

1
2 **Is the patch size distribution of vegetation a suitable**
3 **indicator of desertification processes?:**

4 **Comment**

5
6
7 Kéfi, S.^{1*}, Alados, C.L.², Chaves, R.C.G.³, Pueyo, Y.⁴, and Rietkerk, M.⁵

8
9 ¹Department of Biology, Darmstadt University of Technology. Schnittspahnstr. 10. 64287
10 Darmstadt, Germany

11 ²Instituto Pirenaico de Ecología (CSIC). Avda. Montañana 1005. P.O.Box. 202. 50080
12 Zaragoza, Spain.

13 ³Max-Planck-Institut für Kernphysik, P.O. Box 103980, D 69029 Heidelberg, Germany

14 ⁴Geography Department, University of Zaragoza, Campus Plaza San Francisco. Pedro
15 Cerbuna, 12. 50009 Zaragoza, Spain

16 ⁵Department of Environmental Sciences, Copernicus Institute, Utrecht University, P.O. Box
17 80115, 3508 TC Utrecht, The Netherlands

18
19 * Corresponding author. E-mail: kefi@bio.tu-darmstadt.de

20
21 Manuscript type: Comment

22 With ongoing climate change, the search for indicators of imminent ecosystem shifts is
23 attracting increasing attention (e.g. Scheffer et al. 2009). Recently, the spatial organization of
24 ecosystems has been suggested as a good candidate for such an indicator in spatially
25 structured ecosystems (Rietkerk et al. 2004, Kéfi et al. 2007a, Guttal and Jayaprakash 2009).
26 Arid ecosystems are well-known for the spatial organization of their vegetation cover, which
27 is often characterized by clumps of vegetation in an otherwise bare soil matrix. Two recent
28 studies revealed that the distribution of the vegetation patch size can be described by a power
29 law over a wide range of environmental conditions in arid ecosystems (Kéfi et al. 2007a,
30 Scanlon et al. 2007). Furthermore, deviations from power laws were observed under high
31 grazing pressures, leading to the hypothesis that such deviations could be used as indicators of
32 approaching desertification in arid ecosystems (Kéfi et al. 2007a). This hypothesis now needs
33 to be validated with additional field data, before it can be confidently used as a tool to monitor
34 degradation in arid ecosystems.

35

36 In a recent study, Maestre and Escudero (2009) (hereafter referred to as ME09) aimed to test
37 this hypothesis with data from 29 steppes located on a rainfall gradient in southeast Spain. In
38 all of their sites, the patch size distribution was best described by a truncated power law
39 (TPL)¹. Relating the scaling exponents of these TPLs to soil variables, the authors concluded
40 that 1) the patch size distribution was not directly related to desertification but rather that 2)
41 vegetation cover could be used to monitor desertification. We argue in this comment that the
42 analyses of ME09 do not allow them to draw these conclusions, for the following two
43 reasons. First, because all of their sites were characterized by TPLs, the authors looked only

1 We use here the same terminology as in Kéfi et al. (2007) and Maestre and Escudero (2009), where a TPL refers to a power law with exponential cutoff, i.e. such that $N(S)=CS^{-\gamma}\exp(-S/S_c)$ with N the number of patches of size S, C a constant, γ the scaling exponent (positive) and S_c the patch size above which N decreases faster than in a power law (positive).

44 at the scaling exponents γ of these TPLs to compare the degradation level of the sites.
45 However, γ was not proven to vary with degradation in a consistent manner, and therefore
46 the analyses of ME09 do not allow them to conclude whether vegetation cover is better
47 related to degradation than patch size distribution. Second, although the vegetation cover is
48 often a simple and efficient indicator of degradation, the authors do not take into account the
49 increasing amount of literature that strongly suggests vegetation cover in arid ecosystems is
50 likely to respond in a discontinuous way to gradual, external changes (Rietkerk et al. 1996,
51 Lejeune et al. 1999, Scheffer et al. 2001, von Hardenberg et al. 2001, Kéfi et al. 2007b). In
52 these cases, the vegetation cover alone simply does not provide information on the actual
53 distance to desertification.

