Are channel networks statistically self-similar?

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ABSTRACT

Scaling properties of both field-mapped and threshold-delineated channel networks were studied by applying the box-counting method to three drainage basins in the western United States. This method involves (1) examination of power-law relations between the box size, ε, and the number of boxes, *N*, that intersect channel segments across a range of box sizes appropriate for the method and then (2) examining the standardized residuals for the least squares linear regressions of log *N* vs. log ε used to calculate a fractal dimension (*D*). For each channel network, the slope of the log *N* vs. log ε relation varies from 1 at small length scales to 2 at large length scales, a range that defines the limits to the applicability of the box-counting method. At length scales below which this slope equals 1, the plots simply record the linear aspect of streams; the length scale defining an upper limit to the application of the box-counting method corresponds to a box size large enough to intersect a channel in each box. Although a fractal dimension may be meaningfully defined only between these upper and lower length scales, neither the field-mapped nor the artificially delineated networks that we examined exhibit discrete fractal dimensions within this range. Instead, the slope of the log-log plot systematically varied with box size. The consistent lack of log-linear plots for the networks that we examined violates a fundamental requirement for fractal geometry and contrasts with general assertions about the fractal nature of river networks. A strong correlation between mean source-area size and the length scale above which the slope of plots implies *D* = 2 indicates that, although channel networks are not statistically self-similar, they are space filling at length scales greater than twice the mean source-basin length.

INTRODUCTION

Fractal geometry provides an appealing way to describe the branching pattern of channel networks (Mandelbrot, 1983), and network scaling properties have been used to argue both for a scale independence to landscape dissection and that drainage networks are space filling with a fractal dimension (*D*) of 2 (Tarboton et al., 1988; La Barbera and Rosso, 1989; Beer and Borgas, 1993; Nikora and Sapozhnikov, 1993). Yet field observations demonstrate that channels dissect soil-mantled landscapes over a finite range of scales limited by a threshold of channel initiation, indicating a scale dependence to land form (Horton, 1945; Montgomery and Dietrich, 1992; Dietrich and Dunne, 1993). At first glance, this apparent contradiction can be reconciled by arguing that the scale of channel initiation provides a lower bound to the range of scales over which channel networks exhibit fractal geometry. But for channel networks to be statistically self-similar, a single fractal dimension should describe them across the range of scales for which a fractal dimension is physically meaningful. Here we review previous studies and reexamine the question of whether channel networks are statistically self-similar through the use of the box-counting method over the range of scales for which the method can meaningfully estimate a fractal dimension. We also address the influence of source-basin size on network scaling properties.

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BOX COUNTING

The box-counting method (Lovejoy et al., 1987) can be used to estimate fractal dimensions of channel networks generated from topographic maps or digital elevation models (Tarboton et al., 1988; La Barbera and Rosso, 1989; Klinkenberg and Goodchild, 1992; Helmlinger et al., 1993). This method involves superimposing a square mesh onto a drainage basin. The channel network exhibits scaling properties if there is a power-law relationship between the box size, ε, and the number of boxes, *N*, that intersect channel segments, such that

$$N \cong b\,\varepsilon^{-D}, \qquad (1)$$

where b is a proportionality constant and *D* is the fractal dimension (Bergé et al., 1984; Falconer, 1990).

Analyzing channel networks extracted from U.S. Geological Survey 30 m digital elevation models, Tarboton et al. (1988) showed that *D* = 1 when ε is small, reflecting the linear aspect of stream channels, and *D* = 2 when ε is large, implying that channel networks are space filling. As recognized by Tarboton et al. (1988), these results arise because small box sizes that approach the resolution of the map increasingly sample the hillslopes lying between channel segments, thereby intersecting only short linear channels, whereas larger boxes cannot fit within the intervening hillslopes. Note, however, that at ε length scales above which every box intersects at least one channel segment, the box-counting method simply plots ε versus $1/\varepsilon^2$ due to the use of square grids; *D* must equal 2 at a large enough ε, independent of any fractal properties of the network being measured. Evaluation of whether a natural object exhibits statistical self-similarity requires demonstrating a single power-law exponent based on iterative measurements across at least one order of magnitude (Mandelbrot, 1983) for length scales between those where *D* = 1 and *D* = 2 (Fig. 1) (Bergé et al., 1984; Falconer, 1990). Although previous applications of the box-counting method to channel networks revealed that networks are space filling at sufficiently large box sizes, such studies have yet to demonstrate that channel networks actually exhibit statistical self-similarity across the scale range over which the method can assess a meaningful fractal dimension (i.e., $1 < D < 2$).

