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**Hydrologic Controls on Aperiodic Spatial Organization in the Ridge Slough Patterned
Landscape**

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25 **Abstract**

26 A century of hydrologic modification has altered the physical and biological drivers of
27 landscape processes in the Everglades (Florida, USA). Restoring the ridge-slough patterned
28 landscape, a dominant feature of the historical system, is a priority, but requires an understanding
29 of pattern genesis and degradation mechanisms. Physical experiments to evaluate alternative
30 pattern formation mechanisms are limited by the long time scales of peat accumulation and loss,
31 necessitating model-based comparisons, where support for a particular mechanism is based on
32 model replication of extant patterning and trajectories of degradation. However, multiple
33 mechanisms yield a central feature of ridge-slough patterning (patch elongation in the direction
34 of historical flow), limiting the utility of that characteristic for discriminating among alternatives.
35 Using data from vegetation maps, we investigated the statistical features of ridge-slough spatial
36 patterning (ridge density, patch perimeter, elongation, patch-size distributions, and spatial
37 periodicity) to establish more rigorous criteria for evaluating model performance, and to inform
38 controls on pattern variation across the contemporary system. Mean water depth explained
39 significant variation in ridge density, total perimeter, and length:width ratios, illustrating
40 important pattern response to existing hydrologic gradients. Two independent analyses (2-D
41 periodograms and patch size distributions) provide strong evidence against regular patterning,
42 with the landscape exhibiting neither a characteristic wavelength nor a characteristic patch size,
43 both of which are expected under conditions that produce regular patterns. Rather, landscape
44 properties suggest robust scale-free patterning, indicating genesis from the coupled effects of
45 local facilitation and a global negative feedback operating uniformly at the landscape-scale.
46 Critically, this challenges widespread invocation of meso-scale negative feedbacks for
47 explaining ridge-slough pattern origins. These results help discern among genesis mechanisms

48 and provide an improved statistical description of the landscape that can be used to compare
49 among model outputs, as well as to assess the success of future restoration projects.

50

51 *Keywords:* regular patterning, scale-free patterning, robust criticality, scaling relationships, ridge
52 slough landscape, periodogram analysis, Everglades, wetland restoration.

53 **1 Introduction**

54 The coupling of ecosystem processes operating at different scales can cause vegetation
55 communities to form a wide variety of spatial patterns (Borgogno et al., 2009), ranging from
56 highly regular striping, stippling or maze-like patterns in woodland landscapes (Ludwig et al.,
57 1999), tidal mud flats (Weerman et al., 2012), and boreal peatlands (Eppinga et al., 2010) to
58 scale-free patterning in semi-arid landscapes (Kefi et al., 2007; Scanlon et al., 2007). The
59 mechanisms that produce these patterns are integral to understanding landscape origins, and thus
60 for predicting appropriate remedies where patterns and underlying processes have been degraded
61 and require restoration. The spatial arrangement of vegetation on the landscape has long been
62 viewed as a manifestation of the dominant interactions and drivers (Hutchinson, 1957; Levin,
63 1992), and the scales at which they operate. By quantifying this spatial arrangement we can
64 make process-based inferences about the underlying mechanisms (Gardner et al., 1987; Turner,
65 2005).

66 The ridge-slough landscape comprised ~55 % of the pre-development Everglades in
67 southern Florida (McVoy et al., 2011). However, processes that created, and in some places still
68 maintain, the characteristic ridge-slough patterning are only partially understood (Science
69 Coordination Team, 2003; Larsen et al., 2011; Cohen et al., 2011). The landscape pattern
70 consists of flow-parallel bands of higher-elevation ridges dominated by emergent sedge sawgrass
71 (*Cladium jamaicense*), interspersed within a matrix of lower-elevation sloughs (ca. 25 cm lower
72 in the best conserved portions of the landscape; Watts et al., 2010), which contain a variety of
73 submerged and emergent herbaceous macrophytes. The Everglades has undergone massive
74 hydrologic modification through the construction of a system of levees and canals over the past
75 century (Light and Dineen, 1994), and ensuing ecological degradation has prompted a complex,

76 expensive, and ambitious restoration effort. Because the ridge-slough landscape was so prevalent
77 in the pre-development system, pattern restoration is a central priority (SCT 2003; McVoy et al.,
78 2011). The mechanisms that control the emergence of patterning and explain variation in pattern
79 geometry are thus integral to specifying hydrologic restoration objectives.

80 To understand the landscape processes that produce patterning, and by extension gain
81 insight into how to restore them (Pickett and Cadenasso, 1995), requires a testable mechanistic
82 framework for pattern genesis and maintenance. However, experiments to test alternative
83 mechanisms are constrained by the spatial extent and time scales of peat accumulation responses.
84 Paradoxically, compartmentalization by the extensive canal and levee system has created
85 artificial gradients that are informative for assessing trajectories of landscape pattern
86 degradation. Here we focus on Water Conservation Area 3 (WCA-3), located in the central
87 Everglades, an area historically dominated by the ridge-slough landscape (Fig. 1), and where the
88 best conserved patterning is found. The hydrologic gradient in WCA-3 spans from relatively dry
89 (i.e., short hydroperiod) conditions in the north due to major canals that drain water to the
90 southeast, to extended inundation (i.e., long hydroperiod) in the south and southeast due to
91 impoundment caused by US41/Tamiami Trail (which runs orthogonal to flow) and the L-67
92 levee. The best conserved patterning (SCT, 2003; Watts et al. 2010) is found between these
93 hydrologic extremes.

94 Several alternative hypotheses have been proposed to explain ridge slough patterns, and
95 all have been evaluated using process-based models. The mechanisms invoked vary and include
96 evaporative nutrient redistribution (Ross et al., 2006), flow-driven sediment redistribution from
97 sloughs to ridges (Larsen et al., 2007; Larsen and Harvey 2011; Lago et al., 2010), ponding
98 induced long-range inhibition (Cheng et al., 2011), self-optimization of patterning for discharge

99 and hydroperiod (Cohen et al., 2011; Kaplan et al., 2012; Heffernan et al., 2013), and a suite of
100 mechanisms that couple pattern-hydroperiod effects with anisotropic local contagion processes
101 (Acharya et al., 2015). Clearly, these mechanisms are not mutually exclusive, so process models
102 have sought to explore the sufficiency of each alternative, while acknowledging the potential that
103 multiple processes may overlap. One central criterion used to evaluate the models has been
104 whether simulations can produce morphologies qualitatively consistent with the extant landscape
105 (principally replicating the elongation of patches in the flow direction). To date, however, almost
106 all models either accomplish (Ross et al., 2006; Larsen and Harvey, 2010; Lago et al., 2010;
107 Cheng et al., 2011; Acharya et al., 2015) or strongly imply (Heffernan et al., 2013) this, limiting
108 the ability to discriminate between pattern genesis mechanisms and highlighting the need for a
109 more rigorous and quantitative characterization of landscape pattern.

