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Small fire ant rafts are unstable

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Abstract

In this combined experimental and numerical study, we film the formation of fire ant rafts to determine how they cohere together. Surprisingly, we discover that ants prioritize separation and exploration: they flail legs and bounce off neighbors when they collide. Despite the active repulsion, Fire ants cohere by the Cheerios effect, a capillary force that attracts small floating objects such as breakfast cereal. Experiments reveal that rafts consisting of fewer than ten ants disintegrate within minutes. Predictions by a Langevin model reproduce the stability transition and the critical raft size, which emerges from the balance between their mutual repulsion and the Cheerios effect. This work may inspire physically grounded models for the behavior of natural swarms.

Introduction

Animal groups accomplish tasks that individuals cannot achieve [1, 2, 3]. For example, army ants link their bodies to build bridges over gaps [4]. Slime molds *Dictyostelium discoideum* distribute their spores by building fruiting bodies to grow in height by a factor of 200 [5, 6]. Fish schools reduce energy expenditure and facilitate evasion of predators [7, 8, 9]. One way that we recognize a flock of birds or a school of fish is by its cohesion [10]: members of a swarm remain together despite changes in the swarm’s shape and internal structure. Although cohesion in natural swarms is a simple enough concept to recognize, the mechanism by which it arises is still a mystery. Understanding how individuals cohere may inspire new swarm models and guide the designs of artificial systems. The goal of this study is to investigate the origin of cohesion in fire ant rafts.

Currently, most models of swarms require a “social force” that attracts individuals towards their neighbors or the center of the swarm [11, 12, 13, 14, 15, 16]. The 1995 Vicsek model [17] does not feature social attraction and thus swarms behave unrealistically: they disperse in the open space [18, 11, 19]. A social attraction force is fundamentally different from physical forces such as drag and thrust. It involves a cascade of internal signals in which the animal senses the distance to its neighbors and propels itself to maintain that distance. Social attraction forces have long been used to rationalize the motion of fish schools [20, 21, 22, 23], bird flocks [24, 25, 26], and insect swarms [27]. Although social attraction enables models to emulate various collective behaviors, Lopez et al. [28] cautioned that this approach increases the number of model parameters to be measured from experiments. Furthermore, as a proxy for complex animal interactions and sensory feedback, social attraction is in itself an emergent property. It may be difficult to justify social attraction forces for insect swarms, for which individuals have limited sensing capabilities and intelligence. Despite years of work, it remains unknown if social attraction forces are legitimate or simply a crutch. In this work, we rationalize the formation of ant rafts without invoking social attraction.

We perform experiments with red imported fire ants (*Solenopsis invicta*, **Figure 1A**). Native to the Pantanal wetlands in Brazil [29], this invasive species can now be found on all continents except for Antarctica [30]. Fire ants can link their bodies together to build rafts, towers, and bridges. Ants

40 on the raft perform random walks and expand the raft by accretion of their bodies on the raft edge
41 [31]. Fire ants may also extend pseudopod-like appendages through treadmilling [32] and morph
42 into streamlined airfoil shapes when in flow [33]. Previous studies have focused on large rafts with
43 more than 1000 ants [31, 34, 32] but did not discuss how rafts stayed together. In this study, we
44 focus on rafts with [size 2 to 158 ants](#) to better understand the mechanisms of raft formation.

45 Results

46 Experimental observations: Small rafts are not stable

47 We filmed the behavior of balls of ants placed on the water surface (Movie S1). In total, we
48 performed 72 experiments involving groups ranging from 2 to 158 ants. Surprisingly, we find that
49 ant rafts are only stable if they contain at least $N_c \approx 10$ ants. **Figure 1C** shows a time series of a
50 raft of five ants breaking apart when placed on the water surface. The dense ant ball expands rapidly
51 as it contacts the water surface, and then ants begin to disperse in all directions. **Figure 1B** shows
52 the relationship between N , the number of ants initially in a raft, and P , the proportion of ants
53 that leave the raft after five minutes. Experimental data are shown by orange triangles. Clearly,
54 larger rafts are more stable, with a stark transition to stability at ten ants. Phenomenologically,
55 such a trend is shown by a logistic function(**Figure 1B**),

$$P(N) = \frac{1}{1 + e^{(N-N_c)/\Delta N}}, \quad (1)$$

56 where N_c is the critical number of ants for stability, and ΔN is the width of the transition interval.
57 Note that when $N = N_c$, half of the ants go astray ($P = 0.5$). The dashed orange line shows a
58 least-squares fit to our experiments. The best fit yields $N_c = 9.3$ and $\Delta N = 1.5$ ($n = 72, R^2 = 0.66$).

59 To better understand the factors that lead to the critical raft size, we film the interaction between
60 pairs of ants as they encounter each other on the water surface. Each pair of ants separates after
61 an average interaction time of 77 ± 69 seconds ($n = 14$). [The interaction time is highly variable,](#)
62 [ranging from as little as 10 seconds up to four minutes.](#) During this interaction, they flail their
63 legs, intermittently colliding with each other before ultimately departing in opposite directions.
64 This observation contradicts with the naïve assumption that all swarming individuals have social
65 attraction.

66 To determine the dominant forces on the ants, we calculate common dimensionless groups. The
67 Reynolds number $Re = Ul/\nu \sim 10$, where $l \sim 3$ mm is an ant's characteristic body length, $U \sim$
68 4 mm/s its characteristic swimming speed, and ν the kinematic viscosity of water. The Reynolds
69 number suggests that both inertia and viscous force influence an ant's motion. Indeed, when pushed
70 manually, dead ants can drift for tens of body lengths through their inertia. [The Reynolds's number](#)
71 [remains small if other characteristic length scales are considered such as the body width \$w = 1\$](#)
72 [mm, or the leg width \$w' = 100\$ \$\mu\$ m.](#) The Bond number $Bo = \rho gl^2/\gamma \sim 1.3$ where ρ is the density of
73 water, g is the gravitational acceleration, and γ is the surface tension of water. The Bond number
74 suggests that both surface tension and buoyancy contribute to the weight support of the ants.
75 Indeed, we see that fire ants maintain their position mostly above the water surface, with just their
76 legs' tips and ventral surfaces wetted. From here on, we will characterize their motion on the water
77 as walking rather than swimming.

78 **A Langevin model describing fire ant interactions**

79 We proceed by presenting a model for raft formation that does not rely on social attraction. The
 80 goal of our model is to rationalize the critical number of ants N_c for raft cohesion as well as the
 81 effect of different parameters such as ant activity level and initial spacing. Newton’s law applied
 82 to a single ant of mass $m \approx 1$ mg states:

$$m\ddot{\mathbf{x}}_i = k_a\boldsymbol{\eta}_i - k_f\dot{\mathbf{x}}_i - \sum_{i \neq j} k_c K_1(|\mathbf{d}_{ij}|/l_c)\hat{\mathbf{d}}_{ij} + \sum_{i \neq j, d_{ij} < 2r} k_r \mathbf{d}_{ij} \quad (2)$$

inertia = propulsion + drag + capillary + repulsion

83 where \mathbf{x}_i is the two-dimensional position of ant i and $\ddot{\mathbf{x}}_i$ is its acceleration. The forces experienced
 84 by the ants include propulsion, viscous drag, capillary attraction, and ant-to-ant repulsion. These
 85 four terms are characterized by their corresponding coefficients k_a , k_f , k_c , and k_r .

