

Spatial competition: roughening of the ecological interface

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Andrew J. Allstadt,^{1,*} Jonathan A. Newman,^{2,§} Jonathan A. Walter,^{3,#} G. Korniss,^{4,‡} and Thomas Caraco^{5,†}

1. Department of Forest and Wildlife Ecology, University of Wisconsin-Madison, Madison WI 53706, USA
2. School of Environmental Sciences, University of Guelph, Guelph, Ontario N1G 2W1, Canada
3. Department of Environmental Sciences, University of Virginia, Charlottesville, VA 22904-4123, USA
4. Department of Physics, Applied Physics, and Astronomy, Rensselaer Polytechnic Institute, 110 8th Street, Troy NY 12180-3590, USA
5. Department of Biological Sciences, University at Albany, Albany NY 12222, USA

*Corresponding author, e-mail: allstadt@wisc.edu; §e-mail: jonathan.newman@uoguelph.ca; #e-mail: jaw3es@virginia.edu; ‡e-mail: korniss@rpi.edu; †e-mail: tcaraco@albany.edu.

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2 *Abstract.* Limited dispersal distance, whether due to vegetative growth or localized
reproduction, generates spatial clustering. Many invasive plants, in particular, propagate
4 clonally and aggregate spatially. Local dispersal concentrates intraspecific interactions
within clusters, while most between-species interactions occur near cluster boundaries.
6 Spread of a spatially clustered, invasive plant then becomes motion of an interface between
the invader and resident species, and competition along the interface produces random
8 variation in the extent of invasive advance. Development of these growth fluctuations,
termed stochastic roughening, will often structure the ecological interface as a self-affine
10 fractal. This property implies a series of scaling relationships for the statistics of spatial
growth. For many individual-based processes exhibiting both forward and lateral
12 propagation, the extent of invader advance becomes spatially correlated along the interface,
and the width of the interface (where invader and resident compete directly) increases as a
14 power function of time. Once roughening equilibrates, interface width and the location of
the most advanced invader (the “front-runner”) beyond the mean incursion should both
16 increase as a power function of interface length. To test these predictions, we let white
clover (*Trifolium repens*) invade ryegrass (*Lolium perenne*) experimentally. Spatial
18 correlation developed as anticipated, and both interface width and the front-runner’s lead
scaled as a power law of length. However, the scaling exponents differed, plausibly an effect
20 of clover’s growth morphology. Our results suggest that the theory of kinetic roughening
offers a framework for understanding causes and consequences of spatial pattern in
22 between-species interaction. Although our analysis focuses on growth at the neighborhood
scale, the methods may be applied to invasive fronts at extended spatial scales.

24 **1 Introduction**

Pattern analysis of plant communities commonly reveals spatial mosaics generated by
26 clustered growth of individual species [Cain et al. 1995, Dale 1999, Condit et al. 2000].

Clustering may follow a template set by environmental heterogeneity, if different locations
28 favor different species [Snyder and Chesson 2003], but more often, dispersal limitation
aggregates conspecific individuals [Harada and Iwasa 1994]. For example, most invasive
30 plants are clonal and propagate vegetatively [Sakai et al. 2001, Liu et al. 2006], so that
invaders initially cluster among residents [Cantor et al. 2011].

32 Individual plants usually compete at the nearest-neighbor scale
[Goldberg and Barton 1992, Levine et al. 2004]. Given local competition, clustering
34 influences interaction frequencies and the consequent population dynamics
[Herben et al. 2000, Chesson and Neuhauser 2002]. When different species each aggregate
36 spatially and interact locally, intraspecific competition should predominate within clusters,
while interspecific competition will localize at the interface between clusters
38 [Chesson 2000, Murrell and Law 2003, Yurkonis and Meiners 2004]. This interaction
geometry implies that the advance *versus* extinction of a rare competitor may depend on
40 development and movement of a between-species interface
[Gandhi et al. 1999, Korniss and Caraco 2005]. That is, we envision a non-equilibrium
42 system where increase or decline in a species' abundance drives interface motion.

An invading species' density declines from positive equilibrium to rarity across the
44 width of an ecological interface [O'Malley et al. 2006]. As a competitively superior invader
excludes the resident within the width, the front is pushed forward. Given this simple
46 picture, we ask how varying the length of the interface affects statistical properties of an

invader-resident interaction. We emphasize the relative position of the “front-runner,” the
48 furthest advanced invader, a metric used in both theoretical and applied invasion ecology
[Hajek et al. 1996, Clark et al. 2001, Thomson and Ellner 2003].

50 We treat invasive growth as dispersal-limited stochastic process; our analysis takes the
invader as competitively superior to the resident. We assume that the ecological interface,
52 once roughening has equilibrated, has a particular fractal geometry
[Family and Vicsek 1985, Barabási and Stanley 1995, Cannas et al. 2004]; see Section 2.
54 This assumption has quantitative ecological implications; it predicts that both interface
width and the front-runner’s lead will increase as a power function of the length of the
56 advancing front [O’Malley et al. 2009a].

The next section describes our application of kinetic roughening to ecology. Section 3
58 reports an experiment testing predicted scaling relationships; we let Dutch white clover
(*Trifolium repens*) advance into plots of perennial ryegrass (*Lolium perenne*). Our results
60 suggest a simplifying generalization concerning the spatial organization of local competitive
interactions. Although we apply kinetic roughening at the scale of clonal-plant clusters, the
62 same methods might help organize understanding of invasive fronts at greater scales.

