

1 **Navigational strategies underlying temporal phototaxis in *Drosophila* larvae**

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3 **Running title: Temporal phototaxis in *Drosophila* larvae**

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22

23 **Summary statement**

24 Using a novel closed-loop behavioral assay, we show that *Drosophila* larvae can navigate light
25 gradients exclusively using temporal cues. Analyzing and modeling their behavior in detail, we
26 propose that larvae achieve this by integrating luminance change during runs.

27

28 **Abstract**

29 Navigating across light gradients is essential for survival for many animals. However, we still
30 have a poor understanding of the algorithms that underlie such behaviors. Here we develop a
31 novel phototaxis assay for *Drosophila* larvae in which light intensity is always spatially uniform
32 but updates depending on the location of the animal in the arena. Even though larvae can only
33 rely on temporal cues in this closed-loop setup, we find that they are capable of finding
34 preferred areas of low light intensity. Further detailed analysis of their behavior reveals that
35 larvae turn more frequently and that heading angle changes increase when they experience
36 luminance increments over extended periods of time. We suggest that temporal integration of
37 luminance change during runs is an important – and so far largely unexplored – element of
38 phototaxis.
39

40 **Introduction**

41 Many animals have evolved behaviors to find favorable locations in complex natural
42 environments. Such behaviors include chemotaxis to approach or avoid chemical stimuli;
43 thermotaxis to find cooler or warmer regions; and phototaxis to approach or avoid light (Luo *et*
44 *al.*, 2010; Gomez-Marín *et al.*, 2011; Kane *et al.*, 2013; Gomez-Marín and Louis, 2014; Gepner
45 *et al.*, 2015; Klein *et al.*, 2015).

46 *Drosophila* larvae are negatively phototactic, preferring darker regions (Sawin *et al.*, 1994).
47 To navigate, larvae alternate between runs and turns. During runs, larvae move relatively
48 straight. During turns, they slow down and perform head-casts (Lahiri *et al.*, 2011) to sample
49 their environment for navigational decisions (Gomez-Marín and Louis, 2012; Kane *et al.*, 2013;
50 Humberg *et al.*, 2018; Humberg and Sprecher, 2018). However, it is unclear whether such local
51 spatial sampling is necessary to perform phototaxis. Zebrafish larvae, for example, can perform
52 phototaxis even when light intensity is uniform across space but changes over time with the
53 animal's position (Chen and Engert, 2014). In a purely temporal phototaxis assay, spatial
54 information is absent, so navigation must depend on other cues.

55 Previous work indicates that as brightness increases, *Drosophila* larvae make shorter runs
56 and bigger turns (Kane *et al.*, 2013; Humberg *et al.*, 2018). This is reminiscent of chemotactic
57 strategies, where decreasing concentrations of a favorable odorant increase the likelihood of
58 turning (Gomez-Marín *et al.*, 2011). While it has been shown that temporal sampling of olfactory
59 cues is sufficient to guide chemotaxis (Schulze *et al.*, 2015), it remains unclear whether larvae
60 can use a purely temporal strategy for visual navigation.

61 Using a virtual landscape in which luminance is always spatially uniform but depends on the
62 location of the animal in the arena, we confirm that larvae can perform phototaxis by modulating
63 run-length and heading angle. Our data indicates that larvae achieve this by integrating
64 luminance change during runs.

65

66 **Materials and methods**

67

68 Experimental setup

69 All experiments were performed using wild-type 2nd-instar *Drosophila melanogaster* larvae
70 collected 3–4 days after egg-laying. This age was chosen to ensure consistent phototactic
71 behavior because older larvae might change their light preference (Sawin-McCormack *et al.*,
72 1995). Larvae were raised on agarose plates with grape juice and yeast paste, with a 12h/12h
73 light-dark cycle at 22°C and 60% humidity. Before experiments, larvae were washed in droplets
74 of deionized water. All experiments were carried out between 2 pm and 7 pm to avoid potential
75 circadian effects (Mazzoni *et al.*, 2005).

76 Larvae were placed in the center of a custom-made circular acrylic dish (6 cm radius) filled
77 with a thin layer of freshly made 2% agarose (**Fig. 1A**). As previously described (Bahl and
78 Engert, 2020), spatially uniform whole-field illumination was presented via a projector (60 Hz,
79 AAXA P300 Pico Projector) from below. Light intensity was measured with an iPhone 11 Pro
80 (Lux Light Meter Pro app) at a distance of about 5 cm, giving values from 0 Lux (dark) to 410
81 Lux (white). For tracking, the scene was illuminated using infrared LED panels (940 nm panel,
82 Cop Security). A high-speed camera (90 Hz, Grasshopper3-NIR, FLIR Systems) with an
83 infrared filter (R72, Hoya) was used to track the larva's centroid position in real-time. 8
84 independent arenas were operated in parallel, making the system medium to high-throughput
85 and relatively cost-effective.

