Tributary connectivity, confluence aggradation and network biodiversity

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ABSTRACT

In fluvial networks, some confluences are associated with tributary-driven aggradation where coarse sediment is stored, downstream sediment connectivity is interrupted and substantial hydraulic and morphological heterogeneity is generated. To the extent that biological diversity is supported by physical diversity, it has been proposed that the distribution and frequency of tributary-driven aggradation is important for the magnitude and spatial structure of river biodiversity. Relevant ideas are formulated within the Link Discontinuity Concept and the Network Dynamics Hypothesis, but many of the issues raised by these conceptual models have not been systematically evaluated. This paper first tests an automated method for predicting the likelihood of tributary-driven aggradation in three large drainage networks in the Rocky Mountain foothills, Canada. The method correctly identified approximately 75% of significant tributary confluences and 97% of insignificant confluences. The method is then used to evaluate two hypotheses of the Network Dynamics Hypothesis: that linear-shaped basins are more likely to show a longitudinal, downstream decline in tributary-driven aggradation; and that larger and more compact basins contain more confluences with a high probability of impact. The use of a predictive model that included a measure of tributary basin sediment delivery, rather than symmetry ratio alone, mediated the outcomes somewhat, but as anticipated, the number of significant confluences increased with basin size and basin shape was a strong control of the number and distribution of significant confluences. Doubling basin area led to a 1.9-fold increase in the number of significant confluences and compact basins contained approximately twice as many significant confluences per unit channel length as linear basins. In compact basins, significant confluences were more widely distributed, whereas in linear basins they were concentrated in proximal reaches. Interesting outstanding issues include the possibility of using spatially-distributed sediment routing models to predict tributary-driven confluence aggradation and the need to gather ecological data sufficient to properly test for increases in local and network-scale biodiversity associated with significant confluences and their network-scale controls.

KEYWORDS: confluence, tributary, sedimentary link, Network Dynamics Hypothesis, river biodiversity

1. INTRODUCTION

1.1 Tributary-driven aggradation in river networks

Confluences are nodal points of connectivity in the movement of water and sediment through a drainage network and the interaction of tributaries with their trunk streams is crucial for understanding sediment routing and maturation in river systems (Knighton, 1989; Benda and Dunne, 1997; Rice, 1998; Brierley and Fryirs, 1999; Mosley and Schumm, 2001; Fryirs et al., 2007; Fryirs, 2013). Some confluences, where tributaries supply particularly coarse and voluminous bed loads to their trunk stream, delineate "sedimentary links" that structure changes in slope, morphology and bed sediment character along individual drainage lines (Rice and Church, 1998; Rice, 1999). At these geomorphologically significant confluences, excess coarse sediment from active tributaries is stored in the mainstem channel (and associated tributary fans), forcing bed slope to steepen in order to maintain sediment dispersal downstream. Tributary-driven aggradation typically produces slope reductions and sediment fining upstream and slope steepening and sediment coarsening downstream (Miller, 1958; Church and Kellerhals, 1978; Rice and Church, 1998, 2001; Benda et al., 2004a; Harmer and Clifford, 2006; Hanks and Webb, 2006). These adjustments increase channel physical heterogeneity and, indeed, may be the primary driver of substrate, slope and morphological variability (Swanson and Meyer, 2014).

Augmentation of channel heterogeneity by tributary-driven aggradation has implications for river ecosystem functions and health because the additional habitat diversity may be an important support for biodiversity at local, reach and network scales (Benda, 2004b; Rice et al., 2006; Rice et al., 2008 for a review). Where aggradation is substantial, backwatering may produce upstream flow conditions characterised by lower velocities, deeper water and lower Froude numbers, contrasting with more energetic, higher Froude conditions on the steeper slope below the sediment supply point. In addition, excess sediment is available to build bedforms that add flow complexity and mesohabitats, and bed material sorting may generate diverse substrate characteristics (grain size, stability, microtopography, near-bed hydraulics) over short distances. This type of increased local heterogeneity at confluences has been associated with discontinuities in the longitudinal distribution and diversity of invertebrates (Rice et al., 2001; Knispel and Castella, 2003), periphyton and fish (Kiffney et