2 Local Dispersal and Interface Roughening

64 A dispersal-limited invader’s population growth typically begins as small, nearly circular
clusters of individuals. Despite an invader’s competitive advantage, some small clusters will
66 disappear due to demographic stochasticity. But clusters exceeding a critical size will
continue to grow and displace the resident [Allstadt et al. 2007]. After a single cluster
68 attains sufficient size, or after large clusters coalesce, we can treat the perimeter as a

1-dimensional front that has roughened during advance [O'Malley et al. 2009a]. Some
70 invasions move perpendicularly to a road or shore; they can be treated as initially linear
[Cannas et al. 2004]. The dynamics of an ecological interface distinguishes it from an
72 ecotone, when the latter implies a change in species composition due to abiotic factors that
vary slowly relative to the timescale of population growth
74 [Gastner et al. 2009, Eppinga et al. 2013].

Given an initially linear front, development of spatially correlated growth along an
76 interface is termed stochastic roughening [Kardar et al. 1986, Barabási and Stanley 1995].
Roughening and dynamic scaling offer a useful framework for identifying dynamics shared
78 by correlated growth processes differing in details of local interactions. Applications span
processes in physical materials [Barabási and Stanley 1995], biological tissues
80 [Galeano et al. 2003, Ranft et al. 2014], parallel-computing and information systems
[Korniss et al. 2000, Korniss et al. 2003], and ecological invasion
82 [Cannas et al. 2004, O'Malley et al. 2006]. When we analyze the front-runner's location,
correlated fluctuations along the interface are quite important, since traditional
84 extreme-value statistics [Fisher and Tippett 1928, Galambos et al. 1994], developed for
independent random variables, do not apply [Majumdar and Comtet 2004]. Figure 1 shows
86 an interface from our field experiment. Invasive growth along the interface clearly roughens
with time. The plots also suggest correlated advance at nearby locations.

88 **2.1 Interface roughening: development and saturation**

To apply concepts of statistical physics [Kardar et al. 1986, Barabási and Stanley 1995] to
90 spatial competition, we first define interface attributes and describe development of a
roughened interface. Then we address scaling relationships at equilibrium (after

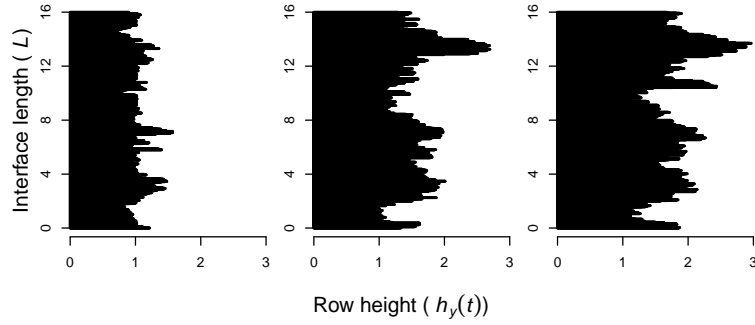


Figure 1: Roughening of clover interface. White clover (*T. repens*, black area) advancing into perennial ryegrass (*L. perenne*), from photographs taken during experiment. Interface length $L \equiv L_y = 16$ m. Row heights $h_y(t)$ in m. June (left), August (center) and October (right) 2010 shown. The interface advances, left to right, and roughens; neighboring heights suggest spatial correlation.

Symbols	Definitions
$L_x, L_y (= L)$	Lattice size ($L =$ interface length = front length)
t	time
$h_y(t)$	Rightmost invader in row y at time t
$\bar{h}(t)$	Mean of $h_y(t)$ (the average is taken across all rows y)
$h_{max}(t)$	Rightmost invader at time t
$\Delta_{max}(t) = h_{max}(t) - \bar{h}(t)$	Distance from front-runner to mean of front
$\langle w^2 \rangle$	Mean squared interface width
$\xi(t)$	Correlation length along interface
t_x	Crossover time, where w^2 equilibrates
α	Roughness exponent
β	Growth exponent
z	Dynamic exponent

Table 1: Definitions of variables.

roughening “saturates”). Table 1 lists symbols we use.

Discrete (“individual-based”) models capture effects of nonlinearity and stochasticity inherent to a dispersal-limited invader’s dynamics at an ecological interface [Antonovics et al. 2006, Pachevsky and Levine 2011]. Therefore, we characterize front roughening as a lattice based process. Our description applies across a variety of individual-based models for growth at an interface [Plischke et al. 1987, O’Malley et al. 2009a].

An $L_x \times L_y$ rectangular lattice represents a habitat occupied by resident and invader species. Each lattice site is either occupied by the invader, occupied by the resident, or empty. Mortality of either species opens occupied sites. An empty site becomes occupied through propagation from a nearest-neighboring occupied site. Restricting propagation to nearest neighbors, of course, imposes dispersal-limitation. The invader's competitive superiority drives interface motion. If invader-resident competition is preemptive only, the invader has the lower mortality/propagation ratio [Allstadt et al. 2009]. If competition combines site preemption and direct interference, the species' demographic rates satisfy conditions in Allstadt et al. [2012].

Suppose that the invader initially occupies only a few vertical columns at the left edge of the lattice; all other sites are occupied by the resident or open. Invasive advance occurs in the x -direction. Importantly, neighborhood geometry (the dispersal constraint) permits both forward and lateral growth. The former pushes the front, and the latter generates spatial correlation along the front [Kardar et al. 1986, Barabási and Stanley 1995]. That is, lateral growth of advanced heights tends to increase height in adjacent rows.

We let $L \equiv L_y$, interface length (hence, front length). At time t , $h_y(t)$ is the location of the most advanced (right-most) invader in row y ; $y = 1, 2, \dots, L$. The front's average location is the mean height among rows, $\bar{h}(t) = \sum_y h_y(t)/L$. We take longitudinal system size L_x as sufficiently large that it does not affect population processes.