86 **Active propulsion**

87 In Equation (2), the first term on the right-hand side is the random propulsive force of ants.
 88 Dropping the i subscript, the propulsive force for an ant may be written as the product of an
 89 activity coefficient k_a and $\boldsymbol{\eta}$, the two-dimensional standard normal distribution with zero mean
 90 and unit standard deviation. Effectively, $k_a\boldsymbol{\eta}$ is the Gaussian distribution with standard deviation
 91 k_a . At each time step, and for each ant i , we randomly sampled a value from this distribution. To
 92 measure activity level k_a , we first describe their trajectories.

93 **Figure 2(A)** shows an overlay of ten individual fire ant trajectories on the water surface. These
 94 trajectories are characterized by looping circular paths with straight-line distances of less than a
 95 few body lengths. Trajectories on water vary significantly from trajectories atop ant rafts, where
 96 their straight line distance is on the order of 4 cm, or over 13 body lengths [31]. For simplicity,
 97 ants in our model are considered circular discs with no heading.

98 The velocity distribution of ants on the water surface is qualitatively similar to that of Brownian
 99 particles such as pollen. **Figure 2(B)** shows the probability distribution of an ant’s speed $U =$
 100 $\sqrt{u^2 + v^2}$, where u and v are the x and y components of the ant’s walking velocity $\dot{\mathbf{x}}_i = [u, v]$. The
 101 two insets of **Figure 2(B)** show that an ant’s translational velocity components (u, v) are normally
 102 distributed around zero, indicating that ants have no directional bias. The standard deviation
 103 σ of velocity in either direction (u, v) is approximately 3.5 mm/s ($n = 96$). [Ants on the water](#)
 104 [locomote at speeds of \$U = 4.2 \pm 2.8\$ mm/s \(\$n = 96\$ \)](#), a fifth of their walking speed on land, 20 mm/s
 105 [35]. Previous work reports that fire ants “showed no directed motion” and categorized them as
 106 non-swimmers compared to other tropical ant species [36]. Notably, fire ants are also smaller than
 107 other tropical species, which may make their locomotion less effective on water.

108 Following the prediction from statistical mechanics, **Figure 2B** shows the probability distri-
 109 bution of the velocity magnitude U , which is well approximated by the two-dimensional Maxwell-
 110 Boltzmann distribution (solid red line),

$$\text{pdf}(U) = \frac{1}{2\pi\sigma^2} e^{-\frac{1}{2}(U/\sigma)^2} \quad (3)$$

111 where pdf is the probability distribution function, and σ is the standard deviation for u and v . The
 112 mean squared displacement (MSD) of ant trajectories is defined as

$$\text{MSD}(\Delta t) = \langle |\mathbf{x}(t + \Delta t) - \mathbf{x}(t)|^2 \rangle, \quad (4)$$

113 where $\langle \dots \rangle$ denotes the average over all samples and time t . **Figure 2C** shows the MSD of ant
 114 trajectories ($n = 96$), where MSD is in mm^2 and the time interval Δt is in seconds. The MSD
 115 reveals that the motion is ballistic at short times ($\sim 7.5\Delta t^2$ for $\Delta t < 5$ s, $R^2 = 0.97$) and diffusive at
 116 long times ($\sim 30\Delta t$ for $\Delta t > 8$ s, $R^2 = 0.98$). These statistical features confirm that the locomotion
 117 of fire ants on the water surface can be modeled by inertial random walkers such as dust particles
 118 in plasmas, mini-robots, and Whirligig beetles [37, 38].

119 The transition between the two regimes is smooth and we could not identify a critical threshold
 120 based on the MSD statistics alone. However, though the coasting dead ant experiments that we
 121 will introduce below, we calculate a time scale for inertial effects (vertical gray dashed line) that
 122 lies in the transition region of MSD.

123 Fitting the MSD at the early ballistic stage yields the characteristic velocity of 2.7 mm/s
 124 ($R^2 = 0.97$), comparable to the average speed in the histograms in **Figure 2B**. From the later
 125 diffusive phase, we calculate the diffusion coefficient D of 7.5 mm^2/s ($R^2 = 0.98$). This diffusion
 126 coefficient suggests that over 22 minutes, an ant's final position on water will be ten centimeters
 127 away from its initial position. We can relate the activity coefficient k_a in our model (Equation (2))
 128 to the friction coefficient k_f through $k_a = k_f \sqrt{2D/\delta t}$ [37], where δt is the time step used in our
 129 simulations (see the Materials and Methods section).

130 Although we neglect turning in our model, we briefly explain the looping trajectories observed.
 131 Directional bias is absent in our experiments: the mean orientational velocity of the ants, $\dot{\theta}$, is
 132 negligible at -0.002 rad/s ($n=97$). Persistent turning explains the circular trajectories in **Figure**
 133 **2A**. Fig. S1 shows that orientational MSD has a slope of 1.7 ($R^2 = 0.995$), indicating that ants'
 134 angular velocities are hyper-diffusive.

135 Fluid drag

136 The second term in Equation (2) is the fluid drag on an ant. We performed experiments by
 137 manually pushing dead ants by hand and recording their deceleration on the water surface due
 138 to hydrodynamic drag (Fig. S2). In the intermediate Re regime ($\text{Re} \sim 10$), drag involves both
 139 pressure drag ($\sim U^2$) and viscous drag (proportional to $\sim U$). However, we found that viscous
 140 drag is sufficient to explain the deceleration. We fit the relationship between fluid drag and the
 141 velocity to obtain the coefficient $k_f = 0.24$ mg/s ($n = 14$, $R^2 = 0.82$). The time scale of the
 142 inertial effect $\tau = m/k_f = 4.3$ s approximately coincides with the transition between the inertial
 143 and diffusive regimes in MSD (vertical gray dashed line in **Figure 2**), as predicted by the Langevin
 144 model for Brownian particles. Indeed, in the absence of interaction terms, Equation (2) describes
 145 Brownian motion [37].

146 Capillary attraction

147 The last two terms of Equation (2) involve the interaction among individuals and vary with $\mathbf{d}_{ij} =$
 148 $\mathbf{x}_i - \mathbf{x}_j$, the distance between a pair of ants. Small floating objects such as paperclips or Cheerios
 149 are drawn together by capillary forces, which act to minimize the deformation of the water surface.
 150 Similarly, in both experiments with live and dead ants, we observe attraction sufficient to draw ants
 151 together if the initial distance is within a few centimeters. Nicolson et al. derived the attraction
 152 force between two floating spheres

$$F_c = k_c K_1(d/l_c), \quad (5)$$

153 where k_c is a fitting parameter measured from experiments, K_1 is the modified Bessel function, d
 154 is the distance between the two objects, and $l_c = 2.7$ mm is the capillary length of water. The

155 parameter k_c depends on the geometry, contact angle, and density of the object [39, 40, 41]. We
156 account for these effects by fitting the interaction between two dead ants. Although ants are
157 elongated and have a rough surface, we neglect these second-order effects and focus on representing
158 the capillary attraction between ants as floating spheres. Through measuring the attraction between
159 pairs of dead ants (see the method section and Fig. S3), we obtain $k_c = 2.6$ nN ($n = 33$, $R^2 = 0.83$).
160 Based on the value of k_c , the attraction force between two ants is comparable to the attraction
161 between a pair of small plastic spheres (diameter 1 mm, density 1.1 g/mL, and contact angle 70°).