HORTON'S LAWS

Perhaps the most common method of determining the fractal dimension of channel networks relies on the Horton laws, which hold that the bifurcation and length ratios, R_B and R_L, do not vary with stream order μ (see Horton, 1945,

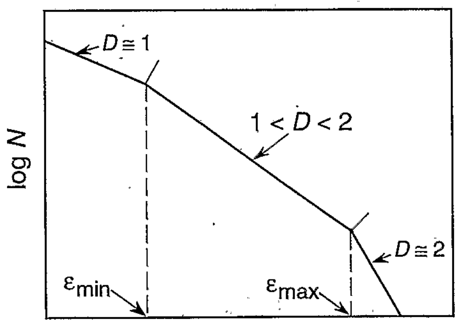

Figure 1. Ideal plot of log N versus log ε for a fractal channel network using the box-counting method to estimate D between lower and upper cut-offs defined by ε_{min} and ε_{max} (i.e., $1 < D < 2$); N is the number of boxes intersecting channels, ε is the box size, and D is the fractal dimension derived from equation 1.

for definitions of these ratios). Tarboton et al. (1988) estimated the total length of streams in a network (L) by

$$L \cong \varepsilon^{1-(\log R_B/\log R_L)}, \quad (2)$$

where in this case ε is the mean length of first-order streams. The length of a fractal curve is also given by

$$L \cong \varepsilon^{1-D}, \quad (3)$$

where L is the curve length measured using a ruler of variable length ε, and D is the fractal dimension of the curve (Mandelbrot, 1983). Hence, Tarboton et al. (1988) noted that for $R_B > R_L$ the fractal dimension of a channel network is given by

$$D = \log R_B/\log R_L, \quad (4)$$

for $R_B > R_L$. An extensive literature reports that $R_B > R_L$ for natural channel networks (see Kirchner [1993] for a review), and many workers have used equation 4 to estimate D for channel networks (e.g., Tarboton et al., 1988; La Barbera and Rosso, 1989; Beer and Borgas, 1993; Helmlinger et al., 1993). As the Hortonian approach implicitly assumes that channel networks are fractal, results obtained from equation 4 cannot address whether channel networks actually are fractal; one could calculate D for any network, whether fractal or not. Although the observation that R_B and R_L generally equal 4 and 2 (Kirchner, 1993) is widely considered to imply that $D = 2$ (Mandelbrot, 1983; Tarboton et al., 1988), Phillips (1993) showed that the fractal dimension of many channel networks defined by equation 4 exceeds 2, the Euclidean dimension of a plane and the embedding dimension of the channel network. Given that equation 4 predicts impossible fractal dimensions for some channel networks, Hortonian laws appear inaccurate at best for estimating the fractal dimension of channel networks. In all, it appears that neither of these approaches for estimating the fractal dimension of channel networks has actually demonstrated the statistical self-similarity of channel networks.

STUDY AREAS, DATA SOURCES, AND METHODS

We analyzed the scaling properties of channel networks in three watersheds: Finney Creek in the Cascade Range of Washington, Mettman Ridge in the Oregon Coast Range, and Tennessee Valley in the central California Coast Range. The Finney Creek watershed occupies 142 km^2 and is underlain by Tertiary volcanic and highly deformed Mesozoic metasedimentary rocks. The watershed as a whole has a mean slope of 23°, and 40° slopes are common in some tributary valleys. Portions of the watershed were glaciated during the Pleistocene, and recent timber harvesting cleared the original forest. Detailed descriptions of the Tennessee Valley and Mettman Ridge watersheds are presented elsewhere (Montgomery and Dietrich, 1989; Montgomery et al., 1997).