110 To better characterize patterns in both the best conserved state and spanning a gradient of
111 degradation requires spatial analyses that yield quantitative properties against which model
112 outputs can be compared. Although numerous metrics have been developed to quantify different
113 pattern attributes (Wu et al., 2007; Yuan et al., 2015), significant gaps in our understanding of
114 how to interpret these metrics remain (Turner, 2001; Rempel and Csillag, 2003). Real
115 landscapes clearly depart from regular Euclidean geometry, making characterization problematic
116 in some cases (Mandelbrot, 1983). Likewise, changes in mapping procedures (e.g., grain size,
117 extent, classification schemes) can yield significantly different metric values for the same
118 landscape (Li and Wu, 2004). To remedy some of these issues, we focused on a set of relatively
119 direct and easily interpreted metrics of fundamental aspects of the pattern, and used multiple
120 maps produced with varying methods to rule out mapping-related artifacts. We were interested in
121 three aspects of landscape patterning: density and shape statistics, patch-size distributions, and

122 spectral (i.e., pattern wavelength) characteristics. For each aspect, we explored the magnitude of
123 site-to-site variation and the support for hydrologic control of that variation.

124 Density and shape statistics focus on the most basic and intuitive geometric properties of
125 the landscape: areal coverage of the patch types (density), landscape pattern complexity
126 (perimeter), and the degree of elongation. While inundation has been shown to control species
127 composition (Givnish et al., 2008; Zweig and Kitchens, 2008; Todd et al., 2010), the relationship
128 between hydrologic drivers and other aspects of landscape pattern remain relatively unknown, so
129 this effort also serves as an inventory of hydrologic controls on pattern geometry.

130 Patch size distributions (i.e., frequency of different patch sizes) have been used in many
131 systems to identify underlying landscape processes (e.g., Manor and Shnerb, 2008a; Kefi et al.,
132 2011; Bowker and Maestre, 2012; Weerman et al., 2012). For example, regular patterning is
133 associated with a characteristic patch size (Rietkerk and van de Koppel, 2008; von Hardenberg,
134 2010), arising in response to an inhibitory feedback operating at a particular spatial scale (van de
135 Koppel and Crain, 2002) that limits patch expansion. Under these conditions, there should be a
136 distinct mode in patch area distribution, or at least the absence of very large patches (Manor and
137 Shnerb, 2008; von Hardenberg, 2010; Kefi et al., 2014). In contrast, patch size distributions that
138 follow a power-law (i.e., $y=x^\alpha$, where α is a scaling parameter) lack a characteristic spatial scale
139 (e.g., Scanlon et al., 2007) and may suggest genesis mechanisms that operate equally across
140 scales. Correspondingly, power law distributions are often referred to as scale-free, in that the
141 distribution form remains the same regardless of the measurement scale.

142 Scale-free distributions can arise via a number of mechanisms (Newman et al., 2005). In
143 a landscape where grid cells are randomly occupied, patch distributions show relatively few large
144 patches, up to a critical density (~ 0.59 ; known as the percolation threshold) at which patches

145 span the domain, yielding power-law area scaling. At densities slightly above and below the
146 percolation threshold, area distributions depart from power-laws. The narrow range of density
147 space over which scale-free area distributions emerge would seem to suggest that this
148 mechanism is rare. However, some systems can endogenously maintain themselves near this
149 critical point in a phenomenon referred to as self-organized criticality (Bak et al., 1989). This is
150 accomplished through disturbance processes that propagate via patch contiguity (e.g., forest
151 fires, see Drossel and Schwabl, 1992), maintaining patterns near the percolation threshold
152 through a cycle of large-scale disturbance and slow recovery (Pascual and Guichard, 2005).

153 Alternatively, power-law scaling of patch areas can arise from the coupled action of local
154 facilitation, which causes patches to expand, and competition for a global resource (Pascual et
155 al., 2002; Scanlon et al., 2007) that ultimately limits the density of that patch type at the
156 landscape scale. In contrast to regular patterning mechanisms, these feedback processes limit
157 landscape-level patch density, but not the size of individual patches, leading to the creation, via
158 local facilitation, of very large patches. This is known as robust criticality because power-law
159 scaling in response can occur over a wide range of external conditions and patch densities,
160 including densities well below the percolation threshold. Robust criticality has been noted in
161 Everglades vegetation distributions (Foti et al., 2012), as well as in a variety of dryland
162 vegetation patterns (Kefi et al., 2011). Widespread occurrence of both local facilitation and
163 global resource competition in ecological systems suggests this process may operate in a
164 multitude of landscapes.

165 Finally, spectral characteristics provide insights on the presence and wavelength of
166 regular landscape pattern. Useful information about the scale at which spatial feedbacks operate
167 in self-organized systems has been obtained by evaluating 2-dimensional pattern periodicity

168 (Couteron, 2002; Kefi et al., 2014). This is particularly important in the Everglades because the
169 prevailing conceptual model for ridge-slough pattern genesis invokes interactions between
170 spatial feedbacks operating on different characteristic scales, resulting in a pattern wavelength of
171 approximately 150 m in the direction perpendicular to historical flow (SCT, 2003; Larsen et al.,
172 2007; Watts et al., 2010). Several models (e.g. Ross et al., 2006; Lago et al., 2010; Cheng et al.,
173 2011) produce distinctly periodic landscapes, which arise from the action of local facilitation
174 feedbacks and, crucially, negative feedbacks on patch expansion that operate at a characteristic
175 scale. In contrast, the feedback between hydroperiod and landscape geometry suggested by
176 Cohen et al. (2011), enumerated by Heffernan et al. (2013), and tested at the landscape scale in
177 Kaplan et al. (2012), operates at the global-scale, implying no characteristic spatial scale. To that
178 end, we tested the hypothesis that the ridge-slough landscape is regularly patterned (i.e., exhibits
179 a characteristic wavelength), consistent with scale-specific negative feedbacks, or whether the
180 landscape lacks periodicity, consistent with scale-free feedbacks.

