Supplementary Information for

The long-distance flight behavior of Drosophila supports an agent-based model for wind-assisted dispersal in insects.

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Materials and Methods

Release chamber and flies
We fashioned the release chambers from 66 x 41 x 34 cm plastic containers (Sterilite, 1757), which we modified in several ways. To allow us to insert our arms into the chambers without releasing flies, we cut a circular hole in the side of one wall, and fitted it with a long cylindrical cloth sleeve. We drilled small holes into the container lid to permit the flow of air, and lined the inner surface of the lid with fabric, which prevented escapes. This lining consisted of two layers, the inner a polyester mesh, and the outer, a tight-woven cotton less permissive to airflow, that we cut into adjustable flaps. To provide food to the adults during storage and transport, we poured a 1-cm thick layer of sucrose agar (16 grams L⁻¹ sucrose, 6.8 grams L⁻¹ agar, 0.75 grams L⁻¹ CaCl₂, 0.73% EtOH) in the bottom of the chamber, which provided an abundance of water and carbohydrates, but very little protein.

The flies we used in this study were descendants of 200 wild-caught Drosophila melanogaster females maintained in our laboratory since 2013. To expand the population for release prior to each experiment, we placed approximately 10 gravid females in 100 - 140 plastic fly bottles (225 ml) filled with standard cornmeal medium. To transfer flies to the release chambers, we lined the inside of each of the fly bottles with transparency film (3M, CG6000) that we laser cut to closely conform to the inner surface of the bottles, above the level of the food, when placed inside (Supplemental Fig. 7). During wandering stage, the larvae would crawl upward and pupate on the inner surface of the sheets, after which we removed these plastic inserts laden with pupae and hung them like coat hangers on horizontal tubing strung in the release chamber for this purpose. We did not quantify post-pupal mortality rates, but we estimate that 80 – 95% of transferred pupae eclosed and remained healthy through the day of the release. Although we did not explicitly test this, we assume that the reared populations consisted of an equal mixture of male and female flies.

After transferring the pupae, we maintained the release chambers at room temperature, but sometimes placed the chambers in an incubator set to adjust flies’ developmental timing relative to permissive weather forecasts at the field site. We regulated humidity within the chambers by visually checking for condensation on the chamber walls and accordingly opening or closing the outermost cotton flaps. Prior to transporting the flies to the field site, we removed the plastic transfer sheets and hung fabric strips from the horizontal tubing to provide the flies with ample surface on which to perch. During transport in an air-conditioned car, we covered each chamber with a reflective tarp to reduce heating.

Field site and trial protocol
We conducted the release-and-recapture experiments at Coyote Lake, a dry lake bed in the Mojave Desert (Fig. 1A), after receiving a permit from the United States Department of the Interior, Bureau of Land Management, Barstow Field Office. We chose this location because the lack of vegetation within the playa provided a relatively simple visual and
olfactory environment. For most experiments, we deployed ten camera traps at a 1-
kilometer radius from our fly release site located at 35.05883° latitude, -116.74556° longitude. In one initial experiment, we deployed 8 traps at a 250-m radius.

The traps were fashioned by modifying 28 x 28 x 17 cm plastic containers with detachable lids (Container Store, 10062800). The surface of each trap consisted of a 28 x 28 cm white polyester woven mesh surface (Joann Fabric, 400075440594) interdigitated with a hexagonal array of 60 mesh funnels projecting downward into the trap cavity. Each funnel entrance had an oval shape of 12 x 18 mm and extended 15 mm into the trap, terminating with an aperture of 2.5 mm. We cut the fabric pieces for the funnels using a laser cutter, sealed the seams with the laser cutter, and then sewed them onto the mesh surface of the trap. When deployed in the field, the mesh top was pulled taut over the top of the container and secured by attaching the original plastic lid in which everything but the sealable rim had been removed.