al. 2006; Torgersen et al., 2008). In addition, the juxtaposition of contrasting physical conditions between the tributary, upstream and downstream links may offer unique opportunities for mobile taxa (Power and Dietrich, 2002), including for example, local (and therefore low-cost) access to contrasts in illumination, substrate stability, turbidity, predator avoidance and water temperature (Kupferberg, 1996; Scrivener et al., 1994; Fraser et al., 1995; Cairns et al., 2005; Katano et al., 2009; Taverny et al., 2012). There are other reasons why confluences are important for river biodiversity including: provision of nutrient or prey subsidies (Wipfli and Gregovitch, 2002; Fernandes et al., 2004; Wellard-Kelly, 2013); the presence of unique confluence-zone habitats (Nakamoto, 1994; Franks et al., 2002; Kreb and Budiono, 2005); the amplification of competition amongst species (Besemer et al., 2013); and bi-directional filtering that affects organism dispersal (e.g. Thornbrugh and Gido, 2010; Wilson and McTammany, 2014; Czeglédi et al., 2004b), where added biological value partly reflects increased physical heterogeneity produced by tributary-forced aggradation.

However, it is clear that only some tributaries cause mainstem aggradation and measureable changes in geomorphology and ecology; many do not. Rice (1998) found that approximately 20% of tributaries along Pine and Sukunka Rivers in British Columbia, had an impact on mainstem grain size or slope. It is therefore unsurprising that some evaluations of tributary impacts on stream ecology are equivocal (e.g. Milesi and Melo, 2014; Clay et al, 2015). Ultimately, this reflects the complex nature of tributary-mainstem interactions and the lack of simple systematic relations between tributary properties and their impact (Rhoads, 1987; Wallis et al., 2008). In low order streams, bedrock controls on channel geometry, disruption of sediment connectivity by wood loading and direct coupling of the channel to hillslope sediment sources may mask tributary effects (Krumbein, 1942; Miller, 1958; Benda and Cundy 1990; Rice and Church, 1996; McEwen and Miller, 1998; Rengers and Wohl, 2007; Al Farraj and Harvey, 2010; Kuo and Brierley, 2014; Menting et al., 2015). In general, across all settings, tributary impacts on mainstem sediment storage may be transient (e.g. Kasai et al., 2005) and are contingent on local factors including degree of valley confinement, lithological variations, past depositional history and upstream sediment connectivity (Rice, 1998; Swanson and Meyer, 2014). For example, along the Sacramento River, California, basin physiography and anthropogenic interventions mean that upstream-

downstream sediment connectivity is weak and tributaries devoid of sediment have no measurable impact on the mainstem (Singer, 2008).

1.2 Controls of tributary-driven aggradation – which tributaries matter?

If not all tributaries cause mainstem aggradation, but such aggradation is important, a key question is: What controls tributary-driven mainstem aggradation? Knighton (1980) argued that tributary sediment load and calibre were important determinants of step-changes in bed material grain size at confluences. Using field data from approximately 100 confluences in north-eastern British Columbia, Rice (1998) identified the product of tributary basin area and distal tributary slope ($\psi_t = A_t.S_t$) and the symmetry ratio ($A_R = A_t/A_m$) as useful surrogate measures of tributary sediment delivery and relative bedload grain size, respectively (where A_t is tributary basin area, A_m is main stem basin area and S_t is distal tributary slope). Logistic regression was used to establish an empirical relation for the probability of tributary impact on mainstem bed material size P_D :

$$\ln\left(\frac{P_D}{1-P_D}\right) = 8.68 + 6.08 \log A_R + 10.04 \log \varphi_t$$
[1]

Benda et al. (2004a) investigated the properties of 168 tributary confluences that had been identified as geomorphologically significant in 14 separate studies from the western United States and Canada. They found that A_R was a useful predictor of impact and defined logistic regression models for the probability of geomorphological impact P_G , for both humid and semi-arid environments, the former being:

$$\ln\left(\frac{P_G}{1 - P_G}\right) = 3.79 + 1.96 \log A_R$$
[2]

Both models [1] and [2] suggest that the probability of a tributary impact increases with A_R , but the data sets show that the bulk of significant confluences fall in the range (0.01 < A_R < 0.1), such that very small tributaries, less than 1/100th of the drainage area of the mainstem, and those approaching the same size as the mainstem are less frequently important.