Figure 2 shows the width of the interface about the invader's average incursion $\bar{h}(t)$. To quantify roughening, we define the width of the interface *via*:

$$w^2(L, t) = \frac{1}{L} \sum_{y=1}^L [h_y(t) - \bar{h}(t)]^2 \quad (1)$$

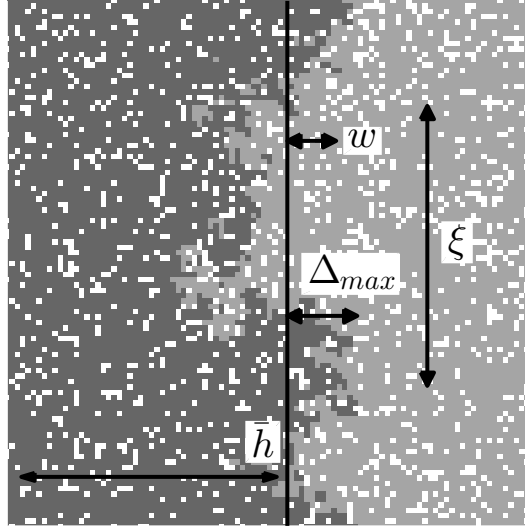


Figure 2: Interface attributes. Width (w) and the extreme advance (Δ_{max}) relative to the mean front position (\bar{h}) in a rough front. For illustration, correlation length ξ is also indicated. Dark: invader, medium: resident and white: open.

120 Roughness $w^2(L, t)$ itself varies stochastically, and we represent its expectation (averaged
over realizations of intrinsic noise) at time t by $\langle w^2(L, t) \rangle$. We take $w = \sqrt{\langle w^2(L, t) \rangle}$ as the
122 width of the front, the typical extent of the interface parallel to the direction of advance.

Power-law scaling relationships should characterize an interface with spatially
124 correlated heights. Importantly, these properties do not, in general, depend on details of
the local growth dynamics [Family and Vicsek 1985, Kardar et al. 1986]. That is, variation
126 in demographic processes among different invader-resident systems should exhibit the same
qualitative scaling effects [Cannas et al. 2004, O'Malley et al. 2009a]. Spatially correlated
128 heights imply that the interface should equilibrate as a self-affine fractal; this structure
produces ecologically interesting scaling laws. A roughened, self-affine interface (or
130 anisotropic fractal) has a width $w(L)$, where L is front length. Suppose that we increase
length according to $L \rightarrow kL$. Then interface width must be re-scaled according to
132 $w \rightarrow k^\alpha w$ to preserve statistical invariance (“look the same” at different scales). Length
and width must be increased by different factors, and the transformation has a power-law

134 form. Numerical calibration of the scaling laws can, of course, differ across species and
environments, but it is the general relationships we emphasize.

136 **2.2 Interface development**

As the invader begins to advance, the interface starts to roughen, and invader heights $h_y(t)$
138 become dependent random variables. That is, a single correlation length $\xi(t)$ develops
along the interface (Fig. 2). Correlation length initially increases with time according to
140 the power-law scaling $\xi(t) \sim t^{1/z}$ [Majumdar and Comtet 2005], where z is called the
dynamic exponent. Once $\xi(t)$ spans the length L of the interface, “crossover” occurs. The
142 interface continues to advance, but roughening has reached statistical equilibrium
(roughening “saturates” at crossover) [Barabási and Stanley 1995]. The duration of
144 interface development, termed crossover time t_\times , increases with interface length; the
power-law scaling is $t_\times \sim L^z$. The development of interface width offers a more easily
146 tested prediction. Prior to saturation, interface width w exhibits temporal scaling behavior
according to $w \sim t^\beta$. β ($\beta > 0$) is called the growth exponent.

148 Spatially correlated growth, shaped by limited dispersal and neighborhood-scale
competition, underlies fractal structure of an interface. The height-height correlation
150 function (Pearson correlation) is:

$$G_t(l) = \frac{\left\langle \left(h_{y+l}(t) - \bar{h}(t) \right) \left(h_y(t) - \bar{h}(t) \right) \right\rangle_y^{1/2}}{\left\langle \left(h_y(t) - \bar{h}(t) \right)^2 \right\rangle_y^{1/2}}. \quad (2)$$

We use $G_t(l)$ to estimate correlation length $\xi(t)$ along the interface; height-height
152 correlation should decline as distance l between rows increases.

We monitor the roughening associated with increasing correlation distance along the
 154 developing interface in two ways; each combines results from windows of length $l < L$. The
 local width, $w_t(l)$, is the average interface width estimated across an ensemble of portions
 156 of the interface, each with length l . The local width at time t is given by:

$$w_t(l) = \left\langle \left(h_y(t) - \bar{h}(y, t) \right)^2 \right\rangle_y^{1/2}. \quad (3)$$

The height-difference correlation function [Karabacak et al. 2001] integrates roughness
 158 during both development and saturation. The height-difference correlation function, at
 time $t > 0$, is given by:

$$C_t(l) = \left\langle \left(h_{y+l}(t) - h_y(t) \right)^2 \right\rangle_y^{1/2}. \quad (4)$$

160 Each average $w_t(l)$ and $C_t(l)$ is taken across all rows y . For $l < \xi(t)$, both $w_t(l)$ and $C_t(l)$
 exhibit power-law scaling over distances along the interface: $w_t(l), C_t(l) \sim l^\alpha$. α ($\alpha > 0$) is
 162 the roughness exponent, and characterizes the fractal nature of the interface
 [Barabási and Stanley 1995]. As the interface roughens with time, the correlation distance
 164 ξ increases. Consequently, the linear dependence of $\ln w_t(l)$ and $\ln C_t(l)$ on $\ln l$, with slope
 α , should extend to greater lengths l along the interface, until saturation.