We baited the traps with a 500 mL solution of apple juice (Tree Top), champagne yeast (Lalvin EC-1118, 1 gm L⁻¹) and granulated cane sugar (Domino or C&H brand, 154 grams L⁻¹). The mixture was allowed to ferment at 24°C for 1.5 to 2.0 days, and on one occasion for 3.0 days, at which point it provided a source of ethanol, CO₂, and other attractive odors. The variability in fermentation time was due to the fact that we could not perfectly predict the wind conditions at the field site, and occasionally had to conduct a release later than originally planned. We poured the ferment into the traps as we deployed them in the field, and also added a small tub of banana puree (Gerber, 113 gm) to provide flies that entered the traps with an attractive place to land.

For each experiment, we positioned the release site and the surrounding ring of traps using a handheld GPS device with stationary accuracy of 2.5 m. We set up an anemometer (MetOne, direction sensor 020C, speed sensor 010C) at the release site, at a height of ~2 m above the ground. We oriented the direction sensor azimuthally using a magnetic compass and later adjusted for declination. We logged anemometer data at 20 Hz on a Raspberry pi computer with custom-written software.

After deploying the anemometer and traps, we drove our two vehicles approximately 1.5 km away from the release site to limit visual and olfactory stimuli within the experimental arena, leaving one or two people to release the flies. In preliminary releases to test our protocol, we marked the flies with fluorescent dust as had been done in previous studies(1, 2). However, after we found no evidence that *D. melanogaster* were ever present at the lake bed (unless we released them), we did not mark the flies as the presence of the fluorescent power could interfere with the animals’ behavior and flight performance. In our initial experiments, we released one chamber of flies; in later experiments, we generally released two chambers at the same time. Five minutes after releasing the flies, we sealed the chamber(s) in plastic bags in an effort to contain olfactory cues and the remaining flies. Approximately one hour after the release, we began collecting trapped flies (Fig. 1C), which we preserved in ethanol. After transporting the preserved flies to the laboratory, we counted the number of *D. melanogaster* and inspected the collection for local species that might be confused with *D. melanogaster* in our camera images. The only other drosophilid fly we found in our traps over the course
of the all experiments, was *Drosophila suzukii*, of which we collected a total of 7 individuals over all the releases.

We monitored our baited traps with cameras (Raspberry pi, Pi NoIR Camera V2) mounted 27 cm above each trap, which took time-lapse images of the trap surface at 0.5 or (in some experiments) 0.33 Hz. We controlled the cameras with Raspberry pi computers, on which we had installed an interface to control camera parameters (https://github.com/silvanmelchior/RPi_Cam_Web_Interface). Among all cameras and our anemometer logger, we maintained clock synchronization within ~1 second by outfitting each Raspberry pi with a real-time clock (Adafruit, DS3231) (Fig. 1C).

**Estimating size of release population**
To estimate numbers of flies released, we counted the pupae on a subset (~30%) of the pupal transfer sheets by taking digital images and subjecting them to a simple machine-vision analysis using OpenCV (3.3.1) for Python. We generated a binary image via adaptive thresholding (threshold and neighborhood area determined empirically, against manual annotation), from which we detected contours. Each image yielded a histogram of contour sizes, and we used the position of the prominent, small-pixel-area peak to estimate the size of a single pupa. Dividing the total contour area by the single pupa area provided our estimate of the number of pupae on that sheet.

**Quantifying fly arrivals at baited camera traps**
We analyzed the time lapse images from each camera with custom-written machine-vision software, supplemented by human annotation. The first step in our machine-vision pipeline was applying a binary mask to exclude the lakebed surface and any corners of trap fabric that might move in the wind. We then ran the masked color image stack through a mixed-Gaussian background subtractor (OpenCV 3.3.1), trained on a sliding window (typically 25 frames) to account for moving shadows. To avoid false negatives in cases in which flies paused on the trap surface, we interposed one or two frames between this background-training window and the analysis frame from which foreground objects would be detected. We detected foreground pixels on the basis of their squared Mahalanobis distance (typically 10 - 25) from the background model. We excluded brighter-than-background pixels and then smoothed and detected contours from this binary image. We classified each contour as: 1) a fly atop the trap, 2) a fly within the trap, or 3) a non-fly on the basis of its area, eccentricity, and contrast relative to surrounding pixels.