86 Three virtual light intensity landscapes were used: a “Valley” stimulus, a “Ramp” stimulus,
87 and a “Constant” stimulus. For the “Valley” and “Ramp” stimuli, the spatially uniform light
88 intensity (λ) was updated in closed-loop according to $\lambda = 410 \cdot (r - 3)^2 / 9$ (**Fig. 1B**) and
89 $\lambda = 410 \cdot (1 - \sqrt{1 - r/6})$ (**Fig. S1C**), respectively, where r is the larva's radial distance to the
90 center of the arena. Both profiles ensure that luminance levels near the wall are high,
91 decreasing the edge preference of larvae and reducing boundary effects. For the “Constant”
92 stimulus, luminance values remained gray ($\lambda = 0.5$) regardless of the larva's position. The
93 position of the animal was defined by its centroid, rather than its head or tail. This choice
94 significantly simplified the experimental procedure and is justified as larvae are small in size
95 relative to the slowly changing always spatially uniform virtual luminance landscapes. The
96 latency between the detection of the animal's position and the closed-loop update of the visual
97 stimulus is estimated to be ~50 ms (tracking delay ~10 ms + ~40 ms delay for the

98 communication between computer CPU, GPU, and projector), which is negligible given the slow
99 crawling speed of larvae.

100 Each experiment lasted for 60 min. For all stimuli, animals were presented with constant
101 gray during the first 15 min, allowing them to distribute in the arena.

102

103 Data analysis and statistics

104 All data analysis was performed using custom-written Python code on the 45 min period after
105 acclimatization. To avoid tracking problems and minimize boundary effects, data were excluded
106 where larvae were within 0.1 cm distance to the edge.

107 The circular arena was binned in three concentric regions depending on the radius r : $r = 0 -$
108 2 cm , $r = 2 - 4\text{ cm}$, and $r = 4 - 6\text{ cm}$. These regions were named the “Bright” center, the “Dark”
109 ring, and the “Bright” ring for the “Valley” stimulus (**Fig. 1B**) and the “Dark” center, the “Gray”
110 ring, and the “Bright” ring for the “Ramp” stimulus (**Fig. S1C**). Animal speed was computed by
111 interpolating the trajectory to 1 s bins and then by taking the average distance of consecutive
112 points (**Fig. 1E**).

113 Turn events were detected using a pose estimation toolbox, DeepPoseKit (Graving *et al.*,
114 2019). 100 frames were manually annotated (head, centroid, and tail) to train the network, which
115 was then used to predict animal posture across all frames from all animals. Body curvature was
116 defined as the angle between the tail-to-centroid vector and the centroid-to-head vector (**Fig.**
117 **2A**). In a few frames, the algorithm detected the head and the tail at the same location, leading
118 to the transient detection of large curvatures. These events were discarded by low-pass filtering
119 traces with a Butterworth filter (cutoff frequency: 3 Hz). Turn events were defined as a local
120 curvature peak above 30° and needed to be separated from the previous such event by at least
121 2 s in time and 0.2 cm in space.

122 Turn angles were defined as the angle between the location in the arena 2 s before a turn
123 event and 2 s after. Run-length was defined as the time between consecutive turn events. Each
124 turn event was labeled as “Dark” or “Bright”, based on the luminance equations and binning
125 described above (Dark: less than 45 Lux, Bright: otherwise), and as “Darkening” or “Brightening”
126 based on the change in luminance since the last turn event (**Fig. 2F,G**). As turn events are
127 typically short and spatially confined, by stimulus design, the whole-field luminance change
128 during such events is nearly zero. Hence, the luminance change during turns was defined as
129 the brightness difference 1 s before and 1 s after the event (**Fig. 2D**). The luminance change

130 during runs was defined as the difference in luminance between two consecutive turn events
131 (**Fig. 2D**).

132 Notably, as a control for the spatial arrangement of our stimulus and boundary effects, the
133 same binning, naming conventions, and analysis methods were also used for the “Constant”
134 stimulus even though the arena remained constantly gray for those animals. For example,
135 control animals that spend time in the “Dark” ring (gray open circles in **Fig. 1D**) actually perceive
136 constant “Gray” during the entire experiment.

137 Two-sample t-tests were used for pairwise comparisons between the experimental and
138 control data. Paired-sample t-tests were used for pairwise comparisons within groups. Larvae
139 were discarded if they spent more than 99% of the experimental time in a single region or if their
140 speed was zero. All data analysis was done automatically in the same way for the experimental
141 and control groups.

142

143 Modeling

144 Simulations (**Fig. 3** and **Fig. S3**) were custom-written in Python 3.7, using the high-performance
145 Python compiler numba. Simulations were performed using Euler’s Method with a timestep of dt
146 = 0.01 s. Model larvae were initialized with a random position and orientation. At each time step,
147 larvae stochastically chose one of two possible actions: They could either move forward, with a
148 speed of 0.04 cm/s (parameter was taken from the experiment, **Fig. 1E**), or turn. The baseline
149 probability for turning was $p = 0.00066$. This value was directly computed from the experiment
150 to match the measured average run-length of $T = 15$ s (**Fig. 2E,F**), following $p = dt / T$. When
151 making turns, turn angles were drawn from a Gaussian distribution with a baseline standard
152 deviation of 32° , matching the experimental value (**Fig. 2C,E,F**). If model larvae reached the
153 edge, a new random direction vector was chosen, preventing them from leaving the arena.

154 In correspondence with our experimental findings (**Fig. 2E,F**), the model was equipped with
155 four additional navigational rules (**Fig. 3A**).

156 “Rule 1”: When the environment is “Dark” (luminance smaller than 45 Lux), turn angles
157 decrease. When it is “Bright” (luminance larger than 45 Lux), turn angles increase.

158 “Rule 2”: When the environment is “Dark” (luminance smaller than 45 Lux), run-lengths
159 increase. When it is “Bright” (luminance larger than 45 Lux), run-lengths decrease.