Benda et al. (2004a) went on to consider the factors that affect the spatial distribution of relative tributary size in a drainage basin and therefore the spatial distribution of likely impacts across river networks, identifying three key factors. First, they argued that shape

should be important, with heart-shaped or compact basin shapes more likely to experience tributary impacts in distal reaches than linear, rectangular shaped basins, because the former have a higher probability of hosting relatively large tributary basins along the entire length of the mainstem. Second, they argued that more densely dissected landscapes (therefore with a higher density of confluences) should have more frequent confluence effects. Third, they pointed out that structural constraints might complicate these general relations by affecting the spacing of tributaries and the angle at which confluent channels meet, with implications for the geomorphic impact (cf. Mosley, 1976; Benda and Cundy, 1990). The role of basin shape was illustrated using predictions of confluence impact based on equation [2], for two sub-catchments of the Siuslaw River, Oregon, and a systematic analysis revealed an anticipated increase in the spacing between significant confluences with distance downstream along the Siuslaw mainstem. Subsequently, Benda (2008) reflected on these analyses and extended them in several ways, identifying eight testable hypotheses pertaining to the impact of tributaries on mainstem geomorphology.

In addition to this empirical work, conceptual models of alluvial regime, for example Lane (1955), and theoretical investigations for both sand- and gravel-bed rivers (Ferguson and Hoey, 2008), suggest that mainstem responses to tributaries are governed by the ratios of tributary to mainstem discharge (Q_R) , bed load flux (F_R) and bed load grain size (D_R) . In a numerical modelling experiment using a 1-D sediment routing model with a tributary input (TRIB), Ferguson et al. (2006) investigated the systematic variation of Q_R , F_R and D_R on mainstem geomorphology, measured as changes in channel slope and grain size. They found that patterns of bed gradation and grain-size change reflect the interplay between the sediment load that a tributary adds and the extra discharge available to transport it. Rice et al. (2006) used TRIB to explore the role of Q_R , F_R and D_R in generating physical heterogeneity around confluences, quantified as the amount of change in slope and grain size from upstream to downstream and within the upstream and downstream reaches. They found that the product $F_R.D_R$ was the key determinant of such heterogeneity, while the momentum ratio Q_R was less important (Rice et al., 2006). This result is consistent with field observations showing that tributaries which introduce large amounts of relatively coarse material are associated with mainstem storage, aggradation, upstream slope reduction and downstream slope increases (e.g. Rice and Church 1998, 2001; Swanston and Meyer 2014)

and with the empirical relations for tributary impact produced by Rice (1998) and Benda et al. (2004a).

1.3 Outstanding issues and aims

Interesting questions about the controls of tributary-driven aggradation and its large-scale implications persist. This paper is concerned with two specific issues. First, is it possible to predict which confluences in a network are likely to exhibit tributary-driven aggradation? This is important because prediction would establish the likely location of geomorphologically significant storage nodes in a fluvial network and sites of enhanced physical heterogeneity and biodiversity. Various approaches to this problem could be taken, including the application of spatially distributed numerical models of sediment transfer processes (e.g. Gasparini, 1999; Sklar et al., 2006; Czuba and Foufoula-Georgiou, 2015) or the statistical interrogation of high-resolution or continuous, longitudinal data (Torgersen et al., 2008). Here, the approach adopted by Rice (1998) and Benda et al., (2004a) is pursued. An appropriate goal is to establish an automated method to predict likely confluence impact, based on extracting relevant predictive variables (e.g. *A*_R, *D*_R, *F*_R) from digital topographic data. Benda et al. (2004a) and Benda (2008) used such an approach to illustrate probable confluence impacts across the Siuslaw watershed, but the results were not systematically evaluated using field data. The first aim of this paper is therefore to:

 evaluate whether an automated version of Rice's (1998) rule (equation 1) can correctly identify the confluences known to be geomorphologically significant along the mainstem of Sukunka River, British Columbia.

Because impacts on longitudinal grain size are driven by geomorphological adjustments to excess tributary sediment supply, P_D values are regarded as probabilities of tributary-driven aggradation, even though equation 1 was formulated to detect changes in bed material grain size. Data from Sukunka River were used to define equation 1, so this aim amounts to an evaluation of how well an automated methodology can capture the key independent variables used by the model (A_R , ψ_t). Also, it is not anticipated that the automated method can improve upon the performance of the manual method (Rice, 1998), rather it would make it possible to apply the method to a large number of confluences relatively quickly.