162 Short-range repulsion

163 The last term in Equation (2) is the short-range elastic repulsion force when two ants collide. In
164 simulations, we approximate ants as a 2D discs with radius $r = 1$ mm, which was chosen to be
165 both comparable to the ant length l and ant width w . Collisions occur when the inter-ant distance
166 $d_{ij} < 2r$. Our simulation results were comparable for most non-zero values of k_r ; therefore we used
167 $k_r = 0.05$ nN/mm.

168 Our final model, Equation (2), is capable of simulating the trajectories of arbitrary numbers of
169 ants. Except for k_r , which was set to avoid overlapping agents when they came too close, there
170 were no free parameters in our model; all parameters were measured from our experiments on both
171 live and dead ants. In the Materials and Methods section, we detail how we measure the four model
172 parameters (k_a, k_f, k_c, k_r) that characterize the four forces acting on the ants.

173 Multi-agent simulations capture the stability transition

174 In this section, we present simulations of raft destabilization and raft formation, in which we vary
175 factors that would be difficult to change experimentally.

176 Raft destabilization simulations begin with ants in a hexagonal lattice, the tightest possible
177 configuration for monodisperse discs. We perform 150 simulations with 15 different raft sizes and
178 10 numerical trials with different values for the random variable η which describes their diffusion.
179 **Figure 3A** and Movie S2 demonstrate that assemblies of seven agents disintegrate, while rafts of
180 19 agents remain stable, similar to the behavior observed in experiments. **Figure 1B** shows P , the
181 proportion of stray ants at the end of the trial of five minutes, decreases with the number of ants
182 N in simulations (gray circles). We fit the simulation results to the logistic function, Equation (1),
183 finding that the critical number of ants $N_c = 9.5$ and $\Delta N = 1.1$ ($n = 150$, $R^2 = 0.88$), matching
184 the experimental logistic function well. We thus conclude that the stability transition emerges from
185 the agent interactions in our model, the combination of random walks, drag, contact repulsion, and
186 Cheerios effects (**Figure 3B**). We next use our model to explore the effect of activity levels and
187 the initial spacing of ants.

188 Next, we consider the effect of ant activity on raft stability. In our experiments, we observed
189 that the leg motion of fire ants dwindles over time. Immediately after being placed on water, ants
190 flail their legs at 20.2 ± 4.5 mm/s ($n = 6$) at their tips. The movement slows down to 10.0 ± 4.5
191 mm/s ($n = 6$) over a span of ten minutes. This slow down with time is consistent with our previous
192 findings that ants reduce exploration and metabolism with time [42, 33]. Could the decrease in
193 activity improve the stability of the rafts? To answer this question, we simulated ants with activity
194 coefficient k_a ranging from 0.5 to 3.4 nN, where the activity level measured from our experiments
195 was 3.0 nN. **Figure 3C** shows the stability diagram of the rafts ($n = 1200$). Larger rafts with
196 less active ants are more stable, as expected. This black dashed curve represents the critical size
197 where half of the ants remain stable in the raft ($P = 0.5$); by fitting to an exponential, we find this
198 stability criteria correspond to $N_c \approx 0.3e^{1.2k_a}$.

199 Now that we have identified how ant rafts remain stable, we investigate how rafts are assembled
 200 in the first place. These simulations were conducted with ants in a square lattice of centroid-
 201 to-centroid spacing L . **Figure 4a** shows the proportion of ants that remain isolated after five
 202 minutes as a function of the activity level and initial spacing L . Each data point is an average of
 203 ten numerical trials per condition ($n = 660$). For ants to assemble into a raft from a dispersed
 204 state, they must be sufficiently close together. Closely spaced ants with a spacing of $L = 16.7$ mm
 205 condense into rafts if the activity is sufficiently low. Higher activity levels lead to collisions that
 206 destabilize the aggregation. Conversely, distant ants with spacing $L = 37.5$ mm rarely encounter
 207 any neighbors within five minutes if their activity is low ($k_a = 0.5$ nN). This phenomenon is observed
 208 in our experiments: satellite ants a few centimeters away from their neighbors remain isolated if
 209 their activity level is too low. Ants must actively locomote on the water surface to encounter
 210 neighboring ants. In our experiments, as ant activity levels naturally dwindle with time, sparsely
 211 distributed ants have increasing difficulty encountering neighbors. Therefore, the initial spacing is
 212 a critical factor for raft formation.

213 **Figure 4B-C** demonstrate the time series of stray ant proportions P for various activity levels
 214 and two initial ant-to-ant spacing, L , of 18.75 mm and 30 mm. At small ant-to-ant spacing,
 215 $L = 18.75$ mm, even though the proportion of ants P at $t = 5$ min is monotonic with activity,
 216 the time-scale to achieve 50 percent assembly is nonlinear. Such nonlinearity is due to the pros
 217 and cons of increasing activity levels: namely, high activity enables ants to find one another but
 218 impedes raft formation upon contact. Conversely, ants of low activity level take longer to find
 219 one another but stick together better once in contact. When the activity is low at $k_a = 0.5$ nN,
 220 rafts assemble slower because it takes longer for ants to find their neighbors. For large ant-to-ant
 221 spacing $L = 30$ mm, even though low-activity ants assemble more slowly, newly formed rafts rarely
 222 break apart. The comparison between **Figure 4B** and **Figure 4C** reveal that for any fixed activity
 223 level k_a , the raft is established more rapidly at low initial spacings (**Figure 4C**). At the spacing of
 224 $L = 18.75$ mm, except for when $k_a = 1.5$ nN, the system either quickly converges to the aggregated
 225 state ($k_a < 1.5$ nN), or maintains the dispersed state ($k_a > 1.5$ nN).

226 Discussion

227 Phase-transition analogy of raft stability

228 Animal swarms can display both behavioral phases (such as Pharaoh ant trail-following [43], and
 229 desert locust swarming [44, 45]) and thermodynamical phases [46, 47, 48, 49, 50, 51, 52]. The
 230 assembly and disassembly of fire ant rafts is analogous to the phase transition of non-living materials
 231 such as water. Here, the raft may be considered the liquid phase; and the dispersed ants, the
 232 vapor phase. Subsequently, the proportion of stray ants is analogous to the vapor quality. In
 233 this viewpoint, we can readily compare **Figure 4A** to the T-V diagram of the water, where the
 234 temperature T corresponds to the ant activity and volume V corresponds to the number of ants.

235 Following the statistical mechanics' framework and assuming detailed balance, we may also
 236 estimate the effective temperature $T_{activity} = 1.4 \times 10^{13}$ K using the Stokes-Einstein relation $D =$
 237 $\frac{k_B T_{activity}}{6\pi\mu l}$, where k_B is the Boltzmann constant, μ the viscosity of water and l the length of the
 238 ants. We can estimate the pressure per unit depth $P_{activity}$ by equating the energy scales (ideal
 239 gas law) $P_{activity}A = k_B T_{activity}$, where A is the surface area of an ant. We obtain $P_{activity} = 0.2$
 240 mN/m, which is around 1/300 of the water surface tension. Note that the pressure drives ants
 241 apart, and surface tension pulls them together.

