1	Bias in the shoreline development index: Ecological implications illustrated
2	with an analysis of littoral-pelagic habitat coupling
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9 10	Short Communication for consideration by <i>Limnologica</i>
11	
12	Abstract
13	We reexamined the relationship between the shoreline development index and metrics of habitat
14	coupling using a bias-corrected variant of the shoreline development index. Our findings suggest
15	that previously reported correlations may be artifacts of scale-dependent bias in shoreline
16	development index measurements. The results highlight the need for careful measurement when
17	seeking to understand links between lake morphology and ecological processes.
18	
19	Text
20	Lakes vary in shape from nearly perfect circles to the almost incomprehensively
21	convoluted (Scheffers and Kelletat 2016; Seekell et al. 2022a). The shoreline development index
22	- the ratio of shore length to the circumference of a circle with the lake's surface area - is widely
23	used to quantify this variability so that it can be related to ecosystem function (e.g., Rawson et al.
24	1960; Gasith and Hasler 1976; Wetzel 2001; Dolson et al. 2009; McMeans et al. 2016; Stiling et
25	al. 2023). For example, the shoreline development index has been identified as a key correlate of
26	habitat coupling - when the dynamics of certain habitats are strongly influenced by adjacent, but
27	ecologically distinct habitats, suggesting a link between lake morphology and ecosystem
28	processes (e.g., Gasith and Hasler 1976; Schindler and Scheuerell 2002; Dolson et al. 2009;

29 McMeans et al. 2016). However, shore length is scale dependent such that measurements based on higher resolution maps are longer than those based on lower resolution maps (Hutchinson 30 31 1957; Kent and Wong 1982; Seekell et al. 2022a). A consequence of this is that the shoreline 32 development index is biased so that it increases with surface area (Seekell et al. 2022a). 33 Therefore, it cannot be used in comparative analyses of lakes with different surface areas, even 34 when the shore lengths and surface areas are mapped at a common scale (Seekell et al. 2022a). 35 Previously reported correlations between habitat coupling and the shoreline development index 36 were based on comparative analyses of lakes with different surface areas, hence there is the 37 possibility that these results do not represent ecologically meaningful connections to lake 38 morphology but rather are the consequence of bias in the shoreline development index.

In this note, we correlate metrics of habitat coupling with a bias-corrected variant of the shoreline development index to test if the relationship between the shoreline development index and habitat coupling is ecologically meaningful. Correlation between metrics of habitat coupling and the bias-corrected variant is indicative of an ecologically meaningful relationship. In contrast, a correlation between metrics of habitat coupling and the traditional index, but not the bias-corrected variant, suggests a spurious relationship driven by scale-dependence induced bias in the shoreline development index.

We used metrics of habitat coupling previously reported by Dolson et al. (2009) for seven Ontario lakes (Table 1). Specifically, we examined trophic position and percentage of pelagic fish in the diet of lake trout (*Salvelinus namaycush*). The metrics were estimated by an isotopic mixing model applied carbon and nitrogen stable isotope analyses of several food web components. We selected this dataset for our analysis because lake trout are highly mobile predators that feed in both pelagic and littoral habitats, but are a cold-water species that can be 52 thermally limited from foraging in large littoral zones, and because these data have been used in 53 several previous analyses (Dolson et al. 2009; McMeans et al. 2016; Stiling et al. 2023). Dolson 54 et al. (2009) hypothesized more reticulate lakes have larger and more complex littoral areas than more circular lakes, and that habitat coupling is weaker in in these lakes (Dolson et al. 2009; 55 McMeans et al. 2016; Blanchfield et al. 2023). A positive correlation between the shoreline 56 57 development index proportion of pelagic fish in the diet of lake trout should emerge due to difficulty in accessing littoral prey (Dolson et al. 2009). This should also be reflected in a 58 59 positive correlation with trophic position because pelagic energy pathways are longer than 60 littoral pathways (Dolson et al. 2009). We measured the surface area (A, m^2) and shore length (L, m) of the study lakes using 61 62 online maps from the Ontario Ministry of Natural Resources online mapping tools

(http://www.ontario.ca/page/topographic-maps). Our measurements were made at the 1:72,223
map scale, which is one of the defaults in the application and which allows for digital
measurement of the full range of lake sizes studied, consistent with best practices of measuring at
a common scale (Seekell et al. 2022a). We used these measurements to calculate the shoreline
development index:

$$D_L = \frac{L}{2\sqrt{\pi A}}$$

Next, we calculated the bias-corrected shoreline development index proposed by Seekell et al.(2022a):

71
$$D_{BC} = \frac{L}{2\sqrt{\pi}A^{(d/2)}}$$

72 *d* in this equation is the fractal dimension, which varies in the range $1 \le d < 2$. The fractal 73 dimension is a metric that characterizes the scale dependence of shorelines. We estimated lake specific fractal dimensions by measuring the shorelines at multiple map scales. We fit

regressions of the logarithm of shore length by the logarithm of scale, and calculated the fractal

76 dimensions as one minus the regression coefficient (Seuront 2010).