There are a variety of ways to delineate channel networks from maps (Smart, 1972; La Barbera and Rosso, 1989) or digital elevation models (Band, 1986; Tarboton et al., 1991; Chorowicz et al., 1992; Helmlinger et al., 1993; Montgomery and Foufoula-Georgiou, 1993; Ichoku et al., 1996). We used standard U.S. Geological Survey digital elevation models of 30 m resolution for Finney Creek and 4 m resolution generated by previous studies of the Mettman Ridge and Tennessee Valley watersheds (Dietrich et al., 1993; Zhang and Montgomery, 1994). For each study area, we delineated a series of artificial channel networks from digital elevation models using different channel initiation thresholds based on the product of contributing area and the square of local slope (AS^2) (see Montgomery and Foufoula-Georgiou [1993] for further discussion of this channel initiation index). We also analyzed field-mapped channel networks for the Mettman Ridge and Tennessee Valley study areas. The total contributing area at each channel head was computed for the network defined by each AS^2 threshold value. The mean source area (a_s) for each channel network was calculated by dividing the total area contributing to channel heads by the number of network sources. The mean source-basin length (l_s) was then estimated based on the empirical relation $l_s = (3\,a_s)^{0.5}$ reported by Montgomery and Dietrich (1992).

We investigated the scaling properties of channel networks by applying the box-counting method and using least squares linear regression of the log-transformed data to determine D over the range of scales where $1 \le D \le 2$. The box size yielding $D = 1$ (i.e., ε_{min}) does not necessarily correspond to the digital elevation model grid-size; similarly ε_{max} is the box size above which the probability for a box grid to be channelized

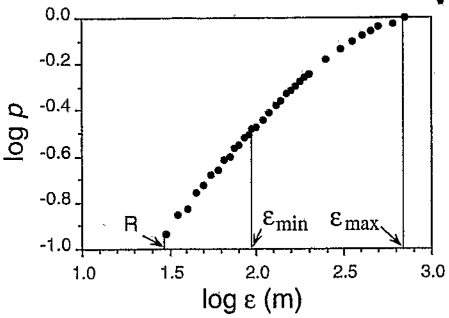

Figure 2. Logarithmic plot of p versus ε used to determine ε_{min} and ε_{max} and thereby define the scaling range appropriate for application of the box-counting method. R is the grid size resolution of the digital elevation model, and p is the probability that a box intersects a channel.

equals 1 (i.e., $D = 2$) (Fig. 2). Examination of the linear regressions for each of the basins consistently revealed distinct curvature in the plots of log N vs. log ε between ε_{min} and ε_{max}, a result that shows that a single D inadequately describes the channel networks. Consequently, we analyzed the residual structure for the least squares linear regression of log N versus log ε to more formally assess whether the channel networks exhibit systematic deviation from strict self-similarity (Andrle, 1992; Klinkenberg and Goodchild, 1992; Beauvais and Montgomery, 1996).

The precision of the box counting method depends on both digital elevation model resolution and the ε-length intervals between subsequent measurements. Following Dubuc et al. (1989) and Liebovitch and Toth (1989), we used a large number of box sizes to estimate fractal dimensions, and we determined the minimum number of boxes containing channels for nine rasterizations generated by shifting the grid origin by one-third of the box size. For each channel network, we employed measurement intervals of 2 m over the ε-length range from 4 to 30 m; 5 m from 30 to 100 m; 10 m from 100 to 200 m; 50 m from 200 to 500 m; and 100 m from 500 to 2000 m, which resulted in 52, 44, and 47 realizations for each network in Finney Creek, Mettman Ridge, and Tennessee Valley, respectively.

RESULTS

Application of the box-counting method to each of the field-mapped and synthetic channel networks allows examination of the variability of their scaling properties over a wide range of potential drainage densities for a given watershed. With greater values of the AS^2 threshold, channel networks delineated in each watershed exhibit increasing mean source-area size (a_s), reduced drainage density, and different ε_{min} and ε_{max} (Table 1). The scale range appropriate for the box-counting method, as defined by ε_{min} and ε_{max}, shifts toward larger length scales for greater AS^2. For the networks derived in Finney Creek, ε_{min} ranges from 30 m to 95 m, and ε_{max} ranges

TABLE 1. APPROPRIATE SCALING RANGE FOR FRACTAL ANALYSIS USING THE BOX-COUNTING METHOD, AND CHANNEL NETWORK CHARACTERIZATION

ACN	Finney Creek				Mettman Ridge				Tennessee Valley			
AS^2 (m²)	ε_{min} (m)	ε_{max} (m)	a_s (m²)	Dd (km⁻¹)	ε_{min} (m)	ε_{max} (m)	a_s (m²)	Dd (km⁻¹)	ε_{min} (m)	ε_{max} (m)	a_s (m²)	Dd (km⁻¹)
250					5	70	395	29.41	20	120	1202	16.67
500					5	85	658	22.73	30	150	2333	11.90
1000	30	250	4803	8.33	14	110	1114	17.24	45	200	4875	8.26
2000	30	350	8374	6.33	30	140	2429	11.76	45	250	10088	5.75
4000	85	500	15576	4.63								
8000	95	700	33647	3.14								
16000	95	900	77728	2.07								
FMCN					40	140	3180	10.20	40	200	11685	5.35