160 “Rule 3”: When the environment is “Darkening” (change since previous turn smaller than
161 zero), turn angles decrease. When it is “Brightening” (change since previous turn larger than
162 zero), turn angles increase.

163 “Rule 4”: When the environment is “Darkening” (change since previous turn smaller than
164 zero), run-lengths increase. When it is “Brightening” (change since previous turn larger than
165 zero), run-lengths decrease.

166 Changes in turn angle were accomplished by adjusting the standard deviation of the
167 Gaussian distribution by $\pm 30\%$, the effect size observed in our experiments (**Fig. 2E,F**). We
168 modulated run-length (T) by scaling them by $\pm 30\%$, thereby modulating the probability of turning
169 ($p = dt / T$). When combinations of those rules were tested (**Fig. 3A**), effects were concatenated.

170 A performance index (PI) (**Fig. 3A**) was used to characterize how well animals or models
171 performed temporal phototaxis. The metric was based on the difference between the
172 experimental and control group for the fraction of time spent in the “Dark” ring. To compute this
173 value, bootstrapping was used to average 1000 samples of randomly chosen differences
174 between experimental and control conditions.

175 For the parameter grid search (**Fig. 3A**), the absolute turn angle and the run-length were
176 varied systematically. To this end, respective baseline values as taken from the experiment
177 (**Fig. 2E,F**), were changed by an order of magnitude by scaling them with two multipliers (run-
178 length multiplier and turn angle multiplier).

179

180 **Results**

181

182 Fly larvae can navigate a virtual luminance gradient

183 We first asked whether fly larvae can perform temporal phototaxis, i.e. navigate a virtual light
184 landscape lacking spatial information. We placed individual animals in an agarose-filled arena,
185 allowed them to freely explore, and tracked their position in real-time (**Fig. 1A**). We presented
186 spatially uniform light from below, with luminance levels following a quadratic dependence of the
187 larva's distance from the center ("Valley" stimulus, **Fig. 1B**). To control for naive location
188 preference, we presented position-independent gray luminance ("Constant" stimulus). For both
189 groups, we analyzed how animals distribute across three concentric regions: the "Bright" center,
190 the "Dark" ring, and the "Bright" ring.

191 Larvae that navigated the "Valley" stimulus spent a significantly higher fraction of time in the
192 "Dark" ring (**Fig. 1C**) than those that navigated the "Constant" stimulus (**Figs. 1D, S1A**). This
193 behavior was most pronounced between minutes 10 and 40 of the experiment (**Fig. S1B**). To
194 verify that this behavior was not an artifact of our specific stimulus design, we also tested a
195 gradient where brightness monotonically "ramps" with radial distance (**Fig. S1C**), and observed
196 that larvae also here navigated to dark regions (**Fig. S1D,E**).

197 Because larvae lacked spatial luminance cues in our setup, it was unclear which behavioral
198 algorithms they employ. One basic, yet sufficient, algorithm would be to reduce movement in
199 darker regions. However, speed was independent of luminance (**Fig. 1E, S1F**), suggesting that
200 larvae employ more complex navigational strategies.

201 We conclude that *Drosophila* larvae are capable of performing phototaxis in the absence of
202 spatial information and that this behavior cannot be explained by a simple luminance-dependent
203 modulation of crawling speed.

204

205 Larval temporal phototaxis depends on luminance change over time

206 In spatially differentiated light landscapes, fly larvae make navigational decisions by sampling
207 luminance differences during head-casts. However, in our setup, larvae experience negligible
208 brightness fluctuations during head-casts. Instead, they might modulate the magnitude and/or
209 frequency of turns as a function of luminance. To explore this possibility, we segmented
210 trajectories into runs and turns. Accordingly, we applied a freely available deep learning-based
211 package, DeepPoseKit (Graving *et al.*, 2019) to extract the larvae's head, centroid, and tail

212 positions from the experimental video (**Fig. 2A** and **Video S1**). From there, we calculated the
213 animal's body curvature to identify head-casting events and quantify turn angles and run-lengths
214 (**Fig. 2A–C**). As mentioned before, luminance changes during the spatially confined turns were
215 much smaller than during runs (**Fig. 2D**).

216 To quantify the effect of luminance on heading angles and run-lengths, we looked at how
217 these parameters varied with the larva's position. During the "Valley" but not the "Constant"
218 stimulus, turns in the "Dark" region led to smaller heading angle changes than in the "Bright"
219 regions (**Fig. 2E**). Similarly, runs before a turn in the "Dark" region of the "Valley" stimulus were
220 slightly longer compared to runs ending in the "Bright" region. However, this also occurred with
221 the "Constant" stimulus, suggesting that the effect might not arise from a visuomotor
222 transformation.

223 Next, we explored whether luminance history affects behavior. As run-lengths were highly
224 variable, ranging from ~3 s to ~40 s (**Fig. 2C**), we focused our analysis on the luminance
225 change between consecutive turns. We classified turns by whether larvae experienced a
226 decrease or increase in whole-field luminance during the preceding run. We found that heading
227 angle changes were smaller and that run-lengths were longer when larvae had experienced a
228 brightness decrease compared to an increase (**Fig. 2F**). We did not observe these effects in
229 control animals.

230 To further quantify the effects of luminance and luminance change on heading angle
231 change, we performed regression analysis directly on turns (**Fig. S2**). While turn angles scale
232 with luminance, they do so more strongly with luminance change.