The rationale behind alternate formulation of the shoreline development index becomes clear when considering that shore length can be recast in terms of area based on the identity: $L = cA^{(d/2)}$, where *c* is a shape constant (Seekell et al. 2021a; Seekell et al. 2022b). Substituting this identity into the traditional shoreline development index formula and simplifying:

$$D_L = \frac{c}{2\sqrt{\pi}} \times A^{(d-1)/2}$$

82 When d = 1, D_L is the ratio of the shape constants c and $2\sqrt{\pi}$. However, when d > 1, the

shoreline development index is also a function of area. In the bias-corrected variant, the exponent d/2 cancels area out of the numerator and denominator regardless of fractal dimension so that the index always only reflects the ratio of the shape constants:

86
$$D_{BC} = \frac{cA^{(d/2)}}{2\sqrt{\pi}A^{(d/2)}} = \frac{c}{2\sqrt{\pi}}$$

We use Bayes factors to evaluate the relative evidence for null (no positive relationship)
and alternative hypotheses (positive relationship) (Wetzels and Wagenmakers 2012). We use this
approach instead of null hypothesis testing (i.e. p-values) because Bayes factors evaluate relative
evidence for the null and alternative hypotheses, something that is important for our

91 interpretation of the correlation analysis, whereas null hypothesis testing only evaluates evidence 92 for the alternative hypothesis. We report BF_{10} , which is the Bayes factor that indicates the weight 93 of evidence for the alternative hypothesis relative to the null hypothesis. $BF_{10} = 1$ indicates that 94 the hypotheses are equally likely, whereas $BF_{10} > 1$ indicates the alternative is more likely, and 95 $BF_{10} < 1$ indicates the null hypothesis is more likely.

96	The range of fractal dimensions was $1.02-1.17$ (median = 1.08), which indicate scale-
97	dependence for all shorelines, and are consistent with the range and median of $(range = 1.02)$ -
98	1.37, median = 1.10) of previously reported measurements for individual lake shorelines (Seekell
99	et al. 2022a) (Figure 1). These fractal dimensions cause dramatic reductions in shoreline
100	development index values when the bias-corrected metric is calculated. Specifically, the range of
101	uncorrected values was $1.02-3.73$ (mean = 2.58), whereas the range of bias-corrected values was
102	1.00-1.93 (mean = 1.29) (Table 1).

103 There is moderate evidence for the hypothesis that shoreline development index is 104 inversely related to the metrics of habitat coupling, which is consistent with previous results 105 based on these data (Dolson et al. 2009; McMeans et al. 2016). This means that there is less 106 habitat coupling by lake trout in highly reticulate lakes compared to more circular lakes. 107 Specifically, there was a positive correlation between shoreline development index and both lake 108 trout trophic position (r = 0.79, $BF_{10} = 5.84$) and proportion of pelagic fish in diet (r = 0.82, BF_{10} 109 = 7.72) (Figure 2). However, there is weak to moderate evidence of no positive relationship 110 between bias-corrected shoreline development index and trophic position (r = 0.15, $BF_{10} = 0.59$) 111 or proportion of pelagic fish in diet (r = -0.37, BF₁₀ = 0.29). This contrasts with the previous 112 results of Dolson et al. (2009) and McMeans et al. (2016) and suggests that the correlation 113 between the shoreline development index and metrics of habitat coupling in those reports reflect 114 bias in the shoreline development index rather than ecologically meaningful relationships. 115 Our statistical results were robust to a variety of priors. Additionally, we generated the 116 same qualitative results when conducting our analysis with Kendall's tau rank-based correlation 117 coefficient, albeit with weaker correlations which is typical when comparing Pearson's 118 correlation coefficient to Kendall's (Rupinski and Dunlap 1996). Specifically, there was a