For each trap analyzed, we used a graphical interface to manually evaluate frames annotated by our automated analysis. We generally found good agreement for the scoring of flies atop the trap, but higher rates of both false positives and false negatives for flies within the trap, which is not surprising given that such flies were obscured beneath the mesh surface. Our automated analysis excluded insects that were either too small or too big, but was generally unable to exclude *Drosophila*-sized insects (e.g. a small beetle) even if a human viewer could easily identify them from the digital image as a different species. Such misclassifications often led to a background level of false positives, essentially a noise floor on which the arrival wave of released flies was superimposed. To better estimate the start of the arrival wave, we smoothed the on-trap data with a sliding
mean of 10 frames, and calculated the mean and standard deviation during the first 200 seconds after the release of the flies, which we considered as the characteristics of our noise floor immediately prior to the arrival of the flies. We then used these statistical values to set minimum and maximum values (0.2*(mean + 2.0 STD) and mean + 2.0 STD, respectively) for a Schmitt classifier. This classifier binarized our time-series data into bouts above, or below, the noise floor. The start of the longest bout above the noise floor was declared the time of the arrival wave. In addition to estimating the start of the arrival wave with our automated analysis, we manually scored the first arrival of a Drosophila-shaped insect in the image stream from each trap, starting at 200 seconds after the fly release and continuing until we unambiguously detected the first fly (Supplemental Fig. 1). While manually scoring, we occluded the time stamps on each image to reduce observer bias.

For each trap, we used the arrival time of the first fly to calculate average groundspeed along the trajectory ($g_{traj}$), by assuming a minimum travel distance of 1 km. The average windspeed along the trajectory ($w_{traj}$) was calculated as:

$$w_{traj} = \frac{\sum_{n=1}^{N} \overrightarrow{w_n} \cdot \overrightarrow{traj}}{N},$$

where $\overrightarrow{w_n}$ is the wind velocity vector and $\overrightarrow{traj}$ is the unit vector of the average trajectory to the trap. The summation includes all the wind measurements made from the time of release (n=1) to the arrival time of the first fly (n=N).

**Simulations off our behavioral models**

Each simulated run of our dispersal models consisted of calculating the resultant vectors according to 1) the rules governing the flies’ azimuthal orientation, and 2) whether flies regulated longitudinal groundspeed (Fig. 5). For models I and II, we fixed the flies’ heading; for models III and IV, we fixed the flies’ trajectory. To generate the variation in wind that mimicked the field conditions, we permuted the direction and speed of the simulated wind in each run, using 180 wind directions linearly spaced around a circle, and 261 windspeeds, sampled randomly from a probability density function measured in the field. This probability function was generated non-parametrically using a kernel density estimate (Gaussian kernel with a standard deviation of 0.1 m s\(^{-1}\)) of vector-averaged windspeeds, $w_{ave}$, calculated from each of the 30 field data points used to evaluate the models:

$$\overrightarrow{w}_{ave} = \frac{\sum_{n=1}^{N} \overrightarrow{w_n}}{N},$$

in which the summation interval includes all wind data points from the time of release (n=1) to the arrival time of the first fly (n=N).

Our models imposed maximum and minimum limits on the airspeeds that flies could actively exert along their body axis ($air_{max} = 1.8$ m s\(^{-1}\), $air_{min} = -0.2$ m s\(^{-1}\)). In the case of models I and III, flies regulated the groundspeed along their body axis to a preferred speed of 1.0 m s\(^{-1}\), and in models II and IV, flies simply exerted a forward airspeed of 1.0
m s\(^{-1}\). Only under one condition did we allow flies to adjust their airspeed in models II and IV: if the wind was blowing them backwards along their body axis, in these cases we allowed flies to increase airspeed up to \(\text{air}_{\text{max}}\). We assumed that flies did not tolerate negative groundspeeds parallel to their body axis (i.e. they would not allow themselves to fly backwards); in all models, if backwards flight was unavoidable given the set airspeed limits, we simply dropped the fly out of the simulation. However, we repeated all simulations without this “dropout” assumption and found that results were qualitatively similar.