54

55 The categorization proposed by Kéfi et al. (2007a) is a qualitative one in that it does not
56 provide a quantifiable distance to extinction: a shift (in time) from a pure power law to a TPL
57 suggests that an ecosystem is degrading and approaching the desertification threshold. The
58 sites studied by ME09 are all described by TPLs. Among sites characterized by similar patch
59 size distributions, Kéfi et al. (2007a) do not propose any criteria to distinguish among sites of
60 varying degradation; currently, such criteria are sorely lacking. In an attempt to compare the
61 degradation levels of their 29 sites, ME09 investigated changes in the scaling exponent γ of
62 the TPL among the different sites. This was not part of the hypothesis formulated by Kéfi et
63 al. (2007a). It is an interesting approach, but it implicitly assumes that γ varies consistently
64 with the level of stress, which has not been proven to be the case. In fact, in the data analyzed
65 by Kéfi et al. (2007a), there does not appear to be any consistent variation of γ among sites
66 characterized by different stress levels (i.e. grazing pressures). For example, with increasing
67 grazing pressure (from medium to high) the absolute value γ of the TPL decreases in the data

68 from Spain but increases in the data from Morocco and Greece (see Fig. 1 in Kéfi et al.
69 (2007a)). The lack of a clear relationship between γ and the stress level could very well
70 explain why ME09 find that γ is not related to the perennial cover. It is noteworthy that this
71 result is in agreement with previous studies on steppes dominated by *Stipa tenacissima* in the
72 arid Mediterranean region. For example, it has been shown that the spatial distribution of *S.*
73 *tenacissima* is not clearly related with its abundance (see Table 1 in Alados et al. (2006)).
74 Furthermore, the exponent γ alone does not provide a complete description of the shape of
75 the TPL; the location of the cutoff, S_c , cannot be ignored. Indeed, the latter describes where
76 the deviation from power law behavior begins, and it is this deviation which was proposed to
77 be linked to the level of degradation in Kéfi et al. (2007a). Thus, we doubt whether γ is the
78 correct parameter to investigate. Further theoretical and empirical work is needed in order to
79 identify the parameters which are best correlated to the stress level and which therefore
80 should be monitored.

81

82 Another concern regarding the analysis of ME09 is that, when fitting TPLs to their data, they
83 find negative power law exponents in the vast majority of their sites (22/29 sites listed in
84 ME09 Table 1 and 7/8 sites illustrated in ME09 Fig. D1), in stark contrast to the positive
85 power law exponents observed by Kéfi et al. (2007a). A TPL with a negative power law
86 exponent can be understood as follows: the number of patches $N(S)$ actually increases with
87 size S until some intermediate path size is reached, at which point $N(S)$ begins to decrease.
88 Thus, in ME09's distributions, it is common for smaller patches to be less abundant than
89 patches of intermediate size. For this reason, a TPL does not appear to be the most appropriate
90 model to use to fit the data. The distributions found by ME09 actually suggest the presence of
91 a dominant spatial scale, contrary to the scale invariance observed by Kefi et al. (2007a).

92 Indeed, some arid areas are characterized by regular vegetation patterns (Rietkerk and van de
93 Koppel 2008), where patch size distributions do not follow power laws but instead reflect a
94 characteristic patch size (or a range of patch sizes). Manor and Shnerb (2008) developed a
95 promising model which can reproduce both the irregular patterns described by power law
96 distributions and the regular patterns characterized by a dominant spatial scale. They showed
97 how the relative strength of competition and facilitation can drive the type of pattern that
98 emerges; strong facilitation favors irregular pattern formation while strong competition favors
99 regular patterns. In systems characterized by regular patterns, it has been suggested that the
100 shape of the patterns can be used to gauge the level of degradation, with spot patterns being
101 the last to occur before desertification (Rietkerk et al. 2004). Further research is needed to
102 determine if these findings can indeed be applied to the sites studied by ME09. More
103 generally, what is currently lacking is a robust way of characterizing the spatial organization
104 of ecosystems, since, depending on the type of patterns (which emerge from different
105 underlying ecological mechanisms), the indicators that need to be monitored may vary.

106

107 Before patch size distributions can be used as a monitoring tool in systems characterized by
108 irregular patterns, many technical issues need to be addressed and further tests need to be
109 conducted in the field. From a practical point-of-view, the patch size distribution is indeed a
110 more complicated tool than the vegetation cover. Among others, there are issues with the
111 binning of the data and the fitting of the mathematical functions.