242 [Fire ant rafts constantly expend energy and are thus out of equilibrium, departing from most](#)
 243 [traditional physical systems. From previous work, we know that ants slow down and ant rafts shrink](#)

244 on the order of hours [33]. To avoid these fatigue effects, which are difficult to model, we chose five
245 minutes as the time frame to perform our observations and simulations. The numbers calculated
246 will vary with the time frame chosen, but the physical picture should remain the same. Further
247 understanding of the collective dynamics of biological systems calls for a statistical mechanical
248 framework that permits temporal variability as well as individual differences.

249 **Biological assemblies on the water surface**

250 Can our model predict if and under what conditions other species can aggregate? Three factors
251 should be considered. Different animals have different physical properties (density, size, hydropho-
252 bicity, etc.), and thus different coefficients for the Cheerios effect attraction k_c . While ants are
253 well described by random walks, other organisms may need different models. For example, the
254 locomotion of whirligig beetles resembles “corralled active Brownian particles” [53]. Chirality is
255 critical in describing starfish embryo assemblies [54].

256 Recently, biologists have identified more ant species that can build rafts, including *Pheidole*,
257 *Formica*, *Wasmannia*, and *Linepithema* spp. [36, 55, 56, 57, 58, 59]. They are often found in
258 habitats prone to inundation. Notably, one common feature of these rafting species is their small
259 body size (< 1 cm), hinting at the potential significance of surface tension and the Cheerios effect
260 in their assembly mechanism. Comparative studies of these species that test the predictive power
261 of our model would be an exciting future direction.

262 As we focus on the fire ant behaviors on the water surface over a short time scale (five minutes),
263 it can be argued that ants have very limited sensory capabilities. Indeed, we demonstrate that ants
264 walking on the water surface cannot recognize neighboring ants and ricochet off them. The nature
265 of the system calls for stochastic dynamics, where the activity is modeled as white noise that does
266 not require any memory or feedback loop. The lack of memory or feedback is similar for swarms
267 of black soldier larvae as well [60].

268 Our research coincides with active matter beyond the over-damped limit [61, 38, 62, 53]. Löwen
269 has shown that rich physics can arise from the addition of the inertial term, such as the co-existence
270 of different temperature phases [38]. There has also been increasing interest in active matter at the
271 fluid interfaces [63, 64, 65, 53, 54, 66]. Our model, Equation (2), shares significant similarity with
272 these systems. Through this combined experimental and theoretical study, we present fire ants as
273 a model system for future explorations on these topics.

274 **Conclusion**

275 We have shown that fire ants cohere on the water surface through capillary forces. Remarkably,
276 the activity of the ants destabilizes the assembly, causing small rafts to disintegrate. We used a
277 Langevin model to simulate raft breakages and reproduced the stability transition condition we
278 discovered in experiments. Further, we used the model to predict the initial ant spacing required
279 to assemble rafts.

280 **Materials and methods**

281 **Raft experiments**

282 Fire ant colonies were collected from the campus of Georgia Institute of Technology, Atlanta,
283 Georgia. We kept them in plastic trays with access to water and food. In all collected colonies,

284 multiple queens were found. To reduce the effects of the artificial rearing environment in the lab,
285 we only used ants harvested within three months for experiments.

286 To make rafts, we used previously published protocols [31]: we selected ants from a colony and
287 placed them into a beaker coated with Insect-a-Slip. Then we swirled the beaker to roll the ants
288 into a ball and placed the ball on the water surface. Ants fewer than 30 in number were manually
289 counted before the experiment. For larger numbers, the beaker was weighed and converted to the
290 number of ants using the average weight of one ant, which was around one milligram. For five
291 minutes, we recorded the trajectories of ants and counted the number of stray ants at the end of
292 the film.

293 Measuring parameters for the Langevin model

294 We tracked 96 ants to determine their activity level on the water surface. Ants were picked up
295 from the colony using tweezers and transferred to the water surface by gently tapping the tweezers.
296 Occasionally, ants landed on their back and could not flip over due to surface tension. These trials
297 were excluded from further analysis. We recorded the trajectories of ants using an Opti-Tekscope
298 USB microscope placed above the water surface. The recordings were analyzed using a custom
299 MATLAB tracking program. The same system was used to obtain the trajectories in the following
300 experiments.

301 To measure drag coefficient k_f and the Cheerios effect coefficient k_c , we used recently deceased
302 ants. We euthanized the ants by placing them in the freezer for around ten minutes. We used
303 tweezers to straighten the ants' bodies and legs before placing them on the water surface. We gently
304 pushed the ant so that it started drifting with an initial velocity. We recorded 14 trajectories as they
305 decelerated due to fluid drag. We used Gaussian smoothing and forward difference to calculate the
306 velocity using a time interval of 0.06 s. We find that velocity decreases exponentially with time (Fig
307 S2), suggesting that fluid drag is proportional to the velocity magnitude. We obtain the coefficient
308 for drag k_f from fitting a straight line to the relationship between the logarithm of velocity $\log(U)$
309 and time t . We measured k_f to be 0.24 mg/s ($n = 14$, $R^2 = 0.82$, Fig. S2).

310 The activity coefficient k_a depends on both drag coefficient k_f and the time step δt . For
311 intuition, consider the random propulsion term $k_a \boldsymbol{\eta}$ as an average value over a period of δt . The
312 larger the δt , the more smoothed out the random signal becomes in each period, hence the smaller
313 the activity coefficient k_a . To estimate k_a , we used $\delta t = 0.1$ s, the same value that we used for
314 integrating Equation (2) in the simulations. Together, we obtained $k_a = k_f \sqrt{2D/\delta t} = 2.88$ nN.
315 Detailed derivation of this relationship may be found in the supplemental materials.

316 The Cheerios effect coefficient k_c was measured by placing two dead ants on the water surface.
317 Through the same procedure above, we calculated the relative velocity and acceleration as they
318 attracted each other. The attractive force was calculated as the sum of inertia and fluid drag
319 terms of the Langevin model, Equation (2). Fig. S3 shows that the attraction force decreases
320 monotonically with the distance between the ants. We fit the data to the modified Bessel functions,
321 which we expect from theory [41, 40, 39]. We arrived at $k_c = 2.56$ nN ($n = 33$, $R^2 = 0.83$).

322 Simulation

323 We performed 1860 agent-based simulations in MATLAB, consisting of 1200 simulations for raft
324 destabilization and 660 for raft assembly. Raft destabilization simulations were performed with
325 ants initially on a hexagonal lattice, and raft assembly simulations with a square lattice. Circular
326 agents were characterized using four coefficients measured from experiments (m , k_a , k_f , k_c) and one
327 free parameter, the close-range repulsion k_r that had little effect on the results when it was above

328 the chosen value. At each time step, the location and the velocity of each agent were updated
329 according to Equation (2). For raft destabilization simulations, we integrated the equations with a
330 semi-explicit scheme with a time step of $\delta t = 0.1$ s. For each parameter combination, we simulated
331 five minutes of ant motion. The results were averaged over ten trials with different seeds for random
332 number generators.

333 For raft assembly simulations, we started the simulations from agents on square lattices. The
334 simulation domain was a square that was 150 body radii wide. Periodic boundary condition was
335 imposed in both directions so that the density within the domain remained constant. At the
336 beginning of the simulations, agents were placed in 4x4 to 9x9 square formations. Similar to the
337 raft destabilization trials, we simulated five minutes of ant motion, and results were obtained after
338 averaging over ten realizations.