**Statistical comparisons of four behavioral models**

From the \(w_{\text{traj}}\) and \(g_{\text{traj}}\) values of all 180 x 261 runs of each model, we generated the two-dimensional probability density function (PDF) using a Gaussian kernel with a standard deviation = 0.05 m s\(^{-1}\). The kernels were not truncated, to ensure that all field data points overlaid non-zero values of the PDF. We then performed a likelihood ratio analysis, testing whether the three alternate models (II, III, and IV) could explain the field data better than model I. The log Bayes factor we report for each pairwise test was calculated as:

\[
\Sigma_{n=0}^{n=30} \ln \left( \frac{\lambda_{n,I}}{\lambda_{n,X}} \right)
\]

where \(\lambda_{n,X}\) is the likelihood score for data point \(n\) given its corresponding probability in the PDF of model \(X\). We performed this procedure over 40,000 bootstrap iterations of the field data, generating a distribution of log Bayes factors for each pairwise model test. In these distributions, any values below zero indicate iterations in which the alternate model explains the resampled field data better than does model I. We performed these analyses twice, once including and once excluding two suspected outlying field data points (annotated with crosses, Fig 6).

**Sensitivity analysis of our model comparisons**

To determine whether our model comparisons were robust to our selection of free parameters for each model, we ran simulations over a wide range of values for each of the free parameters. For models I and III, we ran 864 simulations, testing all permutations of 14 values of \(g_{\text{pref}}\), 14 values of \(\text{air}_{\text{max}}\), and 6 values of \(\text{air}_{\text{min}}\), omitting 312 parameter sets in which \(g_{\text{pref}}\) would have exceeded \(\text{air}_{\text{max}}\) (Supplemental Figs. 2 and 3). For models II and IV, with one free parameter, we tested 10 values of fixed airspeed. We ran a within-model procedure to determine the parameter set that would allow each model to best fit our data. To do this, we chose one set of parameter values as the reference simulation for pairwise comparisons to each other simulation of that same model; these comparisons assessed model fit to our field data (excluding the two outlying data points) using the mean of a bootstrapped distribution of log Bayes factors, as in Fig. 6. After optimizing each model’s parameter values in this manner, we performed pairwise comparisons across the individually-optimized models (Supplemental Fig. 4), again using the same metric as described for Fig. 6.
**Other summary statistics**

To describe the effect of wind on the distribution of final trap counts (Fig. 2), we used both a parametric and non-parametric statistical summary. For the former, we fit a von Mises distribution to the trap counts and report the reciprocal measure of circular dispersion, $\kappa$. For the latter, we calculated the circular variance of trap counts by treating each fly as a vector of length one, pointing in the direction of the trap at which it was caught. These vectors were summed and the resultant length was divided by the total number of flies caught, yielding the vector strength for that release. The circular variance is equal to the vector strength subtracted from 1.

**Advection-diffusion simulation**

Our goal was to use the advection-diffusion equation to estimate the first arrival times at traps placed either 1k or 250m from a release site so that the predictions could be compared directly with the $(w_{\text{traj}}, g_{\text{traj}})$ coordinate pairs based on the ‘first arrivals’ data in our field experiments. Note, that $w_{\text{traj}}$ and $g_{\text{traj}}$ are directly related to the angle and time that an insect arrives at one of the circularly arranged trap rings via a coordinate transformation. For this reason, we initially calculated the probability densities for flies exiting the trap rings as function time and angle. We then converted these data to functions of $w_{\text{traj}}$ and $g_{\text{traj}}$ using the appropriate coordinate transformation. We start with a simplified version of the 2-dimensional advection-diffusion equation, which assumes a constant diffusion coefficient, $D$, and zero divergence velocity field $\vec{v}$:

$$\frac{\partial u}{\partial t} = D \nabla^2 u - \vec{v} \cdot \nabla u,$$  \hspace{1cm} (5)

where $u$ is the variable of interest. The first term on the right-hand side of equation 5 describes the transport of $u$ due to diffusion, the second term describes the transport due to advection.

