Analysis of reach-scale sediment process domains in glacially-conditioned catchments using self-organizing maps

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1 1. Introduction

2 River reaches undergoing excessive rates of adjustment pose hazards to infrastructure and public safety, and contribute to degraded water quality and compromised instream and riparian 3 habitats. In glacially-conditioned mountainous areas, rivers have differing vulnerabilities to 4 adjustment given their topographic setting, variable coupling of hillslope and channel processes, 5 and reworking of glaciogenic sediments (Church and Ryder, 1972; Ballantyne, 2002). The 6 7 geologic and glacial history have imparted longitudinal and lateral variations in valley setting 8 and network position, as well as discontinuities in channel form and process (Rice and Church, 1998; Toone et al., 2014; Phillips and Desloges, 2014a) that influence the dynamics of sediment 9 10 erosion, transport and deposition (Nanson and Croke, 1992; Fryirs et al., 2007). Human disturbances over the last 250 years have also altered patterns of water and sediment routing 11 through the landscape (Leopold, 1994; Noe and Hupp, 2005; Walter and Merritts, 2008). As a 12 13 consequence, rivers have become laterally and vertically disconnected from their floodplains, leading to reduced floodplain storage and increased streambank and channel erosion (Brierley 14 and Fryirs, 2005; Kline and Cahoon, 2010). 15

Water resource managers need tools to identify river reaches most prone to adjustment 16 and which disproportionately load sediment to receiving waters. However, significant 17 18 challenges exist for classification and prediction, given the complexity of sediment dynamics. Patterns of sediment flux and channel adjustment exhibit high variability across spatial and 19 temporal scales (Walling, 1983; Fryirs, 2013), as a function of both watershed-level and reach-20 21 level processes that alter flow and sediment inputs, as well as stream power and boundary 22 resistance. Many factors, including the geologic setting, climate, hydrology, vegetation, and land use, combine in nonlinear ways to adjust reach-scale channel dimensions, profile and planform 23

over time (Benda and Dunne, 1997; Fryirs, 2013). The present channel form is the 24 manifestation of various channel-floodplain processes occurring in response to a suite of natural 25 and human disturbances over a range of flows (Pickup and Rieger, 1979; Wohl, 2018). Rivers 26 are integrating these myriad of stressors overlapping in time and space, and may adjust to an 27 external stressor(s) in complex ways based on: the magnitude, intensity and duration of the 28 stressor; lag effects; intrinsic and extrinsic thresholds; self-reinforcing or self-limiting feedbacks; 29 30 and the presence of antecedent conditions or contingencies (Bull, 1979; Chappell, 1983; Phillips, 31 2003; Toone et al., 2014). Despite these complexities and the uncertain causal factors, the present channel-floodplain form warrants classification to communicate the associated 32 33 consequences for flood erosion hazard, water quality and ecological integrity. Classification is also useful for highlighting reach sensitivity to future disturbances or to hydrologic regime 34 35 change that may be associated with projected increases in magnitude, frequency, and duration of 36 extreme events (Collins, 2009; Guilbert et al., 2014, 2015). .

Various field assessment techniques help to classify river reaches in terms of their 37 stability or sensitivity to adjustment, following the assumption that dominant adjustment process 38 and degree of stability may be inferred from observed channel form (Pfankuch, 1975; Nanson 39 and Croke, 1992; Rosgen, 1996; Montgomery and Buffington, 1997; Raven et al., 1998; Brierley 40 41 and Fryirs, 2005; Rinaldi et al., 2013). Insights gained from these assessments have led to the theory that river networks comprise a longitudinal array of hydrogeomorphic units of relatively 42 uniform composition, structure, and function, or "process domains" that differentially impact 43 sediment connectivity (Montgomery, 1999; Brardinoni and Hassan 2007; Weekes et al., 2012; 44 Lisenby and Fryirs, 2016). 45

46	Parametric statistical methods have been employed to examine correlations between
47	dominant adjustment process and various geomorphic metrics, such as total or specific stream
48	power (Bizzi and Lerner, 2013; Parker et al., 2014; Gartner et al., 2015; Lea and Legleiter, 2016;
49	Yochum et al., 2017); valley confinement (Thompson and Croke, 2013; Surian et al., 2016;
50	Righini et al., 2017; Weber and Pasternak, 2017); and channel geometry (Buraas et al., 2014).
51	Geographic Information Systems (GIS) and high-resolution digital elevation models have
52	enabled remotely-sensed metrics to augment field-based assessment. Large, multi-parameter data
53	sets help to examine interactions among a suite of factors governing channel-floodplain form and
54	process. Multivariate statistical techniques (e.g., principal components analysis, k-means,
55	discriminant analysis, logistic regression, and regression trees) help with data reduction and
56	unraveling the association of channel and floodplain form with process (Flores et al., 2006;
57	Brardinoni and Hassan, 2007; Phillips and Desloges, 2014b; Livers and Wohl, 2015). However,
58	these methods are predicated on linear relationships between variables, which often do not
59	describe geomorphic data well. Moreover, their application assumes the data are normally
60	distributed, while geomorphic variables often do not reliably conform to a Gaussian distribution.
61	Because sediment erosion, transport and deposition processes are a manifestation of
62	multiple factors and nonlinear interactions, Phillips (2003) advocated for the application of
63	nonparametric, computational tools to model nonlinear, complex dynamics. Artificial neural
64	networks are well-suited for nonlinear processes, and handle nonparametric data of varying types
65	(e.g., continuous, ordinal, nominal) and scales. The Self-Organizing Map (SOM) is one such
66	neural network for clustering or classification of multivariate observations (Kohonen, 2013).
67	SOMs have demonstrated superior performance over parametric methods where data contain
68	outliers or exhibit high variance (Mangiameli et al., 1996), and have particular advantages over

69	other methods for data visualization and interpretation (Alvarez-Guerra, et al., 2008). SOMs
70	have been used to classify or cluster multivariate environmental data, including instream species
71	richness (Park et al., 2003), fish community distribution patterns (Stojkovica et al., 2013), lake
72	chemistry data associated with harmful algal blooms (Pearce et al., 2011, 2013), and riverine
73	habitats (Fytilis and Rizzo, 2013). Previous research (Besaw et al., 2009) applied a SOM to
74	reach-based geomorphic assessment data to classify reach-level sensitivity, or the likelihood for
75	channel adjustment (vertical or lateral adjustment) in response to natural or human
76	disturbance(s). However, the authors are not aware of the SOM being applied to classify
77	sediment regime of river reaches.
78	In this work, we use SOMs to characterize and predict the spatial variation in fluvial
79	sediment regimes. Consistent with Wohl and others (2015), we define a sediment regime as a
80	pattern of "inputs and outputs of mobile sediment from a length of channel and storage of
81	sediment within the channel and floodplain over a specified time interval". The research
82	objectives are to: (1) apply the SOM to cluster commonly-assessed stream geomorphic
83	parameters and define a continuum of sediment regimes, using catchments from the glacially-
84	conditioned northeastern United States as a test case; (2) assess this data-driven clustering tool's
85	ability to emulate the decision-making of stream geomorphic experts following an existing
86	reach-scale classification of sediment regimes (Kline, 2010) with a goal to refine the
87	classification and enable future automation; and (3) illustrate the utility of the SOM for data
88	visualization and interpretation.
89	2. Study Area

Our study comprises 193 river reaches located in six relatively undeveloped (≤ 5.3%)
catchments dispersed across the state of Vermont in the northeastern United States (Fig. 1;

Supplementary Table S1), and chosen to represent a mix of biogeophysical regions (Stewart and 92 MacClintock, 1969). Study reaches range from 95 to 4,724 m in length with upstream drainage 93 areas between 0.93 and 302 km² (Table S2). This previously-glaciated landscape consists of a 94 mix of deposits ranging from glacial tills, glaciofluvial, and glaciolacustrine sediments and 95 alluvial fans, deltas, and post-glacial stream terraces (Stewart and MacClintock, 1969). The 96 bedrock underlying these soil parent materials generally consists of erosion-resistant crystalline 97 98 and metamorphosed rocks of the highlands (e.g., gneiss, phyllites, schist, schistose greywacke, slate, granite) and less-erosion-resistant limestones and dolostones in the valleys (Ratcliffe et al., 99 2011). Generally, bedrock channels in the headwaters grade to mixed bedrock-alluvial and 100 101 alluvial channels in the lowlands. Where the river impinges upon hillslopes of glacial till or high terraces of glacial origin (e.g., kame, delta, or lacustrine deposits), landsliding can contribute 102 sediment and large woody debris to the channel (Dethier, et al. 2016). 103

104 Historically, European settlement and the associated deforestation (Foster and Aber, 2004) generated high sediment yields from denuded hillslopes, leading to renewed aggradation 105 106 in many alluvial reaches (Brakenridge, et al., 1988; Bierman et al., 1997). Subsequent reforestation has reduced sediment yields, contributing to channel incision and widening 107 (Bierman, 2010; Schumm and Rea, 1995). Channelization, berming, armoring, and diversion of 108 109 rivers during development, have locally disconnected river channels from the adjacent 110 floodplains (Poff et al., 1997; Kline and Cahoon, 2010). Dams were historically operated at bedrock knick-points in the headwaters to power local mills (Thompson and Sorenson, 2000); 111 however, these small impoundments were typically breached during flood events of the 19th and 112 20th century. At present, four dams remain on the studied reaches, but have limited 113 impoundments and operate in run-of-river mode. Thus, longitudinal hydrologic connectivity is 114





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118 Fig. 1. Location of study area watersheds across biogeophysical regions in Vermont.

