streams. Ironically, these laterally unconfined streams are the ones most emphasized in classic channel planform classification and fluvial geomorphology text books [*Knighton*, 1998], although they are rare in many montane regions [*Fryirs and Brierley*, 2010]. Despite the general similarity between the classification frameworks, different approaches can provide strikingly different answers in several cases, and comparisons of these classification frameworks' results are not always straightforward. Therefore, it is imperative that watershed managers understand the underlying formative processes that control river diversity across their watershed of interest, and implement a classification framework that best suits the aims of the classification.

For example, in watersheds heavily influenced by mill dams or beaver ponds and their associated legacy sediment deposits [*Walter and Merritts*, 2008; *Polvi and Wohl*, 2013], the NCC classification approach may not provide the most informative stream classification as this method attempts to predict pre-disturbance channel planforms. However, in cases where post-colonization channel and landscape alterations are so pervasive that they are reflected in DEMs and vegetation data, the NCC approach will more likely predict a natural channel type expected under current conditions rather than the pre-disturbance condition. In contrast, RCS or RSF both lend importance to local-scale channel dimensions and, particularly in the case of RSF, the patterns of river types in a system, and may be quite revealing in pinpointing stream reaches that vary from expected channel forms. Such understandings are pivotal in appraising prospective adjustments to rivers [*Fryirs et al.*, 2009].

The utility of any classification is highlighted by how each framework can be applied in support of watershed or stream condition assessment or used to aid decision-making. While some frameworks are not inherently designed to provide information about past or future condition (e.g. statistical classifications), they can provide examples of the range of conditions within a set of monitored reaches. For example, reach-level monitoring data acquired from programs like EPA Wadeable stream assessment [*US Environmental Protection Agency*, 2006], PACFISH/INFISH Biological Opinion [*Kershner et al.*, 2004], or the CHaMP reach data used here can be used to identify the range of potential channel forms via statistical classification. When channels are classified across broad spatial extents, those reach types consistent with particular process domains, and their characteristic downstream progression in a basin, can be understood [*Montgomery*, 1999] and anomalous or poor-condition reaches identified.

Both RSF and RCS provide guidance in later stages for determining the condition of individual reaches and prioritizing channel restoration activities. Both classifications have been used in planning for watershed disturbance or restoration [*Brierley et al.*, 2002; *Hey*, 2006]. NCC is a historic planform classification and can be used in concert with knowledge of current channel form to make inference on whether and how changes in sediment supply, floodplain access, hydrology, or vegetation have led to stream degradation. Similarly, these historic forms can be used as restoration baselines where known hydrogeomorphic processes can be restored. Each of these classifications may also provide information regarding habitat availability or suitability for benthic invertebrates, fish, or riparian vegetation, enabling holistic understanding of a stream ecosystem [*Thomson et al.*, 2004]. For example, states and transitions between river styles, statistical classes, or RCS reach types may correspond to observed changes in populations and communities of aquatic biota, although the degree to which these classification frameworks are ecologically meaningful merits further research [*Thomson et al.*, 2004].

In many cases, the degree of data, time, effort, or expertise necessary for the completion of a channel classification (Figure 6) may be a primary determinant of which framework is chosen. Because of these issues of convenience, we caution that care must be taken to assure the information provided by that framework is consistent with the driving processes most related to management concerns in the watershed of interest. It is critical to specify the resolution at which the framework was used and the degree of confidence in the output data. With regard to the classification frameworks examined here, both RCS and statistical clustering are relatively straightforward in application, and require minimal time and data to complete for a set of reaches (Figure 6). The simplicity of RCS's reach-scale classification is one of the major reasons for its widespread use within the watershed management community [*Palmer et al.*, 2005]. In our case, the RCS classification presented here (Section 2.4) required roughly three weeks to complete, excluding field data collection. Although the level of computational and statistical expertise required to complete and interpret the results of a statistical clustering framework is not trivial, the rapidity with which clustering or simple statistical classifications can be completed, altered, and adaptively run is attractive. Once metrics are selected for use in the clustering algorithm (Section 2.5), the classification can be run in a matter of minutes. It is essential to point out that in reach-level methods like RCS and statistical clustering, field-based data collection are imperative for successful classification (and verification of reach types in the case of RCS). Because we used an existing, high-resolution dataset to complete these classifications, the time spent classifying reaches was greatly reduced.

In the case of RCS, the classification produced an output in which we have a high level of confidence: that is, we expect the classified channel type to accurately reflect the site-level conditions in nearly all classified reaches. At the same time, we note that in RCS, field-based measurement and validation of classification is of high importance, and so our confidence in classification output would be increased with subsequent site visits. We are somewhat less confident that statistical clustering will produce groups of channels that always reflect conditions in the field. This is because both the clustering algorithm and the choice of the number of groups – in effect, the number of representative channel forms found at individual reaches – is inherently a choice of the classifier. Much like RSF, the user is forced to compromise between selecting an informative number of classification groups and creating parsimonious groups from which to make generalization (i.e. lumping versus splitting groups), which has major implications for subsequent statistical analyses.

In contrast, the NCC framework and RSF require greater investments of time, and require greater expertise in fluvial geomorphology to achieve meaningful classification results (Figure 6). Not including algorithm refinement, the NCC classification can be completed for a large watershed (e.g. data gathering, preparation, computation time) in roughly two months' time. However, automated classification over broad areas means that we cannot be as confident in the validity of site-level predictions when using NCC; in fact, site visits to confirm predictions of NCC may not be straightforward since the framework attempts to classify pre-disturbance, and not current, channel planform. Stage one of the RSF, as detailed in Section 2.2, required an investment of roughly 3-4 months. This timeframe included a desktop-based classification, field-based refinement of classes, and field-based ratification of reach boundaries which produced relatively high levels of confidence in the outputs produced. In the case of NCC, computational expertise is paramount, in addition to a thorough understanding of the landscape-scale controls (independent of anthropogenic disturbance) on channel planform throughout a watershed of interest. In the case of RSF, a similar understanding of both landscape and local-scale controls on channel form is required, as is the ability to distill the formative processes within a watershed down to the most relevant geomorphic characteristics for classification. Other frameworks that are based on morphometric analyses alone may not provide nuanced process-based understanding, but come with the advantage of requiring less geomorphic expertise for completion.

Perhaps obviously, the increased amount of time and expertise required for implementation of the RSF or NCC is counterbalanced by the larger spatial extent across which either framework can be applied, creating continuous, network-scale results (Figure 2; Figure 6.3; Section 2.7), and in the case of RSF the level of process-based detail that is generated. While it would be difficult, if not impossible, to upscale the results of RCS or statistical clustering to approximate a continuous classification throughout a stream network, this scale of classification is a fundamental component of both RSF and NCC. As such, information regarding reach-scale anomalies in channel characteristics can be easily gleaned from continuous network-scale classification frameworks. Placing classified sites along a continuum of channel types using RCS or statistical clustering requires a full representation of the range of potential channel types. To use either framework for network to watershed scale analyses would be difficult without a significant increase in the amount and resolution of data collected in a watershed.