For the purposes of this model we will assume that the variable of interest, $u(x, y, t)$, represents the probability density of the insect’s position. We assume the velocity field is constant and of the form $\vec{v} = (v_x, 0)$. As described below, we derive the probability density functions for flies exiting the 1k or 250m trap radius, in terms of $w_{\text{traj}}$ and $g_{\text{traj}}$ so we can compare our simulations to our field data as in our agent-based models. This process is summarized by the steps below.

As an idealized representation of the region surrounding the release site, we choose as the domain, $D$, a closed disk of radius $R$ centered at the origin. The boundary of this disk, which we denote $\Gamma$, is a circle of radius $R$ centered at the origin. In order to calculate the probability density for flies exiting the circular boundary, we use an absorbing boundary condition where $u(x, y, t) = 0$ for all $x, y$ on $\Gamma$. This assumption posits that once an insect reaches the boundary, it is absorbed by the boundary and no longer accounted for in the probability density $u$. This boundary condition does not imply a change in the underlying behavioral model for dispersal, which is Brownian motion with drift. Instead it
is used so that the flux across the boundary, $\Gamma'$, can be used to calculate the probability density for first exit across the boundary as a function of angle and time.

At the start of our field experiments, all of the flies were initially located at the center of the ring of traps. We thus select an initial condition for our probability density, $u$, which reflects this initial state. While a 2-dimensional dirac delta function would seem a natural choice, it is problematic to implement with the numerical methods we will employ. Instead, we will use the exact solution of equation 5 on the plane with a delta function initial condition and evolve the solution function for a short period of time. This will give us an initial condition with finite values and with some spatial extent that will work well with numerical methods. For small $t$, the exact solution inside the circle of radius $R$, will be arbitrarily close to the solution of equation 5 on $D$ with an absorbing boundary condition. In addition, we can account for the small amount of time, which is used to “evolve” the delta function, by assuming our numerical solutions start at that time rather than $t = 0$.

The first-exit probability density for crossing the boundary, $\Gamma'$, as a function of $\theta$ and $t$, is calculated in terms of the flux across the boundary $\Gamma'$ as follows:

$$\varphi(\theta, t) = R \{ \vec{v} \cdot \nabla u \} \cdot \vec{n},$$

where $\vec{n}$ is the outward-pointing normal vector.

To compare our model results to the field data, we need a coordinate transformation that allows us to convert the probability density $\phi$, given in equation 6 into a probability density in terms of the variables $g_{\text{traj}}$ and $w_{\text{traj}}$. We can write $w_{\text{traj}}$ and $g_{\text{traj}}$ in terms of the angle $\theta$ and time $t$ at which the insect exits the disk as follows:

$$(w_{\text{traj}}(\theta, t), g_{\text{traj}}(\theta, t)) = (v_x \cos \theta, R/t).$$

This function is two-to-one, since $w_{\text{traj}}$ has the same value for both $\theta$ and $-\theta$. However, we can treat each half of the boundary, $[0, \pi]$ and $[-\pi, 0]$, separately to get well defined invertable coordinate transformations. The separate coordinate transforms are then used to transform the probability density, via change of variables, for each half of the boundary to a function in terms of the coordinates $w_{\text{traj}}$ and $g_{\text{traj}}$. The results from both halves of the boundary are then combined to generate the probability density, $\phi(w_{\text{traj}}, g_{\text{traj}})$ for the whole boundary.

In our treatment of the advection-diffusion equation we assume that wind speed and diffusion coefficient are constants. Thus any individual solution of this equation, and the resulting probability density for exiting the disk, $\phi$, will be specific to this choice of wind speed and diffusion coefficient. However, we want to create a combined probability density function, for exiting the disk that reflects the overall variation in wind speeds encountered during all the 1-km trap experiments (or the single trial condition in the 250-m trap experiment). During the release-and-recapture experiments an anemometer was used to record the wind speed and direction. A probability density for wind speed, $\rho(s)$, was generated non-parametrically from this data using our kernel density estimate
described earlier. We use this empirically generated density for wind speed to create our representative sample of wind speeds and the resulting weights used for summation when creating the combined probability density, which we use for each diffusion coefficient we consider.