233 These observations led us to hypothesize that larvae might integrate information about the
234 change in luminance during runs and that this integration might span several seconds. To obtain
235 an idea about time-scales, we computed a turn event-triggered luminance average (**Fig. 2G**).
236 We observed that, on average, turns performed in the "Valley" stimulus are preceded by an
237 extended period of >20 seconds of brightening, suggesting that long-term luminance dynamics
238 drive turns.

239 In summary, our detailed analysis of turns and runs confirms that, first, luminance levels
240 modulate heading angle change and, second, changes in luminance prior to turns modulate
241 heading angle change as well as run-length.

242

243 [A simple algorithmic model can explain larval temporal phototaxis](#)

244 We next wanted to test whether the identified behavioral features are sufficient to explain larval
245 temporal phototaxis. Based on our experimental findings (**Fig. 2**), we propose four rules as
246 navigational strategies (**Fig. 3A**). For rules 1 and 2, the instantaneous luminance modulates the
247 heading angle change and run-length, respectively. By contrast, for rules 3 and 4, the luminance
248 change since the last turn modulates the heading angle changes and run-lengths.

249 To test these navigational rules, we simulated larvae as particles that could either move
250 straight or make turns while exploring our experimental landscapes (“Valley”, “Constant”). To
251 compare the performances of different models, we calculated a phototaxis index (difference of
252 time spent in the “Dark” ring between experimental and control groups, **Fig. 3A**). For all
253 permutations of our rules, we explored a set of multipliers for the heading angle change and
254 run-length, with a multiplier of one corresponding to the experimental averages (**Fig. 2E,F**). This
255 allowed us to both assess the robustness of our model to parameter choice and observe how
256 performance behaves as a function of each parameter. As expected, with no active rules, the
257 larvae distributed comparably in the “Valley” and “Constant” stimuli. Activating rules 1 or 2,
258 performance did not improve, suggesting that modulation of behavior based on instantaneous
259 luminance is insufficient to perform temporal phototaxis. Activating rules 3 or 4, phototaxis
260 emerged for small run-lengths and large turn angle multipliers. However, for multipliers
261 consistent with the observed data, the resulting phototaxis index was weaker than in the
262 experimental data. Only when combining rules 3 and 4, phototaxis performance matches the
263 experimental values. Combining all four rules yielded minimal improvements. Therefore, for
264 further analysis, we focused on a combination of rules 3 and 4, with both multipliers set to one.

265 Simulated larvae navigating the “Valley” stimulus moved towards darker regions (**Fig. 3B**).
266 As a control for our modeling approach, we applied the same analysis to model data as used for
267 experimental data. Like real larvae (**Fig. 1D,E**), simulated larvae navigating the “Valley” stimulus
268 spent more time in the “Dark” ring than larvae navigating the “Constant” stimulus (**Fig. 3C**)
269 without modulating speed (**Fig. 3D**). Furthermore, distributions of turn angle changes, run-
270 lengths, and luminance changes were comparable to experimental data (compare **Figs. 2C,D**
271 and **3E,F**). When we examined the effects of instantaneous luminance and luminance change
272 on turn angle amplitude and run-length (**Fig. 3G,H**), we observed similar patterns as in the
273 experimental data (**Fig. 2E,F**). It is particularly notable that, even though we only used rules that
274 depend on luminance changes (rules 3 and 4), a significant dependency on instantaneous
275 luminance still arose. This suggests that this observation is an emergent property resulting from
276 how larvae respond to luminance changes. As found in experiments (**Fig. 2G**), turns are
277 preceded by long stretches of increasing brightness (**Fig. 3I**), supporting our hypothesis that

278 larvae integrate luminance change over several seconds. Finally, to verify that our model
279 generalizes to other visual stimulus patterns, we simulated larvae exploring our “Ramp” stimulus
280 (**Fig. S1C**) and observed phototaxis performance comparable to that of real larvae (**Fig.**
281 **S3A,B**).

282 In summary, after implementing our experimentally observed navigational rules in a simple
283 computational model, we propose that the most critical element of larval temporal phototaxis is
284 the ability to integrate luminance change over extended time periods. Modulating turn angle
285 amplitude and run-length based on such measurement is sufficient to perform temporal
286 phototaxis.

287

288 Discussion

289 Closed-loop systems are powerful tools to identify various strategies of an animal's
290 sensorimotor transformation. They have been employed in many animal models including adult
291 and larval *Drosophila* (Bahl *et al.*, 2013; Tadres and Louis, 2019), larval zebrafish (Chen and
292 Engert, 2014; Bahl and Engert, 2020), and *C. elegans* (Leifer *et al.*, 2011; Kocabas *et al.*, 2012).
293 Using a closed-loop behavioral assay, we show that *Drosophila* larvae find the darker regions of
294 a virtual luminance gradient that lacks any spatial contrast cues. Temporal phototaxis behavioral
295 algorithms have already been dissected in open-loop configurations, where stimuli are
296 decoupled from an animal's actions. Following a global luminance increase, larvae modify both
297 their heading angle magnitude and their run-length (Kane *et al.*, 2013; Gepner *et al.*, 2015), in
298 agreement with our findings. We were able to demonstrate that these navigational strategies are
299 in fact sufficient for phototactic navigation. Given that brightness fluctuations in our assay are
300 slow and negligibly small during turns, we suggest that animals integrate luminance change
301 over time to make decisions about the strength and timing of turns.