Finally, we note that one of the as-yet unmentioned hallmarks of a ‘good’ classification framework is repeatability. That is, when confronted with the same watershed (or dataset), to what degree will two individuals come to the same conclusions regarding the number of reach types and their locations throughout the watershed? The answer to this question has major implications for the transferability of a classification across systems and communication to stakeholders. Unfortunately, this is a largely unexplored question, and must be more fully addressed before the utility of individual classifications can be assessed. Given knowledge of the prescribed workflow for each framework, we can attempt to draw inferences regarding the repeatability of each classification used herein. The reliance of NCC and statistical clustering on pre-determined algorithms indicate that they will be highly repeatable between classification runs, *provided* that the same input data (e.g. the same set of measurements) are used during each run. The number of clusters that are settled upon in a statistical clustering workflow is often reliant on a combination of fit statistics and expert judgment on the attributes being clustered, which may lead to variability in the final number of reach types that are classified.

The finite number of selectable reach types in the RCS classification, along with the discrete workflow and associated measurements that must be taken while working through the hierarchical tree, suggest that RCS may also be highly repeatable. While inherent observer variability may lead to differences in final stream type [e.g. *Roper et al.*, 2008], Rosgen [2009] argues that this issue may be corrected by increased field crew training, with particular regard for the identification of bankfull discharge level, which influences entrenchment ratio. The RSF does not set concrete quantitative breaks between distinguishing attributes leading to reach types (with the possible exception of valley confinement; Figure S.2 – S.4) and does not set intrinsic limits on the number of reach types that may be present within a watershed. As such, the number of, and distinguishing factors between, basin-wide reach types using River Styles may differ between investigators.

6. CONCLUSIONS

Classification frameworks are useful for understanding the formative processes that shape channels, either historically or under present conditions. Despite the utility of channel classification, the debate surrounding their relative merits and focus on form versus process of individual frameworks has led to the view that some classification systems are 'better' than others. In fact, the utility of information gained from a particular classification framework depends largely on the classification's intended use. We classified both individual reaches and the full perennial stream network within the Middle Fork John Day River watershed, Oregon, USA, according to four frameworks. In general, we found that the frameworks classified reach types relatively consistently. Where differences occurred between frameworks, those differences could be attributed to variability in (a) the spatial scale of input data used, (b) the relevant metrics and their order in completing a framework's decision tree, or (c) whether the framework attempted to classify current or historic channel form. Additionally, the frameworks require a range of investments of time and geomorphic expertise and result in classification at different spatial scales, from discrete sites to continuous classification across a stream network. The diversity of requisite input data, characteristic timeframe, and necessary investments of time and geomorphic expertise imply that there is no 'best' classification framework. Here we have attempted to highlight the differences so that individual practitioners and researchers can choose the appropriate classification tool for their specific needs.

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Statement of Author Contributions

This manuscript was conceptualized by AK, NH-S and RC and written by NH-S, AK, RC, GB, TB, DLR, JMW, KF, MJ, GO, and NB. Figures and tables were made by AK, NH-S, and MJ. Data was collected, managed, and analyzed by AK, NH-S, RC, HI, MJ, TB, GO, NB. Author order was determined by coin-toss between NHS (tails) and AK (heads). Following AK and NHS, author order is presented alphabetically and reflects equal contributions to the manuscript.

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framework operates. Note that all classifications require either significant data, expertise in statistics and/or geomorphology, and that the position of each framework in panels reflects the stage(s) to which their workflows were completed in this study only.

Table 1.

Classification Framework (abbreviation)	Description	Examples	Data requirements	Classified output	References
River Styles Framework (RS)	A hierarchical, multi-scale classification scheme for describing river character and behavior. River Styles can be used to understand river condition, recovery potential and prioritize management.	Use in river management practice across NSW, Australia [*Brierley et al.*, 2002, 2011*; Fryirs and Brierley*, 2005] Determined correlates to downstream sediment storage and landscape connectivity [*Fryirs and Brierley*, 2001, 2010; *Fryirs et al.*, 2007a, b; *Kuo and Brierley*, 2013] Ecological community composition varies as a function of River Styles [*Thomson et al.*, 2004; *Chessman et al.* 2006]	Field, remote-sensing and other GIS data on geology, hydrology, and stream geomorphic setting to identify broad-scale to local controls on river character and behavior.	Continuous stream network (NHD+)	[*Brierley and Fryirs*, 2001, *Brierley et al.*, 2002, 2011, 2013; *Brierley and Fryirs*, 2005]
Columbia Basin Natural Channel Classification (NCC)	NCC is a model-based stream classification using a machine learning (support vector machine) algorithm to group reaches based on their historic, undisturbed planform. Divides reaches into groups based on channel width before sub-dividing on reach-level remote sensing data.	A historic planform map and dataset for the Columbia River Basin [*Beechie and Imaki*, 2014]	Remotely-sensed channel slope, discharge, valley confinement, sediment supply, and sediment size are used as predictors of channel planform in a modeling framework.	Continuous stream network (NHD)	[*Beechie and Imaki*, 2014]

Rosgen Classification System (RCS)	RCS is a stream-reach taxonomy based on field-collected empirical data that classifies geomorphic stream features to identify stream types by numerically bounded physical metrics. This is arguably the most commonly used stream classification system in North America and the world.	RCS can be employed to successfully restore a reach to a reference condition, provided that the reference reach is stable [*Hey*, 2006] RCS stream type classifications provide inferences into the sensitivity of stream reaches to natural channel changes [*Newman and Swanson*, 2008]	Valley morphology for broad context, and reach-scale monitoring data to calculate basic dimensionless metrics linking form to physical processes.	Individual reaches within a stream network (field-monitored reaches)	[*Rosgen*, 1994; *Rosgen and Silvey*, 1996]
Statistical Classification (SC)	Statistical classification refers to any classification methods used to differentiate or group stream reaches, watersheds, etc. based on multiple physical, chemical, and/or biological attributes. Attributes are often selected for their role in driving or responding to dominant processes within a catchment.	Prioritizing conservation and restoration within mined watersheds [*Merovich et al.*, 2013]; Comparing restored, forested, and urban channels [*Laub et al.*, 2012]; Identifying vegetation communities and environmental filters [*Hough-Snee et al.*, 2014]; Classification of desert washes [*Sutfin et al.*, 2014]	Requires reach-scale monitoring data for "bottom-up" classifications. Requires remote sensing and GIS data to classify reaches from the "top-down" or correlate classified reaches to larger-scale environmental or physical processes.	Individual reaches within a stream network (field-monitored reaches)	*Hough-Snee et al.*, [2014]; *Sutfin et al.*, [2014]; Discussed in *Buffington and Montgomery* [2013]

Table 2.

