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Key Points:

- Longitudinal patterns of emergent fluvial rocks in six streams in Scotland and Australia exhibited fractal behavior (self-similarity)
- Fractal dimensions were related to development of bedform topography and the density and size of available bed materials in the streams
- Fractal dimensions are a promising measure of physical complexity that enable comparisons across ecosystems, scales and disciplines

Supporting Information:

Supporting Information may be found in the online version of this article.

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Using Fractals to Describe Ecologically Relevant Patterns in Distributions of Large Rocks in Streams

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Abstract Measuring the physical complexity of habitats or ecological resources is often achieved using system-specific methods that make comparisons across ecosystems difficult. One measure that is applicable across multiple ecosystems and scales is the fractal dimension, which has the benefit of generality as well as potential scale independence. This study evaluated the use of box-counting and entropy fractal dimensions for characterizing the complexity of emergent rock distributions in six streams across Scotland and Australia. Emergent rocks (ER) are important hydraulic features and ecological resources, including as oviposition sites for aquatic insects and cover for fish. We completed fractal analysis on counts of ER in 5-m segments along longitudinal stretches of the six streams. All six streams exhibited fractal behavior (self-similarity), suggesting that fractals can be used to measure the complexity of longitudinal ER distributions in a way that is scale independent. Entropy was a superior measure due to its ability to differentiate among the six streams whereas box-counting could not. Together, field results and numerical simulations showed that fractal dimensions of emergent rock distributions were related to stream geomorphology. Well-developed bedforms, like alternating pools and riffles had better organized emergent rocks because large bed materials were more likely to be emergent in topographic highs. Streams with coarser bed materials had more chaotic arrangements of emergent rocks because this increased the general abundance of emergent rocks, making differentiation between topographic highs and lows less distinctive. Fractal dimensions, therefore, can measure the complexity of river systems in a way that is relevant to geomorphological and ecological processes.

Plain Language Summary Fractal dimensions are used to characterize the complexity of a wide range of patterns in nature, from single objects (e.g., branched twigs) to whole environments (rainforests), and learn where consistent patterns may occur. We measured the complexity of rock patterns (specifically rocks that emerge above the water's surface) in six rivers from Scotland and Australia using fractal dimensions. These rocks provide important habitat for plants, insects, and fish in rivers, and so are important to overall stream condition and functioning. Less complex, more highly structured rock patterns (lower fractal dimensions) occurred in streams with smaller rocks, which had areas where emergent rocks were concentrated (riffles) and many long pools without emergent rocks. These results suggest that fractal dimensions may be a promising measure of complexity that can help us understand relationships between physical characteristics of streams and their ecology. Fractal dimensions also allow comparison of rock patterns in rivers with other habitats, such as shrubs in grasslands for example. This may allow future research to explain patterns that are consistent across these different ecosystems and so advance general ecological theory.

1. Introduction

The physical structure of environments affects every aspect of ecosystem structure and function (e.g., Cuthbert et al., 2019; Ossola et al., 2016). Physical structure here refers to the three-dimensional configuration of living space: rocky coasts are more physically complex than sandy beaches, forests are more physically complex than grassy plains, and so forth (Bell et al., 2012). Increasing physical complexity creates a greater diversity of resources (e.g., living spaces and food) and results in higher species diversity; this association holds true in every ecosystem that has been tested (Barnes et al., 2013) and requires an explanation, but quantifying physical complexity is difficult. Most researchers address this difficulty by developing

measures that are intrinsic to particular ecosystems, such as counts of cracks and crevices in rocks (Downes et al., 1998), wood loading in streams (Lester et al., 2007), or tributaries across networks (Rice, 2017). Such eclectic measures, while useful within a system, cannot be applied across multiple ecosystems at different scales, thereby precluding general tests of hypotheses and meta-analyses.

General methods for capturing physical complexity exist and one such measure, the fractal dimension (Mandelbrot, 1967), is applicable across multiple ecosystems and scales. Fractal dimensions lie between the well-understood dimensions of 1, 2, and 3 for a line, surface and volume, respectively, and express the extent to which the space is filled. For example, a complex, wiggly line on a 2-dimensional plane (fractal dimension close to 2) would have a larger fractal dimension than a straight line (fractal dimension would be 1 for a perfectly straight line). While natural systems commonly require more than a single exponent to describe their dynamics (multiple scaling; multifractal), one compelling aspect of fractal dimensions is that many environments have the same fractal dimension over a range of spatial scales, in which case they are termed self-similar over those scales (Mandelbrot, 1967). Coastlines (Mandelbrot, 1967) and river networks (Mantilla et al., 2010) are two well-known examples, that is, their maps look the same regardless of the scale at which they are mapped (self-similarity). Where environments are self-similar (fractal-like), fractal dimensions can be used to measure complexity in a way that is scale independent and transferable across ecosystem types.

Fractal dimensions and related functions have proven useful for describing characteristics of river systems, from channel networks (Rinaldo et al., 1992; Rodríguez-Iturbe & Rinaldo, 2001; Tarboton, 1989; Yang & Shi, 2017), through riverbed topography (Sapozhnikov & Foufoula-Georgiou, 1996; Zhong et al., 2012) and planform sinuosity (e.g., Nikora, 1991) to grain-scale topography (e.g., Butler et al., 2001) in one, two and three dimensions. Fractal descriptions have, in turn, offered new insights into fluvial processes, including the generation of bed material fabrics and bedforms, sediment transport, hydraulic resistance and hyporheic exchange (Aubeneau et al., 2015; Lee et al., 2020; Singh et al., 2009, 2011; Stewart et al., 2019). Work using fractals to describe fluvial processes has extended into descriptions of the areal arrangement of large clasts as pebble clusters (Wu et al., 2018), but has not been applied to regional (comparisons among streams) or local (comparisons among habitat types within a stream) scales at which most theoretical ecological models apply (Wiens, 1989). Most applications of fractals by ecologists have been over small spatial scales (e.g., Jeffries, 1993; Warfe et al., 2008), which are less suited to understanding populations.

An outstanding question is whether physical resources for insect populations, namely rocks that protrude above the surface of the water (emergent rocks, ER) exhibit fractal arrangements. Emergent rocks are an important resource for many ovipositing insects, which rely on them for successful recruitment (Lancaster et al., 2010). They also serve as sites for insect emergence (Petersen & Hildrew, 2003) and as substrates for bryophytes (Downes et al., 2003). They create flow structures that provide resting, cover and feeding opportunities for fish (Hayes & Jowett, 1994), trap drifting organic foodstuffs (Hoover et al., 2006), and create microscale habitat heterogeneity that affects the distribution of macroinvertebrates (Bouckaert & Davis, 1998). The spatial arrangement of ER has ecological implications. For example, some caddisflies (*Ulmerochorema* spp.) lay eggs on ER surrounded by fast flow; such ER are typically clumped in areas of high velocity (e.g., riffles) and this can lead to very high local densities of caddisfly eggs and potentially of newly hatched larvae (Lancaster et al., 2003, 2020).

ER also have important roles in stream geomorphology and hydraulics, including affecting drag and shear stress (e.g., Cooper et al., 2013), generating turbulent structures (e.g., Lacey & Roy, 2008), and influencing sediment entrainment, deposition and transport processes (e.g., Monsalve et al., 2017; Papanicolaou et al., 2018). The spatial distribution of ER reflects patterns of sediment supply, dispersal, and sorting across multiple scales. The location of sediment supply points, the volume and size of sediments delivered to the channel, and subsequent sorting by particle size and shape are affected by factors including geology, geomorphological history and hydrometeorology. At local scales, large rocks are arranged into structures via process-form feedbacks with the flow. The resulting bedforms are key components in the definition of channel morphology, for example, cascades, step-pools, plane beds and pool-riffle sequences (Montgomery & Buffington, 1997). It is reasonable to expect ER to be more prevalent in riffles and similar bedforms (steps, cascades) that preferentially store coarse sediments, and where the bed surface is elevated closer to the water surface, making emergence more likely (see Figure 1). Particle characteristics may also affect the

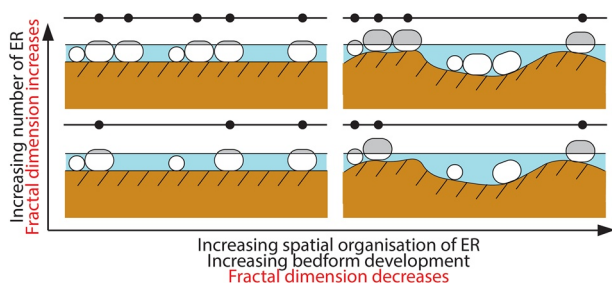


Figure 1. How channel morphology and bed sediment characteristics are expected to influence fractal dimensions. Fractal dimension is affected by the number of points and the arrangement of those points in space. The fractal dimension of a single point is 0 and a line has the well-understood dimension of 1. ER in streams are analogous to points arranged along a line. Continuing to increase the number of points or ER along the line will fill in the space until the points resemble a solid line, and hence this will increase fractal dimension (top vs. bottom panels). If ER become spatially organized (i.e., into clumps due to stream bedform topography), as opposed to a random distribution, then larger empty spaces (i.e., pools) will occur along the line and fractal dimension will decrease (left vs. right panels). How fractal dimension changes with the interaction between ER number, sediment characteristics, and spatial organization is less clear.