The advection diffusion equation was solved using the FEniCS platform (https://fenicsproject.org). Space was discretized using the Galerkin Finite Element Method and a second order implicit Crank-Nicolson finite difference method was used to discretize the time variable. The finite element mesh representing the disk was generated using the mshr mesh generation component of FEniCS with a mesh resolution setting of 100. This resulted in a mesh with approximately 40,000 cells. The cells’ sizes were between 10m and 20m for the 1-km trap radius and between 2.5m and 5m for the 250-m trap radius where the cell size is defined as the greatest distance between any two vertices in the cell. For computing the flux the outer boundary of the disk was partitioned into 50 flux regions each covering a 7.2 degree arc of the outer boundary. The numerical solution was calculated using time steps of t=2s and t=10s for the R=250m and R=1000m disks respectively.
Supplemental Fig. 1. Calculation of arrival time at baited camera traps. (A—I) Nine traps’ arrival dynamics scored by machine vision (colored traces), annotated with the time of the first manually annotated fly arrival (broken lines) and with the time of the arrival wave (black solid lines) calculated from the machine vision trace; for (A) and (B), we show the cropped frame of the first fly’s first appearance. (J) Relationship between the latency to the arrival wave (wave arr.) and latency to the manually-annotated first fly (1st arr.), overlaid with a unity line. Point colors correspond to data in (A—I) above. (K) Relationship between \( w_{\text{traj}} \) (windspeed along trajectory) and \( g_{\text{traj}} \) (groundspeed along trajectory) for all 30 data points (black) used previously (e.g. Fig. 6); colors indicate traps whose machine-vision data are presented in (A—I).
Supplemental Fig. 2. Optimization of each model’s parameters on the basis of fit to the field data. (A–D) For each model, one set of parameter values (star) served as the reference simulation for intra-model comparisons of relative fit to field data, using the mean of a bootstrapped distribution of log Bayes factors (color map). (A) For model I, varying flies’ preferred groundspeed (\(g_{\text{pref}}\), columns) and maximum airspeed (\(a_{\text{max}}\), rows) yields a map of log Bayes factors. The upper-right region, where \(g_{\text{pref}} > a_{\text{max}}\), is biologically implausible and was not explored. Lower log Bayes factors (darker colors) indicate parameter pairs allowing the model to perform relatively better in its fit to field data. The third free parameter, the minimum airspeed (\(a_{\text{min}}\)), was far less influential on model fit (data not shown), so we present the map only for a single value of \(a_{\text{min}} = -0.2\) m s\(^{-1}\). Note the color map saturates well below the highest log Bayes factors. (B) Model II, lacking the feature of groundspeed regulation, has only the fly’s fixed airspeed (varying by row) as a free parameter. (C) Model III has the same free parameters as does model I. Here, also, we only show the map corresponding to \(a_{\text{min}} = -0.2\) m s\(^{-1}\). (D) Model IV’s fit to the field data as a function of its single free parameter, the fixed airspeed.
Supplemental Fig. 3. Interactive figure to illustrate how each model's parameters influence fit to the field data.