Classification framework	Reach types		Total stream length (km)	% Total length	% CHaMP reaches	# CHaMP reaches
River Styles	Confined valley	Boulder bed	1230.7	30.2	3.0	1
		Entrenched bedrock canyon	121.1	3.0	6.1	2
		Occasional floodplain pockets	242.5	6.0	15.2	5
		Step cascade	37.9	0.9	0	0
		Steep ephemeral hillslope	1542.3	37.9	0	0
		Steep perennial headwater	319.4	7.8	0	0
	Partly confined (discontin-uous flood-plains)	Meandering planform controlled discontinuous floodplain	34.5	0.8	12.1	4
		Low sinuosity planform controlled anabranching	18.2	0.5	6.1	2
		Low-moderate sinuosity planform-controlled discontinuous floodplain	170.2	4.2	33.3	11
		Bedrock controlled elongate discontinuous floodplain	113.8	2.8	12.1	4
	Laterally unconfined	Low-moderate sinuosity gravel bed	31.9	0.8	3.0	1
		Alluvial fan	49.3	1.2	3.0	1
		Meandering gravel bed	62.9	1.5	6.1	2
		Intact valley fill	99.4	2.4	0	0
Columbia Basin Natural Channel Classification	Bankfull width > 8m	Straight	132.9	7.8	24.2	8
		Meandering	34.7	2.0	9.1	3
		Island-braided	42.8	2.5	6.1	2
		Confined	76.5	4.5	9.1	3
	Bankfull	Plane bed	431.5	25.4	24.2	8

	width < 8m	Pool riffle		129.9	7.7	15.2	5
		Step pool		595.3	35.1	12.1	4
		Cascade		253.7	14.9	0	0
Rosgen Classification System	Entrenched	A	A4			12.1	4
		F	F3			3.0	1
		G	G4c			3.0	1
	Moderately Entrenched	B	B3c			6.1	2
			B4			24.2	8
			B4a			3.0	1
			B4c			15.2	5
	Slightly Entrenched	C	C3b			3.0	1
			C4b			24.2	8
		E	E3			3.0	1
			E4			3.0	1
Statistical classification	Narrow, sinuous (1)					21.2	7
	Wide, low-gradient (2)					15.2	5
	High-gradient, narrow (3)					48.5	16
	Wide, sinuous (4)					15.2	5

Table 3.

NCC reach type	*River Styles reach type*	*RCS reach type*	*Statistical cluster*
Island Braided	Low Sinuosity Planform Controlled Anabranching (G)	D (G)	2: Wide, Sinuous (M)
	Intact Valley Fill (M)		
	Alluvial Fan (M)		
Meandering	Meandering Gravel Bed (G)	C (G)	4: Wide, Sinuous (G)
	Meandering Planform-Controlled Discontinuous Floodplain (G)	E (G)	1: Narrow, Sinuous (M)
	Low-Moderate Sinuosity Gravel Bed (M)	G (M)	2: Wide, Low-Gradient (M)
	Low-Moderate Sinuosity Planform-Controlled Disc. Floodplain (M)	F (M)	
	Bedrock-Controlled Elongate Discontinuous Floodplain (M)		
	Low-Moderate Sinuosity Gravel Bed (M)		
Straight	Boulder Bed (G)	A (G)	2: Wide, Low-Gradient (G)
	Meandering Planform-Controlled Disc. Floodplain (G)	B (G)	3: Steep, Narrow (G)
	Confined Valley – Floodplain Pockets (G)	G (M)	
	Low-Moderate Sinuosity Partly Confined Disc. Floodplain (G)		
	Low-Moderate Sinuosity Gravel Bed (G)		
	Alluvial Fan (M)		
	Bedrock-Controlled Elongate Discontinuous Floodplain (M)		
Confined	Entrenched Bedrock Canyon (G)	A (G)	1: Narrow, Sinuous (G)
	Confined Valley – Floodplain Pockets (G)	F (G)	3: Steep, Narrow (G)
	Step Cascade (G)	G (G)	2: Wide, Low Gradient (M)
	Steep Perennial Headwater (M)	B (M)	
	Steep Ephemeral Hillslope (M)		

Table 3. (Continued)

NCC reach type	*River Styles reach type*	*RCS reach type*	*Statistical cluster*
Cascade	Step Cascade (G)	B (G)	3: Steep, Narrow (G)
	Boulder Bed (G)	F (G)	1: Narrow, Sinuous
	Floodplain Pockets (M)	G (G)	
	Steep Perennial Headwater (M)	A (M)	
	Steep Ephemeral Hillslope (M)		
Pool Riffle	Meandering Gravel Bed (G)	C (G)	1: Narrow, Sinuous (G)
	Meandering Planform Controlled Discontinuous Floodplain (G)	F (G)	2: Wide, Low Gradient (G)
	Confined Valley – Floodplain Pockets (G)	G (G)	4: Wide, Sinuous
	Bedrock-Controlled Elongate Discontinuous Floodplain (G)	E (G)	
	Low-Moderate Sinuosity Planform Controlled Disc. Floodplain (M)	B (M)	
	Meandering Partly-Confined Floodplain (M)		
Step Pool	Boulder Bed (G)	B (G)	3: Steep, Narrow (G)
	Step Cascade (G)	F (G)	1: Narrow, Sinuous (M)
	Steep Perennial Headwater (G)	G (G)	
	Steep Ephemeral Hillslope (G)	A (M)	
	Confined Valley - Floodplain Pockets (M)		
Plane Bed	Entrenched Bedrock Canyon (G)	A (G)	3: Steep, Narrow (G)
	Confined Valley – Floodplain Pockets (G)	B (G)	1: Narrow, Sinuous (F)
	Bedrock Controlled Elongate Discontinuous Floodplain (G)	C (G)	4: Wide, Sinuous (F)
	Low-Moderate Sinuosity Planform Controlled Disc. Floodplain (G)	F (G)	
	Meandering Planform Controlled Floodplain (M)	G (G)	
	Boulder Bed (M)		
	Steep Perennial Headwater (M)		
	Steep Ephemeral Hillslope (M)		

Table 4.

CHaMP Site ID	Stream name	UTM Easting	UTM Northing	Rosgen Class. System	Statistical Clustering	Natural Channel Classes	River Styles	River Style valley confinement	Agreement
CBW05583-250506	Lunch Creek	377638	4930916	A4	Narrow, sinuous	Step Pool	Boulder Bed	CV	RS: Good RCS: Mod Cluster: Good
CBW05583-004682	Middle Fork John Day River	333505	4971313	B4c	Wide, low-gradient	Island Braided	Entrenched Bedrock Canyon	CV	RS: Poor RCS: Poor Cluster: Poor
CBW05583-021066	Middle Fork John Day River	337657	4968709	F3	Wide, sinuous	Confined	Entrenched Bedrock Canyon	CV	RS: Good RCS: Good Cluster: Mod.
CBW05583-144114	Vinegar Creek	380932	4942422	A4	Steep, narrow	Step Pool	Floodplain Pockets	CV	RS: Mod. RCS: Mod. Cluster: Good
CBW05583-223986	Bridge Creek	379613	4935524	B4	Steep, narrow	Plane Bed	Floodplain Pockets	CV	RS: Good RCS: Good Cluster: Good
CBW05583-456690	Butte Creek	369488	4942756	A4	Steep, narrow	Plane Bed	Floodplain Pockets	CV	RS: Good RCS: Good Cluster: Good
OJD03458-000017	West Fork Lick Creek	357991	4940711	B4a	Steep, narrow	Step Pool	Floodplain Pockets	CV	RS: Mod. RCS: Good Cluster: Good
CBW05583-051954	Dry Fork Clear Creek	383698	4934662	E3	Wide, sinuous	Straight	Floodplain Pockets	CV	RS: Good RCS: Poor Cluster: Poor
CBW05583-189938	Granite Boulder Creek	369068	4945617	B4	Wide, low-gradient	Straight	Alluvial Fan	LUV	RS: Mod. RCS: Good Cluster: Good
CBW0558	Middle	376782	4941104	C4b	Steep,	Meandering	Low-Moderate	LUV	RS: Mod.