As fractal dimensions are influenced by the density of points (here ER) and their arrangement (see Figure 1), we hypothesized that channel morphology and sediment characteristics that increase the propensity for rocks to emerge (and hence increase the number of ER) or which describe the organization of large rocks (into pool-riffle structure for example) would be related to fractal dimension. Larger rocks, particularly in steep, shallow streams, should be more likely to be emergent. In contrast, characteristics associated with bedform development, and hence the spatial organization of ER, are hypothesized

to be negatively correlated with fractal dimension. Bedform development should be associated with pool-riffle structure, long pools without ER or with low ER densities, riffles with high ER densities, and lower stream slopes (see Supporting Information Table S1 for detailed rationale of hypotheses).

2. Methods

We used field data from three streams each in Scotland and Australia to determine whether patterns in ER counts in 5-m segments along ~1km stream lengths were fractal-like. We then tested the above hypotheses proposing how variables related to channel morphology and bed sediment characteristics are correlated with fractal dimensions. The Scottish and Australian sites have contrasting geomorphological histories and lithologies, and the streams vary in size and slope, so the data set captures variations in channel morphology and particle characteristics. Co-variance amongst variables used in hypothesis tests means that the empirical work is necessarily constrained.

2.1. Study Systems

We investigated ER distributions from two sets of streams in SE Scotland and SE Australia (Figure 2; Figure 3), which have been the focus of work on insect oviposition (Lancaster et al., 2010; Reich, 2004). These regions have distinct bedrock geology, hydrometeorology and geomorphological

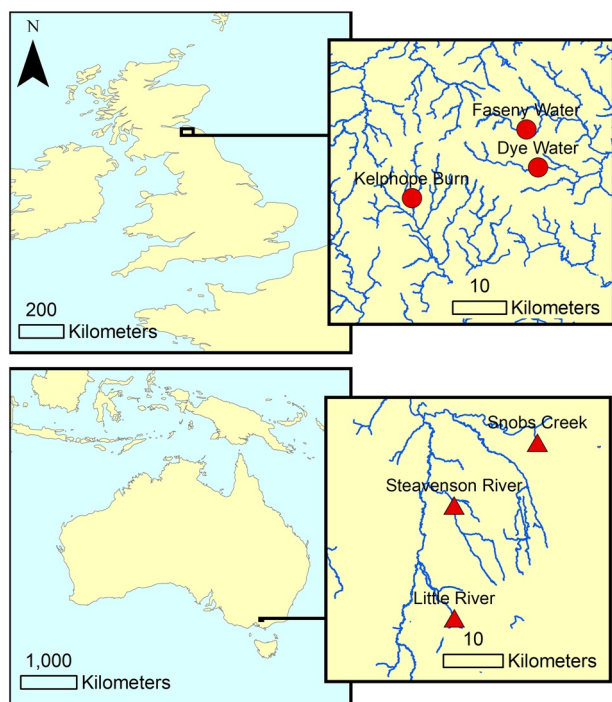


Figure 2. Scottish (circles) and Australian (triangles) study sites.

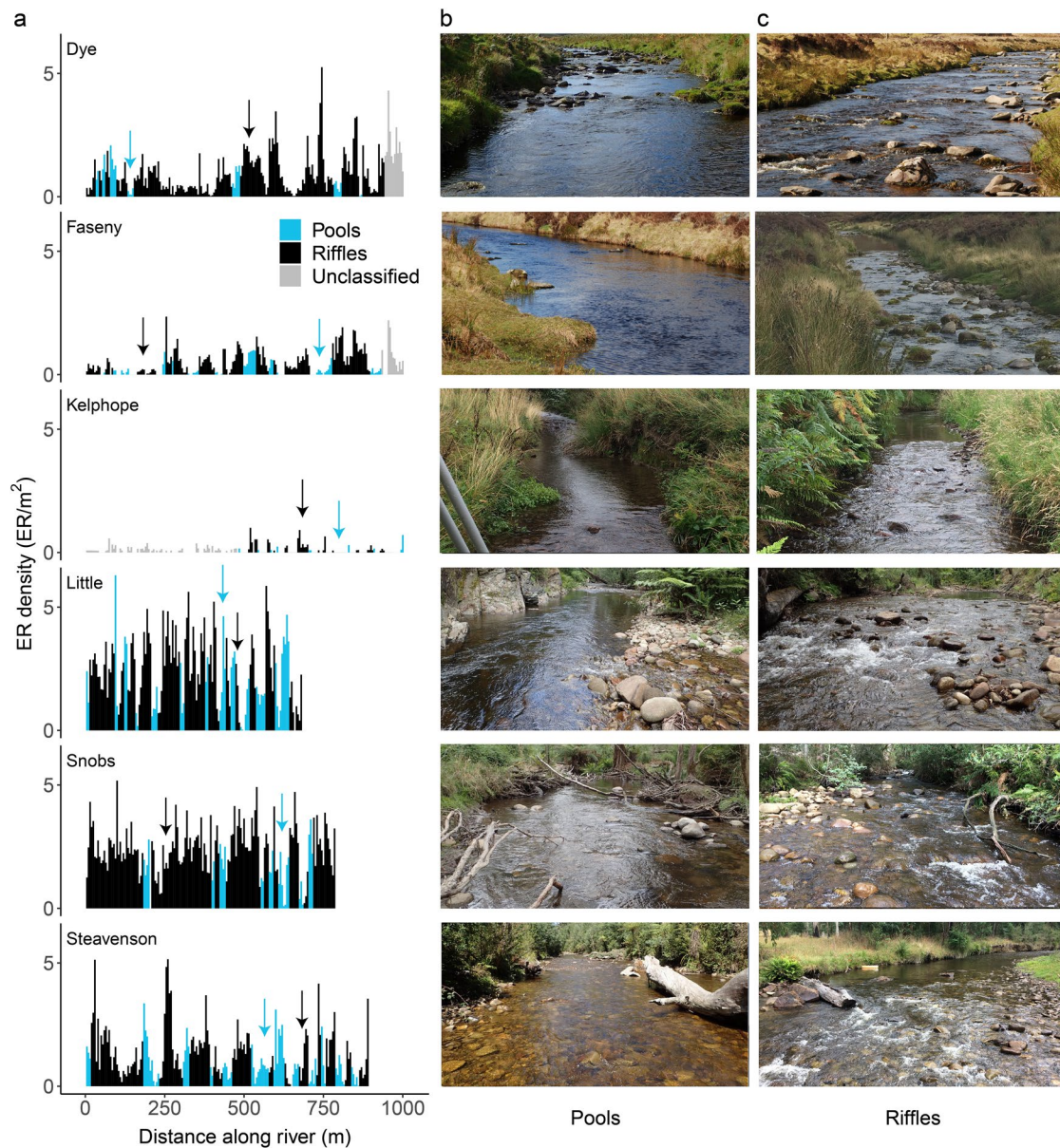


Figure 3. Longitudinal emergent rock (ER) distributions with examples of ER density in riffles and pools. (a) Coloured bars illustrate 5-m segments denoted as pools (blue) and riffle-like segments (black; inclusive of true riffles, step-pool, and plane bed; see Section 2.3) for each of the six streams. Unclassified segments (grey bars) were not surveyed for channel morphology. These were included in the calculation of fractal dimensions but were excluded from simulations of the synthetic streams. Photographs illustrate ER abundance in (b) pools and (c) riffle-like sections. Arrows indicate the location of each photo.