302 Previous work has shown that larvae can navigate olfactory or thermal gradients using only
303 temporal cues (Luo *et al.*, 2010; Schulze *et al.*, 2015). Here, we demonstrate temporal taxis in a
304 visual gradient, enabling future exploration of the shared computational principles and neural
305 pathways across these sensory modalities. Compared to previously used systems our setup is
306 relatively simple, cost-effective, and can operate medium to high-throughput. It employs a
307 neural network-based framework for larval tracking, providing an alternative to custom-written
308 posture estimation code.

309 By demonstrating that *Drosophila* larvae can perform temporal phototaxis, we have
310 improved our understanding of how they process visual information during navigation. However,
311 understanding phototaxis requires studying both the temporal and spatial computations
312 (Humberg *et al.*, 2018). We have presented a strategy to isolate the temporal component.
313 Studying the spatial component is technically more challenging. Even when navigating spatially
314 differentiated landscapes, larvae might still use temporal comparisons of light intensity during
315 head-casts (Kane *et al.*, 2013; Humberg *et al.*, 2018). Pure spatial phototaxis has been studied
316 in zebrafish larvae (Huang *et al.*, 2013) by locking a sharp contrast edge to the center of a freely
317 moving animal's head. Testing such stimuli in *Drosophila* larvae will require more precise real-
318 time position, orientation, and posture measurements, but experimental results could be used to
319 construct a spatial phototaxis model which could then be combined with our proposed temporal
320 phototaxis model.

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324

325 **Author contributions**

326 All authors contributed equally to the design of the project. A.B. built the behavioral setup. M.Z.
327 performed experiments. M.Z. and A.B. analyzed data. M.Z., K.J.H., K.V., and A.B. wrote the
328 manuscript. K.J.H., K.V., and A.B. supervised the work.

329

330 **Competing interests**

331 The authors declare no competing interests.

332

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337

338 **Data availability**

339 The data that support the findings of this study are available from the corresponding author
340 upon request. Source code for data analysis and modeling are available on GitHub
341 (https://github.com/arminbahl/drosophila_phototaxis_paper).

342

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344

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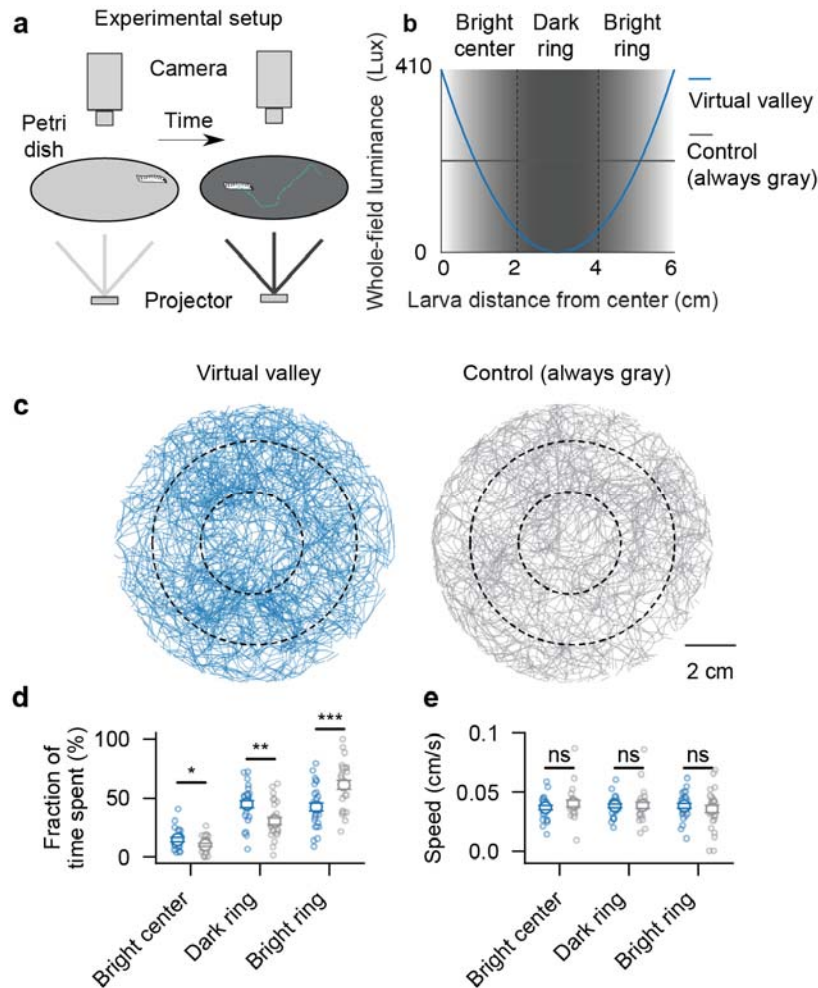
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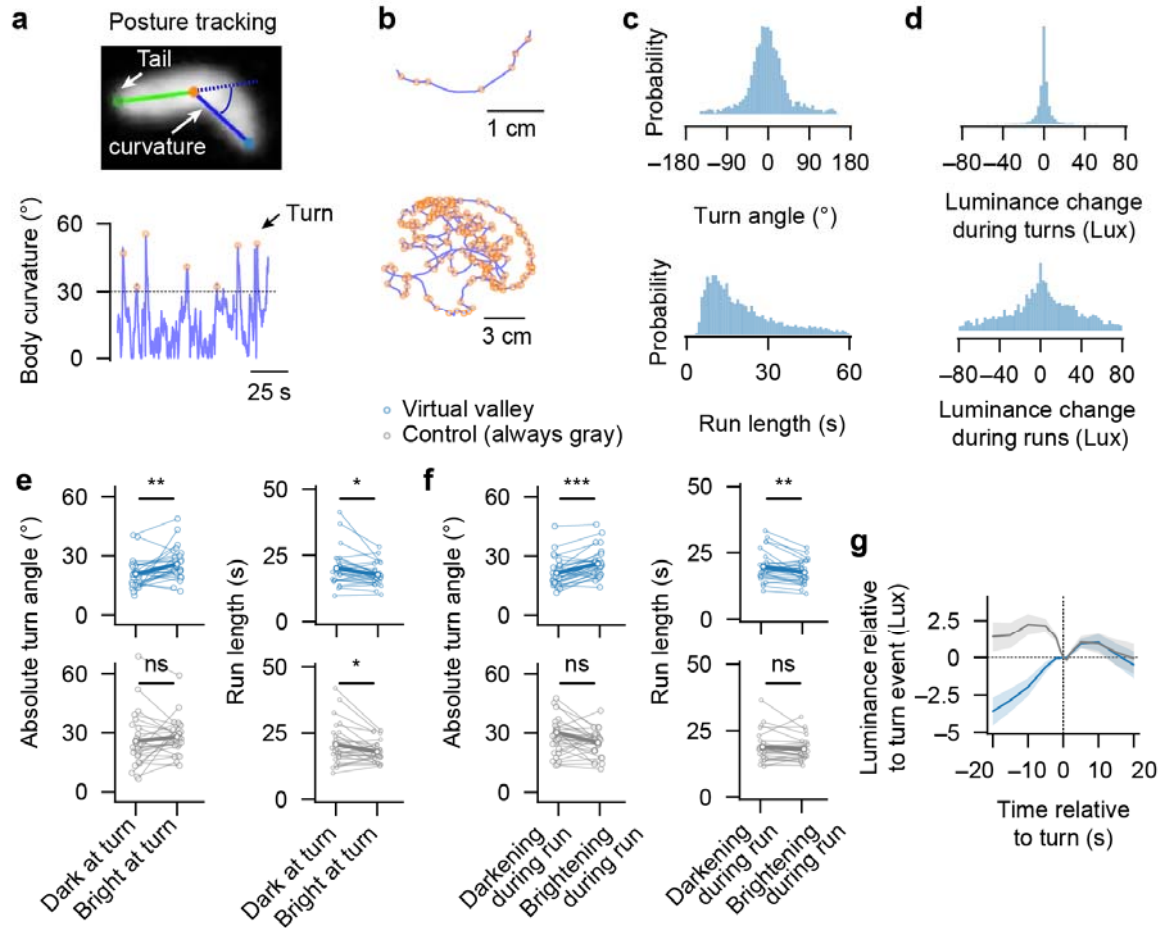
396 **Figures**