166 **2.3 The saturated interface**

After crossover ($t > t_\times$), steady-state properties of the interface depend on its length L
 168 [Schehr and Majumdar 2006]. Interface width w scales with interface length according to
 $\langle w^2(L, \infty) \rangle \sim L^{2\alpha}$; interface width increases as a power function of its length, according to
 170 the roughness exponent α .

Note that we do not predict roughness *per se*, but ask how roughening changes from a

172 shorter to a longer interface. Power-law scaling for $\langle w^2(L, \infty) \rangle$ permits us to ask novel
questions about invasive spatial growth. Cannas et al. [2004] hypothesize that life-history
174 variation among invading tree species might influence the roughness exponent. Our
analysis emphasizes how scaling of width with interface length organizes within and
176 between-species interactions, and how the expected location of the invader’s extreme
advance depends on interface length.

178 In general, the scaling exponents are interdependent: $\alpha = \beta z$ [Kardar et al. 1986].
Dependence arises from the self-affine structure of the interface. Random demographic
180 events render the interface disorderly, and we assume that the interface equilibrates as an
anisotropic fractal [Barabási and Stanley 1995]. “Random demographic events” means
182 local processes including both forward and lateral invader growth. As we noted, forward
growth pushes invasive advance, and lateral growth builds spatial correlations between
184 heights. Without lateral growth, each $h_y(t)$ becomes an independent birth-death process,
implying no spatial correlation.

186 **2.4 Roughening, scaling and the front-runner**

The pace of invasive advance remains an issue in basic and applied ecology
188 [Shigesada et al. 1986, van den Bosch et al. 1992]. Deterministic reaction-diffusion models
offer approximate velocities, but assume continuous densities, and so cannot appreciate
190 consequences of spatially correlated variability in a dispersal-limited invader’s advance
[Clark et al. 2003, Antonovics et al. 2006]. Dispersal limitation reduces velocity, compared
192 to the reaction-diffusion alternative [Moro 2001, Escudero et al. 2004], but analytic
approximation of a discrete, stochastic model’s interface velocity remains a challenge
194 [Pechenik and Levine 1999], especially for two-dimensional environments.

Krug and Meakin [1990] found that a discrete model’s *reduction* in velocity, relative to
 196 the reaction-diffusion wave-speed, varies inversely with interface length. But no scaling
 relationship for either a discrete model’s interface velocity or velocity reduction due to
 198 dispersal limitation is available. Interface velocity depends on specific details governing
 local (*i.e.*, individual-level) propagation and mortality [Moro 2001]. For our purposes, an
 200 important point is that scaling laws involving the roughness exponent α do not depend on
 invasion speed [Barabási and Stanley 1995].

202 **2.5 The front-runner: scaling of extremes**

The maximal invasive advance defines the front-runner’s position. At time t we locate the
 204 front-runner at $h_{max}(t) = \max_y \{h_y(t)\}$. Given mean interface height $\bar{h}(L, t)$, the invader’s
 maximal relative advance at time t is $\Delta_{max}(L, t) = h_{max}(t) - \bar{h}(L, t)$. We assume that
 206 roughening equilibrates before considering the scaling of the expected lead $\langle \Delta_{max} \rangle_L$; note
 dependence on interface length L .

208 The probability density of the front-runner’s excess $\Delta_{max}(L, t)$ has been obtained
 analytically [Majumdar and Comtet 2004, Majumdar and Comtet 2005]. For broad classes
 210 of dispersal-limited stochastic growth models, the scaled variable $\Delta_{max} / \langle \Delta_{max} \rangle$ has an Airy
 probability density, and the steady-state average excess of the front-runner over the mean
 212 height scales with interface length exactly as does the width. That is, $\langle \Delta_{max} \rangle_L \sim L^\alpha$.

Furthermore, we can infer the size of the extremes for an interface of linear size L with
 214 estimates obtained in limited observation windows with size L_{obs} . We have:

$\langle \Delta_{max}(L) \rangle \approx \langle \Delta_{max}(L_{obs}) \rangle k^\alpha$, where $k = (L/L_{obs})$, by the properties of a self-affine
 216 interface [O’Malley et al. 2009b]. Table 2 collects scaling relationships we study.

Regime	Prediction	Comment
<i>Development</i>	$\xi(t) \sim t^{1/z}$ $w_t \sim t^\beta$ $t_\times \sim L^z$ $C_t(l) \sim l^\alpha$	Correlation length, dynamic exponent Interface width, growth exponent Crossover time, interface length Height-difference correlation, $l < \xi(t)$
<i>Stationarity</i>	$w \sim L^\alpha$ $\langle \Delta_{max} \rangle_L \sim L^\alpha$ $\beta = \alpha/z$	Interface width, roughness exponent Front-runner's lead Self-affine fractal

Table 2: Predicted scaling relationships. The interface roughens during development. After spatial correlation spans interface length, interface width remains statistically stationary.

3 Methods

218 We studied dispersal-limited competition between Dutch white clover (*T. repens*) and
perennial ryegrass (*L. perenne*). Both species reproduce mainly through local, clonal
220 growth [Turkington et al. 1979, Schwinning and Parsons 1996a]. *T. repens* propagates
vegetatively through stoloniferous stems [Fraser 1989], while *L. perenne* produces tillers
222 [Fustec et al. 2005]. Competitive interaction between these important forage crops is well
understood [Cain et al. 1995, Schwinning and Parsons 1996b]. We located experimental
224 plots at the University of Guelph Turfgrass Institute in an area homogeneous with respect
to micro-topography (43°33'N, 80°13'W). To minimize spatial heterogeneity, vegetation
226 and top layer of soil were removed, and the soil tilled before the experiment began.