The second issue considered here is how network size and shape affect the distribution and cumulative ecological benefit, in terms of additional physical heterogeneity, of tributarydriven aggradation. This is important because it might help to better understand differences in catchment-scale sediment routing and morphological diversity and (to the extent that physical heterogeneity underpins biodiversity) differences in sum, catchment-scale ecological value and resilience. Benda et al. (2004a, b) and Benda (2008) make an excellent case for such understanding, but empirical tests of their hypotheses have been limited. Following verification of aim 1, that an automated version of Rice's (1998) rule (equation 1) can correctly identify tributary-driven aggradation, that model will be applied across several additional drainage basins, to examine whether basin size and network shape (linear versus compact) affect the spatial distribution and cumulative magnitude of tributary derived heterogeneity. Specifically:

- 2. Do linear basins demonstrate the downstream decline in likelihood of tributary-driven aggradation proposed by Benda et al. (2004a)? Benda's hypothesis assumes that symmetry ratio (equation 2) is the only relevant control, but Rice's model also recognises the role of tributary sediment yield, as parameterised by ψ_t (equation 1), and it is not clear what effect this will have on downstream patterns of tributary impact.
- 3. How does drainage network size and shape affect the frequency distribution of confluence impact probabilities and, in turn, the likely cumulative magnitude of confluence effects? Here, the expectation is that larger and more compact basins will contain more confluences with a high probability of an impact so that compact basins of a particular size have a greater overall confluence-related effect on heterogeneity.

2. METHODS

Aims 1 -3 were addressed using data for three river basins in north-eastern British Columbia, Canada: Sukunka, Pine and Murray Rivers (Figure 1).



Figure 1 . Pine, Sukunka and Murray River basins and river networks determined by D8 algorithm and pruned to match 1:50000 mapping. Inset shows location in British Columbia, Canada.

Aim 1 required automated extraction of the network and drainage basin characteristics necessary to derive the two independent variables used in equation 1 for the mainstem confluences of Sukunka River. This was achieved using RiverTools (v 2.4, Research Systems, Boulder USA) applied to mosaicked GeoBase digital elevation data tiles for the Sukunka catchment (0.75 arc-seconds or approximately 20m resolution). For the whole Sukunka catchment, a flow grid was produced using the D8 algorithm with an improved imposedgradients routine to eliminate parallel flow paths on flat terrain. The river network was isolated and pruned until the derived network matched the blue-line network on 1:50000 National Topographic Survey of Canada mapping. RiverTools was then used to extract pertinent network and topographic properties for each of 1013 links in the network, including their length, gradient and upstream basin area as well as the magnitude, length and relief of the longest upstream chain. These link data were restructured using unique identifiers to produce a spreadsheet organised by confluences, from which 116 confluences along Sukunka mainstem were identified (Figure 1). In each case A_R and ψ_t were calculated from the derived data, using the slope of the tributary link connecting to the confluence as distal tributary slope, S_t . Equation 1 was then used to calculate P_D for each mainstem confluence.

The expectation is that the automated method will have a similar performance to the manual method and correctly identify significant tributaries as significant (true positives) and incorrectly identify insignificant tributaries as significant (false positives) at similar rates to the manual method of Rice (1998). To make these comparisons, confluences with $P_D > 0.8$ are regarded as those which have a high likelihood of tributary-driven aggradation. The choice of 0.8 is essentially arbitrary, driven by the need for some consistent criterion for making comparisons and the need to count as significant only those confluences that have a high probability of significance according to the logistic model. Higher values might exclude significant confluences and lower values might include insignificant confluences. In fact, the shape of the logisitic model, in which the curve flattens out at high probabilities, means that the criterion is quite insensitive to values in the range 0.7 to 1.0. The performance of the automated method ($P_D > 0.8$) match those known to be significant from field evaluation and whether the rate of true and false positives are similar to those for the manual method (Rice, 1998).

Aims 2 and 3 required confluence data for networks which varied in shape, but where equation 1 might be expected to hold. Therefore, the networks of Pine and Murray Rivers, which are adjacent to Sukunka River, were extracted using the same process as for Sukunka River. For Pine and Sukunka, 17 fourth-order and independent third-order sub-networks were also identified (Figure 2). The Pine and Murray networks were pruned, as described above for Sukunka, using RiverTools. Low-order confluences were filtered out of this large

data set because in small headwater streams hillslope coupling, bedrock and woody debris dominate sediment transfer processes so that tributary effects are likely to be indistinguishable from alternative sources of physical heterogeneity. Based on field observations of where such effects were dominant, confluences where the sum of the Strahler order of the upstream links was less than or equal to 3, were excluded. This left a data set of 2028 (56% of the original) confluences across the three large basins.



Figure 2. Pine and Sukunka catchments highlighting the 17 sub-basins utilised to examine relations between basin characteristics and the location and frequency of tributary-driven aggradation t confluences

In addition, one Pine tributary, Centurion Creek, occupies the former valley of the Pine River prior to the main stem's capture by Sukunka River probably during the Late Pleistocene. It is decidedly underfit (Dawson, 1881; Hughes, 1967), flows across the bed of a former glacial lake and rarely accesses coarse tributary deposits stored close to its valley walls. Centurion Creek was excluded because its topography and history are highly unusual compared with all of the other more mountainous sub-basins. RiverTools was used to extract tributary and mainstem basin properties for the remaining 1998 confluences as described above for the mainstem confluences on Sukunka River (Table 1).