181 Together, these spatial analyses encompass a novel and rigorous set of metrics for
182 improved quantification of observed and modeled landscape pattern. While developed to
183 improve descriptions of the ridge-slough pattern, these metrics may also be useful for identifying
184 pattern and discriminating genesis mechanisms in other patterned landscapes.

185

186 **2 Methods**

187 **2.1 Vegetation and hydrologic data**

188 We used multiple vegetation maps of the central Everglades, which vary in scale, extent,
189 mapping schemes, and time frame. For all maps, we aggregated vegetation types into binary
190 classes (reclassification scheme in Table S2) of ridges (*value* = 1) and sloughs (*value* = 0). Our

191 primary map (M1) was produced by the South Florida Water Management District (SFWMD)
192 using 1:24000-scale color infrared photos from September 1994 (Rutchev, 2005). This map was
193 chosen due to its large, continuous spatial extent and fine mapping detail. The presence of small
194 (<25 m²) landscape features allowed us to rasterize polygons of dominant vegetation at 1 m
195 resolution (i.e., 1×1 m cells). While the presence of small features does not imply map accuracy
196 at that fine scale, it does imply loss of patch geometric detail with larger cells. Features at this
197 scale can be subject to mapping error and artifacts, likely under-representing their prevalence. As
198 such, patches below 100 m² were omitted from patch-level analyses.

199 We selected 33 6×6 km sites to span the range of current hydrological conditions (i.e., dry
200 in northern areas to wet in southern areas; Fig. 1). We sought to maximize the number of sites
201 with minimal overlap, while avoiding roads and canals. All sites except 20–22 and 32–33 were
202 rotated to align with the prevailing direction of patch elongation (15° counterclockwise). Ridge
203 cells were grouped into patches if they shared at least one edge with an adjacent ridge (i.e., a von
204 Neumann neighborhood).

205 Within each site, *point-specific* daily average water depths at a grid spacing of 200 m
206 were obtained from the Everglades Depth Estimation Network (EDEN) xyLocator
207 (<http://sofia.usgs.gov/eden/edenapps/xylocator.php>). We note these water depths are spatially
208 interpolated from a network of water elevation monitoring stations and, as such, represent only
209 an estimate of actual conditions. *Site-specific* mean water depth (MWD) values were obtained by
210 averaging all point-specific values in each site over the period of record from 1991–2010.

211 We used two additional maps (M2 and M3), which vary in spatial extent, resolution, and
212 sampling date, to corroborate M1 analyses and test map resolution effects and temporal changes.
213 M2 was generated from 1:24000 scale aerial photographs taken in 2004 (RECOVER 2014) and

214 rasterized at 50 m resolution. M3 was generated from 1 m resolution digital orthophotos and
215 rasterized at 1 m (Nungesser, 2011). Methodological details for both M2 and M3 are given as
216 supplementary information.

217 **2.2 Shape and density**

218 We compared ridge density, edge density, and elongation across sites. Ridge density is
219 the proportion of ridge area to site area, while edge density is total patch perimeter divided by
220 site area. In order to measure elongation, E , we first identify individual lengths and widths (l and
221 w , respectively) as any group of contiguous ridge cells (i.e. unbroken by slough cells) along a
222 row or column. Elongation is the ratio of the mean of these contiguous row and column sections:

$$223 \quad E = \frac{\frac{1}{n_c} \sum l}{\frac{1}{n_r} \sum w} = \frac{n_r}{n_c} \quad (1)$$

224 where n_r and n_c represent the number of contiguous rows and columns. Elongation simplifies to
225 their ratio since the summation terms both yield the total number of ridge cells. Elongation
226 metrics are sensitive to orientation differences between the grid and landscape features. Sites
227 with tortuous flow paths or a poorly aligned grid will underestimate E . We provide estimates of
228 grid alignment with feature orientation as a mean patch angle, \bar{A}_p , where A_p is the angle between
229 the grid y axis and the major axis of an ellipse with the same second moment as the patch.

230 Hydrologic trends were identified by regressing MWD against site-level metrics, and
231 were considered statistically significant at $p < 0.05$. For analyses that are highly dependent on
232 mapping resolution (i.e., edge density), we omit M1 sites north of Interstate-75, as these were
233 mapped using significantly lower resolution than those to the south (Rutchev, 2005). Because
234 elongation values are dominated by the domain shape at very high ridge densities, we omitted
235 sites where ridge density exceeded 0.8.

236 **2.3 Patch size distributions**

237 Patch size scaling properties were evaluated by comparing empirical distributions to
238 several candidate models. Patch size distributions can be described in terms of their
239 complementary cumulative distribution function (CCDF), which gives the probability that the
240 area of an observed patch is greater than or equal to a given area, x . Preliminary analyses showed
241 that empirical CCDFs exhibited extremely heavy tails consistent with power laws, but only
242 above a minimum cutoff, below which patches were less abundant and the CCDFs were rounded.
243 This form is in relative agreement with both the Generalized Pareto (GP) and truncated
244 lognormal distributions. The GP is given by its CCDF as

$$245 \quad P(x) = \begin{cases} \left(1 + \frac{k(x-x_{\min})}{\delta}\right)^{-\frac{1}{k}} & \text{for } k \neq 0 \\ \exp\left(-\frac{x-x_{\min}}{\delta}\right) & \text{for } k = 0 \end{cases} \quad (2)$$

246 for $x \geq x_{\min}$ when $k \geq 0$, and for $x_{\min} \leq x \leq (x_{\min} - \delta/k)$ when $k < 0$. The GP reduces to the
247 exponential distribution when $k = 0$ and $x_{\min} = 0$, and reduces to a power-function when $k > 0$ and
248 $x_{\min} = \delta/k$. For $k > 0$ and $x_{\min} < \delta/k$ the GP shows exponential-like behavior for low values of x ,
249 while the tail asymptotically approaches a power law for $x \gg x_{\min}$. Within this range of
250 parameters, δ indicates the curvature in the upper end of the distribution (higher values
251 correspond to greater curvature and hence, relatively fewer small patches), while k indicates the
252 scaling properties of the tail, such that for $x \gg x_{\min}$, the power-law scaling exponent α
253 approaches $\alpha^* = (1 + 1/k)$ (Pisarenko and Sornette, 2003). Where the GP fits the data well, we
254 can use the estimated parameters as general information about patch size scaling properties. The
255 CCDF for a truncated lognormal distribution uses the mean ($\mu_{\ln x}$) and standard deviation ($\sigma_{\ln x}$) of
256 $\ln(x)$.