A humid temperate climate characterizes the region, with mean annual precipitation 119 ranging from over 1,270 mm along the north-south trending spine of the Green Mountains to a 120 low of 813 mm in the Champlain Valley (Randall, 1966). Spring and fall rains are common, and 121 saturation-excess overland flow conditions dominate during these months, leading to variable 122 123 hydrologic source areas (Dunne and Black, 1970). A majority of the total annual flow in the 124 studied rivers occurs from snow- and ice-melt to late spring in a typical year, due to the occurrence of spring rains falling on saturated or frozen ground, melting of the snow pack stored 125 in higher elevations, and low evapotranspiration rates prior to leafing of deciduous vegetation 126 (Shanley and Denner, 1999). The peak annual flow (1 to 1.5-year recurrence interval) most often 127 occurs during the spring months, although occasionally in the fall or summer (USGS, 2018). 128

129 **3.** Methods

Research progressed in multiple phases: (1) assessments to gather geomorphic and
hydraulic variables; (2) assignment of sediment regime classification; (3) exploratory data
analysis; and (4) the application and (5) training of a SOM clustering algorithm to replicate and
refine sediment regime classifications assigned by experts.

134 3.1. Assessment of geomorphic condition

Reach-scale geomorphic and hydraulic data were compiled from existing remote-sensing 135 resources and field-based assessment for 193 river reaches in six catchments (Fig. 1). Assessed 136 reaches were located along confined to unconfined, steep- to shallow-gradient, mid-to-high order 137 channels that ranged from bedrock to alluvial in nature (Table S2, Fig. S1). Reaches affected by 138 impoundments (artificial or beaver-constructed) or wetland conditions were not included in 139 140 assessments. River reaches were assessed during a relatively quiescent period (2004 through 2011) between significant flood events. The six study area catchments were affected by an 141 extreme event, a state-wide flood of significance (recurrence interval ranging from 25 to 500+ 142 years) in August 2011 during Tropical Storm Irene (USGS, 2018). Except for three of the 193 143 reaches (1.6%), geomorphic data from our study catchments were collected before this extreme 144 145 event, and these three reaches were located in catchment #3 (Fig. 1) where Tropical Storm Irene 146 generated only a 50-yr flood.

Stream geomorphic assessments were conducted following protocols (Kline et al., 2009)
developed by the Vermont Agency of Natural Resources relying on several resources (Wolman,
1954; Pfankuch, 1975; Nanson and Croke, 1992; Harrelson, et al., 1994; Rosgen, 1996;
Montgomery and Buffington, 1997; Knighton, 1998). These quality-assured and peer-reviewed

protocols (Besaw et al., 2009; Somerville and Pruitt, 2004) have been developed and applied to

classify river reaches in terms of their dominant adjustment process, stage of channel evolution, 152 and sensitivity to future adjustment (Kline et al., 2009). Reaches were defined as channel lengths 153 of consistent confinement ratio (confined, semiconfined or unconfined) within which other 154 channel parameters (slope, sinuosity, and bedform) were generally similar – a reach definition 155 conforming to that employed by others (Frissel et al., 1986; Brierly and Fryirs, 2005; Rinaldi et 156 al., 2013; Surian et al., 2016). Additionally, minimum reach lengths were generally greater than 157 158 20 times the bankfull width (Montgomery and Buffington, 1997). Following initial identification 159 through desk-top assessment of topographic and photographic resources, reach delineations were confirmed through direct observation, where sub-reaches of alternate slope or valley confinement 160 161 may not have been apparent at the typical scale (1:24000) of remote-sensing resources used in this study. In some cases, field assessment also defined sub-reaches marked by discontinuities 162 163 (e.g., bedrock grade controls or impoundments) or distinct differences in dominant substrate 164 material or adjustment process (Kline et al., 2009). For clarity of presentation, these sub-reaches are referred to as reaches in this work. Various geomorphic and hydraulic metrics were 165 compiled for each reach (including List A in Table 1) using a combination of remote-sensing and 166 field-based assessment (see supplementary materials). Based on this information, each reach 167 was classified by stream type (Montgomery and Buffington, 1997; Rosgen, 1996), dominant 168 169 style of vertical (degradation or aggradation) and/or planform (widening, narrowing or lateral 170 migration) adjustment, and channel evolution model and stage (Schumm et al., 1984). Additional variables were derived for this study to evaluate their effectiveness to describe 171 sediment regimes and to cluster reaches of similar character. Various methods for estimating 172 stream power (Parker et al., 2011; Parker et al., 2014) and tractive force (Andrews, 1983; 173

174 Ferguson, 2005) were used, relying on regional hydraulic geometry relationships (Jaquith and

Kline, 2001, 2006) and pebble-count data from field assessments to provide an indication of
sediment transport capacity (Supplementary text S1).

177 3.2. Assignment of sediment regime class

We assigned one of six sediment regime classes (Table 2, Fig. 2) to each study reach to 178 describe the present regime for transport of coarse and fine (<63 um) fluvial sediment based on a 179 combination of geomorphic metrics and observations (Kline, 2010). The sediment regime 180 classes lie on a continuum from supply-limited to transport-limited (Montgomery and 181 Buffington, 1997); and classification focuses on processes operating at a temporal scale of 1 to 2 182 years, since classification metrics include dimensions (e.g., width, depth) relative to the bankfull 183 stage, defined as the discharge with an approximate recurrence interval of 1.5 years, or Q1.5 184 (Leopold, 1994). 185

186 This classification scheme (Fig. 2) considers both the vertical and lateral dimensions of sediment (dis)connectivity in the context of varying degrees of channel confinement by valley 187 walls (hillslope-channel coupling in highly-confined to semi-confined settings) and the vertical-188 lateral connectivity to floodplain (floodplain-channel coupling in unconfined settings). Three 189 of the six sediment regime classes describe channels that are vertically connected -i.e., not 190 degraded appreciably below their floodplain (incision ratio $[IR] \le 1.3$), although the floodplain 191 192 itself may be quite limited in areal extent (Fig. 2a); the other three classes are vertically-193 disconnected from the floodplain (IR \geq 1.3; Fig. 2b). The timescale of degradation processes 194 resulting in loss of floodplain connection may be highly variable. Our assessment methods did not include a determination of incision timing beyond a subjective classification of active, 195 historic or post-glacial. 196

Table 1. Geomorphologic and hydraulic variables used to classify sediment regime.

199	А	В	С	Variable	Description	Units	Transformation
200	\checkmark	\checkmark	\checkmark	Slope, S	Channel slope	[%]	† Log S
200	\checkmark	\checkmark		Valley Confinement, VC	Valley width / bankfull width	[-]	† Log VC
201	\checkmark	\checkmark	\checkmark	Incision Ratio, IR	Low-bank height / bankfull channel height	[-]	‡ Log IR
202	\checkmark	\checkmark		Entrenchment Ratio, ER	Floodprone width / bankfull width	[-]	‡ Log ER
202	\checkmark	\checkmark	\checkmark	Width _{bkfl} to Depth _{mn} ratio, W/D	Bankfull width / mean bankfull depth	[-]	‡ Log W/D
203	\checkmark	\checkmark	√	Median grain size diameter, D50	Median grain size diameter from riffle or step pebble count, i.e., 50 th percentile of the grain size distribution	[mm]	$\sqrt[+]{D50}$
204	\checkmark	√	\checkmark	Percent Armoring, pArm	Length armoring normalized to reach length	[%]	<pre>‡ Arcsin(sqrt</pre>
205	\checkmark	\checkmark		# Depositional Bars, nBars	Number of deposition bars normalized to reach length	[#/km]	$\ddagger \sqrt{nBars}$
206	\checkmark	\checkmark	\checkmark	# Flood Chutes, nFCs	Number of flood chutes normalized to reach length	[#/km]	$\ddagger \sqrt{nFCs}$
207		\checkmark		Valley Confinement Ratio, VCrat	VC of subject reach / VC of upstream reach	[-]	† Log VCrat
207		√	√	Grain Size Distribution, D84-D16	Range of two standard deviations around the median, computed as the 84 th percentile minus the 16 th percentile of the grain size distribution	[mm]	‡ Log D84-D16
209		\checkmark	\checkmark	Specific Stream Power, SSP	Unit bed area stream power	[W m ⁻²]	‡ Log SSP
		\checkmark		SSP Balance, SSPbal	SSP of subject reach / SSP of upstream reach	[-]	‡ Log SSP bal
210			\checkmark	Width ratio, Wrat	Regime bankfull width / measured bankfull width	[-]	‡ Wrat
211			√	Mean Depth ratio, Drat	Regime mean bankfull depth / measured mean bankfull depth	[-]	‡ Drat

213 † Normal distribution confirmed by Shapiro-Wilks test at α = 0.05; ‡ or by histogram/normal quantile plot List A variables used to assign sediment regime following criteria in Table 2; List B were inputs to the Coarse SOM (n=193);
214 List C were inputs to the Fine SOM (n=154).