The shape of each basin of interest (the three large basins, the combined basin formed above the confluence of Pine with Sukunka, and the 17 sub-basins within Pine and Sukunka) was quantified using:

$$B = \frac{\sqrt{A}}{d}$$
[3]

where A is basin area (km²) and d is basin diameter (km) defined as the maximum straightline distance between any two points on the basin perimeter. This metric is equivalent to the square root of the form factor (= A / d^2 ; Horton, 1932). Values of B closer to 1.0 indicate more compact basins and smaller values more linear shapes. Evaluation of several shape metrics (including bifurcation ratio) showed that B was most consistent in correctly differentiating basins that were visually categorised by the author as linear or compact.

The impact of basin shape on the longitudinal distribution of tributary-driven aggradation (aim 2) was assessed by examining downstream variations of P_D in the 17 Pine and Sukunka sub-basins. Rather than selecting a single drainage line (e.g. the mainstem), the entire network was included. Confluence position was specified as the maximum distance to the head of a fingertip tributary, essentially distance downstream along the respective network branch. In addition to visualising the downstream pattern of P_D values, the percentage of confluences with $P_D > 0.8$ in the upstream (proximal) half of the mainstem length, X (%), was used as a metric to assess the expectation that in more linear basins a greater proportion of significant confluences would be concentrated upstream. The impact of size and shape on the magnitude of the cumulative, basin-wide, confluence effect (aim 3) was assessed by examining how the total number of confluences likely to be significant ($P_D > 0.8$) differed across the 17 sub-basins. To account for differences in basin size in the analysis of shape effects, the number of significant confluences *n*, was normalised by total channel length, *L*:

$$N = \frac{n_{0.8}}{L}$$
[4]

The expectation was that more compact basins would yield a greater number of significant confluences per unit channel length. Values of *B* varied between 0.48 and 0.70 for the 17 sub-basins (Table 1). For the purposes of testing hypothesised differences in *X* and *N* with shape, basins were placed into three groups according to which third of this distribution they belonged to: compact for 0.63 < *B* < 0.70, linear for 0.48 < *B* < 0.55, mixed for 0.55 < *B* < 0.63. Simple t-tests were performed.

	Area (km²)	Strahler order	Drainage density (km km ⁻²)	Total confluences	Confluences passing coupling rule	Basin Shape	Bifurcation ratio
		_					
Sukunka	2894.6	6	0.742	804	469	0.620	4.020
North Burnt	114.5	4	0.700	28	15	0.695	3.214
Dickebusch	85.0	3	0.705	22	4	0.542	4.750
East Burnt	165.7	4	0.703	40	22	0.482	3.519
Highhat	157.6	4	0.827	56	29	0.503	4.456
Martin	119.9	3	0.806	26	15	0.592	5.786
Brazion	320.4	4	0.701	89	56	0.493	4.496
South Burnt	127.2	4	0.682	29	17	0.573	3.500
Upper Sukunka	697.16	4	0713	185	112	0.543	5.795
Windfall	215.75	4	0.672	49	20	0.595	4.019
Pine	2329.9	5	0.758	652	362	0.531	5.160
Falling	132.6	4	0.736	32	19	0.570	3.375
Beaudette	104.7	4	0.716	22	12	0.545	2.958
John Bennett	91.8	4	0.704	26	16	0.482	3.119
Hasler	193.5	4	0.710	51	24	0.613	3.844
Lemoray	105.7	3	0.609	21	14	0.535	4.700
Mountain	180.8	4	0.713	40	23	0.530	3.806
Callazon	251.8	4	0.755	65	26	0.652	4.167
Pine Pass	141.4	4	0.662	36	18	0.701	3.595
Pine+Sukunka	5224.5	6	0.749	1456	831	0.589	4.700
Murray	6471.7	6	0.836	2085	1167	0.529	4.784

Table 1. Basin and network characteristics for the 17 sub-basins and 3 large basins used in this study

3. RESULTS

3.1 Performance of the automated method

Rice and Church (1998) identified 12 confluences on Sukunka mainstem as significant sediment sources with an impact on channel characteristics. Application of the logistic regression model (equation 1) using data derived from manual map-based measurements (Rice, 1998) correctly identified 11 of these (92%) as 'significant', i.e. they had a predicted probability of impact exceeding 0.8. By the same criterion, the automated method adopted here correctly identified 8 of the 12 (75%) as significant. Of the insignificant confluences along Sukunka mainstem, 97.1% had $P_D < 0.10$ and 100% had $P_D < 0.80$ using the automated method, indicating a strong ability to correctly identify confluences with a low likelihood of mainstem impact.