Note: ACN = artificial channel networks; AS^2 = contributing area X square of local slope; ε_{min} = lower limit of box-counting method resolution; ε_{max} = upper limit of box-counting method resolution; a_s = mean source-basin area; Dd = drainage density; FMCN = field-mapped channel network.

from 250 m to 900 m. For Mettman Ridge, ε_{min} ranges from 5 to 40 m, and ε_{max} ranges from 70 m to 140 m. Derived networks from Tennessee Valley exhibit ε_{min} ranging from 20 m to 45 m, and ε_{max} ranges from 120 m to 250 m. In the case of Finney Creek, ε_{min} is equal to the digital elevation model grid-size (i.e., 30 m) for $AS^2 = 1000$ and 2000 m²; it is always larger than the 4 m digital elevation model grid-size used for both Mettman Ridge and Tennessee Valley (Table 1).

Restricting our analysis to the scaling range limited by ε_{min} and ε_{max} reveals that a single D does not exist for the channel networks that we analyzed. Rather, plots of log N versus log ε for all artificial networks and both of the field-mapped channel networks exhibit a continuous curvature confirmed by highly structured regression residuals (Fig. 3). The fractal dimension implied by equation 4 varies systematically between ε_{min} and ε_{max} and a second-order polynomial equation better fits the data than a single log-linear equation. The curved residuals for the log-linear regressions indicate that the slope of the log-log plots is scale dependent, the implied D continuously increasing from 1 at ε_{min} to 2 at ε_{max}.

The lower and upper bounds to the applicability of the box-counting method also correlate with the mean source-basin length. The lower bound (ε_{min}) increases with larger source-basin length (l_s) (Fig. 4A), and least squares linear regression yields $\varepsilon_{min} = 8 + 0.22\, l_s$, indicating that ε_{min} is approximately equal to one-quarter of the mean source-basin length. The upper bound (ε_{max}) also increases with larger source-basin length (Fig. 4B), and least squares linear regression indicates that ε_{max} is equal to approximately twice the mean source-basin length ($\varepsilon_{max} = -14.3 + 1.98\, l_s$).

DISCUSSION

All natural objects possess length scales beyond which a fractal dimension cannot describe their geometry (Mandelbrot, 1983). The length scales where $D = 1$ and $D = 2$ for channel networks differ from such natural bounds imposed by the physical size of an object, in which case a well-defined D over some range of scales would fall apart at smaller or larger scales. In contrast, our results document the contrary case for channel networks wherein a unique fractal dimension describes their geometry only over length scales that yield results inherent to the method. Our results parallel those of Andrle (1996), who found a similar lack of a single D for the classic problem of the length of the coast of Great Britain.

Two of the primary tests upon which conclusions regarding the fractal nature of channel networks have been based are (1) the ability to calculate fractal dimensions from Horton's laws, and (2) the slope of plots of log N vs. log ε. The former approach can determine D under the assumption that channel networks are statistically self-similar, but provides no test of this proposition. In regard to the second approach, application of the box-counting method beyond the scale range defined by $\varepsilon_{min} \le \varepsilon \le \varepsilon_{max}$ necessarily yields $D = 1$ or $D = 2$, results inconsistent with the possible dimensions of a fractal object embedded in a two-dimensional space (Mandelbrot, 1983). Our analyses demonstrate that log-log plots for channel networks do not indicate statistical self-similarity over scale ranges appropriate for the box-counting method. Although we do not address other methods for determining fractal dimensions for channel networks, we worry that belief in the fractal nature of channel networks might reflect faith as much as it does established fact.