3-449266	Fork John Day River				narrow		Sinuosity Gravel Bed		RCS: Good Cluster: Poor
CBW0558 3-003826	Summit Creek	386503	4937885	G4c	Narrow, sinuous	Pool Riffle	Meandering Gravel Bed	LUV	RS: Good RCS: Good Cluster: Good
CBW0558 3-358130	Squaw Creek	388721	4936107	B4c	Steep, narrow	Pool Riffle	Meandering Gravel Bed	LUV	RS: Good RCS: Mod. Cluster: Poor
CBW0558 3-289522	Middle Fork John Day River	378688	4939623	C4b	Steep, narrow	Island-Braided	Bedrock-controlled Elongate Discont. Floodplain	PC	RS: Poor RCS: Poor Cluster: Poor
CBW0558 3-275954	Middle Fork John Day River	364436	4947549	B3c	Wide, low-gradient	Straight	Bedrock-controlled Elongate Discont. Floodplain	PC	RS: Mod. RCS: Good Cluster: Good
CBW0558 3-290034	Middle Fork John Day River	370912	4944299	B3c	Wide, low-gradient	Straight	Bedrock-controlled Elongate Discont. Floodplain	PC	RS: Mod. RCS: Good Cluster: Good
CBW0558 3-415218	Middle Fork John Day River	361529	4948510	C3b	Wide, low-gradient	Confined	Bedrock-controlled Elongate Discont. Floodplain	PC	RS: Poor RCS: Mod. Cluster: Mod.
CBW0558 3-030730	Camp Creek	352247	4942752	B4	Steep, narrow	Straight	Low-Moderate Sinuosity Planform-Controlled Discontinuous	PC	RS: Good RCS: Good Cluster: Good

							Floodplain		
CBW0558 3-330226	Camp Creek	357015	4947826	B4c	Steep, narrow	Straight	Low-Moderate Sinuosity Planform-Controlled Discontinuous Floodplain	PC	RS: Good RCS: Good Cluster: Good
CBW0558 3-118770	North Fork Bridge Creek	375925	4933066	A4	Narrow, sinuous	Step Pool	Low-Moderate Sinuosity Planform-Controlled Discontinuous Floodplain	PC	RS: Poor RCS: Mod. Cluster: Mod.
CBW0558 3-299658	Clear Creek	382042	4930368	B4c	Narrow, sinuous	Plane Bed	Low-Moderate Sinuosity Planform-Controlled Discontinuous Floodplain	PC	RS: Good RCS: Good Cluster: Mod.
CBW0558 3-438922	Dry Fork Clear Creek	384597	4933274	C4b	Narrow, sinuous	Straight	Low-Moderate Sinuosity Planform-Controlled Discontinuous Floodplain	PC	RS: Poor RCS: Poor Cluster: Poor
CBW0558 3-234122	Clear Creek	382238	4929332	B4	Steep, narrow	Plane Bed	Low-Moderate Sinuosity Planform-Controlled	PC	RS: Good RCS: Good Cluster: Good

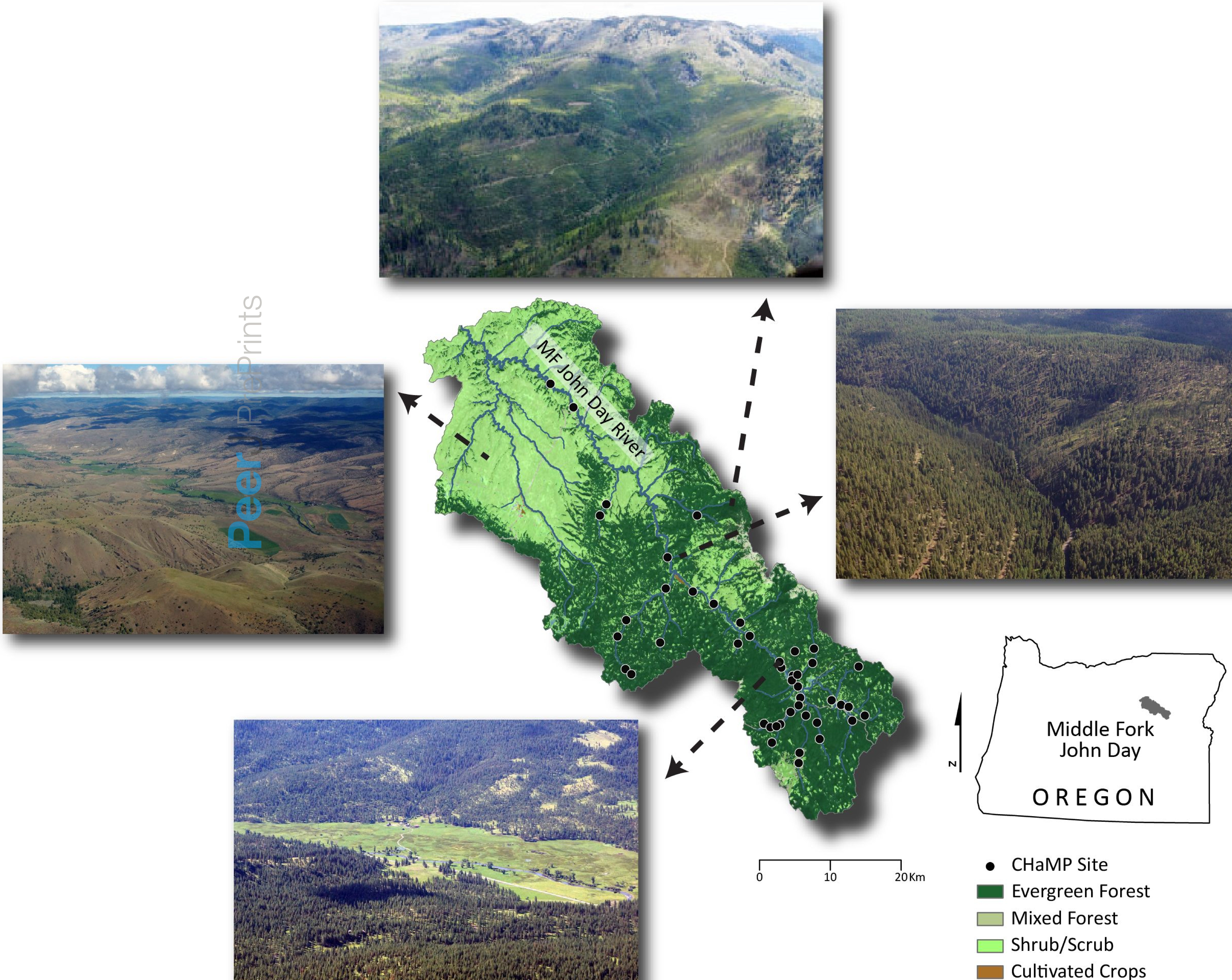
							Discontinuous Floodplain		
CBW0558 3-381682	Vinegar Creek	380718	4944390	C4b	Steep, narrow	Plane Bed	Low-Moderate Sinuosity Planform-Controlled Discontinuous Floodplain	PC	RS: Good RCS: Good Cluster: Good
CBW0558 3-383986	Camp Creek	353774	4936398	C4b	Steep, narrow	Plane Bed	Low-Moderate Sinuosity Planform-Controlled Discontinuous Floodplain	PC	RS: Good RCS: Good Cluster: Good
CBW0558 3-404210	Vinegar Creek	379442	4940614	B4	Steep, narrow	Plane Bed	Low-Moderate Sinuosity Planform-Controlled Discontinuous Floodplain	PC	RS: Good RCS: Good Cluster: Good
CBW0558 3-477938	Clear Creek	381713	4935379	B4	Steep, narrow	Straight	Low-Moderate Sinuosity Planform-Controlled Discontinuous Floodplain	PC	RS: Poor RCS: Good Cluster: Good
OJD0345 8-000536	Vinegar Creek	378654	4940187	C4b	Steep, narrow	Plane Bed	Low-Moderate Sinuosity Planform-Controlled Discontinuous Floodplain	PC	RS: Good RCS: Good Cluster: Good
CBW0558	Summit	390544	4937077	C4b	Wide,	Pool Riffle	Low-Moderate	PC	RS: Mod.