$$P(x) = \frac{\operatorname{erf}\left(\frac{\sqrt{2}[\mu_{\ln x} - \ln(x)]}{2\sigma_{\ln x}}\right) + 1}{\operatorname{erf}\left(\frac{\sqrt{2}[\mu_{\ln x} - \ln(x_{min})]}{2\sigma_{\ln x}}\right) + 1} \quad x \geq x_{min} \quad (3)$$

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We compared empirical distributions to synthetic data sets from Monte Carlo simulations ($n = 20,000$ per model) and compared candidate distributions based on log-likelihood ratios and significance values (Clauset et al., 2009). Distribution testing details are given in SI.

263 **2.4 Spectral characteristics**

264 Spectral characteristics of the ridge-slough landscape were evaluated from 2-D
265 periodograms generated following the methods of Mugglestone and Renshaw (1998). In brief,
266 we constructed a discrete 2-D Fourier transform (available in most computational software
267 packages) for each binary vegetation map (Kefi et al., 2014), and then took the absolute value to
268 obtain the real number component. The resulting 2-D periodogram (i.e. spectral density) is a grid
269 representing the magnitude of cosine and sine waves of possible wavenumbers (i.e. spatial
270 frequencies), and orientations to the spectrum. Values were averaged across all orientations in
271 equally spaced wavenumber bins to generate radial spectra (r spectra), which indicate the relative
272 spectral density for each corresponding wavenumber bin. Local maxima indicate dominant
273 wavelengths, and thus suggest the presence of spatial periodicity (Couteron, 2002; Kefi et al.,
274 2014), or regular patterning. The absence of local maxima indicates the landscape is aperiodic.
275 Because the ridge-slough pattern has been described as regular in the direction orthogonal to
276 flow, we complemented our omnidirectional analysis with a directional r spectrum derived from
277 the spectral density observed at $\pm 10^\circ$ from perpendicular to the main axis of pattern elongation.

278

279 **3 Results**

280 **3.1 Visual comparisons**

281 Visual inspection of the vegetation maps reveals a remarkable range of pattern
282 morphology (Fig. 1). Ridges in northwestern sites (1–5, a) show pronounced striping, which is
283 less apparent in southern sites (18–22, h, i), where ridges appear more elliptical. Eastern sites
284 located below I-75 (5, 9, 13, 14, 17, 28–33, b, f, g, i, j) show fine-scale speckling and
285 disaggregation, with sites 14, 28 and 29 appearing random, with faint outlines of historic pattern.

286 Individual ridges exhibit numerous connections between adjacent elongated portions,
287 with larger patches forming complex webs composed of multiple individual elements. Although
288 this behavior is apparent in all sites, it appears to be density dependent, with most of the
289 landscape spanned by one large patch in denser sites (e.g., M1: 2, 5, 8, 9, 11–13, 23–28, 30–33;
290 M2: 1, 2, 4, 5, 8, 9, 12, 23–28, 30–33; M3: a, b, d, j). Within sites, large patches are always more
291 web-like than smaller ones, which appear more distinctly separated.

292 **3.2 Density and shape**

293 Ridge density was negatively correlated to MWD (Fig. 2a; $R^2 = 0.38$, $p = 0.0002$).
294 Deviation from this association was similar across maps and related to geographic position.
295 Specifically, ridge densities in the eastern half of the domain (sites 9, 13, 14, 17, 23–33; b, f, g, i,
296 j) were consistently higher than in the west, suggesting a strong east–west control on density.
297 The correlation between MWD and ridge density increased markedly when sites were partitioned
298 into east and west blocks (east: $R^2 = 0.81$, $p < 0.0001$; west: $R^2 = 0.61$, $p = 0.0004$). Based on
299 recent aerial imagery, low ridge density in site 1 is a misclassification of sparse sawgrass prairies
300 as slough; that site was omitted from regression analyses.

301 Site-level elongation was also strongly correlated to MWD (Fig. 2b; $R^2 = 0.65$, $p <$
302 0.0001). Sites with ridge densities greater than 0.8 showed elongation values much lower than
303 this trend. Average patch orientations (\bar{A}_p) indicate consistency between the grid and features
304 (i.e., \bar{A}_p values close to zero; Table S1). In sites with values of $|\bar{A}_p| \geq 5^\circ$ (e.g., M1: 1, 22; M2: 9,
305 18, 25, 27, 29, 31; M3: d, g), may possess underestimated elongation may be underestimated due
306 to mismatch between patch orientation and map orientation. Finally, edge density was strongly
307 correlated to MWD, indicating greater perimeter at deeper sites (Fig. 2c; $R^2 = 0.79$, $p < 0.0001$).

308 **3.3 Patch size distributions**

309 Patch area distributions were consistent with the Generalized Pareto distribution (Fig.
310 3c), with 16 of 25 sites passing GP Monte Carlo tests for M1 and 4 of 9 passing for M3 (Table
311 S1). The majority of sites that were not significant contained extremely large patches, but had
312 little deviation in the rest of the distribution; in some cases (e.g., sites 2, 5, 8, 9, 11, 12, 13, 28,
313 31; a, d, j) the largest patch was over an order of magnitude larger than predicted based on the
314 GP distribution. All these sites with extremely large patches have ridge densities above or very
315 close to the percolation threshold of a square lattice (~ 0.59 , Stauffer, 1995). Above this
316 percolation threshold, the largest patch becomes “over-connected”, suggesting that failure of
317 Monte Carlo tests within this group may be density driven, rather than a result of an underlying
318 patterning mechanism. Note that these sites are largely located in the north and eastern sections
319 of the study area, a region typified by high ridge densities. The log-normal distribution was
320 significant in only 4 of 25 sites for M1 and 2 of 9 sites for M3. Although these sites (15, 16, 19,
321 21; c and h) showed slight rounding in the extreme tail, log-likelihood ratios were not different
322 enough to distinguish between the two candidate distributions (Table S1).