If networks are not statistically self-similar, then what are they? Our results indicate that channel networks are space filling for length scales larger than roughly twice the mean source-basin length: Networks fully penetrate the landscape to an extent determined by the controls on where stream channels begin. At intermediate length scales from approximately one-quarter to twice the mean source-basin length, a continu-

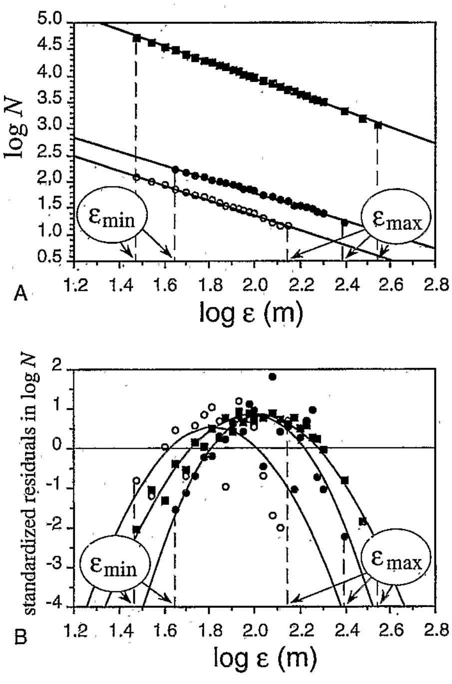

Figure 3. Analysis of channel networks for Finney Creek (black squares), Mettman Ridge (white circles), and Tennessee Valley (black circles) all delineated by AS^2 = 2000 m² where A is the contributing area and S is the local slope. A: Plot of log N versus log ε. Straight lines represent least squares linear regression for $\varepsilon_{min} < \varepsilon < \varepsilon_{max}$. B: Plot of standardized residual structure for plot of log N versus log ε. Curved lines represent least squares linear regression for $\varepsilon_{min} < \varepsilon < \varepsilon_{max}$.

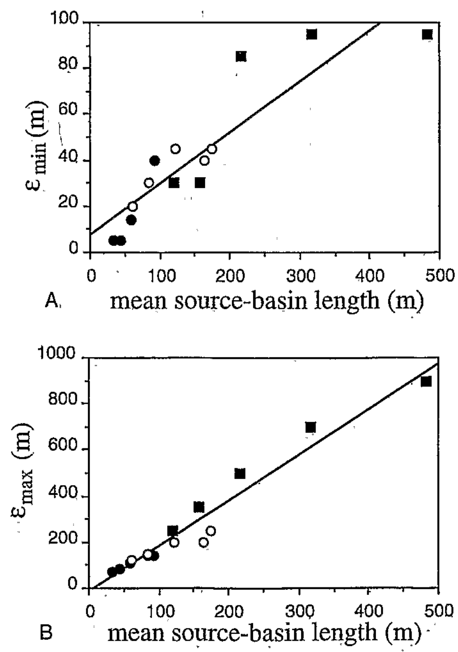

Figure 4. Relations of scaling bounds to mean source-basin length. A: Plot of the lower bound ε_{min} versus mean source-basin length. B: Plot of the upper bound ε_{max} versus the mean source-basin length. See Figure 3 for labels; straight lines represent linear regressions for combined data of three watersheds, equations for which are reported in text.

ously variable slope to the plots indicates that channel networks are not statistically self-similar. Previous reports of the space-filling nature of channel networks (Tarboton et al., 1988; Marani et al., 1991) apparently employed box-counting approaches beyond the range of applicability for the technique, which undermines the generality of conclusions regarding the fractal nature of channel networks. The range of scales over which the box-counting method yields $1 < D < 2$ is quite narrow and depends on the threshold value used to delineate network sources (Helmlinger et al., 1993). Decreasing the box size results in progressively greater proportions of empty boxes that do not intersect the channel network, and hence the slope of the log N vs. log ε plot approaches the dimension of the line segments used to portray the finest channels (i.e., $D = 1$). Once the box size exceeds that necessary for every box to intersect a channel, then the log-log plot simply becomes a plot of the length of a box side versus the inverse of box area, and the slope must equal 2 whether or not the network is fractal. The scale at which networks are space filling (ε_{max}) effectively equals twice the mean source-basin length, which approximates the mean distance between adjacent channel heads (Montgomery, 1991). Hence, channel networks fill space in a manner that supports the concept of a threshold-based limit to landscape dissection (Horton, 1945; Montgomery and Dietrich, 1992).

CONCLUSIONS

Our results show that channel networks are not statistically self-similar when carefully analyzed using the box-counting method, a result that contrasts with the widespread belief in the fractal nature of river networks. The systematic deviation from simple power-law scaling revealed by the box-counting method, when restricted to the range of scales appropriate for the method, demonstrates that channel network planforms are not statistically self-similar, in spite of their seductive branching architecture. Our analysis further reveals that channel networks are space filling at scales larger than twice the mean source-basin length, a result that supports the concept that landscapes are thoroughly dissected to a scale limited by an incisional threshold.

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