Of the four misclassified significant cases: two nevertheless had high predicted probabilities of significance (P_D = 0.73 for Dickebusch Creek and P_D = 0.79 for Baker/Lean-to Creek) so their misclassification reflects the choice of $P_D = 0.8$ as a threshold, rather than a fundamental failing of the method; and one was the same tributary that the manual method failed to identify, which simply reflects the imperfection of the underlying discriminatory model. Of interest in the context of evaluating the automated method's performance, is significant tributary S20, which had $P_D = 0.89$ using the manual method, but $P_D < 0.001$ using the automated method. This is explained by assignment by the automated method of S_t = 0.001, which yields ψ_t = 0.04, so that despite a relatively large symmetry ratio for this confluence (0.09), P_D is small. St is small because in the extracted network the most distal tributary link is a short link that occurs on the valley flat and which is not indicative of the true potential for sediment supply from the tributary. This provides a good example of where automated methods can produce erroneous results. Basin topography may affect the propensity for this particular type of error to occur, but planimetric basin shape is unlikely to make such errors more or less likely, so that there is little likelihood that misclassification errors affect the primary goal here of assessing differences in confluence impacts between basins of different shape.



Figure 3. Three illustrations of typical patterns of downstream change in the probability of confluence significance (P_D): (a) North Burnt is characteristic of compact basins; (b) Highhat River is characteristic of linear basins; and (c) Mountain Creek exemplifies some linear basins where distal tributaries are sufficiently steep to generate aggradation despite small symmetry ratios.

3.2 Basin shape and downstream patterns of confluence impact

Figure 3 provides three illustrative examples of how the likelihood of confluence significance (values of *P*_D) vary with distance downstream across the 17 pine and Sukunka sub-basins. For compact networks, for example in the Central Burnt basin (Figure 3a), the likelihood of tributary impact tends to stays high, as anticipated by Benda et al. (2004a) and Benda (2008), because there is a greater likelihood that a relatively large tributary can join the distal reach of any branch in the network. Some linear basins, for example Highhat River (Figure 3b), lack significant confluences in distal reaches, again as anticipated by Benda et al. (2004a) and Benda et al. (2004a) and Benda (2008). However, a number of linear basins, including Mountain Creek (Figure 3c) do not follow the expected pattern with significant confluences close to their outlets.

For the complete set of 17 sub-basins, the proportion of significant confluences ($P_D > 0.8$) that occur in the upstream 50% of each network *X*, declined as basin shape B, tended toward more compact (Figure 4a) and although the negative correlation between the two variables was not significant at $\alpha = 0.05$ ($r_{(15)} = -0.45$, p = 0.07), mean proximity for the linear basins (X = 67, SD = 17.5) was significantly greater (Figure 4b; $t_{(10)} = 2.01$, p = 0.04) than for the compact basins (X = 44.5, SD = 19.9).



Figure 4. (a) Percentage of significant confluences ($P_D > 0.8$) in the proximal (upstream) half of each sub-basin X, plotted against sub-basin shape, B. (b) Comparison of mean X, with 95% confidence intervals, for sub-basins in the compact (open circle; 0.63 < B < 0.70) and linear (solid circle; 0.48 < B < 0.55) groups.

3.3 Basin size, shape and the frequency distribution of confluence impact probabilities

The number of significant ($P_D > 0.8$) confluences $n_{0.8}$, increases with total network length *L* (Figure 5) and simple linear regression yields the following significant relation across the full range of basin scales (the three large basins and the 17 sub-basins):

$$n = 0.066 L^{0.893}$$
 (R² = 0.95, F_(1,18) = 314.9, p < 0.001) [5]

Drainage area and network length are strongly correlated ($r_{(18)} = 0.99$, p < 0.001) and an equivalent using A is:



$$n = 0.042 A^{0.920}$$
 (R2 = 0.95, F_(1, 18) = 317.0, p < 0.001) [6]

Figure 5. Relation between total channel length L (km), and the number of significant confluences $n_{0.8}$, in the 17 sub-basins and three large basins. The plotted line is described by equation 5 and was fitted using least squares linear regression.