112 Traditionally, data is binned when visualizing frequency distributions (Newman 2006, Bauke
113 2007, White et al. 2008, Clauset et al. *In press*). When the data are binned into bins of equal
114 sizes (so-called linear binning), the right-hand side of the distribution is often noisy: the
115 largest elements are rare, and, therefore, each bin contains only a few elements which creates

116 large variations in bin counts among bins (Newman 2005, Bauke 2007). This is a concern
117 when dealing with patch size distributions, since we are especially interested in the behavior
118 of the putative power law in the area around the largest, i.e. the rarest, patches. To decrease
119 the noise in the right-hand tail of the distribution, logarithmic binning is typically employed,
120 where the bins in the tail of distribution receive more elements than with linear binning.
121 Various techniques have been proposed to estimate the optimum bin size (e.g. Sturges' rule,
122 Scott's rule, and the Freedman-Diaconis rule); all strive to achieve a reasonable balance
123 between the number of bins and the number of elements in each bin. However, these
124 techniques do not always yield consistent results, which makes the choice of binning fairly
125 arbitrary. A better way of plotting the data is to use the cumulative distribution function,
126 which does not involve the binning of the data (Newman 2005, Bauke 2007, White et al.
127 2008).

128 After binning the data, a linear fitting of the log-log transformed data is typically performed
129 using least squares regression (Newman 2005, Bauke 2007, White et al. 2008, Clauset et al.
130 *In press*). Fitting methods based on binning and least squares regression are widely used in
131 ecology and in other fields to fit models to data and to estimate the scaling exponents of
132 frequency distributions. White et al. (2008) recently demonstrated that such methods give
133 biased results and therefore cannot be relied upon. While these biases are dangerous with
134 regards to estimating the scaling exponent of a distribution, binned-based methods can also
135 lead to differences in the determination of which distribution best fits the data. For example, a
136 data set that is best described by a power law using a given bin size could be best described
137 by a TPL when using a different bin size.

138 Independently of the way the data are plotted, a reliable alternative to least square linear
139 regression is to use fitting methods based on maximum likelihood estimation (MLE) to

140 extract the scaling exponent of the frequency distribution (e.g. Goldstein et al. 2004). White et
141 al. (2008) showed that MLE is the single most accurate method for estimating the scaling
142 exponents of frequency distributions. Currently, MLE is available for the pure power law
143 distribution (Goldstein et al. 2004, Newmann 2005, Bauke 2007) but not for the TPL
144 distribution as defined here, which limits the application of MLE to this particular case for
145 now, but is a promising line of future research.

146

147 In conclusion, although looking at the vegetation cover is still the most obvious and practical
148 way of assessing the "health" of an arid ecosystem, there are notable cases where the cover
149 fails to predict desertification. Desertification can occur in sudden shifts, where ecosystems
150 switch from an unknown vegetation cover to desert. Theoretical studies increasingly suggest
151 that ecosystems which include facilitation may respond to gradual external changes in an
152 abrupt, rather than gradual manner (e.g. Lejeune et al. 1999, Scheffer et al. 2001, von
153 Hardenberg et al. 2001, Rietkerk et al. 2004, Kéfi et al. 2007b). In these cases, the vegetation
154 cover is not an appropriate indicator of proximity to shifts and, therefore, other potential
155 indicators (e.g. the patch size distribution) need to be further developed so that they can be
156 used in addition to the cover. In the meantime, we advocate the continued but cautious use of
157 the cover as a means to gauge an arid ecosystem's health, but reiterate the need to explore
158 more robust techniques before a reliable early-warning system can be implemented.

160 **References**

161

162 Alados, C. L., P. Gotor, P. Ballester, D. Navas, J. M. Escós, T. Navarro, and B. Cabezudo.

163 2006. Association between competition and facilitation processes and vegetation

164 spatial patterns in alpha steppes. *Biological Journal of the Linnean Society* **87**:103-

165 113.

166 Bauke, H. 2007. Parameter estimation for power-law distributions by maximum likelihood

167 methods. *The European Physical Journal B - Condensed Matter and Complex*

168 *Systems* **58**(2):167-173.