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References

- [1] Anderson, C., Theraulaz, G. & Deneubourg, J.-L. Self-assemblages in insect societies. *Insectes sociaux* **49**, 99–110 (2002).
- [2] Sumpter, D. J. The principles of collective animal behaviour. *Philosophical transactions of the royal society B: Biological Sciences* **361**, 5–22 (2006).
- [3] Camazine, S. *et al.* *Self-organization in biological systems* (Princeton university press, 2020).
- [4] Reid, C. R. *et al.* Army ants dynamically adjust living bridges in response to a cost–benefit trade-off. *Proceedings of the National Academy of Sciences* **112**, 15113–15118 (2015).
- [5] Bonner, J. T. A descriptive study of the development of the slime mold dictyostelium discoideum. *American Journal of Botany* 175–182 (1944).
- [6] Bonner, J. T. & Frascella, E. B. Variations in cell size during the development of the slime mold, dictyostelium discoideum. *The Biological Bulletin* **104**, 297–300 (1953).
- [7] Weihs, D. Hydromechanics of fish schooling. *Nature* **241**, 290–291 (1973).
- [8] Liao, J. C., Beal, D. N., Lauder, G. V. & Triantafyllou, M. S. Fish exploiting vortices decrease muscle activity. *Science* **302**, 1566–1569 (2003).
- [9] Liao, J. C. A review of fish swimming mechanics and behaviour in altered flows. *Philosophical Transactions of the Royal Society B: Biological Sciences* **362**, 1973–1993 (2007).
- [10] Ward, A. & Webster, M. *Sociality: The Behaviour of Group-Living Animals* (Springer International Publishing, 2016). URL <http://link.springer.com/10.1007/978-3-319-28585-6>.
- [11] Grégoire, G. & Chaté, H. Onset of collective and cohesive motion. *Physical review letters* **92**, 025702 (2004).
- [12] Aoki, I. A simulation study on the schooling mechanism in fish. *Bulletin of the Japanese Society of Scientific Fisheries* **48**, 1081–1088 (1982).
- [13] Reynolds, C. W. Flocks, herds and schools: A distributed behavioral model. In *Proceedings of the 14th annual conference on Computer graphics and interactive techniques*, 25–34 (1987).
- [14] Huth, A. & Wissel, C. The simulation of the movement of fish schools. *Journal of theoretical biology* **156**, 365–385 (1992).
- [15] Couzin, I. D., Krause, J., James, R., Ruxton, G. D. & Franks, N. R. Collective memory and spatial sorting in animal groups. *Journal of theoretical biology* **218**, 1–11 (2002).
- [16] Shimoyama, N., Sugawara, K., Mizuguchi, T., Hayakawa, Y. & Sano, M. Collective motion in a system of motile elements. *Physical Review Letters* **76**, 3870 (1996).
- [17] Vicsek, T., Czirók, A., Ben-Jacob, E., Cohen, I. & Shochet, O. Novel type of phase transition in a system of self-driven particles. *Physical review letters* **75**, 1226 (1995).
- [18] Grégoire, G., Chaté, H. & Tu, Y. Moving and staying together without a leader. *Physica D: Nonlinear Phenomena* **181**, 157–170 (2003).

- 378 [19] Couzin, I. D., Krause, J. *et al.* Self-organization and collective behavior in vertebrates. *Ad-*
379 *vances in the Study of Behavior* **32**, 10–1016 (2003).
- 380 [20] Katz, Y., Tunstrøm, K., Ioannou, C. C., Huepe, C. & Couzin, I. D. Inferring the structure and
381 dynamics of interactions in schooling fish. *Proceedings of the National Academy of Sciences*
382 **108**, 18720–18725 (2011).
- 383 [21] Herbert-Read, J. E. *et al.* Inferring the rules of interaction of shoal-
384 ing fish. *Proceedings of the National Academy of Sciences* **108**, 18726–
385 18731 (2011). URL <https://www.pnas.org/content/108/46/18726>.
386 <https://www.pnas.org/content/108/46/18726.full.pdf>.
- 387 [22] Hinz, R. C. & de Polavieja, G. G. Ontogeny of collective behavior reveals a simple attraction
388 rule. *Proceedings of the National Academy of Sciences* **114**, 2295–2300 (2017).
- 389 [23] Zienkiewicz, A. K., Ladu, F., Barton, D. A., Porfiri, M. & Di Bernardo, M. Data-driven
390 modelling of social forces and collective behaviour in zebrafish. *Journal of Theoretical Biology*
391 **443**, 39–51 (2018).
- 392 [24] Ballerini, M. *et al.* Interaction ruling animal collective behavior depends on topological rather
393 than metric distance: Evidence from a field study. *Proceedings of the national academy of*
394 *sciences* **105**, 1232–1237 (2008).
- 395 [25] Bialek, W. *et al.* Statistical mechanics for natural flocks of birds. *Proceedings of the National*
396 *Academy of Sciences* **109**, 4786–4791 (2012).
- 397 [26] Lukeman, R., Li, Y.-X. & Edelstein-Keshet, L. Inferring individual rules from collective be-
398 havior. *Proceedings of the National Academy of Sciences* **107**, 12576–12580 (2010).
- 399 [27] Puckett, J. G., Kelley, D. H. & Ouellette, N. T. Searching for effective forces in laboratory
400 insect swarms. *Scientific reports* **4**, 1–5 (2014).
- 401 [28] Lopez, U., Gautrais, J., Couzin, I. D. & Theraulaz, G. From behavioural analyses to models
402 of collective motion in fish schools. *Interface focus* **2**, 693–707 (2012).
- 403 [29] Tschinkel, W. R. *The fire ants* (Belknap Press, 2013).
- 404 [30] Morrison, L. W., Porter, S. D., Daniels, E. & Korzukhin, M. D. Potential global range
405 expansion of the invasive fire ant, *solenopsis invicta*. *Biological invasions* **6**, 183–191 (2004).
- 406 [31] Mlot, N. J., Tovey, C. A. & Hu, D. L. Fire ants self-assemble into waterproof rafts to survive
407 floods. *Proceedings of the National Academy of Sciences* **108**, 7669–7673 (2011).
- 408 [32] Wagner, R. J., Such, K., Hobbs, E. & Vernerey, F. J. Treadmilling and dynamic protrusions
409 in fire ant rafts. *Journal of the Royal Society Interface* **18**, 20210213 (2021).
- 410 [33] Ko, H., Yu, T.-Y. & Hu, D. L. Fire ant rafts elongate under fluid flows. *Bioinspiration &*
411 *Biomimetics* **17**, 045007 (2022). URL <https://doi.org/10.1088/1748-3190/ac6d98>.
- 412 [34] Mlot, N. J., Tovey, C. & Hu, D. L. Dynamics and shape of large fire ant rafts. *Communicative*
413 *& integrative biology* **5**, 590–597 (2012).
- 414 [35] Morrill, W. L. Red imported fire ant foraging in a greenhouse. *Environmental entomology* **6**,
415 416–418 (1977).