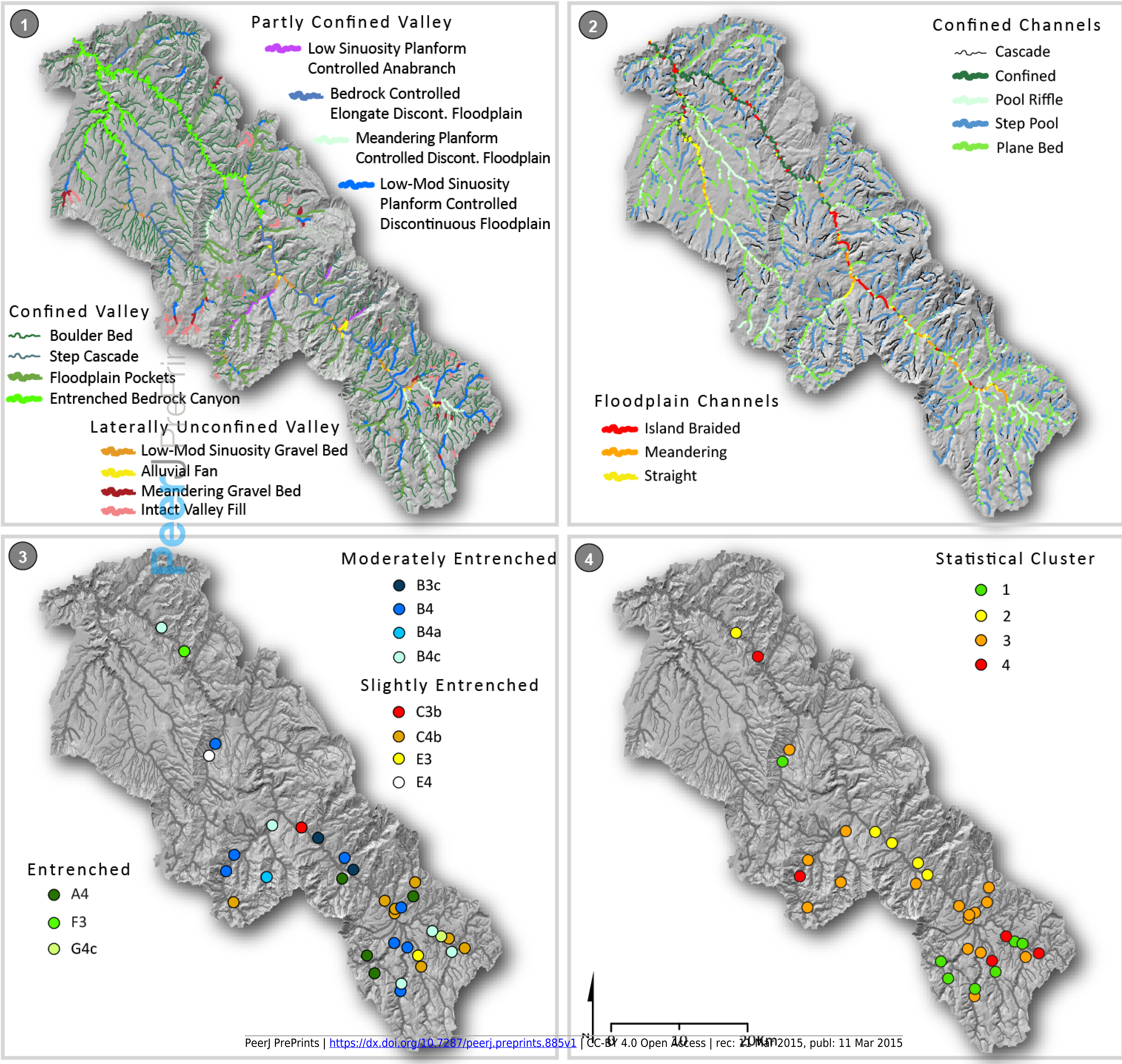
3-325362	Creek				sinuous		Sinuosity Planform-Controlled Discontinuous Floodplain		RCS: Good Cluster: Good
OJD0345 8-000031	Camp Creek	351579	4940332	B4	Wide, sinuous	Confined	Low-Moderate Sinuosity Planform-Controlled Discontinuous Floodplain	PC	RS: Poor RCS: Mod. Cluster: Poor
CBW0558 3-144394	Slide Creek	344959	4955342	E4	Narrow, sinuous	Pool Riffle	Meandering Planform-Controlled Discontinuous Floodplain	PC	RS: Good RCS: Good Cluster: Good
CBW0558 3-429810	Summit Creek	387760	4937802	C4b	Narrow, sinuous	Meandering	Meandering Planform-Controlled Discontinuous Floodplain	PC	RS: Good RCS: Good Cluster: Mod.
CBW0558 3-013322	Slide Creek	345607	4957140	B4	Steep, narrow	Pool Riffle	Meandering Planform-Controlled Discontinuous Floodplain	PC	RS: Good RCS: Mod. Cluster: Poor
CBW0558 3-298738	Middle Fork John Day River	385006	4938373	B4c	Wide, sinuous	Meandering	Meandering Planform-Controlled Discontinuous Floodplain	PC	RS: Good RCS: Poor Cluster: Good