119	positive correlation between shoreline development index and both lake trout trophic position (τ
120	= 0.52, BF_{10} = 2.67) and proportion of pelagic fish in lake trout diet (τ = 0.62, BF_{10} = 4.27), and
121	weak evidence of no positive relationship between bias-corrected shoreline development index
122	and trophic position ($\tau = -0.05$, BF ₁₀ = 0.41) and proportion of pelagic fish in diet ($\tau = -0.14$,
123	$BF_{10} = 0.34$). Our statistical evidence for the null hypothesis is not overwhelming, but this is not
124	surprising given the limited sample size. However, there are additional reasons to believe that the
125	shoreline development index is not correlated with habitat coupling. Specifically, expected
126	correlation is premised on the existence of a relationship between shoreline development index
127	and the relative size of littoral habitats, but the empirical evidence for this is weak despite being
128	widely stated in limnology textbooks (e.g., Wetzel 2001). Most lakes are small (< 1 km ²) and
129	shallow (mean depth < 5 m, maximum depth < 10 m), with the entire lake comprising littoral
130	habitat regardless of variation in shoreline development index (Seekell and Pace 2011;
131	Verpoorter et al. 2014; Cael and Seekell 2016; Cael et al. 2017; Seekell et al. 2021b; Cael and
132	Seekell 2022). Hence, shoreline development index and littoral area are often disconnected and
133	correlations weak when examining large numbers of lakes (Seekell et al. 2021b).
134	The fractal dimension of a group of shorelines can be estimated by regressing the
135	logarithm of the perimeters by the logarithm of surface areas. This is much faster than measuring
136	fractal dimensions for individual lakes and facilitates estimation of fractal dimensions during
137	syntheses of historical datasets when morphometrics but not original maps are available (Seekell
138	et al. 2021a). However, these values are typically biased upwards compared to the average of
139	shoreline fractal dimensions measured at the individual level and it is best practice to use
140	individually measured fractal dimensions when bias correcting the shoreline development index,
141	as we have done in our analysis (Matsushita et al. 1991; Seekell et al. 2022a). While conducting

142	our analysis, we observed another reason to avoid using average shoreline development index						
143	values - the underlying selection of lakes may not be representative. For example, the fractal						
144	dimension calculated from the perimeter-area regression of the sample lakes in our study would						
145	be implausibly high, probably because the lakes were sampled uniformly across a wide range of						
146	shoreline development index values even though the underlying distribution of shoreline						
147	development index values is highly skewed, with most lakes having low index values compared						
148	to the overall range in values (Schiefer and Klinkenberg 2004; Verpoorter et al. 2014). This						
149	sampling strategy is common in comparative limnology and perimeter-area analysis cannot be						
150	used to adjust the shoreline development index in such studies.						
151	Lake morphometry is so fundamental to aquatic sciences that it often seems trivial. Our						
152	analysis demonstrates that this is not the case and morphometry requires careful attention to						
153	detail to ensure that ecologically relevant relationships are correctly identified.						
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156	'For the purpose of open access, the author(s) has applied a Creative Commons Attribution (CC-BY)						
157	license to any Author Accepted Manuscript version arising'.						
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Figure 1. Shore lengths measured at different map scales. The fractal dimension is one minus theregression coefficient when a linear regression is fit on log-log axes.



Map scale



Figure 2. Correlations between habitat coupling metrics and shoreline development indices. Theshoreline development index must be greater than or equal to one.



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Lake	Latitude	Longitude	Area (m ²)	Perimeter (m)	Fractal Dimension (<i>d</i>)	D_L	D_{BC}	Trophic Position	Pelagic Fish in Diet (%)
Gilmour	46.07°	-78.29°	1,626,185	5,297	1.02	1.17	1.00	3.56	51
Canoe	45.53°	-78.72°	3,691,778	20,905	1.15	3.07	1.02	4.73	73
Three Mile	45.98°	-78.9°	4,225,976	17,801	1.03	2.44	1.93	4.30	50
Catfish	45.92°	-78.55°	4,595,905	28,375	1.17	3.73	1.05	4.56	86
White Partridge	45.83°	-78.1°	5,748,242	14,270	1.05	1.68	1.17	4.44	49
Burntroot	45.85°	-78.67°	9,503,755	29,427	1.08	2.69	1.46	4.64	68
Hogan	45.87°	-78.5°	12,595,497	40,857	1.10	3.25	1.41	4.72	61

Table 1. Morphometric and food web data used in this analysis. Trophic position and pelagic fish in diet were reported by Dolson et
 al. (2009) and were estimated based on stable isotope analyses. Morphometric data are original to the present study.