3.1 Experimental design

228 We established plots with interface length $L = 1, 2, 4, 8,$ and 16 m , with four replicates of
each length. To avert edge effects, we added a 0.5 m buffer, where no data were collected,
230 at both ends of every plot. A plot had dimensions of $L \times 3$ m ; all plots were initially split
lengthwise by plastic dividers into sections of 1 m and the remaining 2 m . We planted *T.*
232 *repens* in the one-meter sections, and *L. perenne* in the two meter sections; we anticipated

that clover would advance, given the soil resources and occasional mowing. Appendix A
234 details experimental methods.

By spring 2009 mono-cultures were established, and we removed the plastic barriers
236 between species. In June 2010 we began recording the monthly advance of *T. repens* in
each plot. We resolved measurements at a scale of 1 cm^2 , the size of an individual clover
238 ramet [Silvertown 1981]. We marked each 1 m^2 subsection of every plot permanently, to
reference growth measurements. Each such subsection was photographed from above after
240 monthly mowing. We re-projected each photo to correct for perspective, and combined
photos from the same plot. We recorded row heights $h_y(t)$ for *T. repens* in each plot, and
242 noted the front-runner’s lead on the mean clover height.

We tested power-law relationships against alternative linear and exponential models
244 [Solow et al. 2003]. Additionally, we fit power-law models with two different assumptions
regarding error distribution. The first assumed normally distributed, additive error; the
246 second assumed log-normally distributed, multiplicative error [Xiao et al. 2011]. Our
scaling laws, Table 2, predict the latter. We compared relative support for each model
248 using differences in AIC scores (ΔAIC); we considered models with $\Delta AIC < 2$ as
supported substantially [Burnham and Anderson 2002].

250 **4 Results**

During the 2010 growing season, clover advanced rapidly; several longer fronts approached
252 the far end of the plot by October. Figure 3A shows each plot’s mean height $\bar{h}(t)$ against
time. Overall mean clover height increased for five consecutive months. However, several
254 clover fronts began to experience winter die-back in October. Therefore, our analysis

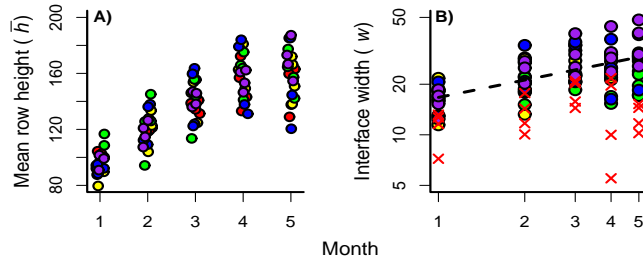


Figure 3: Experimental interface development. A. Mean plot heights (cm) by month. Red, yellow, green, blue, and purple indicate, respectively, $L = 1, 2, 4, 8, 16$ m . “Noise” added to abscissa for visibility. B. Each plot’s interface width by month; note the logarithmic axes. Dashed line indicates scaling of the first 4 months (development). Estimated growth exponent $\beta = 0.31$. 1 m plots marked as X, signifying earlier saturation; see text.

treated data from June through August as the interface-development period, and treated
 256 data from September (month 4) as stationary. This is an approximation, since correlation
 lengths for larger values of L continued to grow during October.

258 4.1 Spatial correlation

Spatial correlations between row heights $h_y(t)$ both increased in strength and extended to
 260 greater distances along the interface as clover advanced. Since development of correlation
 length should not depend on L , we pooled observations from all plots. We estimated
 262 correlation $G_t(l)$ between row heights $h_y(t)$, as a function of distance, for each of the five
 months. Figure 4A shows the resulting correlogram; spatial correlation increased every
 264 month across most distances less than 200 cm .

The height-difference correlation $C_t(l)$ corroborated the previous result; see Figure 4B.
 266 Each month $C_t(l)$ scaled as a power law for an increasing distance along the interface.

Using the result for month 4, our model selection procedure strongly supported a power-law
 268 relationship with multiplicative error (Table 3). Power-law behavior of the height-difference
 correlation allows an estimate of the roughness exponent, since $C_t \sim l^\alpha$, for $l < \xi(t)$.

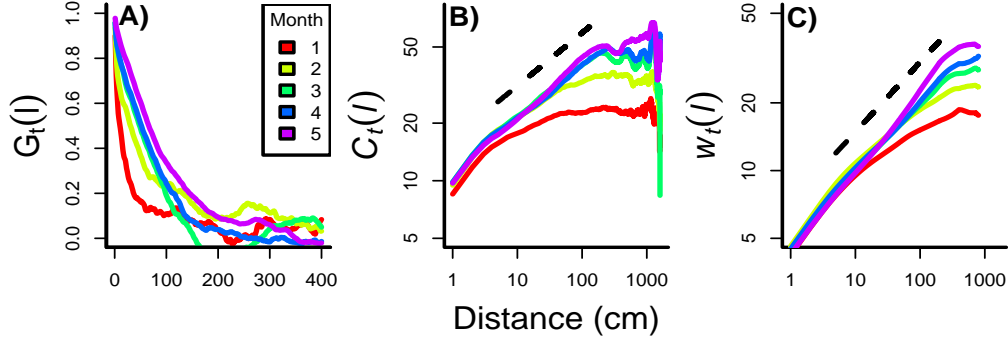


Figure 4: Interface development, field experiment. A. Spatial correlogram: correlation of row heights, $G_t(l)$. The strength and lag distance at which correlations $G_t(l)$ remained significant increased through time, indicating increasing correlation length $\xi(t)$ along the interface. Key indicates month 1 through 5; plots combined. B. Height-difference correlation function, $C_t(l)$, for months 1 through 5, plots combined. Distance over which power-law scaling holds increases with time; that is, distance along the front over which the log-log plot remains linear increases as correlation distance increases. Dashed line indicates month-4 scaling: $\alpha = 0.277$. C. Local interface width $w_t(l)$ across months. The dashed line indicates the scaling relationship for month 4, where the estimated roughness exponent was $\alpha = 0.311$.