- 416 [36] Yanoviak, S. P. & Frederick, D. Water surface locomotion in tropical canopy ants. *Journal of*
417 *Experimental Biology* **217**, 2163–2170 (2014).
- 418 [37] Pathria, R. K. & Beale, P. D. *Statistical Mechanics* (Elsevier/Academic Press, 2011), 3rd ed
419 edn.
- 420 [38] Löwen, H. Inertial effects of self-propelled particles: From active brownian to active langevin
421 motion. *The Journal of chemical physics* **152**, 040901 (2020).
- 422 [39] Nicolson, M. M. The interaction between floating particles. *Mathematical Proceedings of the*
423 *Cambridge Philosophical Society* **45**, 288–295 (1949).
- 424 [40] Chan, D., Henry Jr, J. & White, L. The interaction of colloidal particles collected at fluid
425 interfaces. *Journal of Colloid and Interface Science* **79**, 410–418 (1981).
- 426 [41] Vella, D. & Mahadevan, L. The “cheerios effect”. *American journal of physics* **73**, 817–825
427 (2005).
- 428 [42] Ko, H., Komilian, K., Waters, J. S. & Hu, D. L. Metabolic scaling
429 of fire ants (*Solenopsis invicta*) engaged in collective behaviors. *Biology*
430 *Open* **11** (2022). URL <https://doi.org/10.1242/bio.059076>. Bio059076,
431 <https://journals.biologists.com/bio/article-pdf/11/2/bio059076/2141612/bio059076.pdf>.
- 432 [43] Beekman, M., Sumpter, D. J. & Ratnieks, F. L. Phase transition between disordered and
433 ordered foraging in pharaoh’s ants. *Proceedings of the National Academy of Sciences* **98**,
434 9703–9706 (2001).
- 435 [44] Simpson, S. J., McCaffery, A. R. & Hägele, B. F. A behavioural analysis of phase change in
436 the desert locust. *Biological reviews* **74**, 461–480 (1999).
- 437 [45] Ariel, G. & Ayali, A. Locust collective motion and its modeling. *PLOS Computational Biology*
438 **11**, e1004522 (2015).
- 439 [46] Ling, H. *et al.* Behavioural plasticity and the transition to order in jackdaw flocks. *Nature*
440 *communications* **10**, 1–7 (2019).
- 441 [47] Nave Jr, G. K. *et al.* Attraction, dynamics, and phase transitions in fire ant tower-building.
442 *Frontiers in Robotics and AI* **7**, 25 (2020).
- 443 [48] Chen, Y. & Ferrell, J. E. C. elegans colony formation as a condensation phenomenon. *Nature*
444 *communications* **12**, 1–10 (2021).
- 445 [49] Liu, Q.-X. *et al.* Phase separation explains a new class of self-organized spatial patterns in
446 ecological systems. *Proceedings of the National Academy of Sciences* **110**, 11905–11910 (2013).
- 447 [50] Becco, C., Vandewalle, N., Delcourt, J. & Poncin, P. Experimental evidences of a structural
448 and dynamical transition in fish school. *Physica A: Statistical Mechanics and its Applications*
449 **367**, 487–493 (2006).
- 450 [51] Liu, G. *et al.* Self-driven phase transitions drive myxococcus xanthus fruiting body formation.
451 *Physical review letters* **122**, 248102 (2019).
- 452 [52] Sinhuber, M. & Ouellette, N. T. Phase coexistence in insect swarms. *Physical review letters*
453 **119**, 178003 (2017).

- 454 [53] Devereux, H. L., Twomey, C. R., Turner, M. S. & Thutupalli, S. Whirligig beetles as corralled
455 active brownian particles. *Journal of the Royal Society Interface* **18**, 20210114 (2021).
- 456 [54] Tan, T. H. *et al.* Development drives dynamics of living chiral crystals (2021). 2105.07507.
- 457 [55] Nielsen, M. G. Ants (hymenoptera: Formicidae) of mangrove and other regularly inundated
458 habitats: life in physiological extreme. *Myrmecological News* **14**, 113–121 (2011).
- 459 [56] Lude, A., Reich, M. & Plachter, H. Life strategies of ants in unpredictable floodplain habitats
460 of alpine rivers (hymenoptera: Formicidae). *Entomologia Generalis* 75–91 (1999).
- 461 [57] Purcell, J., Avril, A., Jaffuel, G., Bates, S. & Chapuisat, M. Ant brood function as life
462 preservers during floods. *PloS one* **9**, e89211 (2014).
- 463 [58] Avril, A., Purcell, J. & Chapuisat, M. Ant workers exhibit specialization and memory during
464 raft formation. *The Science of Nature* **103**, 1–6 (2016).
- 465 [59] Fernandes, G. W., de Castro, F. S., Camarota, F., Blum, J. C. & Maia, R. Ant rafting in an
466 extreme ecosystem. *Sociobiology* **68**, e7430–e7430 (2021).
- 467 [60] Ko, H. *et al.* Air-fluidized aggregates of black soldier fly larvae. *Frontiers in Physics* **9** (2021).
468 URL <https://www.frontiersin.org/articles/10.3389/fphy.2021.734447>.
- 469 [61] Klotsa, D. As above, so below, and also in between: mesoscale active matter in fluids. *Soft
470 matter* **15**, 8946–8950 (2019).
- 471 [62] Zampetaki, A. V., Liebchen, B., Ivlev, A. V. & Löwen, H. Collective self-optimization of
472 communicating active particles. *Proceedings of the National Academy of Sciences* **118** (2021).
- 473 [63] Deng, J., Molaei, M., Chisholm, N. G. & Stebe, K. J. Motile bacteria at oil–water interfaces:
474 *Pseudomonas aeruginosa*. *Langmuir* **36**, 6888–6902 (2020).
- 475 [64] Molaei, M., Chisholm, N. G., Deng, J., Crocker, J. C. & Stebe, K. J. Interfacial flow around
476 brownian colloids. *Physical Review Letters* **126**, 228003 (2021).
- 477 [65] Thomson, S. & Harris, D. Non-equilibrium capillary self-assembly. *Bulletin of the American
478 Physical Society* **66** (2021).
- 479 [66] Chisholm, N. G. & Stebe, K. J. Driven and active colloids at fluid interfaces. *Journal of Fluid
480 Mechanics* **914** (2021).