397

398 **Figure 1 | *Drosophila* larvae can perform temporal phototaxis.** (A) Setup for tracking freely-crawling
399 *Drosophila* larvae. (B) Whole-field luminance versus larval position for the “Valley” and “Control” stimulus.
400 (C) Raw trajectories. Dashed circles delineate regions (“Bright” center, “Dark” ring, “Bright” ring). (D)
401 Fraction of time spent in regions (left to right: $p = 0.045$, $p = 0.001$, $p < 0.001$; two-sided t-tests). (E)
402 Crawling speed in regions (left to right: $p = 0.304$, $p = 0.891$, $p = 0.479$; two-sided t-tests). Error bars in
403 (D,E) represent mean \pm SEM. Blue solid lines and dots in (B–E) indicate “Valley” stimulus larvae; gray
404 indicate “Constant” stimulus larvae. $N = 27$ larvae for both groups. Open small circles represent individual
405 animals.

406

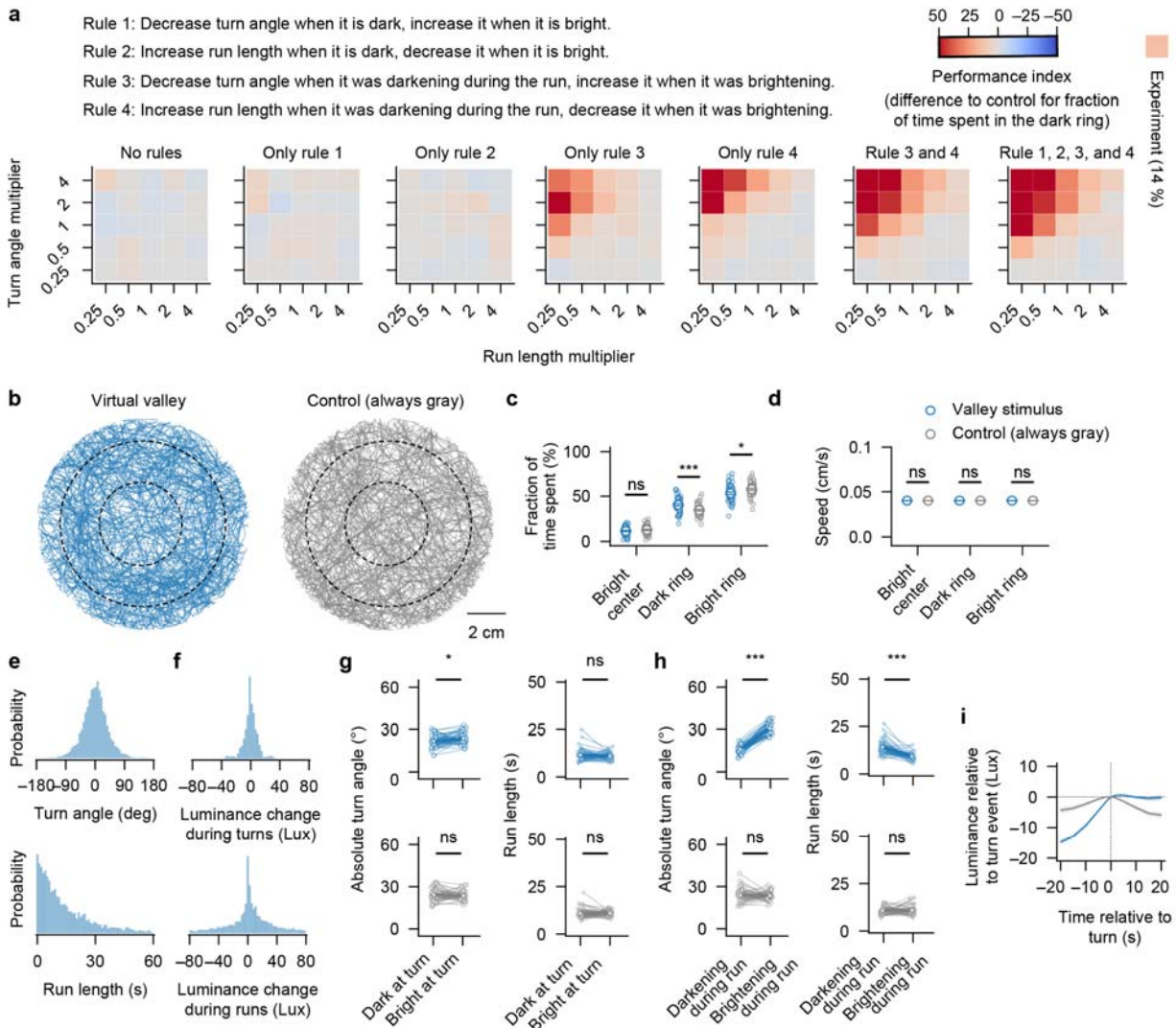


407

408 **Figure 2 | Brightness and brightness history modulate navigational decisions.** (A) Posture tracking
409 for estimating larval body curvature (angle between solid and dashed blue lines). Turns (orange circles)
410 are curvature peaks above a threshold (30°). (B) Example trajectory with detected turns for an inset view
411 (top) and the entire arena (bottom). (C,D) Probability density distributions for turn angles and run-length
412 (C) and respective luminance changes (D). (E,F) Turn angle and run-length as a function of light intensity
413 (dark: < 45 Lux; bright: otherwise; see luminance profile, Fig. 1B) and as function of luminance change
414 since the previous turn (left to right: $p = 0.004$, $p = 0.010$, $p < 0.001$, $p = 0.006$ for the “Valley” stimulus
415 and $p = 0.289$, $p = 0.018$, $p = 0.066$, $p = 0.221$ for the “Constant” stimulus; paired t-tests). (G) Turn event-
416 triggered luminance for the “Valley” and the “Constant” stimulus (mean \pm SEM over all turns from all
417 larvae, $n = 3153$ and $n = 2981$ turns, respectively). $N = 27$ larvae for both groups. Open small circles and
418 thin solid lines in (E,F) represent median turn angle and run-length for individual larvae.