This file is hosted at
https://kateleitch.github.io/s.html#SF3_interactive
Supplemental Fig. 4. Comparing optimized models confirms that models incorporating longitudinal groundspeed regulation best explain the field data. (A–D) After undergoing parameter optimization (see Supplemental Fig. 3), each model generates relationships between \( w_{\text{traj}} \) (abscissa) and \( g_{\text{traj}} \) (ordinate). Grayscale shading denotes each models’ normalized probability density function (PDF). Field measurements (circles) are plotted over each model’s PDF; model likelihood values were compared pairwise. In an alternate analysis, two points considered possible outliers (overlaid with crosses) were excluded from the likelihood-ratio calculation. (A) PDF generated by model I, with optimized values of \( \text{air}_{\text{min}} = -0.5 \text{ m s}^{-1}, \text{air}_{\text{max}} = 2.0 \text{ m s}^{-1}, \) and \( g_{\text{pref}} = 1.25 \text{ m s}^{-1}. \) (B) PDF generated by model II, with its optimized airspeed of 1.5 m s\(^{-1}\). (Inset) Bootstrapping the field data over 40,000 iterations generated a distribution of log likelihood ratios. Positive values denote iterations in which the optimized model I predicted resampled data better than did optimized model II. The mean of this distribution was 169 (black histogram); excluding the two outlying data points, 104 (gray histogram). (C) PDF generated by model III, with its optimized values of \( \text{air}_{\text{min}} = -0.2 \text{ m s}^{-1}, \text{air}_{\text{max}} = 2.0 \text{ m s}^{-1}, \) and \( g_{\text{pref}} = 1.5 \text{ m s}^{-1}. \) (Inset) Comparing optimized model I with optimized model III. Distribution mean, 9; excluding outliers, 70. (D) PDF generated by model IV, with its optimized airspeed of 1.5 m s\(^{-1}\). (Inset) Here comparing optimized model I with optimized model IV. Distribution mean, 203; excluding outliers, 150.
Supplemental Fig. 5. In all behavioral models, the angular distribution of population trajectories narrows with increasing wind speed. All four behavioral models, plus the advection-diffusion model, show a decrease in the circular variance of simulated flies’ azimuthal trajectories with increasing wind speed. For each model, we calculated circular variance in two ways: first, by simply including all simulated flies (right-shifted), and second, by including only those simulated flies that reached the 1-km trap radius within an hour (left-shifted). The areas between these two lines are filled for graphical clarity. Our field data (repeated from Fig. 2C, black circles) are overlaid for reference.
Supplemental Fig. 6. Stochasticity in flies’ headings can slightly improve the fit of agent-based model I to the field data. Twelve variants of model I (Fig. 6E) in which durations of straight flight were punctuated by random turns. These twelve model variants explored two aspects of stochasticity. First, depicted column-wise, we varied the run-length distributions, from which flies randomly drew their straight-flight durations (left column, $\mu = 1$, a bias toward long run-lengths; right column, $\mu = 2$, a bias toward short run lengths; central column, $\mu = 1.5$, intermediate run-lengths), where $\mu$ is the power law scaling parameter and the run length distributions which ran from 1 s to 1000 s. Second, depicted row-wise, we varied the distributions from which flies randomly drew the heading angle for each subsequent bout of straight flight (top row, $\kappa = 0.1$, an almost uniformly circular distribution of headings; bottom row, $\kappa = 500$, a distribution with extremely low variance; central two rows, $\kappa = 1$ and $\kappa = 10$, heading distributions with intermediate variance). For each of these twelve models augmented with stochasticity, grayscale shading shows the normalized probability density function (PDF) for the relationship between our two field-measureable parameters, $w_{\text{traj}}$ and $g_{\text{traj}}$. Field measurements (circles) are plotted over each PDF; and likelihood values at each point were used for pairwise model comparisons. Insets: bootstrapping the field data over 40,000 iterations generated a distribution of log likelihood ratios comparing each stochastic variant with the original, straight-path model I (Fig. 6E). Positive values denote iterations in which model I, without stochasticity, better predicted the resampled data than did the stochastic variant. Black distributions consider all field data points, and gray distributions exclude two outliers (overlaid with crosses). Each inset is annotated with its bootstrapped distribution means.
Supplemental Fig. 7. Rearing Drosophila for synchronized field release. (A) Oblique view of a fly-rearing bottle with a pupal sheet partially inserted; when fully inserted, the sheet conforms to the bottle’s inner wall. (B) A sheet bearing hundreds of pupae, removed from the bottle for pupal counting and transfer to the release chamber.
SI References