Table 2. Geomorphic characteristics of sediment regime classes.

Class	Transport (TR)	Confined Source and Transport (CST)	Unconfined Source and Transport (UST)	Fine Source and Transport/ Coarse Deposition (FSTCD)	Coarse Equilibrium/ Fine Deposition (CEFD)	Deposition (D
Color Key						
Valley Confinement	< 6	< 6	≥4	≥4	≥4	≥ 6
Slope	> 2 %	> 2%	< 4%	< 2%	< 2%	< 2% typically; >2% occasiona
Incision Ratio (IR)	< 1.3	≥ 1.3	≥ 1.3	≥1.3	< 1.3	< 1.3
Entrenchment	< 1.4	> 2.2	> 2.2	> 2.2	> 2.2	> 2.2
Ratio (+/- 0.2)	1.4–2.2 (B)		1.4–2.2 (B)	1.4–2.2 (B)		
Width/Depth	< 12 (A, G)	< 12 (A, G)	< 30	> 30	< 30	> 30
Ratio (+/- 2)	> 12 (B, F)	> 12 (B, F)	< 12 (E)	> 12 (E); > 40 (D)	<12 (E); < 40 (D)	(> 40, alluvial
Common Channel Evolution Stage †	I, V	II, III, IV	II, III	II, III, IV	I, V	
Rosgen (1996) Stream Type	A, B, G, F	A, B	G, F, B, E, C, Bc	E, C, Bc, F, D	C, E, D	C, D, Ca, Cb
Median Grain Size	bedrock, boulder,	cobble, gravel, sand	cobble, gravel,	cobble, gravel,	cobble, gravel,	cobble, gravel,
(D50)	cobble, (occas. gravel)	1 / 1	sand	sand	sand, silt	(occas. bouider
Bedforms	step-pool	plane bed	bed, riffle-pool	тіпіе-рооі	riffle-pool, dune- ripple	braided
Planform	single-thread linear to sinuous imparted by bedrock structure	single-thread linear to sinuous imparted by bedrock or encroachments	single-thread	single-thread meandering, localized bifurcations	single-thread, meandering	multiple-thread braided
Type	Bedrock, mixed	mixed	mixed	Alluvial	alluvial	alluvial



Fig. 2. Schematic of typical cross section for six sediment regime classes. Horizontal blue line depicts water surface of $Q_{1.5}$ discharge. Class abbreviations and color scheme are identified in Table 2.

In order from minor to major degree of lateral adjustment, representing bedrockdominated to alluvial channel types, the three vertically-connected sediment regime classes (Fig.
232 2a) are:

Transport (TR) reaches are confined- to semi-confined by their valley walls (VC \leq 6) and are 234 supply-limited due to resistant channel boundaries and the relatively steep gradient (>2%). 235 236 TR reaches are not considered a significant source of coarse and fine sediments due to the high erosion resistance offered by the typical bedrock boundaries. Planform is controlled by 237 the underlying bedrock structure, and floodplain areas for sediment storage are typically 238 limited and discontinuous in areal extent (Wohl, 2010). 239 Coarse Equilibrium and Fine Deposition (CEFD) reaches comprise self-formed (fully 240 mobile) alluvial channels located in unconfined valley settings with low- to moderate-241 gradient (<2%; riffle-pool and dune-ripple bedforms, occasionally plane bed). These 242

channels are not incised (IR \leq 1.3), and therefore deposit fine sediments (suspended load) in

their floodplains during floods of \geq 2- 5-year RI. A coarse-sediment quasi-equilibrium

- condition is inferred from the condition over time of no net change in meander belt width,
- 246 profile and average channel dimensions.

Deposition (DEP) reaches are generally unconfined (VC > 6) and of lesser gradient (< 2%)
 but may have moderate to steep slopes (2% to 6%), e.g., Rosgen Ca or Cb stream types.
 Often DEP reaches are located immediately downstream of a steeper and more confined
 reach, and therefore represent locations of increased deposition and lateral migration due to
 the decreased stream competence imparted by the transition in valley topography (e.g.,
 alluvial fans).

The remaining three classes (Table 2, Fig. 2b) represent channel reaches that exhibit a moderate to major degree of floodplain disconnection (IR \ge 1.3), resulting from either natural or human-induced conditions, or both. Consequently, the channel becomes entrenched below an abandoned floodplain or terrace of glacial origin. Presented in order of increasing degree of lateral adjustment:

<u>Confined Source and Transport (CST)</u> reaches exist in semi-confined to confined settings
 (higher degree of hillslope-channel coupling) of moderate to steep gradient and have more
 erosion-prone boundary conditions than TR reaches.

 Unconfined Source and Transport (UST) reaches occupy partly confined (by encroachment and channelization) to unconfined valley settings of moderate to low gradient (< 4%) and are characterized by a moderate to high degree of vertical separation from the floodplain (1.5 < IR < 4). By virtue of this incision, the sediment regime has shifted from a depositiondominated condition to a transport-dominated condition (channel evolution stage II or early III). Width/depth ratios are generally small but variable.

<u>Fine Source and Transport and Coarse Deposition (FSTCD)</u> reaches are located in
 unconfined valley settings of low gradient (<2%) and are moderately to substantially incised

(IR > 1.3). They are dominated by lateral adjustment processes including widening,

planform adjustment accompanied by aggradation, typically in channel evolution stage III orIV.

272 Once reaches were classified into one of the above sediment regimes, , assessment 273 variables were examined to discern which ones had statistical power to differentiate between 274 expert-assigned sediment regime classes using One-way Analysis of Variance (ANOVA) 275 followed by Tukey Honest Significant Differences (HSD) tests between individual group means. 276 For those variables (or their transformations) that were not normally distributed, nonparametric 277 methods were applied (Kruskal-Wallis).

278 3.3. Pre-processing input data for SOM training

Reach-scale geomorphic and hydraulic metrics were explored using conventional 279 280 statistical methods (e.g., Pearson or Spearman Rank correlations and Principal Components Analysis [PCA]) to select the SOM inputs (Lists B and C in Table 1). Variables that were very 281 closely correlated to each other (i.e., Pearson correlation > 0.80) or which had little power to 282 explain variance by PCA were dropped as inputs to the SOM. Data were also examined to help 283 determine the appropriate SOM lattice configuration and size. A PCA was run on transformed 284 variables, following the heuristic of Cereghino and Park (2009) that the optimal lattice column-285 286 to-row ratio approximates the ratio of the first two principal components. Statistical tests were 287 performed in JMP (v. 12.0, SAS Institute, Cary, North Carolina).

288 *3.4. Clustering algorithm*

We clustered our reaches using an unsupervised algorithm – a Self-Organizing Map (SOM; Kohonen, 2001); the data set has *p* observations of *n* independent variables. The "unsupervised" descriptor means that data were presented to the clustering algorithm without

their expert-assigned sediment regime classifications, and without a predetermined number of 292 outcome clusters (i.e., sediment regime classes). Like conventional clustering techniques that are 293 also data-driven (e.g., k-means and unsupervised hierarchical clustering), the SOM will 294 aggregate p observations into k groups, each with internally similar values for the n independent 295 variables. However, certain features unique to the SOM technique (described below) ensure that 296 clustering proceeds in a manner that is more robust to outliers, non-continuous data types, and 297 298 data that are not normally distributed (e.g., the latter two conditions would violate underlying 299 assumptions of traditional clustering techniques). Similar to traditional methods such as PCA, regression trees, and logistic regression, the SOM is useful for reducing the dimensionality of 300 301 data and for selecting variables that strongly influence clustering or classification (i.e., feature selection). Yet, the SOM has advantages over these traditional methods for exploratory data 302 303 analysis and visualization (Eshgi et al., 2011).

The SOM reduces a multidimensional data space to a lower-dimensional space, typically a 2-D plane or lattice having a number of individual nodes, also called a Kohonen feature map (Kohonen, 2013). The outcome of a converged lattice is such that observations introduced to the SOM self-organize into "a kind of similarity diagram" (Kohonen, 2013) where similar observations will cluster and be mapped to a similar location on the lattice/map. Each of the input variables may also be viewed on the converged lattice in what is known as a "component plane", where values of the input variables can be observed with their associated cluster.