169 Clauset, A., C. R. Shalizi, and M. E. J. Newman. Power-law distributions in empirical data.

170 *SIAM Review*. *In press* arXiv:0706.1062.

171 deMenocal, P., J. Ortiz, T. Guilderson, J. Adkins, M. Sarnthein, L. Baker, and M. Yarusinsky.

172 2000. Abrupt onset and termination of the African Humid Period: rapid climate

173 responses to gradual insolation forcing. *Quaternary Science reviews* **19**:347-361.

174 Foley, J. A., M. T. Coe, M. Scheffer, and G. Wang. 2003. Regime shifts in the Sahara and

175 Sahel: interactions between ecological and climatic systems in northern Africa.

176 *Ecosystems* **6**:524-539.

177 Goldstein, M. L., S. A. Morris, and G. G. Yen. 2004. Problems with fitting to the power-law

178 distribution. *The European Physical Journal B - Condensed Matter and Complex*

179 *Systems* **41**(2):255-258.

180 Guttal, V., and C. Jayaprakash. 2009. Spatial variance and spatial skewness: leading

181 indicators of regime shifts in spatial ecological systems. *Theoretical Ecology* **2**:3-12.

182 Kéfi, S., M. Rietkerk, C. L. Alados, Y. Pueyo, V. P. Papanastasis, A. ElAich, and P. C. de
183 Ruiter. 2007a. Spatial vegetation patterns and imminent desertification in
184 Mediterranean arid ecosystems. *Nature* **449**:213-217.

185 Kéfi, S., M. Rietkerk, M. van Baalen, and M. Loreau. 2007b. Local facilitation, bistability and
186 transitions in arid ecosystems. *Theoretical Population Biology* **71**:367-379.

187 Lejeune, O., P. Couteron, and R. Lefever. 1999. Short range co-operativity competing with
188 long range inhibition explains vegetation patterns. *Acta Oecologica* **20**:171-183.

189 Maestre, F. T., and A. Escudero. 2009. Is the patch size distribution of vegetation a suitable
190 indicator of desertification processes? *Ecology* **90**:1729-1735.

191 Manor, A., and Shnerb, N. 2008. Facilitation, competition, and vegetation patchiness: From
192 scale free distribution to patterns. *Journal of Theoretical Biology* **253**:838-842.

193 Newman, M. E. J. 2005. Power laws, Pareto distributions and Zipf's law. *Contemporary*
194 *Physics* **46**(5):323 – 351.

195 Rietkerk, M., S. C. Dekker, P. C. de Ruiter, and J. van de Koppel. 2004. Self-organized
196 patchiness and catastrophic shifts in ecosystems. *Science* **305**:1926-1929.

197 Rietkerk, M., P. Ketner, L. Stroosnijder, and H. H. T. Prins. 1996. Sahelian rangeland
198 development: a catastrophe? *Journal of Range Management* **49**:512-519.

199 Rietkerk, M., van de Koppel, J. 2008. Regular pattern formation in real ecosystems. *Trends in*
200 *Ecology and Evolution* **23**(3): 169-175.

201 Scanlon, T. M., K. K. Caylor, S. A. Levin, and I. Rodriguez-Iturbe. 2007. Positive feedbacks
202 promote power-law clustering of Kalahari vegetation. *Nature* **449**:209-U204.

203 Scheffer, M., S. Carpenter, J. A. Foley, C. Folke, and B. Walker. 2001. Catastrophic shifts in
204 ecosystems. *Nature* **413**:591-596.

205 Scheffer M., J. Bascompte, W.A. Brock, V. Brovkin, S.R. Carpenter, V. Dakos, H. Held, E.H.
206 van Nes, M. Rietkerk, and G. Sugihara. 2009. Early-warning signals for critical
207 transitions. *Nature* **461**: 53-59.

208 von Hardenberg, J., E. Meron, M. Shachak, and Y. Zarmi. 2001. Diversity of vegetation
209 patterns and desertification. *Physical Review Letters* **87**19.

210 White, E. P., B. J. Enquist, and J. L. Green. 2008. On estimating the exponent of power-law
211 frequency distributions. *Ecology* **89**:905-912.