histories and vary in their reach-scale channel morphology sufficiently to provide a range of ER arrangements. These systems include three streams in SE Scotland (Dye Water [Dye], Faseny Water [Faseny], and Kelphope Burn [Kelphope]) and three in SE Australia (Little River [Little], Snobs Creek [Snobs], and Steavenson River [Steavenson]). The Scottish lithology is predominantly marine sedimentary (Silurian greywacke) (Davies et al., 1986), whereas the Australian streams are underlain by volcanic complexes and marine sediments (Marsden, 1973). The hydrology of the Scottish system is quite flashy with short-lived floods (Lancaster, 2000), whereas the Australian system is less so. Mean annual rainfall is ~830 mm in the area encompassing the Scottish streams (Scottish Environmental Protection Agency, <https://apps.sepa.org.uk/rainfall>) and exceeds 1000 mm in the Australian catchment (Australian Government Bureau of Meteorology, <http://www.bom.gov.au/climate/data/>). The Scottish streams in the Lammermuir Hills have a history of Pleistocene glaciation and post-glacial landscape adjustment. Each of the study reaches is

located on floodplains of restricted width, set within convex hills with steep lower slopes. Intermittent coupling to hillslopes, occasional bedrock outcrops and floodplain erosion introduce some sediment to the streams but sediment supply is primarily from upstream, headwater tributaries. The Australian streams, in the Goulburn River catchment of Central Victoria, have not experienced recent glaciation and are set within a steeper, more mountainous landscape. The reach settings are similar to the Scottish streams, with limited floodplains, some points of hillslope coupling and occasional bedrock outcrops that affect channel orientation and recruit sediment. Woody debris is present in the Australian streams but not in the Scottish streams. Using the Montgomery and Buffington (1997) classification, channel morphology differs among the streams (Table S2). Dye, Faseny, and Snobs are dominated by plane bed morphology that tends toward cascades in places (steeper, smaller depth to grain size ratio) with limited true riffles. Pools between plane bed sections are common on Faseny, less common on Snobs and limited on Dye. Steavenson, Little and Kelpheope comprise mostly pool-riffle morphology, most prominent in Steavenson but with increasing presence of plane bed sections in Little and Kelpheope. Both regions have large variations in the proportion of pools in the study reaches (Australia: 19%, 34% and 38% of the stream length; Scotland: 14%, 27% and 40% of stream length bed (Figure 3; Table S2). Channel width varies among the streams, from Kelpheope (2.5 ± 0.5 m; mean \pm SD), to Snobs (5.8 ± 1.4), Faseny (5.8 ± 1.7), Little (6.1 ± 1.7), Dye (6.6 ± 1.3), and Steavenson (9.5 ± 2.6).

2.2. (Q1) Are Longitudinal ER Distributions, at Scales of up to a Kilometer, Self-Similar (Fractal)?

Longitudinal profiles of ER counts were acquired to test whether patterns in ER are fractal-like and consequently whether fractal dimensions reflect geomorphological features, including measures of rock shape and channel morphology. ER of the Scottish streams were originally surveyed by Lancaster et al. (2010) and the Australian streams were surveyed during the Austral summer (December–February) of 2016/17. Over the study length (685–1,000 m) of each stream, ER were counted within contiguous 5-m segments to describe the spatial distribution of patterns along the stream lengths. The length of 5-m corresponds roughly to the average channel width of the streams. ER were defined as any rock protruding above the water surface, with a maximum b-dimension (width, perpendicular to longest axis) (Gordon et al., 2004) of at least 5 cm and in at least 5 cm of water based on those typically used for oviposition by many aquatic insects. These surveys were carried out at or near summer base flows.

Several methods are available for calculating fractal dimensions. Box counting is the default method, which has been used to measure complexity of forest understory and canopies (Denny & Nielsen, 2017), rocky shores (Meager & Schlacher, 2013), and aquatic plant habitat (Ferreiro et al., 2011), for example. Although wide use of the box-counting method makes it well placed for comparisons among physical environments, it is a binary method calculated by counting the number of occupied boxes (N_B) and thus the underlying data are simplified to presence/absence, which results in a loss of information (Halley et al., 2004). An alternative method, the information dimension, is based on the information science parameter, entropy, and involves determining the sum of the proportion of total ER (N_E) within each box, with weighting and correction for bias (Basharin, 1959; Miller, 1955). This method retains an estimate of the relative proportion of the variable of interest in the calculation (here ER density), thus retaining more of the underlying data and potentially providing better explanatory power for systems where relative amounts of a resource are important (Halley et al., 2004). Because entropy is not commonly used for calculating fractal dimensions, we apply both to allow comparison with other studies.

Box-counting (D_B) and entropy (D_E) fractal dimensions were calculated using methods prescribed by Seuront (2009). Both methods involve dividing the stream into a set of nested equal-sized boxes, of size δ . All possible values of δ were used, i.e., 5, 10, 15, ..., 1,000 m, however, the data set was reduced to include only unique values of N_X (i.e., values of δ which did not result in a change in the values of N_X were excluded for either method, N_B or N_E). $\log_e(\delta)$ versus $\log_e(N_X)$ plots provide an estimate of the fractal dimensions from the absolute slope, and linearity of these plots indicates the possible presence of self-similarity (i.e., fractal structure) (Figure 4). For our datasets, D_B will span a range of 0 (a single point) to 1 (a solid line), however D_E retains a measure of relativity and so we might expect values greater than 1.