270 Regression analysis of the $C_t(l)$ results yielded $\alpha = 0.277 \pm 0.002$; see Figure 4B.

4.2 Front roughening

272 As the interface roughens, its width should increase with time according to

$$\langle w^2(L, t) \rangle^{1/2} \sim t^\beta. \text{ Figure 3B shows each plot's interface width against time. We tested}$$

274 the predicted scaling after excluding data for $L = 1 \text{ m}$, since roughening in those (smallest)

plots equilibrated earlier than observed for larger L . Model selection found support for the

276 power-law model with multiplicative error (Table 3). Using this model, we estimated the

growth exponent β as 0.34 ± 0.12 (mean \pm 95% confidence interval; $R^2 = 0.355$). Inclusion

278 of plots where $L = 1 \text{ m}$ had little effect; the resulting estimate is $\beta = 0.313$; see Figure 3B.

Figure 4C shows how scaling of the local interface widths $w_t(l)$ extended further as the
 280 interface roughened. Each month $w_t(l)$ scaled as the same power law for a greater distance
 along the interface.

Clover Growth Analysis	Linear	Exp 1	Exp 2	Pow 1	Pow 2
$w^2(t)$	411.21	407.82	4.65	0	408.72
$C(l)$	2014.94	1716.08	754.1	0	1398.53
$w^2(l)$	3629.0	3061.25	1528.87	0	2528.99
$w^2(L)$	118.44	117.02	2.56	0	117.18
$\langle \Delta_{max} \rangle_L$	158.15	155.15	6.48	0	155.76

Table 3: ΔAIC scores. Models compared are as follows. Linear: $y = x + \epsilon$; Exp 1: $y = \log(x) + \epsilon$; Exp 2: $\log(y) = x + \epsilon$; Pow 1: $\log(y) = \log(a) + b \log(x) + \epsilon$; Pow 2: $y = ax^b + \epsilon$. ϵ is a random error term with zero expectation and finite variance. Results support power-law models of Table 2.

282 We estimated interface velocity as the difference in monthly mean clover height.

Combining all plots, clover advanced fastest during the first month of growth. September

284 velocities (after roughening saturated) were independent of interface length L . After

September, longer fronts continued to advance, but some shorter fronts receded as the

286 growing season ended. During the period of interface roughening, overall mean clover

height advance at 20 *cm/mo*. This exceeds mean stolen-elongation rates cited by Cain et

288 al. [1995], but is within the observed range of clover “dispersal distances” discussed by

Schwinning and Parsons [1996a]. Interface velocity appeared more sensitive to seasonal

290 effects than did the roughened structure of the interface.

4.3 Stationary roughness and the front-runner: power laws

292 Assuming that roughening equilibrated in month 4, we tested the predicted scaling form

against alternatives in two ways; each used the final month’s data. The first test uses the

294 local roughening analysis, and the second asks how mean interface width increases with L .

After saturation, the local width $w(l)$, where ($l \leq L$), should scale as $w(l) \sim l^\alpha$. We

296 combined month-4 data from different plots to characterize local roughening; see Figure

4C. Our AIC-criterion strongly supported the power-law formulation with multiplicative

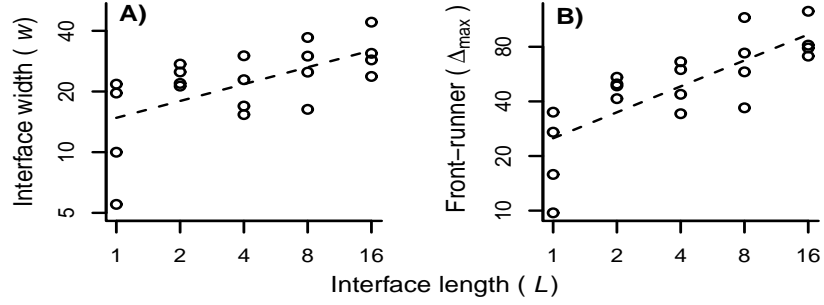


Figure 5: Saturated roughening. A. Interface widths (cm) for different front lengths L , data from September (month 4). Dashed line indicates power-law scaling. B. Front-runner's lead (Δ_{max}), in cm , for different interface lengths L ; data from month 4. Dashed line indicates power-law scaling.

error (Table 3). The associated estimate of the roughness exponent was $\alpha = 0.311 \pm 0.002$.

The mean roughening analysis treated each plot's width $w(L)$ separately. Using September estimates (see Figure 5A), the model selection procedure again provided substantial support for a power-law relationship with multiplicative error (Table 3). The power-law model for mean interface width as a function of interface length gave an estimate α as 0.278 ± 0.18 .

Once roughening has equilibrated, the average lead of the front-runner, beyond the mean interface height, should scale with length as $\langle \Delta_{max} \rangle_L \sim L^\alpha$. Our model selection procedure once again found support for power-law scaling with multiplicative error (Table 3). Using the preferred model, the front-runner scaling estimated the roughening exponent as $\alpha = 0.475 \pm 0.19$; $R^2 = 0.6$; see Fig. 5B.

