

# 1    **Reply to “Mathematical characterization of fractal river networks”**

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7    Optimal Channel Networks (OCNs) are virtual constructs that reproduce topology and scaling of real  
8    rivers<sup>1,2,3</sup>. Commonly used in hydrology, they also proved useful for ecological studies<sup>4,5</sup>. However, also  
9    because their computation has been less accessible until recently<sup>6</sup>, other approximations, such as random  
10    networks, have been used in ecological studies. In a recent study<sup>7</sup>, we compared random networks with  
11    OCNs and real rivers, both in terms of their geomorphological character and of ecologically-relevant  
12    metrics. We found that OCNs accurately match properties of real rivers, while this is generally not true for  
13    random networks. We also resolved a common misunderstanding in the use of random river models in  
14    ecology: the branching probability with which these are derived is not an inherent property of rivers, but  
15    depends on the observational scale. In a Matters Arising article<sup>8</sup>, Terui disputed our conclusions, and  
16    criticized two aspects of our work: concerning the definition of scale invariance, and on the use of  
17    dimensions and units. We respectfully but strongly disagree with both claims. Here, we show that both are  
18    incorrect and inappropriate, and neither of them is related to the core finding of our work, namely that  
19    OCNs are best at capturing ecologically-relevant features of river networks.

## 20    **Definition of scale invariance**

21    Firstly, Terui claimed that scale invariance is falsely defined in our study<sup>7</sup>, and specifically argued that  
22    “*branching probability has a property of scale invariance*”<sup>8</sup> because we found that branching ratio  $p_r$  scales  
23    as a power law of threshold area  $A_T$ . First of all, we note that we did not provide any formal definition of  
24    scale invariance in our study<sup>7</sup>, as this was not required to support our findings. Notably, scale invariance is

25 defined as a property of a function  $y = f(x)$  (that is, the relationship between  $y$  and  $x$ ), not of the  
 26 dependent variable  $y$  itself. Quoting Proekt et al.<sup>9</sup> (also referred to by ref.<sup>8</sup>): “a function  $f(x)$  is said to be  
 27 scale-invariant, if on multiplying the argument of the function by some constant [...] the same shape is  
 28 retained but with a different scale”. Therefore, the claim on branching probability being scale-invariant is  
 29 misleading. If  $p_r \sim A_T^Z$ , one can say that the relationship between  $p_r$  and  $A_T$  is scale-invariant, not that  $p_r$  is  
 30 scale-invariant per se. To make an ecologically relevant example, if this were not the case, one would  
 31 conclude that the number of species is scale-invariant, because species-area relationships are power laws.  
 32 Yet, the number of species does depend on the scale (habitat area) at which it is observed; it is the  
 33 relationship between area and species number that is scale-invariant.

34 More importantly, the interpretation of the definition of scale invariance is immaterial for the limitation we  
 35 highlighted in our study<sup>7</sup>: given a river network, it is not possible to univocally characterize its  $p_r$ , because it  
 36 depends on the scale at which the network is observed (that is, the depth/width/discharge above which a  
 37 river is defined, subsumed by  $A_T$  in our study<sup>7</sup>), just as one cannot assign an intrinsic length to a coastline  
 38 because it depends on the length of the “ruler” used to measure it. Even if one could univocally determine  
 39 the position of channel heads (and hence the number of links, that is the numerator of  $p_r$ ),  $p_r$  would still  
 40 depend on its denominator, that is the number of network nodes. We<sup>7</sup> used the pixel size as the extent of a  
 41 network node, because this is the smallest dimension at which one can measure the features of a river  
 42 network. We<sup>7</sup> also argued that the dimension of a node could be defined from an ecological perspective as  
 43 the extent of a local population. In this case, different species (with different local population ranges)  
 44 inhabiting the same real river network would perceive the network as partitioned into a different number  
 45 of nodes, hence leading to different  $p_r$  values.

## 46 **On dimensions and units**

47 Secondly, Terui<sup>8</sup> claimed an improper treatment of dimensions by our use<sup>7</sup> of pixels as units to measure  
 48 lengths and areas, which would allegedly lead to issues in the analysis of real river networks.

49 First, the distinction between pixel lengths and pixel areas is immaterial and does not affect our analyses in  
50 any way. Indeed, the numerator of  $p_r$  is dimensionless, while the denominator is measured in pixel lengths,  
51 and  $p_r$  is hence in principle measured in pixel lengths<sup>-1</sup>. However, we treated  $p_r$  as de facto dimensionless,  
52 as we did not attribute any specific dimension to the pixel size. This allowed a comparison between real  
53 river networks spanning different catchment areas in km<sup>2</sup> (see following paragraph). To this end, we also  
54 observe that previous works<sup>10–13</sup> using the concept of branching probability  $p$  expressed  $p$  as a  
55 dimensionless parameter, which is self-evident for a probability. The distinction between branching  
56 probability  $p$  and branching ratio  $p_r$  that we operated in our study is here irrelevant, because also  $p$   
57 depends on the length that is attributed to a node.