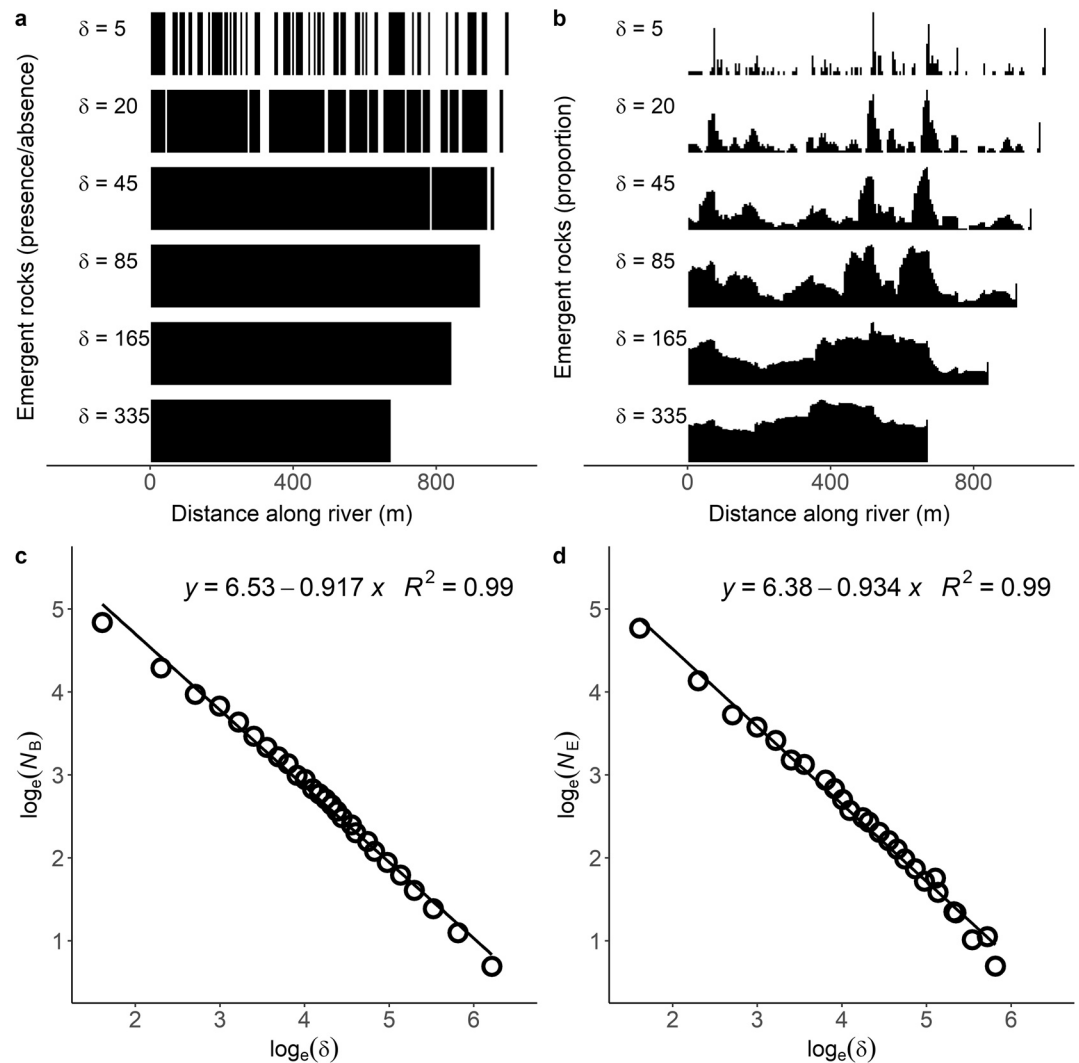


Figure 4. Calculating fractal dimensions of emergent rock (ER) distributions. To calculate fractal dimensions, longitudinal counts of ER in 5-m segments along a 1-km stream stretch are observed at different box sizes (δ). The minimum box size in fractal dimensions calculations corresponds to the 5-m segments ($\delta = 5$). The box-counting fractal dimension (D_B) and the entropy fractal dimension (D_E) methods use the presence (a) or proportion (b) of ER in each box, respectively. For all possible box sizes (only six values of δ are illustrated), the box-counting method calculates N_B from the sum of boxes containing ER, whereas the entropy method calculates N_E from the sum of the proportions of ER within each box. Significant linearity in $\log(N_B)$ (c) and $\log(N_E)$ (d) plots with changing $\log(\delta)$ indicates the possible presence of a fractal structure. The absolute slope of this line can be used as an estimate of fractal dimension (here, D_B and D_E are 0.917 and 0.934, respectively). Equations are expressed in log-transformed units.

To avoid making assumptions of linearity in the log-log plots, we followed Seuront's (2009) three-step procedure to detect fractal-like properties in natural patterns. This ensures that only patterns that are fractal are described as such. These steps included the: (a) R^2 - SSR [sum of squared residuals] Procedure, (b) the Zero-Slope Procedure and (c) the Compensated-Slope Procedure. Seuront (2009) specified that data sets could be considered fractal-like if they satisfied any two criteria of the three-step procedure. Reported estimates of the fractal dimensions (D_X ; unspecified method) in the results were taken from the Compensated-Slope Procedure because this estimate is more robust to random non-fractal structure (i.e., artefacts of the data). All computations were undertaken using packages ggpmisc, stats, lmodel2 and plyr in the open-source software R (R Core Team, 2019). A more detailed description of calculating fractal dimensions using Seuront's (2009) three-step procedure (Text S1; Figure S1) and the corresponding R script (Script S1) can be found in Supporting Information.

2.3. (Q2) Do Fractal Dimensions Capture Differences in ER Distributions Between Rivers Associated With Differences in Channel Morphology and Sediment Characteristics?

As we confirm below, all six rivers are self-similar, which means their fractal dimensions capture scale-independent aspects of how ER are distributed in these streams. Next, we tested how fractal dimensions of ER vary with geomorphological variables related to bed topography, because this affects the propensity of ER to be emergent and structured in space (e.g., the strength of alternating pool-riffle development), and with the size and shape of bed materials, because these affect the abundance of ER (Figure 1). We conducted surveys to provide measures of these characteristics.

Channel morphology surveys were carried out in September 2018 in Scotland and February 2018 in Australia when discharges were at or near summer base flows. Surveys of morphology and ER were aligned to ensure spatial compatibility. Morphological surveys were carried out on a reduced section of the ER survey length (525–940 m; Figure 3), which was visually classified for morphology at 2–3 m intervals using Montgomery and Buffington (1997) typology, as described above and in Table S2. The primary purpose was to characterize the distribution and arrangement of morphological units that are more or less likely to contain ER. We therefore used a simplified binary morphological classification of pools and “riffle-like”, lumping together true riffles, plane beds and step-pools as sections where the flow is relatively shallow and bed materials are more likely to be exposed. For simplicity, we refer to these sections as riffles and pools, hereafter.

To document bed and water surface topography, a longitudinal survey was completed using a dumpy level, with measurements at each interval along the thalweg. Channel width was measured during the ER surveys at intervals of every 10 m for Scottish streams and every 20 m for Australian streams. The latter were measured at a coarser scale due to an observed lack in variance. The shape and size of ER and submerged rocks were also surveyed. Dimensions of ER and submerged rocks were measured at the top, middle and bottom of each survey length using Wolman counts of 100 rocks at each location (Wolman, 1954). We measured a (length), b (width), and c-axes (thickness) of each rock to the nearest 5 mm (Gordon et al., 2004; Rice & Church, 1996). We characterized both ER and a random sample of submerged rocks to determine whether the attributes of the ER themselves (which were used to calculate the fractal dimensions) or the characteristics of the available bed materials, which are better represented by the submerged rocks, are related to fractal dimensions.

Given the exploratory nature of the work, we calculated a suite of relevant variables from these field data (Table S1; Table S3) and tested for significant correlations with fractal dimensions. For morphology, variables included stream slope, mean riffle and pool lengths (calculated relative to the study length) and the number of pool-riffle transitions. For grain size we used the mean of b- and c-axes and for shape we calculated mean values of equancy (c-axis/a-axis) and flatness (c-axis/b-axis) ratios (Blott & Pye, 2008). Some of these measures were correlated with each other, particularly measures of sediment size and shape (Table S4). Moreover, the expectation of finding more ER in riffles than pools simplifies what is often a complex pattern and is probably unrealistic in some streams. Our field observations confirmed that, on average, riffles contained more ER than pools but also that most pools also contained some ER in varying amounts. We therefore included several additional metrics (Table S3) in the correlation tests, which were intended to accommodate some of this uncertainty. First, we calculated the mean ER density in each study reach to capture differences in the relative abundance of ER between the streams. Second, we removed stream morphology altogether by dividing the reaches into sections with and without ER and calculating metrics for those units, including the number of segments without ER (Table S3). These measures allow us to ask the fundamental question of whether fractal dimensions are related to patterns of ER presence and absence, irrespective of whether that presence or absence is related to the pools and riffles identified in the field surveys.

Tests of correlations (Pearson's product moment coefficient) were used to determine whether fractal dimension is able to capture between-stream differences in ER associated with differences in channel morphology and sediment characteristics, differences in the density of ER in pools and riffles, and differences in the pattern of reaches with and without ER. These were one-tailed tests because, as explained in the Introduction, fractal dimension can only increase with numbers of ER, and can only decrease with an increase in the spatial structure of ER. Relationships in the opposite directions are either mathematically impossible or at least improbable for the range of variable values likely to be encountered for ER in rivers.

2.4. (Q3) Using Synthetic Streams, Which Aspects of Stream Morphology are Responsible for Driving Differences in Fractal Properties?

Multiple variables affecting fractal dimension were correlated with each other, hence we created synthetic streams in a numerical model. These synthetic streams allowed some stream characteristics to be manipulated individually and with greater replication to test how the characteristics influence fractal dimensions. Simulations were carried out in R based on empirical measurements of morphological characteristics and ER numbers (for example see Supporting Information Figure S3), although some empirical data could not be simulated (e.g., rock shape and size). Synthetic stream stretches were created by first randomly drawing riffle and pool lengths from log-normal distributions. Riffle and pool lengths were alternated for the length of the synthetic stream (1,000 m). ER counts were then randomly drawn from negative-binomial distributions and assigned to each 5-m segment of the riffle and pool lengths. Log-normal distributions of riffle and pool lengths were produced from the observed lengths of pools and riffles, which were fit to separate log-normal distributions. Log-normal distributions were chosen because riffle and pool lengths are continuous, positive (>0) and skewed with few high values. ER counts in riffle and pool segments were fit to separate negative-binomial distributions. Negative-binomial distributions were chosen because these data are discrete, nonnegative (≥ 0), and skewed (i.e., suitable for few high ER counts). As the ER distributions of the study streams fell into two distinct groups (those with few vs. many segments without ER), separate negative-binomial distributions were produced from these two groups to capture these differences (see Supporting Information Text S2 and Figure S2 for illustration). Low-zero streams (few segments containing zero ER) were simulated from the ER count distributions of Dye, Little, Snobs, and Steavenson. High-zero streams (many segments containing zero ER) were simulated from the ER count distributions of Faseny and Kelphope.