Typically, the SOM input data are normalized so that variables of higher magnitude do not overly dominate the clustering process. Our variables were each range-normalized to a value between 0 and 1 before beginning SOM training (Alvarez-Guerra et al., 2008):

314
$$norm(x_i) = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}.$$

A hexagonal lattice topology (Fig. 3) was selected, given the potential for conditional 315 bias between input variables (Kohonen, 2001). At the initial state of the lattice, each node is 316 assigned a vector, **m**, of random values (i.e., weights) ranging from 0 to 1; the vector length is 317 equal to the number of input variables, n. One of the p observations is then selected at random 318 from the data set, and its vector **X** of *n* variables $\{X_{p,l}, X_{p,2}, X_{p,3}, \dots, X_{p,n}\}$ is presented to the 319 vector of weight values $\{m_{y,1}, m_{y,2}, m_{y,3}, m_{y,4}, \dots m_{Y,n}\}$ in each lattice node, y. The distance, or 320 321 dissimilarity, between the observation vector and each weight vector for each lattice node (y_1, y_2) y_2, \dots, y_Y) is computed. Euclidean distance is commonly used (Kohonen, 2013), and was also 322 used in this study. The SOM uses a competitive ("winner-takes-all") algorithm to ensure that the 323 324 selected node has a weight vector that is most similar to the observation vector. The weights of this Best Matching Unit (BMU), along with a user-defined neighborhood of nodes (N_c) around 325 326 the BMU, are incrementally adjusted to be more similar to the input vector. This user-defined 327 neighborhood of nodes is one of the features that distinguishes the SOM from other more common methods of clustering, such as k-means (which only updates weights of a single node). 328 The weights of the BMU and neighborhood units are adjusted gradually by a distance that 329 amounts to a small fraction of the total distance between the input vector and each weight vector. 330 This fractional distance is applied in accordance with a user-specified learning rate parameter. A 331 332 next observation vector is then selected at random from the data set and compared to the weight 333 vectors of each lattice node; a BMU is identified, and its weights and that of its neighbor nodes 334 are adjusted, as the process is repeated in each successive iteration. Commonly, both the size of the updating neighborhood and the learning rate are decreased linearly with progressive 335 iterations, moving from a coarse to fine tuning process. Over multiple iterations, the lattice 336 weights are adjusted by smaller amounts and the algorithm converges (self-organizes). At 337

convergence, the adjusted weight vectors will more closely reflect the input vectors and will be
arranged across the lattice such that similar stream reach observations are aggregated together.
The distance (or dissimilarity) between weight vectors at convergence is then examined to define
clusters of nodes containing similar weights. Several methods are available; often hierarchical
clustering is used (Vesanto and Alhoniemi, 2000) as was the case in this study. The SOM
algorithm was implemented in the R programming language (R Core Team, 2017) applying the
"kohonen" package (Wehrens and Buydens, 2007, v. 3.0.2 released 2017).



Fig. 3. Architecture of Self-Organizing Map illustrating the competitive algorithm (after Kohonen, 2001). Weights of the best matching unit (BMU) and lattice nodes within a userspecified neighborhood (N_c) surrounding the BMU are updated to make them slightly closer to values of the input vector.

360 *3.5. SOM computation, training and cluster validation*

361 SOM training was performed in 900 iterations. The learning rate was set initially at 0.05 362 and decreased linearly to 0.01. The neighborhood size decreased linearly from a radius 363 encompassing two-thirds of the lattice, to a value of 0 at one-third of the iterations - at which 364 point, the algorithm was only updating the BMU (analogous to k-means clustering).

For a given data set, several multi-iteration SOM runs were performed utilizing lattices with varying configurations and numbers of nodes. Column-to-row configurations were chosen to closely approximate the ratio of the first two principal components of the transformed variables (Cereghino and Park, 2009). As an additional constraint, the final grid size (*Y* nodes)

approximated a value of $5\sqrt{Y}$ following the heuristic of Vesanto et al. (2000), yet did not exceed 369 the number of input variables. For each converged lattice configuration, clusters of similar 370 371 weights were identified using hierarchical clustering specifying k groups, where $k = \{3, 4, \dots 8\}$. We identified the "optimal" number of clusters for a given input data set by examining cluster 372 separation and compactness of clusters to maximize a nonparametric F statistic (Anderson, 373 2001), computed as the ratio of between-cluster to within-cluster variance. At the same time, we 374 identified the number and configuration of lattice nodes with best resolution to achieve a local 375 minimization of quantization error (Kohonen, 2001; Cereghino and Park, 2009). Calculation of 376 the nonparametric F statistic was aided by the "adonis" function in the "vegan" package in R 377 378 (Oksanen et al., 2017).

Clusters were also examined *post hoc* to further understand variables driving the clustering. For each input variable, the intra-cluster mean (on a normalized scale) was plotted against the overall mean, and the magnitude and direction relative to the overall mean were examined. While traditional statistical methods (see Section 3.2) largely guided which geomorphic and hydraulic variables were used as inputs to the SOM, these variable plots by cluster and the component plane for each variable were examined to further refine a parsimonious list of input variables.

386 **4. Results**

Our results are organized to first summarize the geomorphic condition of the 193 assessed reaches. We then describe the expert-assigned sediment regime classes and review those geomorphic metrics with most power to predict class membership. Finally, we summarize the clustering outcomes from the SOM, performed in two stages, and highlight the ability of this nonlinear algorithm to replicate expert-assigned classifications.

392 4.1. Geomorphic condition

393 Bedforms most commonly encountered in the 193 study reaches included step-pool, plane bed, riffle-pool and dune-ripple (Fig. 4a). Riffle-pool and dune-ripple bedforms were 394 associated with channel gradients less than 2% in unconfined valley settings. Our data set 395 included fewer occurrences of bedrock, cascade and braided bedforms (Fig. 4b). In general, the 396 397 assessed reaches transitioned from confined headwaters to unconfined downstream valley 398 settings (Fig. S1). However, a stepped longitudinal profile was evident for many streams due to 399 the influence of exposed bedrock knickpoints that typically coincided with valley pinch points. Example longitudinal profiles of study area streams and tributaries indicate the typical 400 401 sequencing of stream types from upstream to downstream and the relative location of more macro-scale features including bedrock knick points and glacial and post-glacial landforms 402 including glaciolacustrine or glaciofluvial terraces and alluvial fans (Fig. 4c, d, e, f). 403



404

Fig. 4. Distribution of bedforms by: (a) slope – relative roughness plot; and (b) sediment regime
class (n=193). Braided (n=3) bedrock (n=10) and cascade (n=2) bedforms omitted from panel
a. Column widths in panel b vary by sample size. Longitudinal profile of reach classifications
for (c) Roaring Branch (Battenkill), (d) Fayville Branch (Battenkill), (e) Lewis Creek and (f)
Hollow Brook (Lewis). Map locations of these streams are included in Supplementary Fig. S1.

410 *4.2. Sediment regime classification by experts*

411 Sediment regimes assigned to the 193 study reaches by the investigators included

412 representatives from each of the six categories (Fig. 4b). Thirty-five (18%) of the assessed

reaches were in confined settings (TR, CST), while the remaining reaches (158; 82%) were in 413 naturally-unconfined settings. The expert-assigned classifications were occasionally somewhat 414 subjective, particularly where classification rules overlapped. Stream assessment protocols allow 415 for some variation in the threshold values of Entrenchment Ratio and Width/Depth Ratio that 416 define sediment regime classes. The threshold value for Entrenchment Ratio can vary by +/- 0.2 417 units, and the threshold value for Width/Depth ratio can vary by +/- 2 units (Table 2). Given the 418 419 uncertainty associated with channel-floodplain measurements, and the "scaling up" of 420 measurements collected at the cross-section scale to represent the reach scale, a few reaches did not easily conform to all of the rules for a given sediment regime class, and instead spanned two 421 422 classes, requiring domain experts to make a final determination of class membership.

423

4.2.1. Confined Reaches

Valley confinement (VC; Fig. 5a) and Entrenchment Ratio (ER; Fig. 5b) generally had 424 425 power to distinguish confined reaches in TR and CST classes from the unconfined sediment regimes (ANOVA/Tukey HSD on log-transformed values, p<0.05), with the exception that their 426 mean ER values were not significantly different from that of UST reaches (p = 0.12 and p=0.49, 427 428 respectively). The confined reaches (TR, CST) were generally found in steeper settings (> 2%) and most often in the case of TR were co-located with bedrock gorges (e.g., Fig. 4e). However, 429 a few reaches of gradient < 2% were classified in either TR (12 of 25) or CST (2 of 10) where 430 bedrock boundary conditions controlled the confinement at a mid-valley pinch point (i.e., VC 431 ratio less than 1, Fig. S2e). The Specific Stream Power balance (SSP_{bal}) distinguished TR reaches from 432 the unconfined sediment regime classes (ANOVA/Tukey HSD on log-transformed values, p<0.0001). 433 434 However, means were not significantly different in pairwise comparisons between the other classes 435 (p>0.10; Fig. 5f).



436

Fig. 5. Box plots displaying range and central tendency of geomorphic and hydraulic variables by assigned sediment regime class. Solid, black horizontal lines depict median values; black diamonds depict arithmetic mean of non-transformed values. Blue horizontal lines depict threshold values discussed in the text. Unique letters indicate statistically-significant differences between class means by ANOVA/Tukey HSD on transformed variables ($\alpha = 0.05$). See supplementary for details.