Scaling	Estimate \pm 95% CI	Months
$C_t(l) \sim l^\alpha$	$\alpha = 0.277 \pm 0.002$	1 - 5
$w(l) \sim l^\alpha$	$\alpha = 0.311 \pm 0.002$	4
$w(L) \sim L^\alpha$	$\alpha = 0.278 \pm 0.18$	4
$\langle \Delta_{max} \rangle \sim L^\alpha$	$\alpha = 0.475 \pm 0.19$	4
$w(t) \sim t^\beta$	$\beta = 0.34 \pm 0.12$	1 - 5

Table 4: Estimates of scaling exponents. The first column indicates the predicted scaling law; the second shows the numerical result. Months 1 - 5 consider development; month 4 assumes equilibrated roughening. α is the roughness exponent, and β is growth exponent.

Table 4 lists values of the scaling exponents inferred from the clover-interface data.

310 The length-based estimates of the roughness exponent α are consistent; scaling of the
front-runner suggests greater roughness; see see Appendix B. But every statistical analysis
312 involving either the growth or the roughness exponent supported a power-law formulation
over alternative linear and exponential models, as follows from kinetic-roughening theory.

314 **5 Interface profiles and local interactions**

Interface geometry affects contact frequency between spatially clustered competitors, and
316 exclusion *versus* coexistence can depend on interactions at the interface
[Chesson and Neuhauser 2002, Allstadt et al. 2007]. A rougher interface (larger α) might
318 therefore accelerate local population dynamics, driving invasive advance. The more obvious
interface attribute is the width; $w \sim L^\alpha$. As long as greater roughening does not increase
320 local density of empty sites, a larger interface width increases interdigitation of invader and
resident, so that the density of asymmetric competitive interactions will increase.

322 To emphasize the role of width w_t , we examine experimental interface profiles, plots of
the fraction of L rows occupied by clover as a function of distance from the current mean
324 height. Figure 6 shows interface profiles from one experimental plot (16 m , same as Fig. 1)
for five months. Every month clover and ryegrass occurred with nearly equal frequency at
the mean height. The first month's (June) profile drops sharply; the competitors mix very
326 little as the interface begins to develop. Closer to saturation, the profiles show that
interface width increases, and the species mix at the neighborhood scale.
328

We approximated observed interface profiles with the complementary error function. If

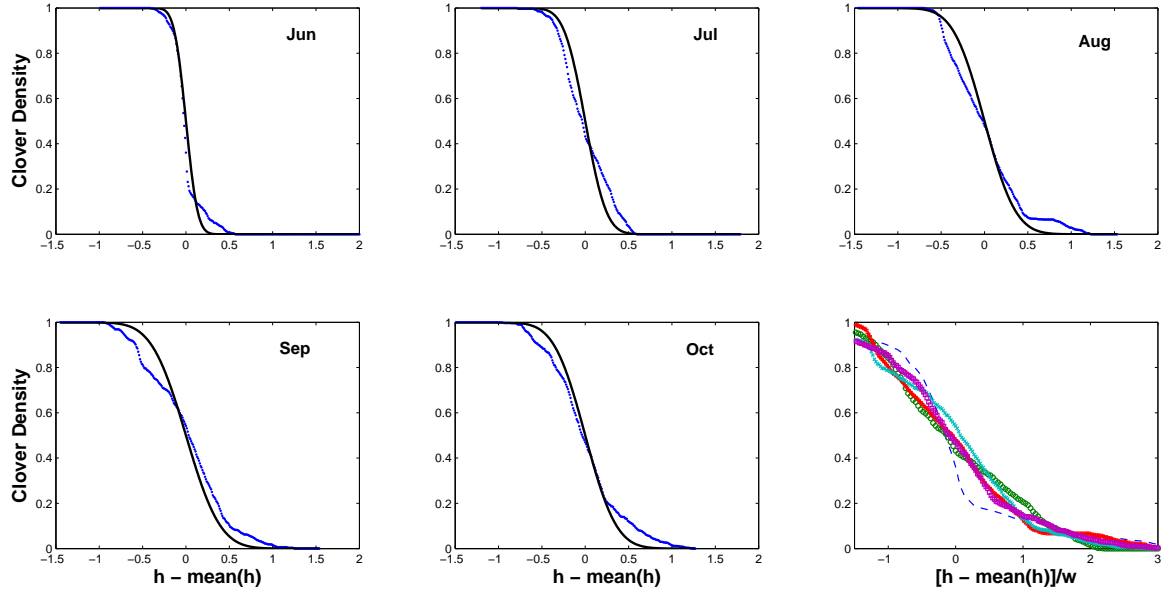


Figure 6: Density profiles of interface width, June through October (as indicated). $L = 16 m$. Each month's empirical profile indicated by (\bullet) . Associated complementary error function for each month, parameterized by observed width, approximates data. Interface widths for consecutive month are, respectively, $w = 0.15, 0.27, 0.4, 0.44, 0.4$. Lower right. Data collapse. Dividing height (relative to front's mean position) by width indicates that last four months' clover-density profiles share structural organization. First month (broken line) insufficiently roughened to "fit." Symbols are empty circle (Jul), square (Aug), \times (Sep) and closed circle (Oct).

330 $\rho_t(h)$ represents clover density at height h and time t . Then:

$$\rho_t(h) = \frac{1}{2} \operatorname{erfc} \left([h - \bar{h}(t)] / w_t \right) \quad (5)$$

where w_t is interface width estimated at time t . The complementary error function is:

$$\operatorname{erfc}(x) = \frac{2}{\sqrt{\pi}} \int_x^\infty \exp[-z^2] dz$$

332 Equation 5 reasonably approximates observed profiles, since mean invader density has a roughly Gaussian decline across the interface; see Foltin et al [1994].