To determine the effect of stream characteristics on fractal dimension, pool length, riffle length, and ER density were varied either individually or in combination and replicated 20 times. To disentangle the pattern of segments without ER from the total number of segments without ER, an additional set of synthetic streams was produced by alternating riffles with ER (randomly drawn from the negative-binomial distributions) and pools without ER of the same lengths. The lengths of the riffles and pools were not drawn using random processes but were systematically set to 14 different lengths, including: 5 (every second 5-m segment has no ER), 10 (two 5-m segments with ER, two 5-m segments without ER), 25, 50, 75, 100, 150, 200, 250, 300, 350, 400, 450, and 500 m. For lengths that are factors of 1,000 (the length of the stream), the pattern of segments without ER will change, but the number of segments without ER remains constant at 100 [500 m]. Twenty replicate synthetic streams were produced for each of the 14 riffles and pool lengths. A total of 1,360 synthetic streams were simulated using both the random and systematic processes. For a more detailed description of these simulations and the R script, see Supporting Information Text S2 and Script S2, respectively. As a first test to see whether the ER distributions of low and high zero synthetic streams produced systematically different values of D_E , t-tests were used. To test for differences in the variation of D_E and variation in the number of ER between the two distributions, modified signed-likelihood ratio (M-SLR) tests were used (Krishnamoorthy & Lee, 2014). M-SLR tests were implemented using the R package CVEQUALITY (Marwick & Krishnamoorthy, 2018). Two-tailed linear regression analyses were performed to test for relations between fractal dimensions and channel morphology characteristics. The slopes of lines show not only the direction of relationship with fractal dimension but also the relative effect of each independent variable; steep slopes signal greater change in fractal dimension than shallow slopes.

3. Results

3.1. (Q1) Are Longitudinal ER Distributions, at Scales of up to a Kilometer, Self-Similar (Fractal)?

The ER distributions of all six streams were fractal-like using both the box-counting and entropy methods. All streams satisfied at least two of the three tests developed by Seuront (2009); this is sufficient to illustrate fractal behavior (Table S5). Further, coefficients of determination for all streams ranged from 0.99 to 1.0 for both the box counting and entropy fractal dimensions (Figure S4). Fractal dimensions varied among the six streams and with the method of calculation (Figure 5). There was very little discrimination among the streams using the box-counting method (Table S5; Figure 5a): four streams (Steavenson, Dye, Snobs

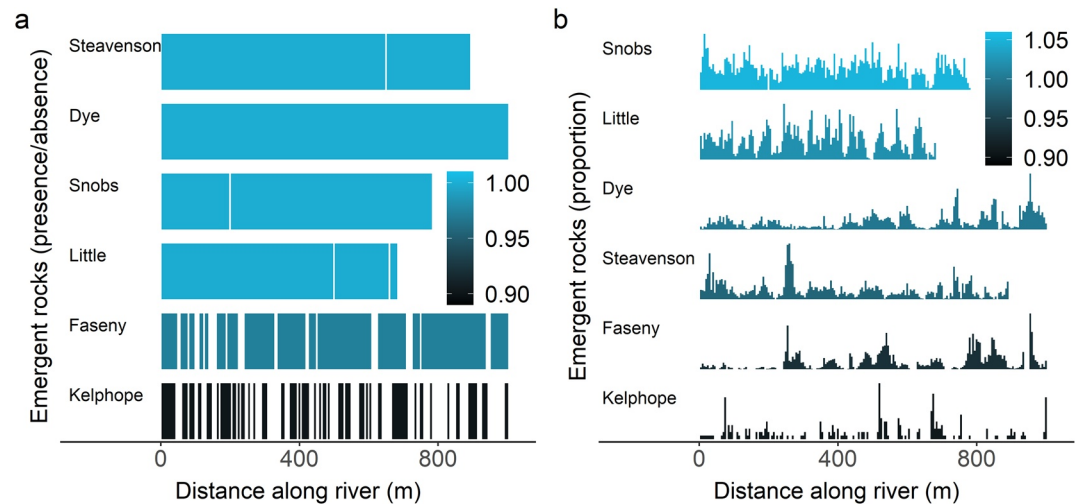


Figure 5. Fractal dimensions of emergent rock (ER) distributions. ER distributions along stretches of three Australian streams (Little; Snobs; and Steavenson) and three Scottish streams (Dye; Faseny; and Kelphope). Bars represent the presence (a) or proportion (b) of ER in each 5-m segment (the minimum box size used in fractal dimensions calculations) and fill color and the order of the streams reflects the box counting fractal dimensions (D_B for a) or the entropy fractal dimensions (D_E for b) of the ER distributions.

and Little) had the same value for D_B and this value did not differ from the fractal dimension of a straight line (1.00), because very few segments (≤ 2 ; equivalent to ≤ 10 m) in these streams contained zero ER. Of the remaining streams, D_B was 0.97 for Faseny (although statistically the log-log slope was not significantly different from 1; Figure S4) and 0.90 for Kelphope. Significant breaks in the box-counting log-log slopes were found for all streams except Snobs and Steavenson (Figure S5).

The entropy fractal dimension (D_E) largely matched the rank order of streams using the box-counting method, but it discriminated numerically between all six streams. Values of D_E ranged from 0.91 to 1.05. The rank order of streams from lowest to highest D_E was Kelphope (0.91), Faseny (0.93), Steavenson (0.98), Dye (1.00), Little (1.02), and Snobs (1.05) (Figure 4b). This produced two groups, whereby log-log slopes for Kelphope and Faseny were significantly different from that of Steavenson, Little and Snobs (Figure S4). Dye was only significantly different to Kelphope. The log-log slopes for all streams except Dye were significantly different from 1 (Figure S4). Significant breaks in log-log slopes were found for all streams; the position of these varied among the streams and was significantly correlated with pool length and pool-riffle ER density ratio (Figure S5). Due to its superior ability to differentiate among streams, we consider D_E the better method of measuring the complexity of ER distributions in our six streams. Therefore, analysis for Q2 and Q3 used only the entropy fractal dimension (box-counting results can be found in Supporting Information Table S6, Table S7, and Table S8).

3.2. (Q2) Do Fractal Dimensions Capture Differences in ER Distributions Between Rivers Associated With Differences in Channel Morphology and Sediment Characteristics?

Entropy fractal dimensions correlated well with some stream characteristics. D_E was negatively correlated with three stream characteristics that relate to the spatial arrangement of ER: mean proportional pool length, the number of segments without ER and the maximum length without ER (Table 1). D_E was positively correlated with slope and ER density, which relate to the number of ER. D_E was also positively related to sediment characteristics of submerged rocks: the c-axis length, and equancy ratio. Given the small sample size ($n = 6$), these results should be interpreted with caution given the prospective lack of statistical power for some tests. More critically, some of the independent measures of stream characteristics are correlated with each other, as well as with fractal dimension, which creates uncertainty about cause and effect (Supporting Information Table S4).

Table 1
Study Streams: Correlation Tests (One-Tailed) of Associations Between Various Stream Characteristics and Entropy Fractal Dimensions

Characteristic	Expected direction	r	p
<i>Stream morphology</i>			
Median depth	Negative	0.791	0.969
Stream slope	Positive	0.737	0.047
Mean proportional pool length	Negative	−0.870	0.012
Mean proportional riffle length	Positive	0.054	0.460
Number of pool-riffle transitions	Negative	0.241	0.677
<i>Bed sediment</i>			
SR (submerged rock) axis B	Positive	0.653	0.080
SR axis C	Positive	0.950	0.002
SR equancy ratio (C/A)	Positive	0.765	0.038
SR flatness ratio (C/B)	Negative	0.755	0.958
<i>ER density measures</i>			
Mean ER density over entire site	Positive	0.917	0.005
Pool-riffle ER density ratio	Negative	0.541	0.866
<i>Segments without ER</i>			
Number of segments without ER	Negative	−0.832	0.020
Maximum length without ER	Negative	−0.895	0.008

Note. Bold text indicates $p < 0.05$ in the direction expected for the one-tailed correlation tests; $DF = 4$ for all tests. Tests involving sediment size and shape of ER were all non-significant and are reported in Table S6.