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CST reaches were themselves distinguished from TR reaches by Incision Ratio, which

reflected a significantly higher degree of vertical disconnection for this class (p < 0.001)

Additionally, SSP_{bal} had some power (p = 0.02) to distinguish CST from TR reaches. We infer

that both fine and coarse sediment fractions are exported through reaches in these TR and CST

classes. Elevated values of SSP (Fig. 5e) would support this interpretation, although it would 448 take a flood event greater in magnitude than the Q1.5 to exceed the critical SSP required to 449 mobilize the D85 particles or larger, as suggested by the SSPcr ratio (Fig. S2u). Due to the 450 somewhat incised status of CST reaches and more erodible boundary conditions (i.e., not 451 consistently bedrock), reaches in this class can be a source as well as a transporter of coarse and 452 fine sediments. Close-coupling to hillslopes can lead to lateral inputs of sediment and large 453 454 woody debris, but our CST reaches exhibited varying degrees of valley confinement, and thus hillslope coupling (Fig. S2d), with some but not all characterized by mass wasting from either 455 glacial till or glaciolacustrine sediment sources (Fig. 4c, d, e, f). 456

457

4.2.2. Unconfined Reaches

Unconfined reaches in CEFD, UST and FSTCD classes had significantly higher valley-458 to bankfull-width ratios than their confined reach counterparts (Fig. 5a), and occupied lower-459 460 gradient valley settings (Fig. S2g) that within our study area were underlain by a mix of glaciolacustrine, glaciofluvial, post-glacial fluvial and glacial till parent materials (Fig. 4). The 461 VC ratio (subject reach to upstream reach VC) was generally above 1 for these unconfined 462 classes, reflecting the prevalence of increasing valley and channel widths with downstream 463 distance. However, some reaches had values below 1, indicative of longitudinal variability and 464 465 discontinuities imparted by bedrock and glacial deposits (Fig. S2e).

466 CEFD reaches were distinguished from UST and FSTCD reaches by statistically-higher
467 mean values for ER and lower values of IR (p < 0.001; Fig. 5b, c, respectively). These low-
468 gradient reaches were well-connected to their floodplains and characterized by finer-grained bed
469 sediments (Fig. S2h) that were generally well-sorted (i.e., low D84 – D16 differential, Fig. S2i).
470 High values for the R_h/D84 ratio in CEFD reaches reflect these smaller grain sizes, as well as the

generally higher hydraulic radius values characteristic of sinuous channels with dune-ripple 471 472 bedforms (Fig. 4a) that comprise a subset of reaches in this class (Fig. 4b). Mean SSP values for the CEFD class were lower than the UST or FSTCD classes (p<0.001). The unconfined, well-473 connected CEFD reaches exhibited a mean and median SSP of 41 and 34 W m⁻², respectively, 474 with an interquartile range from 16 to 55 W m⁻² (Fig. 5e). The median and mean SSP_{bal} values 475 were below 1, suggesting deposition-dominated conditions. For reaches in this CEFD class, we 476 477 infer quasi-equilibrium transport of coarse sediment from the condition of near-regime values for 478 channel dimensions (Fig. S2p, q) and meander belt width (not presented). Fine-sediment (suspended load) deposition in the connected floodplains is expected during overbank floods 479 480 which would correspond to a recurrence interval ≥ 1.5 years due to the low incision ratios (Fig. 5c). 481

UST and FSTCD reaches on the other hand were vertically disconnected from their 482 floodplains (IR \geq 1.3; Fig. 5c). Reaches in both classes had statistically greater mean SSP values 483 than CEFD reaches (p <0.0001; Fig. 5e). Yet the two classes were distinguished from each other 484 485 by their W/D ratios (p < 0.0001; Fig. 5d), due to differences in boundary resistance to erosion. 486 UST reaches were more likely to have artificial armoring (Fig. S2m) and exhibited greater percentages of channel straightening (Fig. S2y), associated with a higher degree of floodplain 487 encroachment by roads and development. Along with human-constructed features (e.g., bank 488 armoring or road embankments), various natural features of these channels (e.g., presence of 489 490 woody riparian buffers, cohesive channel bed and bank sediments, lateral exposures of bedrock) 491 may have also formed resistant channel-boundary conditions. Where channel boundaries are not 492 stabilized by armoring or vegetation, we infer both fine and coarse sediment fractions are

sourced and exported through UST reaches due to enhanced stream bed and bank scour impartedby the incised and entrenched cross section.

Due to lower boundary resistance, FSTCD reaches had significantly higher width/depth 495 ratios than UST (or CEFD) reaches (p < 0.0001; Fig. 5d). FSTCD reaches were also 496 characterized by a higher degree of coarse sediment deposition than UST reaches (Fig. S2n), 497 greater numbers of flood chutes (Fig. S2o) and riffle cross sections that were wider and 498 499 shallower than regime (Fig. S2p, q). We infer net deposition of coarse sediments in these reaches due to reduced stream competence in the wide and shallow cross section; yet, the incised 500 and entrenched status of that cross section relative to the surrounding floodplain means that fine 501 sediments will continue to be sourced from lateral bank migration and transported to downstream 502 reaches. 503

The DEP class had a small sample size in the studied reaches (n=3; 1.6%), and therefore is not represented in Fig. 5; this is a typical representation for this class in Vermont, based on field experience of the investigators. One DEP reach was located at the transition from a 4thorder channel to a downstream reservoir delta; the remaining two reaches were located in alluvial fan settings (e.g., Fig. 4c).

509 4.3. Clustering outcomes

To determine whether the above expert-assigned sediment regime classes could be replicated by a data-driven, unsupervised clustering algorithm, we introduced a variety of geomorphic and hydraulic variables to the SOM, but withheld the above class assignments. A two-stage implementation of clustering was warranted to control for different scales of classification - essentially, a coarse-tuning SOM for all 193 reaches ranging in character from steep bedrock channels to alluvial channels, followed by a fine-tuning SOM applied to the subset

of 154 reaches comprising unconfined, low-gradient (<2%), self-formed alluvial channels. The
coarse-tune SOM was trained using largely reach-scale geomorphic variables, while the fine-tune
SOM was trained by adding cross-section-scale hydraulic variables that reflect stream
competence as affected by channel-floodplain configurations.

520

4.3.1. Coarse-tune SOM

The coarse-tune SOM was trained using List B of input variables (Table 1). These input 521 522 data self-organized into seven clusters, broadly corresponding to our six sediment regime 523 classifications (Table 2). The multivariate input data for the 193 training reaches were reduced to a two-dimensional 6 x 13 lattice for visualization (Fig. 6a). The column-to-row ratio for this 524 525 lattice (2.2) approximated the ratio (4.6/1.9) of the first two principal components of the 526 (transformed) input data. The multivariate reach observations self-organized on the SOM lattice 527 during training, such that reaches with similar variable sets aggregated together; and logical 528 groupings of these observations were partitioned into seven clusters. To illustrate an advantage of the SOM over other multivariate statistical techniques for pattern visualization, component 529 planes for a select number of the SOM input variables are provided in Fig. 6b (see also Fig. S3). 530 Each input variable may be superimposed on the converged SOM lattice to generate a 531 "component plane", where the range-normalized values vary in magnitude across the lattice. For 532 533 example, reach observations that aggregated to Cluster 4 in the upper-left corner of the lattice, 534 are characterized by high values of slope relative to other observations, as illustrated by the warmer tones in that region of the component plane for slope. These are also vertically-stable 535 reaches, as suggested by the low values (cool tones) in the same region of the component plane 536 for IR. Reach observations that aggregated to Cluster 7 of the SOM lattice are also vertically-537



stable (low values for IR), but are characterized by low slope values, and higher values than

539 other reaches for VC and ER.

540

538

Fig. 6. Coarse-tune SOM clustering of study area reaches, including (a) converged SOM lattice
showing clusters; and (b) component planes for selected input variables, in which the color
scheme represents a "heat map" grading from low (cool blue tones) to high (warmer red tones)
range-normalized values for each independent variable. Component planes for additional
variables are presented in Supplementary Fig. S2.

546 547

Bar plots of intra-cluster means (on a normalized scale) relative to overall means for each

- 548 parameter suggest which variables are important in defining the sediment regime clusters (Fig.
- 549 7a). Two TR clusters (4 and 5) comprised vertically-stable reaches confined by valley walls
- 550 (Fig. 7a). These reaches were characterized by steeper-than-average slopes, greater-than-average
- 551 SSP, and coarser bedload (dominated by bedrock in each case). Cluster 5 reaches were
- distinguished from Cluster 4 by a high SSP_{bal} value (>1; see Supplementary data). While this
- condition might suggest the propensity for incision, the bedrock boundary conditions would be



- 555 *Fig. 7. Coarse-tune SOM clustering of study area reaches, including (a) vertically-stable*
- reaches in confined settings, Clusters 4 and 5; (b) vertically-stable reaches in unconfined
- settings, Clusters 6 and 7; (c) vertically-disconnected reaches in unconfined settings, Clusters 1,
- 558 2 and 3 (n = number of reaches per cluster; y-axis represents range-normalized values); (d)
- summary of expert-assigned sediment regimes by cluster. Color scheme of bar plots corresponds
 to cluster colors in Fig. 6a.
- 561
- 562

expected to offer resistance in the present hydrologic regime. Therefore, in this data set (n=193)
and our study area (which includes reaches from a range of topographic settings), SSP_{bal} is a
variable with ability to discern bedrock-controlled knickpoints at a transition from a lessergradient upstream reach.