323 Within each map, GP parameters were remarkably consistent across sites, with almost
324 constant estimates of k and δ for sites that passed Monte Carlo tests (Table S1). Area scaling in
325 the tail of the distribution is illustrated by α^* (analogous to the scaling exponent of a power-law
326 distribution) = 1.77 ± 0.06 for M1 and 1.87 ± 0.13 for M3. The δ parameter indicates how
327 sharply the distribution head deviates from a power-law, with larger values indicating that
328 smaller patch areas are exceedingly rare. For M1 and M3, $\delta = 474 \pm 88$ and 1490 ± 219 ; these
329 differences are likely due to map resolution, with M3 under-representing smaller patches.

330 **3.4 Spectral characteristics**

331 We found no evidence of periodicity from the omnidirectional r spectra. The absence of
332 peak values other than the smallest wavenumber indicates that no dominant pattern wavelength
333 exists, a finding consistent across hydrologic conditions and pattern morphologies (Fig. 3a).
334 Directional r spectra are consistent with the omnidirectional r spectra, but are noisier due to
335 reduced sample sizes (Fig. 3b). Spearman correlations, ρ , show the r spectra monotonically
336 decreased across all sites (Table S1), consistent with maximum spatial variation at the largest
337 scale, and decreasing consistently at smaller scales. For M1, each site had $\rho < -0.999$ and $\rho < -$
338 0.99 for the full and directional r spectra, respectively.

339 The r spectra were roughly linear in log-log space, and were approximated by a power-
340 law relationship. For the full r spectra, all sites in M1 had $R^2 \geq 0.98$; $p < 0.0001$; $\alpha = -1.31 \pm$
341 0.03 , while for the directional r spectra, $R^2 \geq 0.97$; $p < 0.0001$; $\alpha = -1.35 \pm 0.03$ (see Table S1).
342 Slight rounding at the extreme ends was observed; rounding at high wavenumbers is consistent
343 with the loss of fine-scale features due to a low sampling resolution, while rounding at low
344 wavenumbers arises from a spatial extent of the domains, and is consistent with undersampling

345 of large features at low wavenumbers. Some highly disturbed sites (e.g. 9, 13, 14, 17, 22, 24, 25,
346 30, 31, 33) showed slightly more rounded r spectra but still lacked any evidence of periodicity.

347

348 **4 Discussion**

349 **4.1 Water depth controls pattern attributes**

350 Our results provide strong observational support for water depth as a dominant control on
351 several key shape and density properties of the ridge-slough landscape. The observed decline in
352 ridge abundance with MWD is consistent with conceptual models that predict that changes in
353 water levels precipitate transitions between ridge and slough by modifying production and
354 respiration dynamics (Givnish et al., 2008; Watts et al., 2010) and inducing state changes in
355 vegetation composition (Zweig et al., 2008). The implication that these dynamics differ in
356 eastern and western sections of the study area was unexpected, and points to unexplained
357 controls on ridge expansion. The largest difference between the east and west trends occurs at
358 low water depths, indicating that this control is most pronounced in drier sites. In short, the
359 deviation seen in eastern sites represents a shifting of the relationship to favor sawgrass
360 expansion in extremely dry sites, rather than a general reduction of the hydrologic limitation
361 (since deep sites remain the least affected).

362 Mean water depth also exerted strong control on ridge-slough pattern shape. The most
363 salient features of the pattern, elongation and perimeter, both showed strong dependence on
364 MWD, with maximum elongation observed at low to intermediate water depths and minimum
365 perimeter values at low water depths. This is consistent with ridge features fragmenting into
366 smaller, less elongated patches under deeper water conditions, a finding previously observed
367 anecdotally (McVoy et al., 2011) and in the spatial statistics of soil elevation (Watts et al., 2010).

368 Likewise, sites with very low MWD show a significant loss of pattern, with ridge densities
369 approaching unity and elongation values that are largely isotropic. The coherent response of
370 these pattern features to hydrologic modification suggests promise for their use as restoration
371 performance measures (Yuan et al., 2015).

372 In this work we provide support for hydrological controls on ridge-slough pattern shape;
373 however landscape patterning (specifically ridge density and elongation) has also been shown to
374 exert reciprocal control on regional hydrology (Kaplan et al., 2012). Loss of sloughs in sites with
375 very low MWD alters drainage characteristics. Coupled to observations of patch fragmentation
376 in sites with higher water depths, these results strongly reinforce the commanding role of
377 hydrology in maintaining landscape pattern, indicating that reversal of modern hydrologic
378 modification is paramount for ongoing restoration.

379

380 **4.2 The ridge-slough landscape is aperiodic and scale-free**

381 Both spatial periodogram results and patch size distributions strongly suggest the ridge-
382 slough landscape pattern is aperiodic, a marked departure from extensive literature qualitatively
383 describing the pattern as periodic (SCT 2003; Wetzel et al., 2005; Ross et al., 2006; Larsen,
384 2007; Givnish et al., 2008; Larsen and Harvey, 2010; Lago et al., 2010; Watts et al., 2010; Cheng
385 et al., 2011; Nungesser, 2011; Sullivan et al., 2014). Because negative feedbacks operating at a
386 characteristic spatial scale result in regular patterning (Rietkerk and Van de Koppel, 2008),
387 aperiodic patterning in the ridge-slough landscape implies the absence of such feedbacks, ruling
388 out many of the mechanisms invoked to explain pattern formation (Borgogno et al., 2009).

389 Instead, the observation that patch size distributions uniformly follow power-law scaling,
390 suggests a scale-free patterning process. While power-law scaling can be produced via several

391 mechanisms (Newman et al., 2005), our results can be used to rule out some alternatives. For
392 example, power-law scaling of patch areas can arise in systems near the percolation threshold
393 (i.e., at criticality), which occurs within a relatively narrow region of patch density. Observed
394 patch area scaling in our study occurs across a wide range of patch densities, suggesting robust
395 criticality that comports with Foti et al. (2012), who observed similar power-law scaling
396 behavior over a wide range of vegetation types and densities.