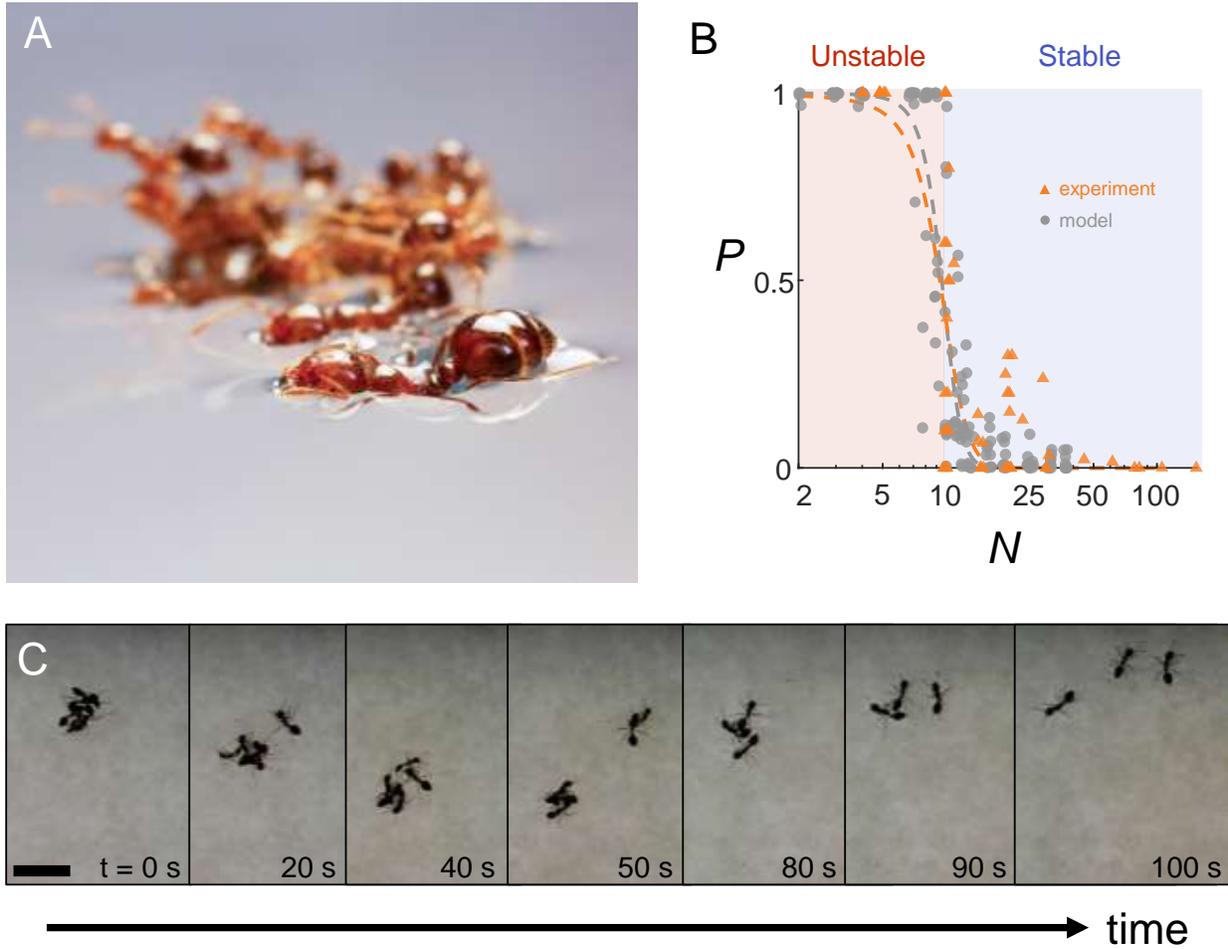


Figure 1: Small rafts are unstable. (A) A raft of twenty ants on the surface of water. (Photo credits: Andre L Magyar and Candler Hobbs) (B) Proportion of stray ants P as a function of the raft size N . Orange triangles indicate experimental results ($n = 72$) and gray circles simulation results ($n = 150$). Orange and gray dashed lines represent the respective best-fit logistic functions for experiments and simulation. (C) A time series showing the destabilization of raft of five ants over 100 s. Scale bar is 1 cm.

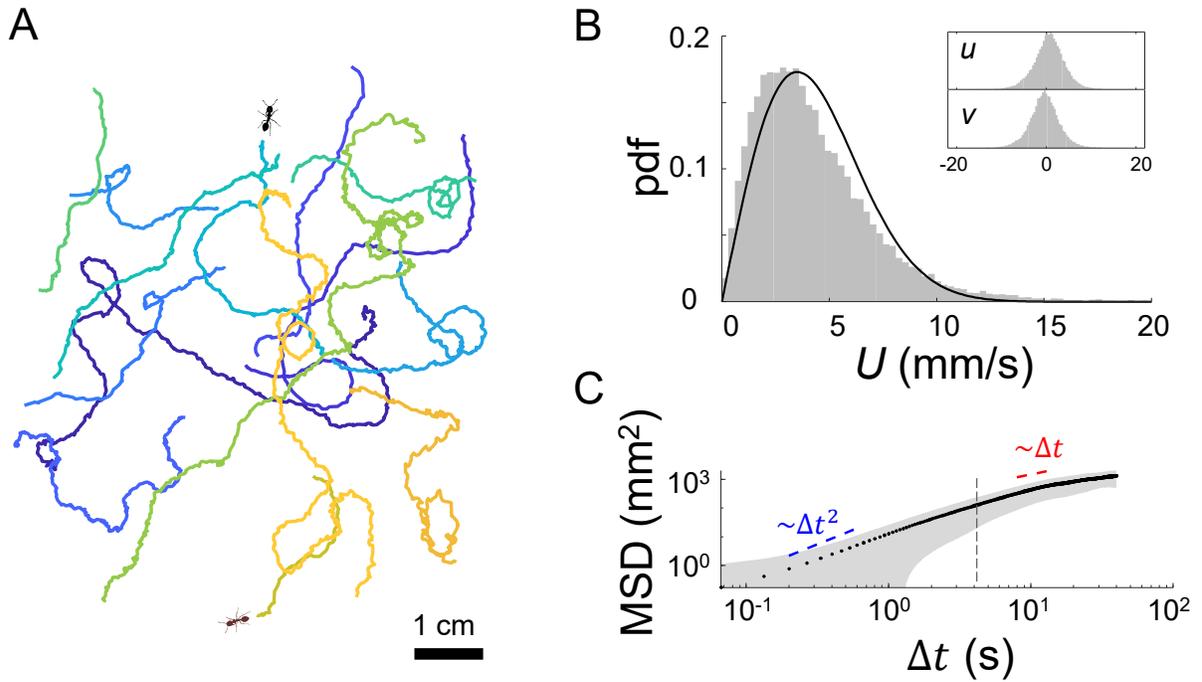


Figure 2: Ants on the water surface behave as inertial random walkers. (A) Ten representative ant trajectories. (B) Probability distribution of the velocity magnitude U . Velocity components u and v are shown in the insets. The red solid line is the two-dimensional Maxwell-Boltzmann distribution with a standard deviation 3.5 mm/s. (C) Mean squared displacement of ant trajectories. The blue dashed line has a slope of 2 and the red a slope of 1, and both are offset from the best fit for clarity. The vertical gray dashed line marks the time scale we obtain through a separate series of experiments $\tau = m/k_f$ 4.3 s. The shaded area represents one standard deviation, which appears distorted under the logarithmic scale. $n = 96$ for both (B) and (C)