At the opposite end of the sediment transport continuum, representing transport-limited 567 conditions, two clusters (6 and 7) in unconfined settings were characterized by larger-than-568 569 average VC and ER values (Fig. 7b). Cluster 6 (DEP) reaches comprise coarser-than-average 570 bedload and very high W/D ratios (braided channels). Cluster 7 (CEFD) reaches, however, were distinguished by their lower-than-average W/D ratios, lesser slopes and finer-grained bed 571 572 material. These reaches were further characterized by a marked transition to a much more open 573 valley setting compared to the upstream reach (i.e., high VC ratio). In our study region, Cluster 7 reaches were located along the edge of post-glacial Lake Vermont, a higher-stage pre-cursor to 574 575 Lake Champlain (Stewart and MacClintock, 1969), and channel boundaries were composed of cohesive glaciolacustrine silts and silty-sands with varying percentages of clay (dune-ripple 576 bedforms). 577

The remaining reach observations in this coarse-tune SOM aggregated to three clusters of 578 vertically-disconnected reaches in unconfined settings (Fig. 7c). In general, Class 1 contained 579 580 reaches associated with a higher-than-average IR, lower-than-average ER and coarser-grained, 581 well-graded, bed material. Class 2 reaches, however, were much less incised (on average), and exhibited higher ER values, lower slopes, and finer-grained, well-sorted, bed materials. Variables 582 including number of depositional bars, number of flood chutes, percent armoring, and SSP were 583 useful in distinguishing between Clusters 1 and 2, as the cluster means for these factors trended 584 in opposite directions from the overall average. 585

To evaluate the utility of the coarse-tune SOM for partitioning reaches into sediment 586 regimes, we have summarized by cluster (Fig. 7d) the sediment regime classifications assigned 587 to reach observations in Section 4.2. We have also overlaid reach observation numbers on the 588 lattice nodes to which they clustered, color-coded by the assigned sediment regime classification 589 (Fig. 8). Based on 13 independent variables (list B in Table 1), the coarse-tune SOM was able to 590 distinguish reasonably well between sediment regimes at the extremes of the lateral-confinement 591 592 continuum for vertically-stable reaches (Fig. 8a). Clusters 4 and 5 are two variations of the TR 593 regime, with the latter representing local knickpoints. Cluster 6 contains the DEP reaches, while Cluster 7 represents a subset of the CEFD classification comprised of fine-grained, cohesive 594 595 channel types. Thus, along the lattice-horizontal dimension, the reach observations have selforganized into a configuration that is suggestive of the continuum of reach types from supply-596 597 limited to transport-limited (left to right in Fig. 8), as proposed by Montgomery and Buffington 598 (1997). Along the lattice-vertical dimension, an increasing gradient of vertical disconnection from the floodplain is evident (Fig. 8b). An increasing degree of channel or catchment stressors 599 600 may also be suggested by the distribution of parameter values that can be visualized on the component planes for IR, ER, percent armoring, and numbers of depositional bars and flood 601 chutes (Fig. S3). 602

Reaches in Clusters 1 and 2, on the other hand, each have a mix of expert-assigned sediment regimes (Fig. 7d), although the former is dominantly represented by UST, and the latter by CEFD regimes. Thus, governing variables used in the coarse-tune SOM may have only moderate power to discern between sediment regimes, particularly in the context of the full range of stream types from bedrock-cascade to silt-dune-ripple channels. Therefore, a second fine-

tune SOM was applied to cluster observations from only the unconfined, low-gradient (< 2%),



609 self-formed alluvial channels.

Fig. 8. Reach observation numbers (color-coded by expert-assigned sediment transport regime –
see key above) plotted to SOM to visualize where observations clustered on the coarse-tune
SOM.

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4.3.2. Fine-tune SOM

615 The fine-tune SOM was trained on the subset of 154 reach observations consisting of both geomorphic and hydraulic input variables (list C of Table 1). These reaches were 616 unconfined, low-gradient (<2%) channels predominantly alluvial in nature, although 617 characterized by the occasional bedrock grade controls or valley pinch points. Multivariate (p =618 10) input data for the 154 training reaches were reduced to a two-dimensional 6 x 12 lattice, with 619 620 a column-to-row ratio (2.0) similar to the ratio of the first two principal components of the 621 (transformed) input data (4.1/2.2). Non-transformed, but range-normalized, input data mapped to three clusters (Fig. 9a) that are characterized by different combinations of input variables (Fig. 622 9b). 623

The fine-tune SOM has closely replicated the expert-assigned sediment regimes (Fig. 9c), 624 and performed better than the coarse-tune SOM for these unconfined CEFD, UST and FSTCD 625 classes. Variable plots (Fig. 9b) illustrate that CEFD (Cluster 1) reaches were differentiated 626 from the other two classes, principally by their lower-than-average IR (≤ 1.3), and lower slopes 627 and SSP. The FSTCD (Cluster 3) reaches were discerned from their UST counterparts (Cluster 628 2), by elevated values for width ratio and W/D ratio, a higher incidence of flood chutes, and 629 lower-than-average mean depth ratio, reflecting the "wide-and-shallow" nature of these channels. 630 631 If the expert-assigned regimes are taken as "correct", the fine-tune SOM resulted in a correct classification rate of 64%, overall, with slightly higher classification rates for UST and CEFD 632 633 classes (66% and 65%, respectively) than the FSTCD class (60%).





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653 **5.** Discussion

654 5.1. SOM refinement of sediment regime classifications

Multivariate stream geomorphic assessment data for 193 Vermont stream reaches self-655 organized into seven clusters (sediment regimes) that broadly replicated and refined six 656 classifications offered in a VT Agency of Natural Resources River Corridor Planning Guide 657 utilized for river management (Kline, 2010). These sediment regimes are a function of both 658 geomorphic and hydraulic variables operating at the cross-section scale (e.g., relative roughness, 659 depth) and reach-scale (e.g., valley confinement, slope). While these metrics are based largely 660 on observations of form, the assigned sediment regimes reflect the spatial and temporal context 661 662 of multiple historic and active processes that have manifest the present channel and floodplain configuration (Wohl, 2018). These sediment regime classes could be considered as fluvial 663 process domains of Montgomery (1999), or "spatially identifiable areas characterized by distinct 664 suites of geomorphic processes", if we extend this conceptual framework to define reach-scale 665 patterns of sediment sourcing, deposition and transport dynamics. Our sediment regime classes 666 667 are developed at a more granular scale than the process domains (glacial vs. fluvial) of Livers 668 and Wohl (2015) defined for a study area undergoing active glaciation (Colorado Front Range of western US). Our study reaches are lower in elevation and would all be classified as fluvial, but 669 are influenced by former glacial activity. Multiple bedforms can occur in a given sediment 670 regime (Fig. 4b). Downstream sequencing of these sediment regime classes and their associated 671 bedforms is variable and influenced in part by the spatial and temporal context of macro-scale, 672 glaciogenic landforms as well as periodic bedrock exposures that create a stepped longitudinal 673 674 profile (Fig. 4c, d, e, f). In this sense, our results are consistent with findings from a

mountainous region of coastal British Columbia with a similar glacial legacy. Brardinoni and 675 Hassan (2007) applied multivariate discriminant analysis paired with PCA to channel and 676 floodplain metrics for classification of process domains, and identified a variation on the 677 idealized downstream continuum of stream types after Montgomery and Buffington (1997), 678 related to the presence of glaciogenic landforms and varying degrees of hillslope-channel 679 coupling. Their study considered relatively high-relief, undeveloped catchments of consistent 680 681 land use. In contrast, our lower-relief study catchments comprise a greater range of developed 682 and agricultural uses (Table S1). Thus, the fluvial geomorphic condition of our Vermont reaches also reflects the impacts of historic and active channel and floodplain encroachments and 683 684 disturbances (i.e., channelization, dredging, armoring, berming, gulllying) superimposed on inherited glacial landform effects. 685

686 Our sediment regimes comprise the full continuum of stream types proposed for 687 mountain systems by Montgomery and Buffington (1997), excluding colluvial channels. Our results extend this framework, by considering the vertical disconnection of a channel from its 688 floodplain resulting from a variety of natural and human disturbances. Similarly, Phillips and 689 Desloges (2014b) identified channel entrenchment as a factor contributing to within-class 690 variability among unconfined, alluvial channel types from a glacially-conditioned setting in 691 692 southern Ontario. Channel incision in our study area may have occurred over post-glacial to historic time frames during base-level lowering upon draining of high-elevation post-glacial 693 lakes (Stewart and MacClintock, 1979) or as a result of human stressors channel manipulation 694 (Kline and Cahoon, 2010), sediment-starved conditions downstream of historic mill dams 695 (Magilligan et al., 2008) or watershed-scale stressors such as increased runoff from urbanization 696 or deforestation (Booth, 1990). For several reaches, we inferred a complex history of 697

degradation, with active or historic incision overprinted on post-glacial incision. Regardless of
the cause, the present channel form and degree of vertical disconnection imparts varying
sensitivities to future adjustment, and influences fine and coarse sediment production, transport
and deposition.