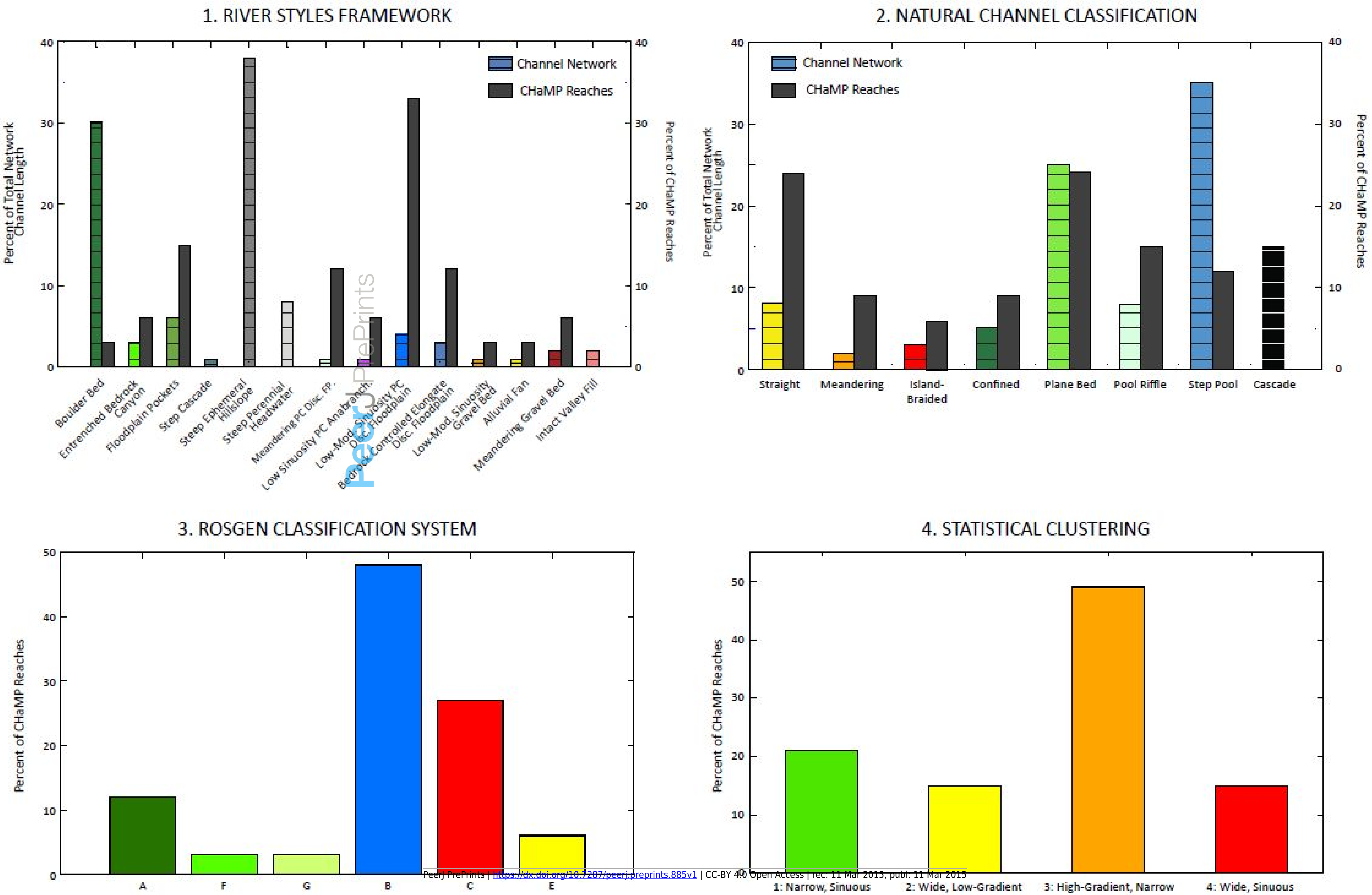
Table 5.

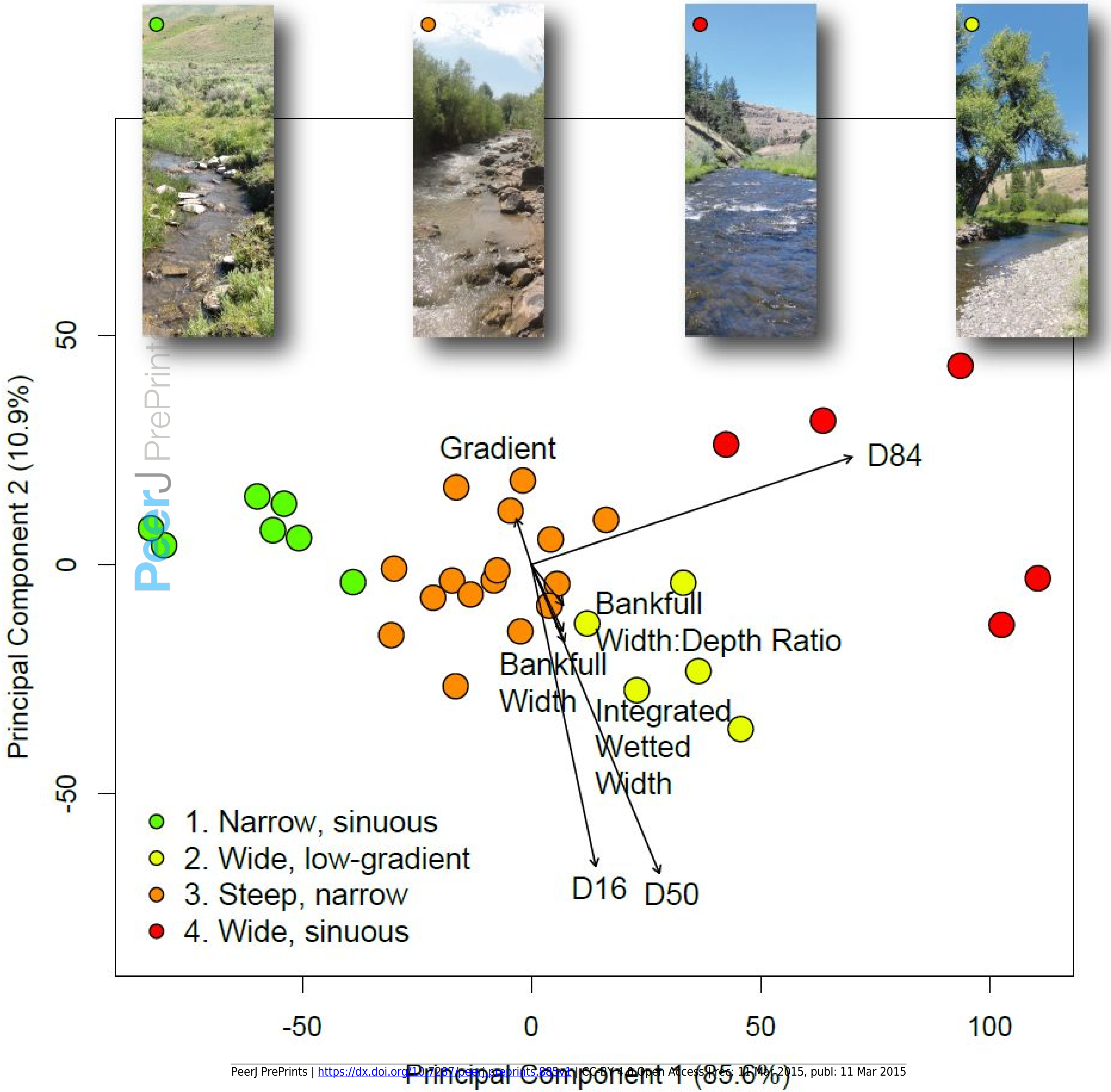
Classification framework	Potential advantages	Potential drawbacks
River Styles	Explicitly uses watershed-, reach- and geomorphic unit-scale processes to classify stream segments [*Thomson et al.*, 2004]. Bi-directional (top down/bottom up) approach captures holistic vision of watershed (e.g. *Kuo and Brierley*, 2013)	Requires relatively high-level understanding of fluvial and landscape geomorphology
	Uses flexible, defined criteria of both river forms and processes to identify groups of reaches and their requisite driving processes [*Brierley and Fryirs*, 2005]	Data-intensive; requires a combination of spatially extensive desktop data along with field-based information on reach/unit-scale channel form
	Open-ended and generic approach that can be used in any watershed [*Brierley and Fryirs*, 2005]	Open-ended and generic approach that can be used in any watershed [*Brierley and Fryirs*, 2005]
	Includes components for appraising channel condition, recovery potential and prioritizing restoration and management [*Brierley and Fryirs*, 2005, 2008].	Time-Intensive; examination of spatial data and development of river styles tree requires large time investment
Columbia Basin Natural Channel Classification	Spatially extensive, pre-calculated planform classification for channels > 3 m in width across the Columbia River Basin.	NCC channel classes are currently limited to the Columbia River Basin, but the methodology is transferable to other locations.
	Identifies possible restoration targets where planform has been modified by watershed disturbance, changes in hydrologic regime or sediment supply.	Pre-disturbance planform may not reflect current watershed disturbances or processes. Conversely, the NHD channel network reflects current conditions, which may lead to errors in predicted natural channel pattern where channel alignment has been modified.
	This classification method complements stream monitoring programs across the Columbia River Basin that measure channel attributes to infer habitat trend (e.g. CHaMP and PacFish InFish Biological Opinion; *Kershner et al.*, 2004).	Cannot be used to assess current channel condition and limiting processes without additional information on stream disturbance and condition following European settlement.
	Machine learning workflow can be modified for other watersheds with known relationships between landscape setting, channel attributes, and planform	Relies on coarse-resolution landscape and channel data that may not be ideal for creating model training data in all channels and landscapes.
Rosgen	Effectively used to help develop restoration plans for stable	Metrics for stream type classification are based on