58 Second, we respectfully disagree with the claim on the improper use of dimensions in our study. The  
59 probability distribution of drainage areas is invariant under coarse graining<sup>3</sup>, hence it is absolutely correct  
60 to compare DEMs constituted by pixels of different sizes, which we did in our analysis. We specifically  
61 included real river basins spanning a wide range of catchment areas, as this proves that the same scaling  
62 features (e.g., relationship between  $p_r$  and  $A_T$ ) emerge irrespective of the pixel size, i.e., irrespective of the  
63 size of these catchments. In contrast, we respectfully note that Fig. 1 in ref.<sup>8</sup> does not invalidate our results  
64 whatsoever: panel b is simply obtained by shifting the lines of panel a along the x-axis. However, values on  
65 the y-axis are unchanged, hence our conclusion that different rivers rank differently in terms of  $p_r$  when  
66 extracted at different scales remains unaltered. For instance, in Fig. 1b, river Magra has the highest  $p_r$   
67 value when extracted at the coarsest resolution, but does not rank among the most “branching” rivers  
68 when extracted at the other two resolutions. If one extrapolated the trend lines of Fig. 1b and drew a  
69 vertical line at, say,  $A_T=1$  km<sup>2</sup>, one would indeed observe a higher  $p_r$  value for the larger catchments (e.g.,  
70 Klamath, Owyhee) than the smaller ones (e.g., Kleine Emme, Chisone). However, this comparison is  
71 improper, as  $A_T=1$  km<sup>2</sup> may be a very fine scale to extract river networks in large (in terms of km<sup>2</sup>) basins,  
72 but a very coarse scale for smaller catchments. A fair comparison with  $A_T$  expressed in km<sup>2</sup> would require  
73 the use of basins of similar areas in km<sup>2</sup> and extracted from DEMs with same (or similar) pixel size. Fig. 1b in

74 ref.<sup>8</sup> indeed shows that even for such rivers (e.g. Piave, Tanaro, Magra – see data for these rivers in Table  
75 S2 in ref.<sup>7</sup>), the  $p_T$ -rank is not maintained as  $A_T$  changes.

76 Also other claims, such as *“it is very likely that substantial errors are contained [...] that underpin their main*  
77 *conclusion that OCNs most accurately predicted the metapopulation stability and capacity”*<sup>8</sup> are neither  
78 substantiated nor proven. Our analysis was designed to compare networks with similar numbers of pixels,  
79 the only meaningful way to perform a fair comparison, as the number of pixels (and hence, of network  
80 nodes) exerts a major control on the metapopulation metrics. In fact, we ensured that BBTs, RBNs, OCNs  
81 and real rivers have the same parameters (number of nodes and branching probability, Fig. S8 in ref.<sup>7</sup>)  
82 when metapopulation properties are compared. It is indeed unclear how one should have *“tweaked virtual*  
83 *networks”* to overcome this alleged *“fundamental problem”*<sup>8</sup>, given that the only two parameters of  
84 random networks are number of nodes and branching probability, and no parameter controlling for the  
85 scale/dimension of these networks is provided.

86 We conclude that neither of Terui’s critiques are justified, and we strongly oppose the statement that our  
87 findings are *“merely an artefact”*. Both claims are not only incorrect, but actually inappropriate, as not  
88 substantiated. We also respectfully disagree with alleged indirect critiques, such as implications that  
89 random networks would be better than OCNs because these *“methods have only few parameters that*  
90 *control river network size”*<sup>8</sup>. The choice of a method is not (only) about the number of parameters needed,  
91 but rather about its accuracy and suitability. Importantly, we acknowledge that Terui agrees that OCNs are  
92 capable of reproducing the scaling properties of real river networks, and concludes that a re-interpretation  
93 of the importance of river network structure in ecology should be assessed. Actually, this is exactly what we  
94 did in our study<sup>7</sup>: proving that OCNs can reproduce ecologically-relevant metrics of real river networks,  
95 while random networks do not. Consequently, the use of random networks in ecological studies should be  
96 abandoned in favor of OCNs.

97     **Data availability statement**

98     Data sharing not applicable to this article as no datasets were generated or analysed during the current  
99     study.

100    **Author contributions**

101    L.C. and F.A. equally contributed to this work.

102    **Competing interests**

103    The authors declare no competing interests.

104    **Acknowledgements**

105    Funding is provided by the Swiss National Science Foundation Grants No. 31003A\_173074, PP00P3\_179089  
106    (to F.A.), PZ00P2\_202010 (to L.C.), the University of Zurich Forschungskredit Grant No. K-74335-04-01 (to  
107    L.C.) and the University of Zurich Research Priority Programme (URPP) Global Change and Biodiversity.

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