Our nonlinear clustering algorithm appears reasonably robust to these complex and 702 multivariate interactions and was able to identify unique sediment regimes for reaches 703 704 comprising a range of channel types from confined to unconfined, steep- to shallow-gradient, 705 mid-to-high order, and bedrock to alluvial channels types. To resolve differences between sediment regime classes, application of the SOM in two stages was required, each incorporating 706 707 unique combinations of hydraulic and geomorphic variables,. The coarse-tune SOM identified 708 sediment regime classes at the supply-limited and transport-limited extremes of the continuum. 709 Bedrock channels and confined, steep-gradient reaches were identified as transport-dominated 710 reaches (TR). At the supply-dominated extreme, braided, depositional channels (DEP) were identified at alluvial fan or delta settings. The coarse-tune SOM also identified the unique case 711 712 of an alluvial fan head trench (Schumm, 2005) that likely formed under post-glacial times related to base-level lowering as proglacial lakes impounding downstream reaches were drained 713 (DeSimone, 2000). 714

CST reaches were less well defined by the coarse-tune SOM which may reflect the variable degrees of hillslope coupling noted in our reaches, consistent with findings of Brardinoni and Hassan (2006, 2007) in formerly-glaciated coastal British Columbia. This finding may also reflect temporal variability in sourcing of materials and the importance of episodic inputs from extreme events that recur on an interval exceeding the Q1.5 scale of our sediment regime. Evidence from the region (including some of the study area catchments)

suggests that mass wasting processes from our coupled hillslopes (where they exist) may be most
significant during low-frequency, high-magnitude flows (Dethier, et al., 2016).

The second-stage, fine-tune SOM nuanced differences in sediment sourcing and transport 723 724 for the alluvial, unconfined reaches, although it required sub-setting of the data to only the 725 unconfined reaches and slight modification of input variables. In this sense, the SOM is similar to traditional statistical techniques used to cluster fluvial process regimes, where optimal 726 727 performance requires pre-filtering by consistent land cover/ land use (e.g., Brardonini and 728 Hassan, 2007) or valley setting. For example, Phillips and Desloges (2014b) used k-means clustering, PCA, and discriminant analysis of geomorphic parameters to identify four channel-729 730 floodplain types. Their analysis was constrained to low-gradient, single-thread channels in unconfined settings, corresponding generally to C3, C4, E5, and E6 stream types of Rosgen 731 (1996). 732

The relatively low mean and median SSP (41 and 34 W m⁻², respectively) characterizing 733 the vertically-connected and quasi-equilibrium state CEFD reaches of our study area are similar 734 735 to stability thresholds identified by others in humid temperate regions. For catchments in the United Kingdom, Bizzi and Lerner (2013) identified an unconfined-channel stability threshold of 736 34 W m⁻² separating erosion-dominated reaches from those in a quasi-equilibrium state. Brookes 737 (1987) identified a similar threshold at 35 W m⁻² marking a transition between erosion-738 dominated and deposition-dominated channels for study areas in Denmark and the United 739 Kingdom. Our vertically-disconnected UST and FSTCD reaches exhibited SSP values in an 740 interquartile range that exceeded this stability threshold, although this variable had limited power 741 742 to distinguish between these two classes. It is important to note that our SSP values were generated from regional hydraulic geometry relationships and would not necessarily reflect the 743

influence of channel-floodplain manipulations that have persisted for UST reaches; rather,
elevated SSP values would largely reflect the steeper gradients of the UST and FSTCD reaches
as compared to CEFD reaches.

747 5.2. SOM advantages for addressing uncertainty in sediment regime classifications

Uncertainty will arise when attempting to classify the complex, nonlinear dynamics of 748 fluvial sediment regimes from large sets of independent variables, particularly when rule sets or 749 750 models are inadequate to define threshold effects or multivariate interactions. Since there are no 751 sharp boundaries ("edges") between sediment regimes, these classifications reflect a continuum of change, both temporally and spatially. The nonlinear, unsupervised SOM has particular 752 advantages over conventional and linear statistical techniques for addressing these uncertainties 753 and highlighting the potential influence of variable spatial and temporal scales of assessment. 754 755 The hierarchical nature of spatial scales in a catchment suggests that the channel-floodplain 756 geometry measured at a cross section scale can be relied upon to infer processes characteristic of the reach scale (Frissel et al., 1986), provided the reach length is appropriately delineated to 757 758 reflect relatively homogeneous characteristics. In this study, cross-section locations were chosen 759 to be representative of the reach and not influenced by localized sources of instability, such as stream crossings. However, subjectivity in this choice may have introduced bias, and it is 760 761 possible that select geomorphic or hydraulic parameters obtained at the cross section may reflect processes operating at a more granular scale than is characteristic of the reach as a whole (Lea 762 763 and Legleiter, 2016). For example, channel aggradation upstream of large woody debris might locally skew the D50 or D84 minus D16 values captured at a cross section. 764

In this study, executing the SOM in two stages helped to address uncertainty introduced
by different spatial scales of classification for our broad range of stream types (bedrock-cascade

to silt-dune-ripple). Coarse SOM results for the lumped range of stream types, and List B input
variables, indicate that certain sediment regimes are more predictable (e.g., TR, DEP), while
remaining regimes have more uncertainty. The latter group may represent reaches closer to
thresholds and "more vulnerable to small perturbations" (Phillips, 2003). Using only the subset
of reach data from unconfined settings (i.e., controlling for valley confinement and slope), the
fine-tune SOM and a slightly different set of input variables (List C) were better able to
differentiate between sediment regime classes.

774 Another source of uncertainty reflected the temporal context of our classifications. Varying states of recovery from past disturbance may have introduced error in both our expert 775 776 classifications and SOM clustering outcomes. It is likely that some reaches are in transition 777 between sediment regimes as the channel evolves in response to past floods and other natural and human disturbance(s), and therefore may have been mis-classified. By plotting the color-coded 778 779 expert-assigned reach observations directly on the converged lattice of an SOM (Fig. 8b and 9c), these "outliers" (i.e., mis-classified reach observations) could be readily identified. Notably, 780 781 they were often positioned at the boundaries, or transitions, between clusters.

A third source of uncertainty in our sediment regime classifications represents an 782 783 opportunity for future research. Classical studies have identified relatively frequent, moderate recurrence-interval flow events as the dominant discharge important in governing channel-784 floodplain form and transporting a majority of the sediment from the watershed (Wolman and 785 Miller, 1960). More recent studies suggest that a wider range of recurrence interval floods are 786 important in governing channel form and sediment flux (Lenzi et al., 2006; Downs, et al., 2016). 787 Particularly in bedrock-controlled headwaters, extreme events play a more dominant role in 788 shaping the channel and transporting sediment (Wolman and Gerson, 1978; Lenzi et al., 2006). 789

790 While the metrics in our sediment regime classification (e.g., W/D ratio, IR, SSP) are derived for 791 bankfull (Q1.5) stage, and the sediment classifications constitute the continuum of regimes characteristic of higher-frequency, low- to moderate-magnitude discharge (Q2 to Q50), we 792 recognize that extreme events (> Q50) can exert significant controls on channel and floodplain 793 response - both in terms of the event itself, and by influencing channel change through post-794 flood recovery phases (Wolman and Gerson, 1978). Extreme events have legacy impacts on 795 796 channel adjustment that can persist long after the event by altering boundary conditions 797 including valley slopes, source sediment volumes, landscape and streambank vegetation conditions, and instream large woody debris densities (Dethier et al., 2016). The current 798 799 sediment regime may be a manifestation of recovery from a past extreme event, more so than characteristic of the bankfull-flow regime (Dethier et al., 2016). To some degree, the different 800 801 outcomes of our coarse-tune versus fine-tune SOMs may have been reflecting these contrasting 802 temporal and spatial contexts for reach-scale sediment production, transport and deposition, but more study would be needed. 803

804 5.3. SOM advantages for visualization

The SOM and its component planes have advantages over traditional statistical methods when visualizing the multivariate features that interact in nonlinear ways to manifest in a given sediment regime. The reduction of multi-dimensional data to a two-dimensional lattice (e.g., Fig. 8b and 9c) simplified the data analysis, and component planes (Fig. 6b and S2) and bar plots (Fig. 7b-d and 9b) provided insight into which variable (or combinations of variables) may be a governing factor(s) in any particular cluster (i.e., sediment regime).