397 Caution is warranted when using contemporary aerial imagery to infer pre-drainage
398 landscape conditions; the first aerials were taken ~65 years after Everglades drainage began.
399 Several pattern attributes (e.g., density, perimeter) may adjust readily with hydrologic
400 modification, and while some areas remain largely unchanged since initial imagery was obtained,
401 pattern in many other areas has degraded, sometimes entirely (Wu et al. 2006, Nungesser 2011).
402 However, pattern properties that are relatively invariant with hydrologic modification (e.g. *r*
403 spectrum, power-law scaling of patch areas) are more likely to reflect pre-drainage conditions. In
404 contrast, measures that vary with hydrologic modification are useful for understanding landscape
405 responses to hydrologic forcing, but may be less informative for inferring pre-drainage
406 conditions and long-term processes such as landscape formation.

407 Self-organized criticality can also produce power-law scaling at varying densities (i.e., far
408 from the percolation threshold), but requires large temporal variation in ridge density as the
409 system endogenously readjusts towards criticality following disturbances (Pascual and Guichard,
410 2005). Recent paleoecological evidence (Bernhardt and Willard, 2010) suggests that ridge-
411 slough configurations and densities have remained relatively stable since initial formation 2700
412 years before present, which is inconsistent with the requisite temporal variation in density.
413 Moreover, no documented disturbance regime exhibits the characteristic separation of time

414 scales between growth and disturbance associated with self-organized criticality. While peat fires
415 could be invoked, there is little evidence for widespread incidence and large-scale impacts of
416 these prior to modern hydrologic modification (McVoy et al., 2011).

417 Rather, smooth variation in ridge densities along environmental gradients is consistent
418 with robust criticality, wherein local facilitation induces clustering (i.e., patch growth) while a
419 global limitation maintains landscape heterogeneity (Pascual and Guichard, 2005). Although
420 robust criticality is typically suggested in isotropic landscapes, Acharya et al. (2015) recently
421 showed that anisotropy in the local facilitation kernel of a robust criticality model can produce
422 directional banding without periodicity, yielding simulated ridge-slough patterns with high
423 statistical and visual fidelity to the observed landscape. Local facilitation may take the form of
424 autogenic peat accretion (Larsen et al., 2007), clonal propagation of sawgrass (Brewer, 1996),
425 nutrient accumulation dynamics (Cohen et al., 2009, Larsen et al. 2015), or local seed dispersal,
426 although the relative importance and directionality of these mechanisms remains unknown
427 (Acharya et al., 2015). Screening possible mechanisms for anisotropic local facilitation emerges
428 from our analysis as a priority for future investigations.

429 Several candidate processes could limit patch expansion in the ridge slough landscape.
430 Each implies a distinct spatial pattern geometry, and we can use the extant scale-free and
431 aperiodic geometry to evaluate their respective plausibilities. A key distinction between limiting
432 processes that produce periodic versus scale-free patterning is the spatial range over which the
433 limiting factor acts (Manor and Shnerb, 2008a; von Hardenberg, 2010). When the limiting effect
434 of patch expansion locally is spread uniformly across the landscape, the effect is considered
435 global or uniform. Conversely, when the limiting effect act in a more localized manner,
436 limitation gradients can develop and produce periodic patterning.

437 Phosphorus limitation and sediment transport mechanisms are both potentially important
438 feedbacks on patch expansion. While phosphorus is strongly limiting of primary production in
439 the Everglades (Noe et al., 2001), and can be dramatically enriched in tree-islands (Wetzel et al.
440 2009) and ridges (Ross et al. 2006) via multiple mechanisms, this process of local enrichment
441 and depletion is inconsistent with robust criticality. Indeed, the presence of strong local
442 phosphorus gradients indicates that limitation feedbacks are distinctly local, and not spread
443 uniformly across the landscape. If phosphorus limitation were the dominant control, the result
444 would be regular patterning. Similarly, sediment transport mechanisms (Larsen et al., 2007; Lago
445 et al., 2010) yield a balance between entrainment and deposition governed by focused flow in
446 sloughs, the velocity of which is controlled by cross-sectional occlusion of flow by ridges.
447 Because patch expansion and contraction is controlled by local heterogeneity in flow velocity,
448 this suggests an inhibitory feedback operating at a limited spatial scale.

449 Water level (and hydroperiod) is another potential feedback on patch expansion. Our
450 observations of water depth control on ridge density comport with numerous studies (Givnish et
451 al., 2008; Zwieg and Kitchens, 2008; Todd et al., 2012) suggesting ridges are significantly
452 impacted by water depths. Moreover, pattern geometry strongly influences landscape hydrology
453 (Kaplan et al. 2012, Acharya et al. 2015). As ridges expand into adjacent sloughs, they displace
454 water and alter landscape flow capacity, causing regional water levels to increase (Kaplan et al.,
455 2012), and creating a negative feedback that likely limits further ridge expansion (Cohen et al.
456 2011). Because water depths equilibrate quickly, local patch expansion effects are distributed
457 rapidly and relatively evenly across the landscape. This consistent with the global limitation
458 necessary to create the observed aperiodic and scale-free pattern. Therefore, water depth effects
459 are strong candidates for the requisite global feedback necessary for ridge-slough formation.

460 The ridge-slough landscape pattern has emerged as a key measure of restoration
461 performance in one of the largest and most ambitious ecosystem management endeavors ever.
462 Enumeration of spatial pattern statistical features is a prerequisite for assessing landscape
463 condition and for comparing models with alternative landscape genesis mechanisms. Our results
464 inform the metrics for comparison between real and simulated landscape patterns, and provide
465 insights into the controls on pattern variation across the contemporary system. Given the
466 potentially significant differences in water management implied by comparative genesis
467 explanations, these metrics of real and simulated landscapes are important for restoration
468 planning and assessment.

469 Our results also indicate that elongated landscape features do not necessarily require
470 pattern periodicity, suggesting that spatial structures in numerous ecosystems may have been
471 misclassified as regularly patterned, and that aperiodic banding may be more prevalent than the
472 literature suggests. Invoking robust criticality and anisotropic local contagion, as in Acharya et
473 al. (2015), may be of general value for explaining aperiodic banding in other settings.