3.3. (Q3) Using Synthetic Streams, Which Aspects of Stream Morphology are Responsible for Driving Differences in Fractal Properties?

Consistent with the study streams, D_E of synthetic stream stretches was associated with stream characteristics that relate to the spatial arrangement of ER, namely the number of segments without ER, the maximum length without ER, and pool length. Without manipulating stream characteristics (pool length, riffle length, or ER density), D_E was significantly different for simulations using the two ER distributions, that is, low versus high zero streams ($t = 34.2$, $p < 0.001$). This suggests that the number of segments without ER influence D_E , however the number of ER in pools and riffles could also contribute to this result. Variation in D_E was significantly larger for the high-zero streams (Mean $D_E \pm SD$; 0.93 ± 0.012) compared with the low-zero streams (1.02 ± 0.002 ; M-SLR = 39.03, $p < 0.001$). By definition the number of segments without ER and the maximum length without ER differed between the two ER distributions. However, as these simulations mimic the natural systems, they also differed significantly in ER density ($t = 69.8$, $p < 0.001$) and variance (M-SLR = 9.13, $p = 0.003$). Interestingly, the difference in ER variance was in the reverse direction to the variation in D_E , with the low-zero streams having higher ER variance (Mean ER/m $\pm SD$; 10.90 ± 0.51) than the high-zero streams (1.94 ± 0.26). D_E of simulated stream stretches was also negatively associated with the number of segments without ER for high-zero streams with pool lengths manipulated to influence the number of segments without ER (Table 2, Figure 6a). The maximum length of segments without ER was not related to D_E for these simulations (Table 2, Figure 6b), which contradicts the results from the study streams. However, systematic introduction of pools without ER resulted in a clear non-linear pattern of D_E with the maximum length of segments without ER (Figure 6d). For

these simulations, minimum D_E resulted from pools (and riffles) of 50–75 m (10–15 segments) in length and maximum D_E was observed with pools of 350 m (70 segments) in length. D_E was also negatively associated with the length of pools, even when almost all segments contained ER, as seen by manipulating pool length of low-zero streams (Table 2). The same trend was seen for high-zero streams however, this increased pool length and the number of segments without ER concurrently.

Relating to the number of ER, only ER density could be manipulated in simulations to create certainty about cause and effect, whereas depth, slope and sediment characteristics could not be simulated. Unlike the study streams, D_E was not correlated to overall ER density of simulated stream stretches, as tested by manipulating the number of ER in pools and riffles in combination (Table 2; Figure 7). D_E decreased with ER density when only the number of ER in riffles was manipulated (Table 2; Figure 7a), however this negative relationship conflicts with our expectations and the results from the study streams. This manipulation concurrently created a gradient in the pool-riffle ER density ratio, which may have produced the unexpected relationship. This is supported as further exaggeration of pool-riffle structure by manipulations of ER density and pool length together, such that the highest ER densities were paired with the longest pools creating the strongest relative difference (Figures 5c and 5d), increased the magnitude of the slopes of D_E for both high-zero streams and low-zero streams. Taken together, these results demonstrate that the spatial arrangement of ER (pool-riffle structure) has a stronger effect on D_E than ER density.

4. Discussion

4.1. (Q1) Are Longitudinal ER Distributions, at Scales of up to a Kilometer, Self-Similar (Fractal)?

Fractal dimensions can be used to measure the complexity of ER distributions in streams in a way that is scale independent. Six streams exhibited fractal behaviour (self-similarity) according to the criteria

Table 2

Synthetic Streams: Linear Regression Tests (Two-Tailed) for Relationships Between Various Stream Characteristics and Entropy Fractal Dimensions, for Low-Zero Streams (LZS) and High-Zero Streams (HZZ) in Different Simulations. For Each Simulation Pool and Riffle Lengths, and the Number of ER in Pools and Riffle Segments Were Held Constant Except for the Manipulated Variables

Independent variable	Manipulated variable(s)	ER dist.	DF	Slope	t	p	R ²	Fig.
<i>Stream morphology</i>								
Mean proportional pool length	Pool lengths	LZS	78	-8.9×10^{-5}	3.48	<0.001	0.13	7b
		HZS	78	-7.8×10^{-4}	4.84	<0.001	0.23	
Mean proportional pool length	Pool lengths, riffle ER	LZS	77	-3.8×10^{-3}	15.5	<0.001	0.76	7d
		HZS	77	-4.6×10^{-3}	8.46	<0.001	0.48	
Mean proportional riffle length	Riffle lengths	LZS	77	8.2×10^{-6}	0.88	0.38	<0.01	NA
		HZS	77	1.3×10^{-6}	1.88	0.06	0.04	
<i>ER density measures</i>								
ER density	Riffle ER, pool ER	LZS	78	-1.3×10^{-6}	0.70	0.49	<0.01	NA
		HZS	78	7.1×10^{-5}	0.83	0.41	<0.01	
Mean density of riffle ER	Riffle ER	LZS	78	-1.1×10^{-4}	12.3	<0.001	0.66	7a
		HZS	78	-4.2×10^{-4}	5.02	<0.001	0.24	
Mean density of riffle ER	Pool lengths, riffle ER	LZS	77	-3.2×10^{-4}	22.4	<0.001	0.87	7c
		HZS	77	-1.9×10^{-3}	17.1	<0.001	0.79	
Pool-riffle ER density ratio	Riffle ER	LZS	78	0.075	11.9	<0.001	0.64	NA
		HZS	78	0.093	4.97	<0.001	0.24	
Pool-riffle ER density ratio	Pool lengths, riffle ER	LZS	77	0.19	13.3	<0.001	0.69	NA
		HZS	77	0.38	9.71	<0.001	0.55	
<i>Segments without ER</i>								
Number of segments without ER	Pool lengths	HZS	78	-1.2×10^{-3}	6.18	<0.001	0.33	6a
Maximum length without ER	Pool lengths	HZS	78	-1.8×10^{-3}	1.29	0.20	0.02	6b
Number of segments without ER	All ^a	LZS	278	-3.1×10^{-3}	7.91	<0.001	0.18	6c
		HZS	278	-3.9×10^{-3}	9.12	<0.001	0.23	

Note. t-tests indicate whether slopes differ from zero, significant tests are shown in bold text. See supporting material for full description of simulations.

^aAlternating riffles with ER (randomly drawn from the negative-binomial distributions) and pools without ER of the same lengths.

developed by Seuront (2009) for both the box-counting and entropy methods. It seems likely that fractal dimensions may also measure complexity at scales smaller than the reach (e.g., single riffles) and beyond our reach lengths (regional scales). However, we provide some evidence that our study streams exhibit multiple scaling behavior as discerned by breaks in the slope of the log-log plots, which may indicate that different scaling regions (ranges of δ) are described by different fractal dimensions. The position of the breaks varied among the streams and could be associated with the scale of bedform spacing (Figure S5). This could also be an artifact of reaching the limits of the data sets, and so further exploration is needed to determine whether a single or multiple relationship is better linked to channel geomorphology. Because at least three orders of magnitude are recommended for fractal analysis (Falconer, 1993) and our datasets confirm fractal behavior, even when these breakpoints are crossed, we will continue the discussion with the box-counting and entropy fractal dimensions calculated using the entire data set to ensure the relevance of the fractal analysis.