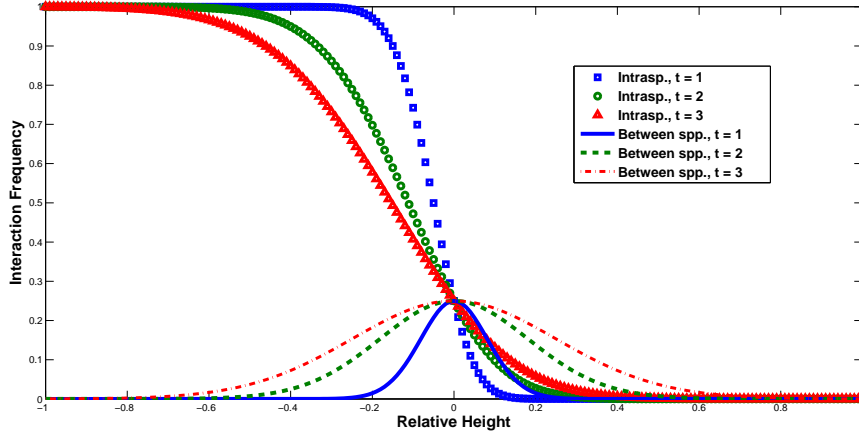


Figure 7: Invader interaction frequencies. $w(t = 1) = 0.15$ (blue), $w(t = 2) = 0.27$ (green), and $w(t = 3) = 0.4$ (red). As time advances, interface width increases. As width increases, (1) decline in intraspecific competition behind mean height exceeds increase in intraspecific competition in front of mean height, and (2) interspecific competition increases symmetrically about mean height.

334 The final subplot in Fig. 6 (lower right) indicates “data collapse” of the last four
 months’ density profiles. Re-scaling height as $[h - \bar{h}(t)]/w_t$ reveals that the profiles share a
 336 common structural dependence on interface width, close to/at saturation. That is, the
 re-scaled plot shows a basic relationship for which the July through October profiles are
 338 examples. The first profile, a relatively un-roughened interface, has a different dependence.

Interface profiles neglect open sites and average across spatially correlated invader
 340 density, but indicate how biotic interactions are organized within the interface. If
 intraspecific interactions occur at height h in proportion to $[\rho_t(h)]^2$, their frequency will
 342 decline faster than invader frequency within the interface width. Interspecific interactions,
 if proportional to $\rho_t(h)[1 - \rho_t(h)]$, will increase initially, peak at $\bar{h}(t)$, and then decline.
 344 Given this approximation, greater roughening increases interspecific mixing at the interface
 in a quantifiable manner; see Figure 7. Extending this basic picture, we can ask how
 346 interface width affects, and is affected by, ecological detail. For example, when within and
 between-species effects act across differently sized neighborhoods [Murrell and Law 2003],

348 or when dispersal-limited parasites prefer one of two competing hosts [Borer et al. 2007],
interface geometry might modulate local population dynamics.

350 **6 Discussion**

Clonal organisms dominate many communities [Gough et al. 2002, Kui et al. 2013], so that
352 dispersal limitation must often generate clustered growth patterns. Consequently, invasive
growth and competitive interactions may commonly occur within the width of an ecological
354 interface, where interaction neighborhoods overlap. Our general depiction of spatial
competition, common to numerous detailed models, invites application kinetic-roughening
356 theory as a way to understanding pattern and process in the spatial structure of
dispersal-limited organisms.

358 In our field experiment, clover advanced, displacing ryegrass. Simultaneously, clover's
spatial correlation length along the interface increased. After a self-affine interface has
360 saturated, the fractal exponent D is given by $D = 2 - \alpha$. Taking our length-based
estimates of α , we have $D \approx 5/3$; cover growth we observed “fills space” more than
362 predicted by a model where invader and resident grow forward and laterally at the same
rate [O'Malley et al. 2006]. That is, lattice models for clonal growth usually assume that
364 an individual (ramet) will propagate forward, backward and laterally; any unoccupied,
nearest-neighboring site can be colonized at the same stochastic rate. But Cain et al.
366 [1995] carefully mapped the architecture of clonal growth in a white clover population.
Node-to-node branching angles of apical meristems centered on 0° (straight ahead), but
368 some large angles were observed. Lateral meristems branched off with a bimodal angular
distribution, concentrated at $\pm 60 - 70^\circ$. Clover, then, exhibits forward and lateral growth,

370 but with a bias toward forward propagation. The resulting morphology could have induced
the difference between the scaling of the front-runner's lead and the scaling of interface
372 roughening.

We studied an interface at the level of clustered individuals competing for space; a
374 lattice site in our field experiment had area 1cm^2 . Cannas et al. [2004] invoked kinetic
roughening in analyzing an individual-based simulation of an invasive tree advancing into a
376 forest; they assumed each site had area 25m^2 . The methods of kinetic roughening should
apply beyond individual-based scales. For example, expansion or contraction of a species'
378 geographic range might be characterized as interface movement between habitats, driven
by gain and loss of local demes. The obvious complication across greater distances is
380 ecological heterogeneity [Gastner et al. 2009]. Spatial heterogeneity in demographic rates,
varying at a scale much greater than local dispersal distance, implies that the roughness
382 exponent α will vary along the length of an extended interface. In this case the front has a
multi-affine, or turbulent, structure, and local estimates of roughness will not predict
384 larger-scale behavior [Barabási and Stanley 1995]. More generally, spatial heterogeneity,
whether fixed or temporally variable, can affect the likelihood an invasion begins
386 [O'Malley et al. 2010] and front velocity when invasion succeeds [Shigesada et al. 1986].

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