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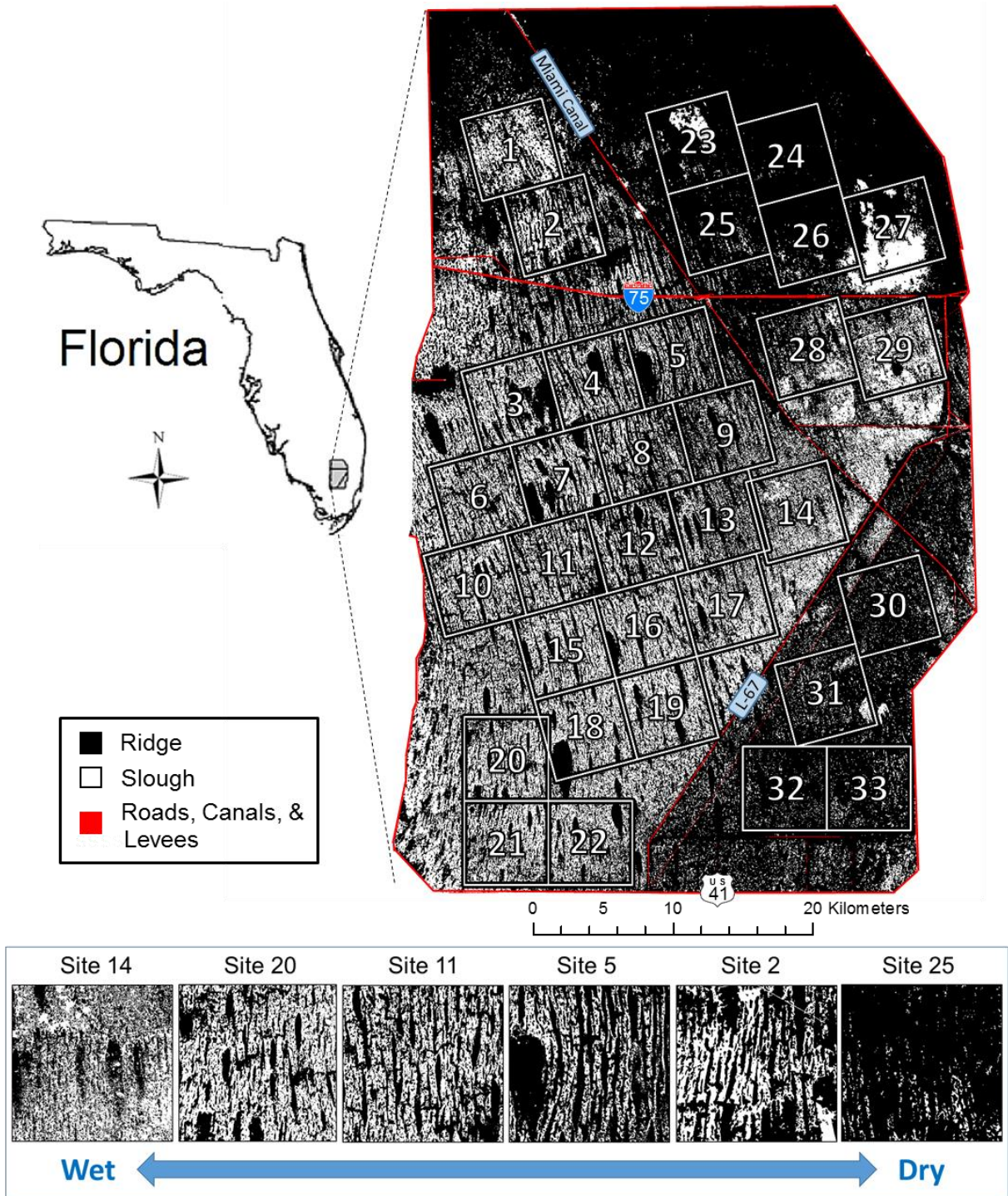
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Figure Legends

Figure 1: Study area and site locations, including major roads, canals, and levees for the primary map (M1). Sites spanning the pattern gradient in WCA3 are shown in the bottom panel. Two additional maps (supplementary information) were used to corroborate the primary results.

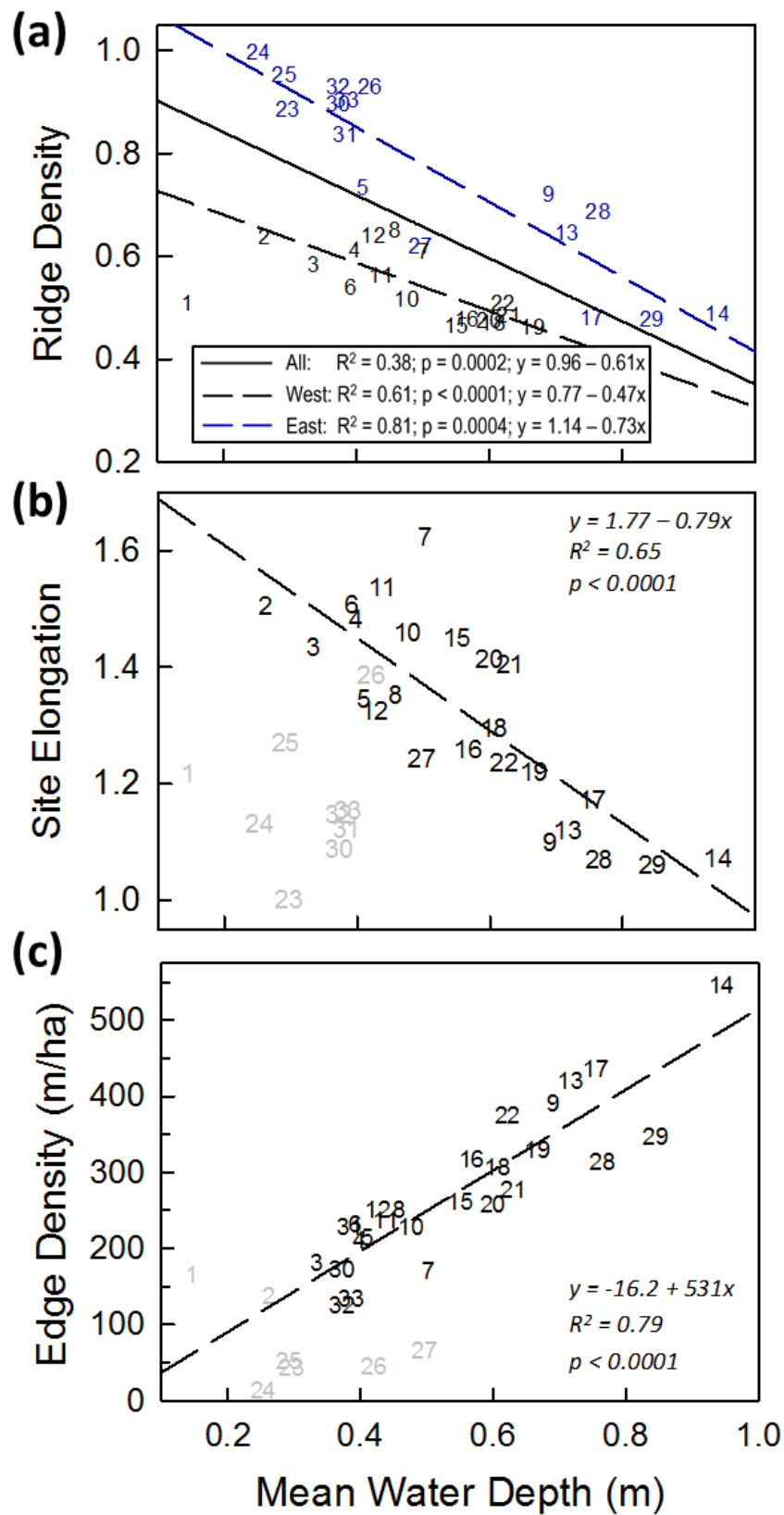
Figure 2: **(a)** Ridge density is negatively correlated with mean water depth. Eastern sites (blue) show consistently higher ridge densities than those in the west (black). Trends associated with east–west segregation (dashed lines) show much stronger relationships than the composite trend (solid line). Site 1 was omitted due to possible misclassification. **(b)** Site elongation shows a strong negative relationship with mean water depth. Sites with ridge densities greater than 0.8 (indicated in grey) were omitted from regressions and show elongation values lower than expected from this trend. **(c)** Edge density is positively correlated to mean water depth indicating higher perimeters in deeper sites. Sites indicated in grey were mapped at lower resolution, and were omitted from regressions. The relationships observed for site elongation and edge density are both consistent with patches becoming disaggregated with increased water depth.