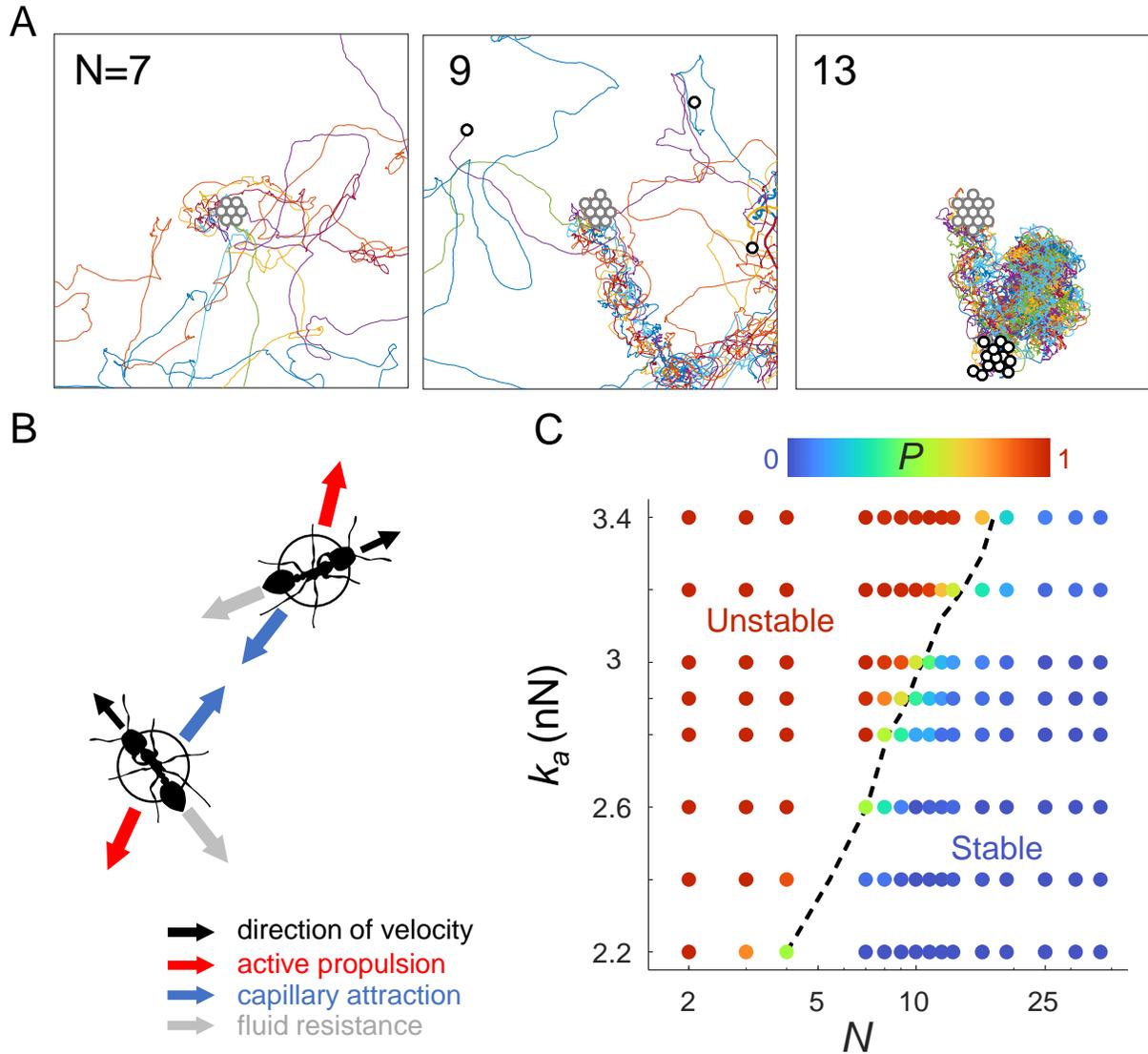


Figure 3: Destabilization of simulated ant rafts. (A) Trajectories of simulated ants as they start from a dense, ordered raft. Initial state of ants shown in red circles and end state shown with black circles. Note that many of the ending states have gone beyond boundaries of the figure. As the number of ants on the raft increases from 7 ants (left) to 9 ants (middle), and to 13 ants (right), rafts become more stable. (B) Schematic of our Langevin model (Equation (2)). (C) Raft stability diagram. Color represents the proportion of stray ants P after five minutes. Black dashed line marks the transition point where half of the ants go astray ($P = 0.5$).

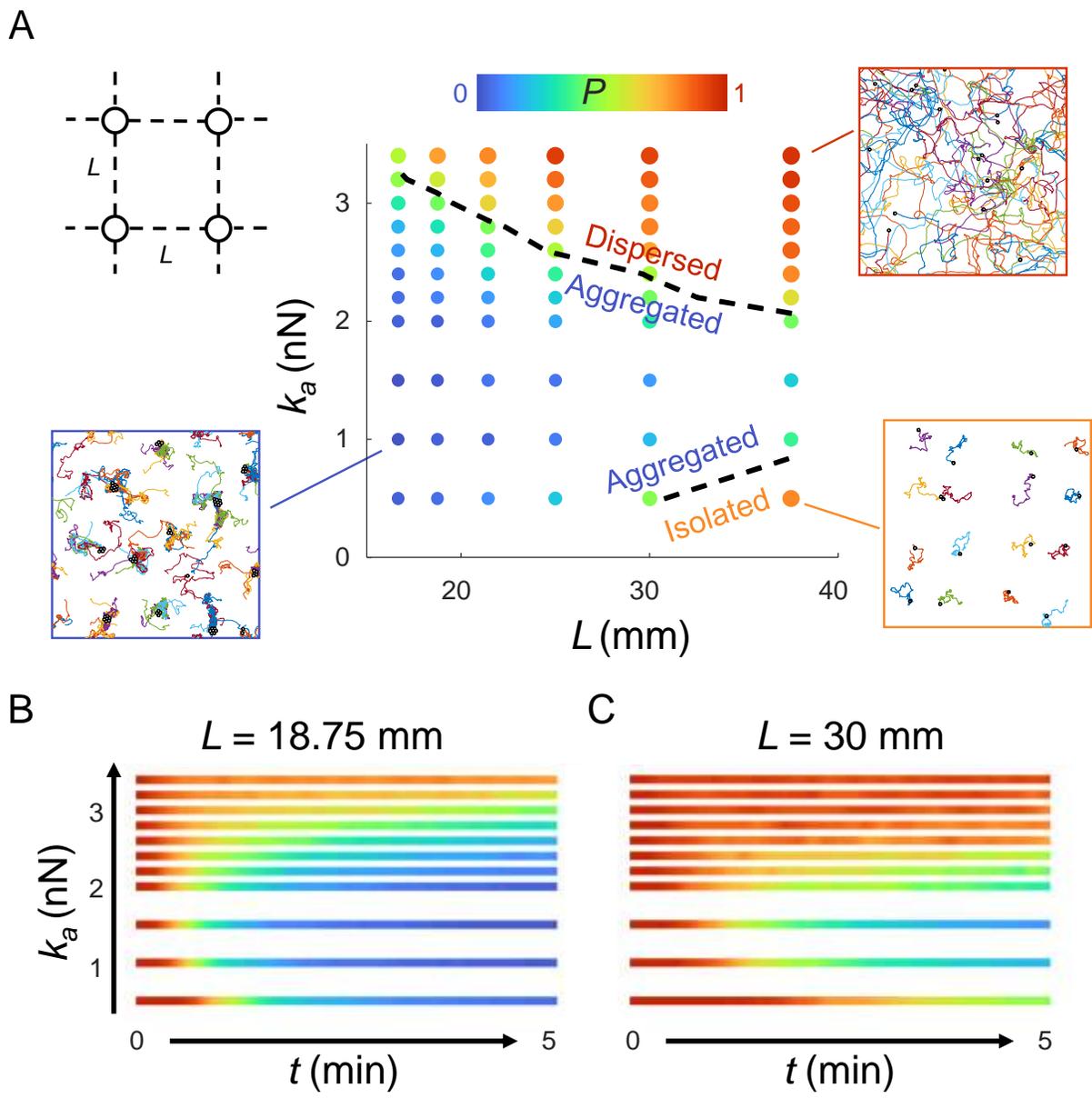


Figure 4: Assembly of ant rafts from different initial spacings. (A) Proportion of stray ants P as a function of activity level k_a and initial spacing L . Top left inset show the definition of initial ant spacing L . The remaining insets show representative trajectories of ants across a time frame of five minutes. Time series of P for (B) small initial spacing $L = 18.75$ mm and (C) large initial spacing 30 mm. Color represents the P for all subplots.