811 By applying a space-for-time substitution, the converged lattice also represents a kind of 812 process domain space (Montgomery, 1999) that can help visualize the transition of a channel

reach from one sediment regime to another as it progresses through channel evolution stages 813 (Fig. 10). For example, consider a low-gradient, gravel-dominated, riffle-pool reach with good 814 connection to its floodplain (i.e., IR<1.3) - all conditions that suggest a quasi-equilibrium state 815 816 (channel evolution stage I) characterized by a CEFD sediment regime. If this reach was subjected to channelization and dredging that lead to channel incision (IR > 1.3) and floodplain 817 disconnection, it would move to stage II, characterized by UST and FSTCD regimes (Fig. 10a 818 819 and 10c). The individual component planes for IR and W/D ratio demonstrate monotonic trends 820 in the lattice-vertical and lattice-horizontal dimensions that are consistent with this idea. The predisturbance reach would plot near the top-center of the lattice. Upon dredging, this same reach 821 822 would shift vertically downward and right on the lattice to areas characterized by higher IR 823 values. With subsequent widening, this reach would move lattice-left to a region typified by 824 higher W/D ratios (and greater numbers of depositional bars; Fig. S2). As channel widening 825 reduces stream competence leading to progressive aggradation, this reach might transition to a more transport-limited state - moving further lattice-left and -up toward a region characterized 826 827 by increasing numbers of depositional bars and lower W/D ratio. Finally, with progressive channel-narrowing, the channel may return to a quasi-equilibrium state (stage V) and return once 828 again to the top-center of the lattice. Thus, the SOM lattice provides a way to explicitly consider 829 830 and "map" the trajectory of shifting geomorphic process domains with time.



831
832 Fig. 10. Representation of (a) sediment regime classes by channel evolution stage (Schumm et al., 1984) superimposed on (b) the fine-tune SOM lattice; and (c) SOM component planes.

835 Classifying the current sediment regime of river reaches is of value for water resource managers to highlight the potential for impacts to property, water quality and habitat, and to 836 inform prioritization schemes for allocation of limited resources (Brierley and Fryirs, 2005; 837 Kline and Cahoon, 2010; Thorp et al., 2013). Vertically-disconnected reaches have greater 838 propensity for vertical and lateral channel adjustments with the potential to impact adjacent built 839 infrastructure. In confined settings of the glacially-conditioned Northeastern US, roads, rail 840 841 berms, bridges and culverts are commonly located within narrow, steep river valleys. In Vermont, this transportation infrastructure is commonly located adjacent to vertically-842 843 disconnected CST reaches and is at enhanced risk of damage during moderate to extreme events 844 (Anderson et al., 2017). In unconfined reaches, varying degrees of vertical disconnection from the floodplain would subject a channel to increased magnitudes of SSP, particularly during low-845

^{834 5.4.} Management implications

frequency flood events, with implications for enhanced erosion. Fig. 11 is based on a case of 846 contiguous reaches in the Mad River watershed in central Vermont, where reach A (UST) has 847 been subjected to historic dredging, channel straightening and berming to the extent that it has 848 become disconnected from the floodplain (IR = 2.6). While a nearby downstream reach of 849 similar drainage area (reach B; CEFD) and valley slope and confinement remained relatively 850 unmodified and well connected to the floodplain (IR=1.0). A range of storm flows was 851 852 simulated using a 1D hydraulic model for a regional flood study (Dubois and King, Inc., 2017), 853 and main channel SSP was computed as the product of average shear stress and average velocity. At the 2.3-year RI peak discharge, the relative difference in channel SSP between reaches A and 854 855 B is largely the result of differing channel configurations. In the entrenched cross section (reach A), a steeper slope (from historic channel straightening practices) and slightly greater hydraulic 856 857 radius (more efficient cross section) minimizes friction (due to smaller wetted perimeter) leading 858 to higher velocities and greater SSP. For the range of flows above a 2.3-year RI, however, the channel relationship to floodplain becomes most important. Since modeled flood flows of all 859 stages above Q2.3 were able to access the floodplain in the non-entrenched reach B, the channel-860 bed SSP has much lower magnitude across the array of peak flows than the entrenched cross 861 section of reach A. Conversely, given the degree of incision and entrenchment at reach A, SSP 862 863 continues to rise steadily until overtopping of the bank occurs somewhere between a Q100 and Q500 flood peak. Magnitudes of SSP at the reach A cross section greatly exceed the 300 W m⁻² 864 value suggested by Magilligan (1992) as a threshold for major channel adjustment. Fig. 11 865 illustrates the enhanced potential of incised and entrenched (i.e., UST) channels to serve as a 866 source of sediment to downstream reaches. 867



868
869 Fig. 11. Channel-bed SSP estimated for a range of modeled return interval storms in contiguous
870 reaches of the Mad River, VT with differing channel configurations (IR, ER).

871

872 CEFD reaches that are well-connected with the floodplain can be prioritized for corridor protection strategies in municipal or regional planning and zoning to maintain their floodplain 873 storage function. On the other hand, FSTCD reaches that are presently disconnected from the 874 875 floodplain may be prioritized for conservation easements to curtail river management and allow the unfolding channel evolution process to create new floodplain as an "attenuation asset" 876 (Kline, 2010). Particularly, where such reaches are located upstream of developed areas with a 877 greater degree of channel encroachment, they may be targeted for protection and worthy of 878 public investment for the attenuation of flood peaks and associated reduction in flooding hazards 879 880 to downstream communities (Kline and Cahoon, 2010; Watson et al., 2016).

In the northeastern US, where magnitude, frequency and intensity of extreme storm events are projected to increase (Guilbert et al., 2014), vertically-disconnected channels will have an enhanced potential to serve as a source of sediment to downstream reaches. CST reaches are vulnerable to increased fine sediment export under extreme events where these channels impinge upon hillslopes and high terraces comprised of glaciolacustrine or glacial till deposits (Yellen, et al., 2014; Dethier, et al., 2016). Since, the trajectory of SSP rise with storm
recurrence interval is much steeper for incised and entrenched UST and FSTCD reaches, it can
be inferred that they will have greater potential to export sediment than CEFD reaches. Coarse
sediment will have the potential to aggrade and drive lateral adjustments and avulsions in
downstream reaches, while fine sediments will be carried to receiving waters and further degrade
water quality.

892 To address water quality concerns on a river network scale, this sediment regime classification approach could be used to identify reaches that are disproportionately responsible 893 for loading of coarse and fine sediments. For example, streambank erosion has been identified 894 as a source of phosphorus contributing to harmful algal blooms in Lake Champlain in the 895 northwestern region of Vermont (Isles et al., 2015). In the Total Maximum Daily Load plan, 896 897 estimates of phosphorus loading from streambanks are based on the dominant reach-based 898 channel evolution stage at a HUC 12 scale (USEPA, 2016). Our algorithm could be used to refine estimates of streambank sediment loading at a more granular scale to identify "hot spots" 899 (McClain et al. 2003) and to optimize best management practices for the reduction of sediment 900 and nutrient loading. 901

902 6. Conclusions

Multivariate stream geomorphic assessment data have been clustered into sediment process domains that constitute net sources or sinks of coarse and fine sediment on a mean annual temporal scale (i.e., Q1.5 discharge) using a two-stage Self-Organizing Map (SOM). The iterative process of streamlining input parameters and training the SOM identified a parsimonious set of geomorphic and hydraulic variables that meaningfully separated reaches into these sediment regimes. Our results illustrate the importance of landscape controls including

bedrock knickpoints and glaciogenic landforms in governing downstream trends in sediment
regime, as well as the impacts of channel-floodplain encroachments and modifications that have
been superimposed on these inherited glacial landform effects.

While this classification scheme has been applied to characterize sediment process 912 913 domains in the glacially-conditioned and mountainous areas of northeastern US, the framework 914 is transferable to other regions (utilizing additional or alternate independent variables). The 915 geomorphic and hydraulic variables used to cluster the studied reaches were similar to parameters commonly inventoried during assessment protocols in widespread. As channels 916 917 evolve over time in response to stressors or management practices, these data-driven, nonparametric clustering tools can be quite easily updated with new assessment results, 918 supporting an adaptive approach to river corridor management that offers data visualization 919 920 capabilities.

To our knowledge, this current study is the first application of a neural network to 921 examine geomorphic data for a range of stream types and to classify a reach-based sediment 922 923 regime that explains the nature of the adjustment (vertical, lateral) within the trajectory of channel evolution. Our results extend the supply-limited to transport-limited continuum of reach 924 types suggested by Montgomery and Buffington (1997), through the additional dimension of a 925 channel's increasing degree of vertical disconnection from the floodplain that can result from a 926 variety of natural and human disturbances. Through its effect on channel stream power, this 927 928 vertical-lateral connectivity condition can influence the sediment transport regime in channels 929 and has implications for inundation and erosion flooding hazards, as well as water quality and ecological integrity in the active river corridor. 930

Future work will explore automation of this algorithm, and variable weighting of input 931 parameters informed by a panel of domain experts. Linking this algorithm to existing stream 932 geomorphic assessment data in a GIS will enable model predictions statewide and the analysis 933 for potential autocorrelation of sediment regimes with distance along stream networks. The 934 anticipated framework will facilitate scenario testing to evaluate how sediment transport regimes 935 of a given reach (or river network) might shift in the event of future channel and floodplain 936 937 manipulation or restoration, or in response to regional changes in climate. The GIS framework 938 could also be used to forecast estimates of channel adjustment to optimize best management practices for the reduction of sediment and nutrient loading from streambanks. 939

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