Figure 3: **(a)** Omnidirectional r spectra for the full angular range ($0^\circ - 180^\circ$) monotonically decreased with no evidence of peaks, indicating strictly aperiodic behavior. The r -spectra across sites approximately follows a power-law (red line), with rounding at both extremes attributed to mapping extent and resolution issues. **(b)** Directional r spectra limited to $\pm 10^\circ$ in the direction perpendicular to the pattern also indicate aperiodic patterning, even when inference is constrained to the direction of presumed regularity. **(c)** Across sites, patch size distributions are well described by the generalized Pareto distribution (red lines). Sites with high ridge densities (e.g. sites 2, 5 and 25) have maximum patch sizes much greater than expected from the GP distribution. Conversely, sites in the deeply inundated southern section of WCA-3A (e.g. site 20) show slightly steeper tails, consistent with the lognormal distribution (blue lines), although the deviation is not significant enough to rule out the GP for these sites.



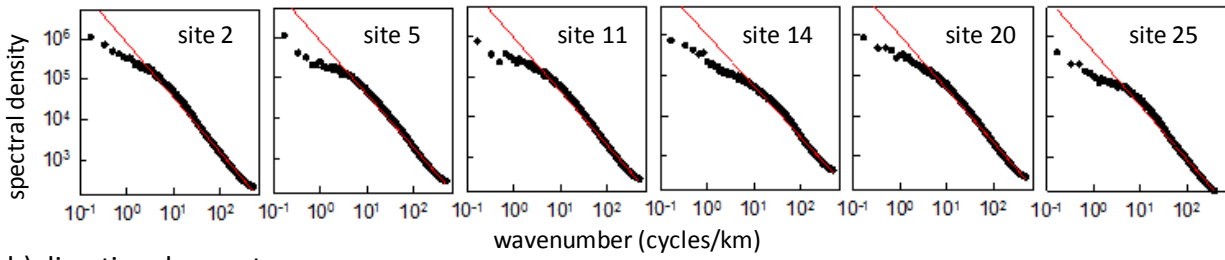
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Figure 1

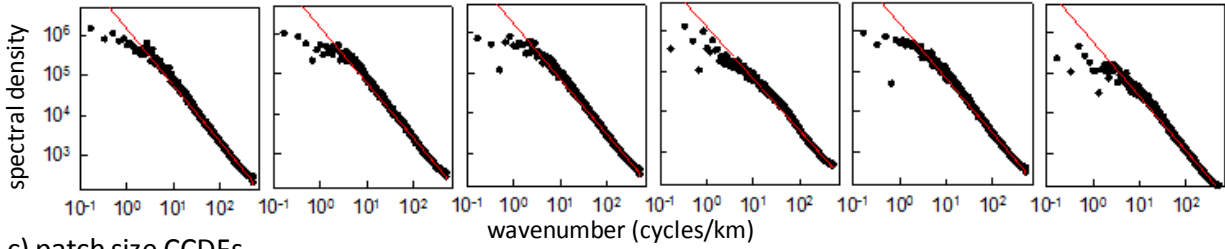


678 Figure 2
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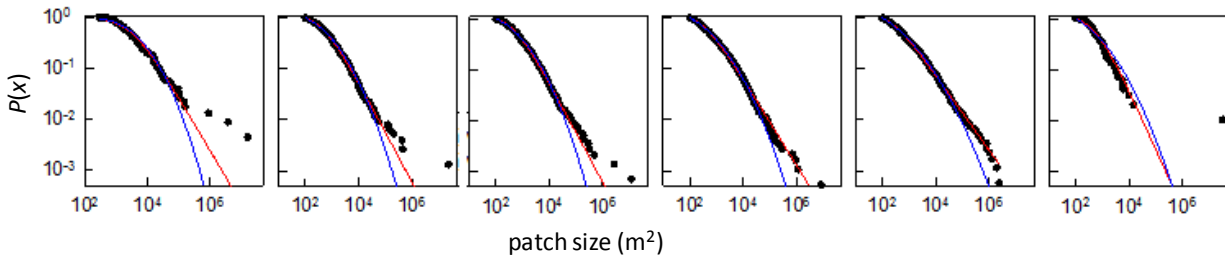
a) omnidirectional r spectra



b) directional r spectra



c) patch size CCDFs



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Figure 3