Fractal dimensions varied among the six streams and with the method of calculation. The box-counting method only differentiated between streams with many (1 stream), few (1 stream) and no (4 streams) segments without ER. This is problematic for comparison of upland streams where the vast majority of segments in streams have at least one ER, which results in $D_B \sim 1$ (the value for a straight line). With a higher resolution, the entropy method separated all six streams, indicating that the arrangement of ER varies among the streams. D_E ranged from 0.91 to 1.05, and while this is likely a narrow distribution out of a greater range of fractal dimensions that are possible for real rivers, this range provides some opportunity to

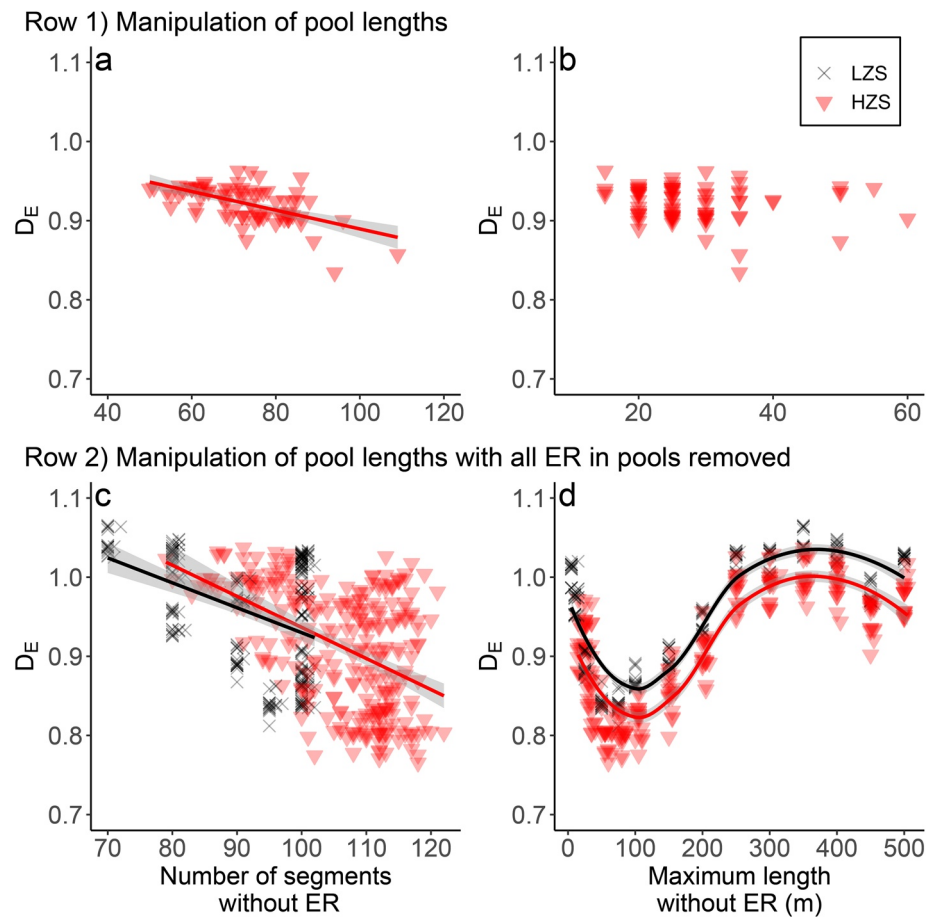


Figure 6. Using synthetic stream stretches to determine the influence of segments without ER on D_E (a)-(b) The number of segments without ER was altered by manipulating pool lengths of high-zero streams (HZS: red triangles). D_E was associated with the number of segments without ER (a) but not the maximum length of segments without ER (b). Low-zero streams (LZS) were not included in this analysis as increasing pool lengths did not largely influence the number of segments without ER (c)-(d) Further simulations whereby segments without ER were included by alternating pools without ER and riffles with ER (using LZS (grey crosses) and HZS riffle distributions) for the length of the site (1,000 m). Pools and riffles were of length 5 (every second 5-m segment has no ER), 10 (two 5-m segments with ER, two 5-m segments without ER), 25, 50, 75, 100, 150, 200, 250, 300, 350, 400, 450, and 500 m. In accord with the first set of simulations, increasing the number of segments without ER resulted in a linear decline in D_E (c), however, the length of segments without ER resulted in a clear non-linear relationship with D_E (d). Loess curves are fit to non-linear relationships to illustrate patterns. See Table 2 for summary of statistical tests.

relate ER arrangement to channel morphology and sediment characteristics using the study streams. However, multi-collinearity in the natural systems necessitates the use of synthetic streams to isolate the causes of variation in D_E among streams.

4.2. (Q2) Do Fractal Dimensions Capture Differences in ER Distributions Between Rivers Associated With Differences in Channel Morphology and Sediment Characteristics?

Our field data showed that entropy fractal dimensions correlated well with stream characteristics that relate to the number and spatial arrangement of ER. Concerning the number of ER, D_E was related to ER density and channel morphology and sediment characteristics that influence the propensity for large rocks to emerge. As expected, D_E was positively correlated with the c-axis and particle equancy (c/a) of the bed materials, as characterized by random sampling of submerged sediments. Submerged rocks likely provide a better characterization of the bed materials than ER (which were not correlated with D_E), which capture only a subset of the sediment distribution. At a given water depth, grains that have a large c-axis and are

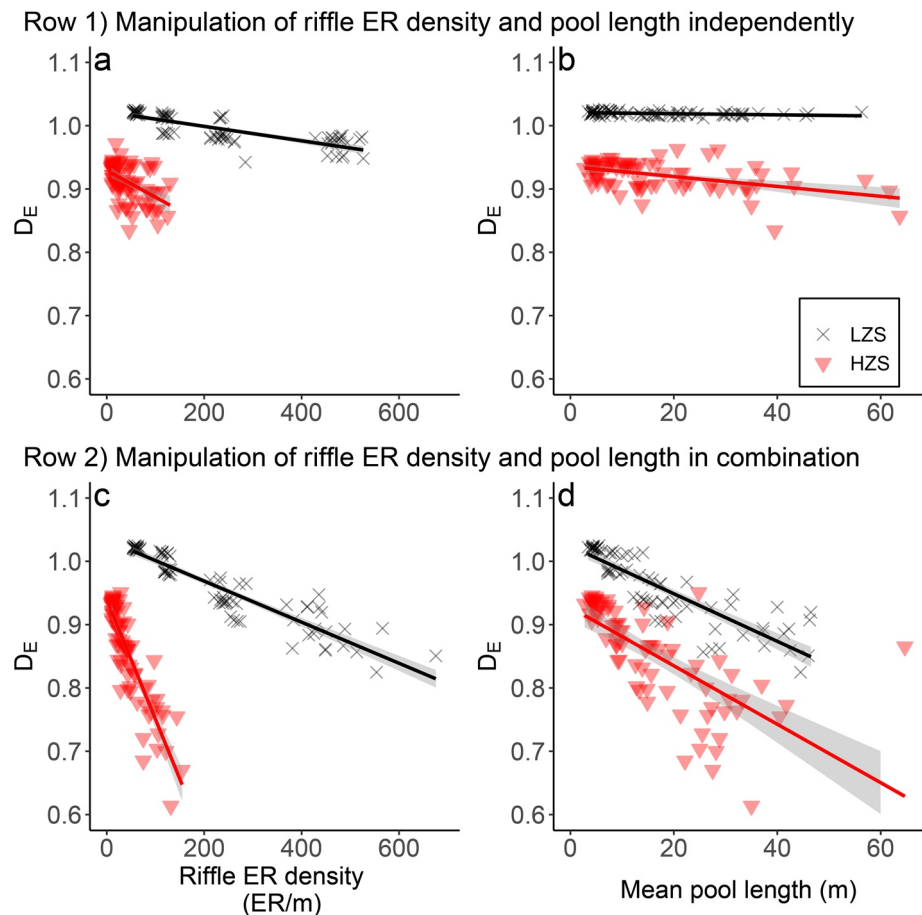


Figure 7. Using synthetic stream stretches to determine the influence of pool-riffle structure on entropy (D_E). D_E is influenced by pool-riffle structure when described by the relative difference in ER density between pools and riffles and the relative length of pools and riffles. Simulations used the two ER distributions: low-zero streams, LZS (grey crosses) and high-zero streams, HZS (red triangles) with manipulations of (a) ER density in riffles or (b) pool length, independently of each other, or (c)-(d) both ER density in riffles and pool length *in combination* (i.e., panels c and d are drawn from a single set of simulations). ER density in riffles and pool length independently influenced LZS and HZS simulations, however a greater effect (steeper slope) occurred when both stream characteristics were manipulated. See Table 2 for summary of statistical tests.

more equant are more likely to be emergent because most grains rest on their a-b plane, so that the c-axis then determines the elevation of the upper surface of the particle. Notwithstanding differences in water depth between streams, larger mean c-axis and equancy are therefore likely to increase the abundance of ER. Indeed, our data showed a significant positive correlation of both c-axis and particle equancy with ER density. This suggests that rock shape may influence the likelihood of emergence more than size (b-axis was not correlated with D_E). However, there is also an expectation that c-axis varies with channel slope, such that larger bed materials are more common in steeper channels (because slope is generally adjusted to generate shear sufficient to transport the coarsest materials) and that as channel length (or drainage area) increases, so the maximum particle size declines due to sorting and abrasion processes. As slope also influences bedform development, causation may be linked more closely to the spatial arrangement of ER.