The number of significant confluences per unit channel length *N*, increased as basin shape *B*, tended toward more compact (Figure 6a) and there was a significant ($\alpha = 0.05$) positive correlation between the two variables; $r_{(17)} = 0.59$, p = 0.01. Also, mean *N* for linear basins (N = 0.036, SD = 0.013) was significantly less (Figure 6b; $t_{(10)} = 2.16$, p = 0.03) than for compact basins (N = 0.054, SD = 0.014).



Figure 6. (a) Number of significant confluences ($P_D > 0.8$) per unit channel length N (km⁻¹), plotted against sub-basin shape, B. (b) Comparison of mean N, with 95% confidence intervals, for sub-basins in the compact (open circle; 0.63 < B < 0.70) and linear (solid circle; 0.48 < B < 0.55) groups.

4. DISCUSSION

In a systematic test of an automated method for identifying tributary significance, using a criterion for significance of $P_D > 0.8$, insignificant confluences were never misclassified as significant, but 25% of significant tributaries were misclassified as insignificant. Only 1 of 4 misclassifications was caused by errors introduced by the automated method. The success rate of 75% (or 83% if the significance criterion is reduced to $P_D = 0.70$) compared with 93% for the equivalent manual method, suggests that the automated method provided an adequate means of deriving predictions of confluence significance. However, it is safe to suggest that the predictions of significance made herein are conservative and may underestimate the true population of significant confluences by one third. In general, this highlights how difficult it is to predict tributary impacts using simple algorithms that use basin-scale characteristics as surrogates for the key controls of tributary impact: relative bedload flux, grains size and discharge.

Nevertheless, empirical analysis of confluence significance across the study area confirmed expectations (Benda et al., 2004a; Benda, 2008) that the number of significant confluences increases with total network length and drainage area. The relation between $n_{0.8}$ and A

(equation 6) suggests an eight-fold increase in the number of significant confluences for a ten-fold increase in basin area, or a 1.9-fold increase in significant confluences for a doubling of basin area. Also as anticipated by Benda et al. (2004a) and Benda (2008), basin shape was a strong control of both the number of significant confluences and their spatial distribution: relatively compact basins tended to host a greater number of significant confluences the network. In contrast, relatively linear basins were more likely to be distributed across the network. In contrast, relatively linear basins were more likely to have fewer aggradational confluences that were concentrated in proximal reaches. Figure 6a suggests that, on average, the most compact basins in the study area ($B \approx 0.70$) contained approximately twice as many significant confluences per kilometre of channel as the most linear basins ($B \approx 0.48$).

The relation between basin shape and the downstream distribution of significant confluences, did not match the expectation in every case, with significant tributaries in the distal portions of several linear basins. This reflects the key difference in Rice's (1998) predictive equation, which was used here, compared with Benda et al.'s (2004a) model. While the latter uses symmetry ratio as the only independent parameter, Rice's model includes a bedload supply parameter that is proportional to tributary slope (equation 1). Some of the linear basins encountered here are predicted to have distal tributaries that are important for aggradation, even though symmetry ratios are relatively small, because those tributaries are steep. This may reflect the physiography of the mountainous terrain of these Rocky Mountain foothill rivers. The major trunk streams (Pine, Sukunka, Murray) sit in relatively wide, flat alluvial valleys but receive water and sediment from steeper tributaries that lack strong alluvial development and, themselves, are supplied by streams draining steep, mountainous terrain. In linear basins it is therefore possible that distal tributaries, although small, are steep with the potential to supply large quantities of coarse sediment that forces aggradation.

These results matter for sediment connectivity, because tributary-driven aggradation at confluences interrupts the sediment cascade, promotes sediment storage on various timescales and is associated with the modification or 'resetting' of key mainstem parameters that define river form and functions (available grain size, bedload flux, channel slope and in some cases available discharge too). Aggradational confluence locations are therefore likely to be sites of morphological adjustment and longitudinal change, which

along with other controls on sediment supply, transfer and deposition (e.g. structural, lithological, hydroclimatic and anthropogenic effects) define network-scale patterns of sediment connectivity and channel morphology. While these other factors vary in their importance from basin to basin, all river networks contain confluences such that confluence aggradation and the associated sedimentary links are ubiquitous controls that structure the operation and morphology of river channels.