Classification System	meandering gravel and cobble bed rivers, provided a correct reference reach is identified [*Hey*, 2006].	empirical data from selected streams [*Rosgen*, 1994].
	Provides a common language for specialized professionals in watershed science to communicate when referencing stream types [*Rosgen*, 1994; *Miller and Ritter*, 1996].	Can be incorrectly applied due to seemingly 'cookbook' style of some reference materials [*Roper et al.*, 2008; *Rosgen*, 2009].
	Correctly identified stream types have inherently different recovery potential, sensitivity to disturbance, and interactions with vegetation that can be used to inform management and restoration decisions [*Rosgen*, 1994].	As a restoration tool, success is primarily based on locating a stable and 'correctly identified' reference reach [*Hey*, 2006; *Simon et al.*, 2007].
Statistical Classification	Can identify relationships between many interrelated reach-scale or watershed-scale processes [*Sutfin et al.*, 2014].	Can find unrealistic or hydrogeomorphically irrelevant patterns in noisy data [*Caratti et al.*, 2004]
	Can take top-down (landscape – watershed – reach) or bottom-up (reach – watershed) approaches [*Hough-Snee et al.*, 2014].	Requires *a priori* selection of important processes within a given watershed or set of reaches.
	Numerous statistical approaches are available for clustering, classifying, and testing for between-group differences across multiple reaches.	Relies on statistical expertise for effective implementation and interpretation.
	Classified groups of reaches make discrete units from which qualitative bioassessment for aquatic biota or habitat can take place.	Often relies on correlations to biotic processes to differentiate "high quality" reaches from "lower quality" reaches.
	A long tradition in ecology, hydrology, and geomorphology has developed well-understood methods that can be implemented in many software packages.	Rapidly developing methods in statistics machine learning allow for "black box" correlative models that can be difficult to interpret, understand or explain to managers.
	Allows for user-defined watershed attributes for defining classification groups.	Workflows can be time consuming and difficult to interpret to non-expert users.
	Can be used in the absence of "reference" reaches to identify typological gradients between many reaches.	Requires moderate to large sample sizes and relatively high quantities of remotely sensed or field-collected data to find meaningful patterns at large scales.

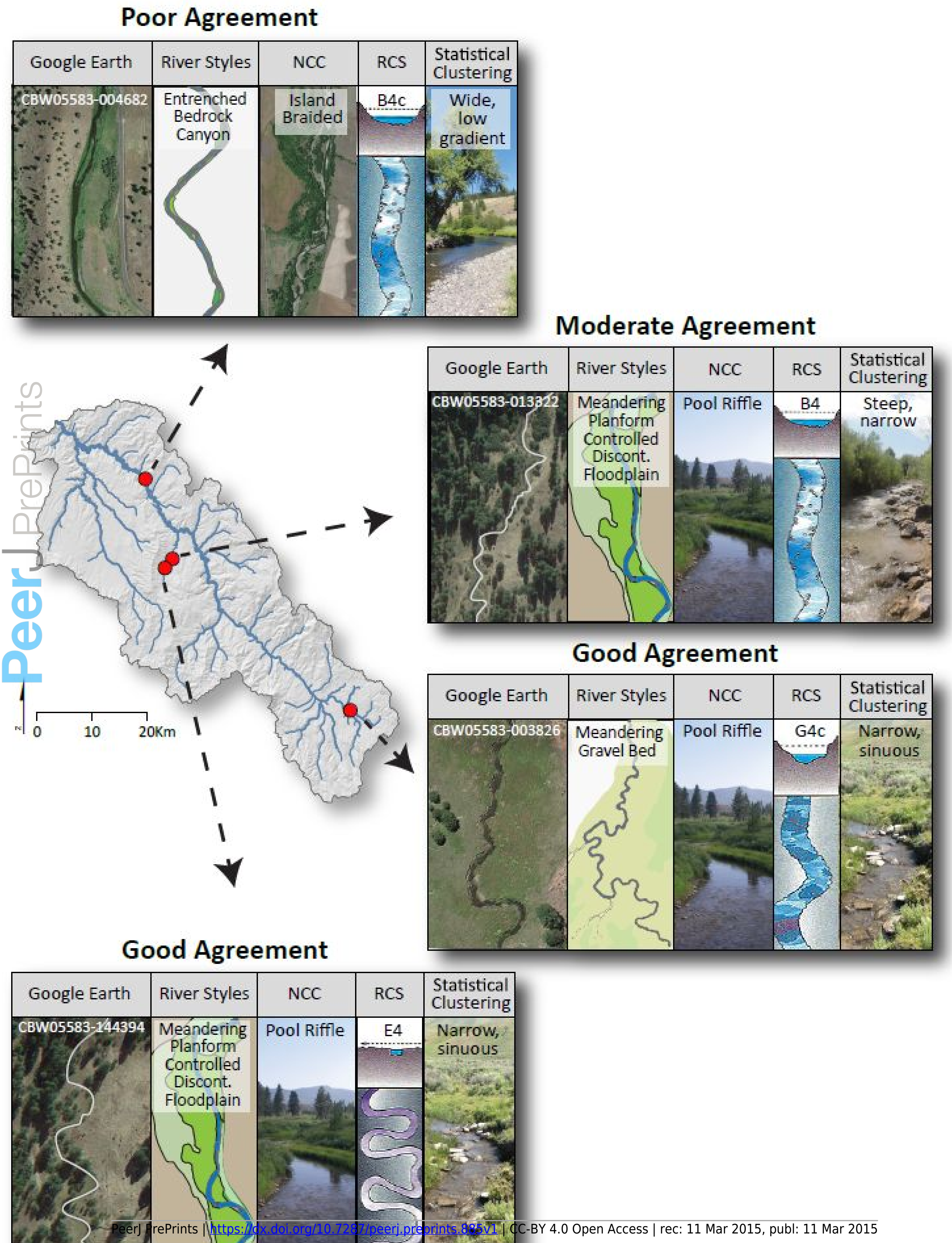

MF John Day River
0
10
20 Km
N
Middle Fork John Day
OREGON
CHaMP Site
Evergreen Forest
Mixed Forest
Shrub/Scrub
Cultivated Crops