Our expectation that the fractal dimension would be related to the spatial arrangement of ER was supported by stream characteristics that identify the presence of pool-riffle structure. These included negative correlations of D_E with the number and maximum length of segments without ER, mean proportional pool length, and slope. Segments without ER provide the first evidence of pool-riffle structure, however, at this coarse scale, pools are simplified to segments without ER, which rarely occurs. At a finer scale, all streams showed some degree of pool-riffle structure, with riffles in each stream having higher ER density compared

to pools. This structure was greater for three streams (Kelphope, Faseny, and Steavenson) where pools had fewer than half as many ER as riffles ($<0.5:1$; pool:riffle ER ratio); this resulted in the lowest values for D_E . Accordingly, these streams have well-developed macro-scale bedforms like alternating pools and true riffles (e.g., Steavenson) or alternating pools and plane bed sections (e.g., Faseny). For the remaining streams (Snobs, Little and Dye), the ratio of ER in pools and riffles was less pronounced ($>0.7:1$) and led to the highest values of D_E . Topographic bedform development is weak in these streams (e.g., Dye and Snobs), and hence there is more chaotic, limited organization of ER. In reaches dominated by plane bed or with weak pool-riffle development, an absence of long pools suggests that sediment storage dominates throughout, with little longitudinal topography. This storage of sediment uniformly elevates the bed closer to the water surface and there is a greater chance of rocks emerging. In contrast, where storage is organized into distinctive topographic highs and lows, the propensity for large rocks to emerge is alternately higher and lower. It is also notable that the steepest streams in each region (Dye, Snobs) are those with the more irregular ER distributions whereas those on lower slopes (Faseny, Little, Steavenson) have better developed bedforms and ER organization. This reflects the well-known association between channel steepness and bedform type, with the development of true riffle and pool sequences on slopes typically below 1% (e.g., Buffington & Montgomery, 2013).

The study streams provide evidence that larger, more-equant grain sizes are associated with greater abundance but weaker longitudinal organization of ER. This reinforces the suggestion that steeper, and also smaller, catchments are more likely to be associated with high D_E . This study is the first to investigate the fractal behavior of ER in streams and so comparisons with previous studies are limited. However, relationships with catchment characteristics align with previous work on fractal dimensions of river networks, which are related to runoff and sediment yield (Yang & Shi, 2017), flood frequency (Zhang et al., 2015), climate (Wang et al., 2009), and tectonic forces (Shen et al., 2011). Ultimately, the number of emergent rocks and the presence of well-developed topographic bedforms reflects the interplay of many underlying geomorphological processes. This creates difficulties when attempting to identify relationships between those variables and other constructs, such as fractal dimension, because variables are not independent and mechanisms are difficult to disentangle. Simulating streams provides an elegant way to address these issues.

4.3. (Q3) Using Synthetic Streams, Which Aspects of Stream Morphology are Responsible for Driving Differences in Fractal Properties?

The simulated synthetic streams provided a clear basis upon which to hypothesize mechanisms that underpin the relationship between any individual measure of stream morphology and fractal dimension. They revealed a clear relationship of decreasing fractal dimensions, and therefore stronger longitudinal organization of ER, with increased pool-riffle structure (Figure 7). To illustrate this clearly, pool-riffle structure was exaggerated by increasing pool lengths, the number of segments without ER in pools, and ER density in riffles relative to pools (each manipulated independently from each other and in combination). The strongest effects were seen when these characteristics were manipulated in combination, and changes were greater than the sum of the individual effects. This shows that fractal dimensions capture the dynamics of multiple characteristics, making them more useful than measuring any single characteristic. The use of simulations to investigate these dynamics allows unhindered interpretation of results and have provided clear complementary support for the arguments made using the empirical analysis for a relationship between pool-riffle structure and fractal dimension in the study streams.

Taken together, the field and simulated components of this study have helped to disentangle the geomorphological processes that may generate variation in physical complexity. Fractal dimensions captured well-known patterns that arise from sediment sorting, abrasion, and storage processes and are associated with longitudinal fluvial gradients. Upstream, steeper slopes, less well-developed bedform topography, and greater abundances of large rocks lead to an irregular organization of ER and high fractal dimension. Downstream, the development of true riffle and pool sequences on low slopes and lower abundances of large rocks result in stronger longitudinal organization of ER and low fractal dimension. Variation in D_E values between streams relates to aspects of stream morphology and sediment character. As such, the entropy fractal dimension is a promising measure of physical complexity that captures differences in ER distributions and organization driven by geomorphological processes. D_E is, therefore, a useful metric in both

geomorphological and ecological studies, which frequently rely on measurements of geomorphological characteristics to explain ecological patterns.

4.4. Fractal Dimensions Across Ecosystems

Landscape complexity generates patchiness in environmental conditions (e.g., flow resistance, turbulence, etc.) and resources (e.g., living spaces and food) that drive ecological processes (Huffaker, 1958). This patchiness can facilitate or impede dispersal of organisms, abundance and persistence of species, and interactions among species. Entropy, which describes the complexity of the physical landscape, is likely to be related to these ecological processes with the added benefit of being comparable across disciplines and potentially across subject matter. The entropy fractal dimension may therefore be useful for bridging the gap between ecology and geomorphology, enabling general questions of assembly to be tested across ecosystem types.

Self-similarity allows fractal dimension metrics to be transferred across ecosystem types even when they are measured at different scales. While we have shown that the entropy fractal dimension may be a useful method to describe the landscape complexity of streams, the box-counting method is still more commonly used across many disciplines. Using a common method allows integration of ecosystem patterns and broad-scale hypotheses tests across landscapes scales, and so corresponding results using box counting are presented in the Supporting information (Table S6, Table S7 and Table S8). While integrating patterns among ecosystems was not the purpose of this study, it is interesting to note that the complexity and lack of structure of ER habitats ($D_B = 0.92\text{--}1.00$) seen here is generally greater than that reported for other systems where D_B has been measured in one dimension, including evergreen forest canopy (0.78–0.95), deciduous forest canopy (0.69–0.95), understory shrubs (0.70–0.81), grassland shrubs (0.61) and grassland grasses (0.80) (Denny & Nielsen, 2017; Ritchie, 2009) (slopes of log-log plots are reported here to provide consistency with other papers). How this relates to ecological response variables in these habitats (i.e., species diversity, dispersal) is an interesting avenue for further research. Ultimately, determining whether fractal dimensions provide a meaningful description of physical landscapes across scales and locations will be contingent on the overarching goals in any attempt to integrate ecosystem patterns more broadly.

Despite its promise, calculating fractal dimensions to measure landscape complexity has its challenges (Halley et al., 2004). These start with identifying an appropriate measure of fractal dimension but also include choosing the range of scales over which to calculate fractal dimensions, that is, the smallest and largest scales of observation (in this study, 5 m segments and 685–1,000 m river lengths, respectively). We identified the largest scale for each stream individually, recognizing that these would then vary across streams, and used the associated fractal dimension for each for comparative purposes. Alternative choices included applying a single set of delta values (δ) for comparison across all streams, using the scale at which the maximum (or minimum) entropy value was calculated, among others. These different choices have a material effect on the resultant fractal dimensions and the ranking of streams and, therefore, are likely to affect the outcome of comparative studies. Very little published literature assists with these choices, despite their impact on the final fractal dimensions calculated. Thus, fractal dimensions should be applied thoughtfully, and additional guidance is needed to ensure that ecologists and geomorphologists apply the techniques in a mathematically robust manner.

4.5. Conclusions

Here, the entropy fractal dimension was a meaningful measure of the complexity of ER distributions, whereas the box-counting method was less useful for comparisons among upland streams where most segments had at least one ER. The entropy fractal dimension was principally driven by the development of well-defined bed topography, for example in the form of pool-riffle sequences, as this affected longitudinal patterns of ER distribution and, to some degree, by rock size as this affected the propensity for ER to be abundant irrespective of bedform topography. Due to this ability to reflect the physical characteristics of the environment, the entropy fractal dimension shows great potential to measure the complexity of river systems in a way that is relevant to ecological processes, provided it is calculated consistently across the systems of interest.

Data Availability Statement

To foster transparency, our data is available on Deakin University's research repository.

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