Moreover, increased physical heterogeneity produced by tributary-driven aggradation is a source of potentially important habitat heterogeneity in river ecosystems (Benda et al., 2004b; Benda, 2008; Rice et al., 2001; 2008). Confluences are important ecological elements for a number of other reasons too and there is broad recognition amongst ecologists that understanding confluence, link and networks effects is essential for improving understanding of the spatial and temporal distribution of river organisms and the collective health of river ecosystems (Davey and Lapointe, 2007; Poole 2002; Benda et al., 2004b; Thorp et al., 2006; Grant et al., 2007; Widder et al., 2014; Thorp, 2014; Erös and Grant, 2015; Lanthier et al. 2015; Hauer 2015). The simple relations identified here, between the frequency and likelihood of tributary-driven aggradation and basin shape and size, support Benda's Network Dynamics Hypothesis (Benda et al., 2004b). In combination with Rice et al.'s (2001) Link Discontinuity Concept, this suggests that compact shaped basins are more likely to contain drainage lines with repeated shifts from relatively low-gradient, low Froude reaches with finer bed materials (upstream of significant confluences, at the distal end of sedimentary links) to higher gradient, higher Froude reaches with coarser, but fining, bed materials (downstream of significant confluences at the proximal end of sedimentary links). In turn, to the extent that physical heterogeneity matters for biodiversity and ecosystem health, the cumulative ecological benefit of tributary-driven aggradation should be greater in more compact basins; a hypothesis that remains to be tested.

Given the potential geomorphological and ecological value in being able to identify the location, number and distribution of significant confluences, but the limited ability of simple models like the one used here to successfully identify all of them, it is appropriate to consider alternative methods. Numerous distributed numerical models of sediment transfer through river networks (Gasparini et al., 1999; Sklar et al., 2006; Lewicki et al., 2007; Neupane and Yager, 2013; Gran and Czuba, this volume) or across landscapes (Gasparini et al., 2007).

al., 2004, 2008; van Balen et al., 2010; Coulthard and Van de Wiel, 2012) include spatially explicit, time-dependent adjustment of bed material grain size and bed elevation that could be used to detect confluence aggradation. Czuba and Foufoula-Georgiou (2015) have recently offered a numerical modelling framework for identifying places of excess sediment accumulation ("clusters") in river networks. Such models are applicable to the problem of predicting the location of tributary-driven aggradation, but to date none of them have been used to explicitly address this question. This is an area where fruitful progress might be made.

Similarly, remote sensing technologies are making it increasingly feasible to collect information about rivercapes (Fausch et al., 2002) at network scales (Marcus and Fonstad, 2008; Hugue et al., 2016) and new analytical tools are being developed to make maximum use of that ability (e.g. Fonstad and Marcus, 2010). Early progress toward automated estimation of bed material grain size at bar-scales (Chandler et al., 2004; Verdu et al., 2005) and along entire rivers (Carbonneau et al., 2004, 2005) has been extended by using imagery to accomplish the necessary grain-size calibration (Dugdale et al., 2010), by avoiding the need for calibration at all (Buscombe and Masselink, 2009; Buscombe et al., 2010) and by using hyperspatial data (<100mm resolution) to map sub-pixel grain sizes (Black et al., 2014). These advances mean that it is feasible to aquire continuous bed material grain size information and identify tributary-driven confluence aggradation and sedimentary links at network scales (Fonstad and Marcus, 2010). While such an approach is currently not a routine undertaking, it could provide data for testing the ideas presented here and, in due course, mapping of grain size and might become a straightforward means of mapping local heterogeneity across whole networks.

5. CONCLUSION

An automated process for establishing the likelihood of confluence impact on bed material grain size provided a means to examine the likely impact of tributaries on channel aggradation and hence morphological and habitat diversity at over 3500 confluences, across three large drainage basins with a total area of approximately 11700 km². Contrasting subbasin sizes and shapes allowed empirical evaluation of several hypotheses surrounding

basin-scale controls on the number and distribution of significant confluences (Benda, 2008). As anticipated, significant confluences were found to be more abundant in larger basins and compact basins tended to host a greater number of significant confluences, which were more likely to be distributed across the network. In some linear basins, distal tributaries were associated with significant aggradation because their steepness and therefore potential for coarse sediment delivery compensated for relatively small size. The most compact basins contained approximately twice as many significant confluences per unit channel length as the most linear basins. These results are important, because they suggest that differences in basin size and shape, via impacts on the amount and distribution of tributary-driven confluence aggradation, are key controls of coarse-sediment connectivity and habitat heterogeneity in river networks. To the extent that physical heterogeneity matters for biodiversity, this has implications for cumulative ecosystem health, with potentially greater aquatic biodiversity in compact basins; a hypothesis that remains to be tested.

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