1
Partly Confined Valley
Low Sinuosity Planform Controlled Anabranch
Bedrock Controlled Elongate Discont. Floodplain
Meandering Planform Controlled Discont. Floodplain
Low-Mod Sinuosity Planform Controlled Discontinuous Floodplain
Confined Valley
Boulder Bed
Step Cascade
Floodplain Pockets
Entrenched Bedrock Canyon
Laterally Unconfined Valley
Low-Mod Sinuosity Gravel Bed
Alluvial Fan
Meandering Gravel Bed
Intact Valley Fill
2
Confined Channels
Cascade
Confined
Pool Riffle
Step Pool
Plane Bed
Floodplain Channels
Island Braided
Meandering
Straight
3
Moderately Entrenched
B3c
B4
B4a
B4c
Slightly Entrenched
C3b
C4b
E3
E4
Entrenched
A4
F3
G4c
4
Statistical Cluster
1
2
3
4
N
0
10
20Km

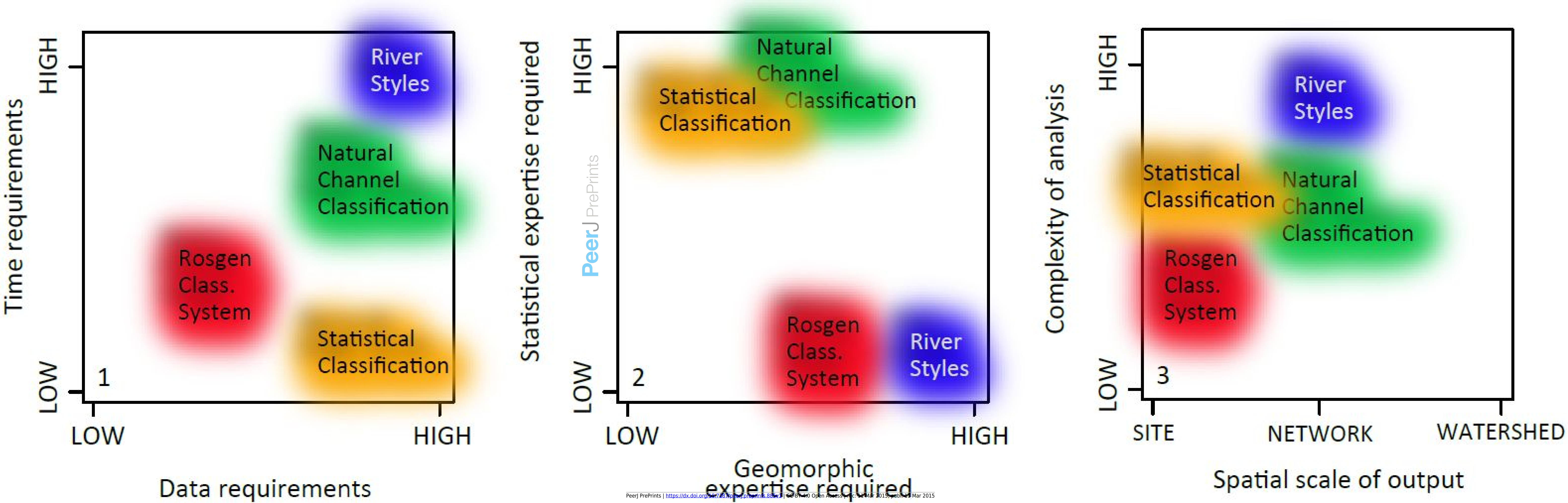

1. RIVER STYLES FRAMEWORK
Channel Network
CHaMP Reaches
Percent of Total Network Channel Length
Percent of CHaMP Reaches
Boulder Bed
Entrenched Bedrock Canyon
Floodplain Pockets
Step Cascade
Steep Ephemeral Hillslope
Steep Perennial Headwater
Meandering PC Disc. FP.
Low Sinuosity PC Anabranch.
Low-Mod. Sinuosity PC Disc. Floodplain
Bedrock Controlled Elongate Disc. Floodplain
Low-Mod. Sinuosity Gravel Bed
Alluvial Fan
Meandering Gravel Bed
Intact Valley Fill
2. NATURAL CHANNEL CLASSIFICATION
Channel Network
CHaMP Reaches
Percent of Total Network Channel Length
Percent of CHaMP Reaches
Straight
Meandering
Island-Braided
Confined
Plane Bed
Pool Riffle
Step Pool
Cascade
3. ROSGEN CLASSIFICATION SYSTEM
Percent of CHaMP Reaches
A
F
G
B
C
E
4. STATISTICAL CLUSTERING
Percent of CHaMP Reaches
1: Narrow, Sinuous
2: Wide, Low-Gradient
3: High-Gradient, Narrow
4: Wide, Sinuous



Gradient
D84
Bankfull
Width:Depth Ratio
Bankfull
Width
Integrated
Wetted
Width
D16
D50
1. Narrow, sinuous
2. Wide, low-gradient
3. Steep, narrow
4. Wide, sinuous
Principal Component 2 (10.9%)
Principal Component 1 (85.6%)
50
0
-50
-50
0
50
100



Poor Agreement
Google Earth
River Styles
NCC
RCS
Statistical Clustering
CBW05583-004682
Entrenched Bedrock Canyon
Island Braided
B4c
Wide, low gradient
Moderate Agreement
Google Earth
River Styles
NCC
RCS
Statistical Clustering
CBW05583-013322
Meandering Planform Controlled Discont. Floodplain
Pool Riffle
B4
Steep, narrow
Good Agreement
Google Earth
River Styles
NCC
RCS
Statistical Clustering
CBW05583-003826
Meandering Gravel Bed
Pool Riffle
G4c
Narrow, sinuous
Good Agreement
Google Earth
River Styles
NCC
RCS
Statistical Clustering
CBW05583-144394
Meandering Planform Controlled Discont. Floodplain
Pool Riffle
E4
Narrow, sinuous
0
10
20Km



HIGH
Time requirements
LOW
River Styles
Natural Channel Classification
Rosgen Class. System
Statistical Classification
1
LOW
HIGH
Data requirements
HIGH
Statistical expertise required
LOW
Natural Channel Classification
Statistical Classification
Rosgen Class. System
River Styles
2
LOW
HIGH
Geomorphic expertise required
HIGH
Complexity of analysis
LOW
River Styles
Statistical Classification
Natural Channel Classification
Rosgen Class. System
3
SITE
NETWORK
WATERSHED
Spatial scale of output