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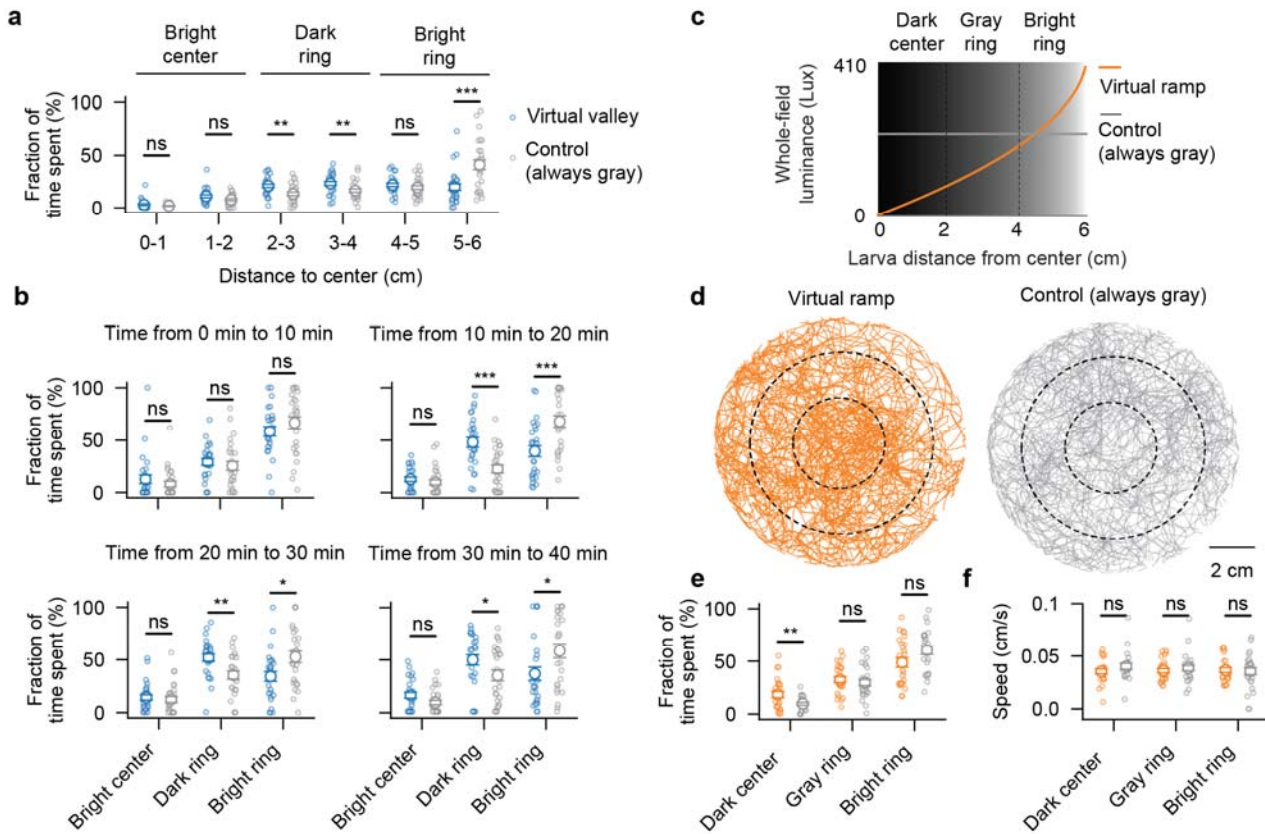


421

422 **Figure 3 | Simulated larvae perform temporal phototaxis.** (A) Characterization of combinations of four
 423 potential navigational rules, with a grid search for the parameters run-length and turn angle. Model
 424 performance quantified by a phototaxis performance index. (B–I) Simulations using only Rules 3 and 4,
 425 with turn angle and run length multiplier set to one. (B–D) Raw trajectories, fraction of time spent in
 426 regions, and crawling speed (as in Fig. 1C–E). Left to right: (C) $p = 0.181$, $p < 0.001$, $p = 0.015$; two-sided
 427 t-tests; (D) $p = 0.531$, $p = 0.651$, $p = 0.665$; two-sided t-tests. (E–I) Analysis of turns and runs (as in Fig.
 428 2C–G). (G,H) Left to right: $p = 0.003$, $p = 0.468$, $p < 0.001$, $p < 0.001$ for the “Valley” stimulus; $p = 0.406$,
 429 $p = 0.861$, $p = 0.406$, $p = 0.409$ for the “Constant” stimulus; paired t-tests. Open circles and thin solid lines
 430 in (C–I) represent individual model larvae. $N = 50$ simulation runs for both groups using different random
 431 seeds. $N = 5331$ and $n = 5334$ events in (I).

432

433 **Supplementary figures**

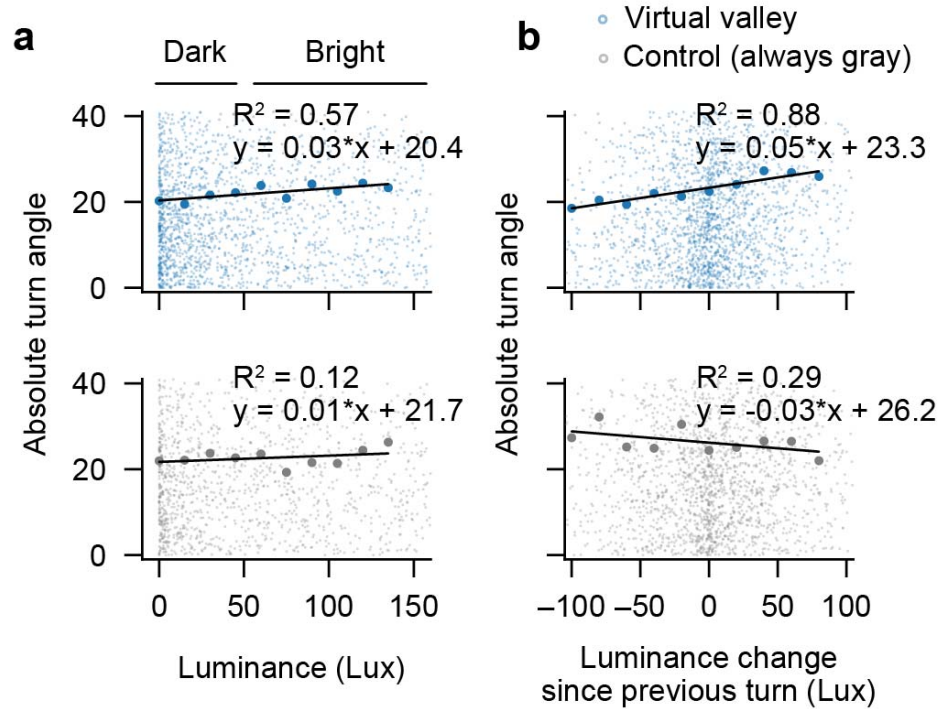


434

435 **Supplementary Figure 1 | Detailed analysis of behavioral performance during temporal phototaxis.**

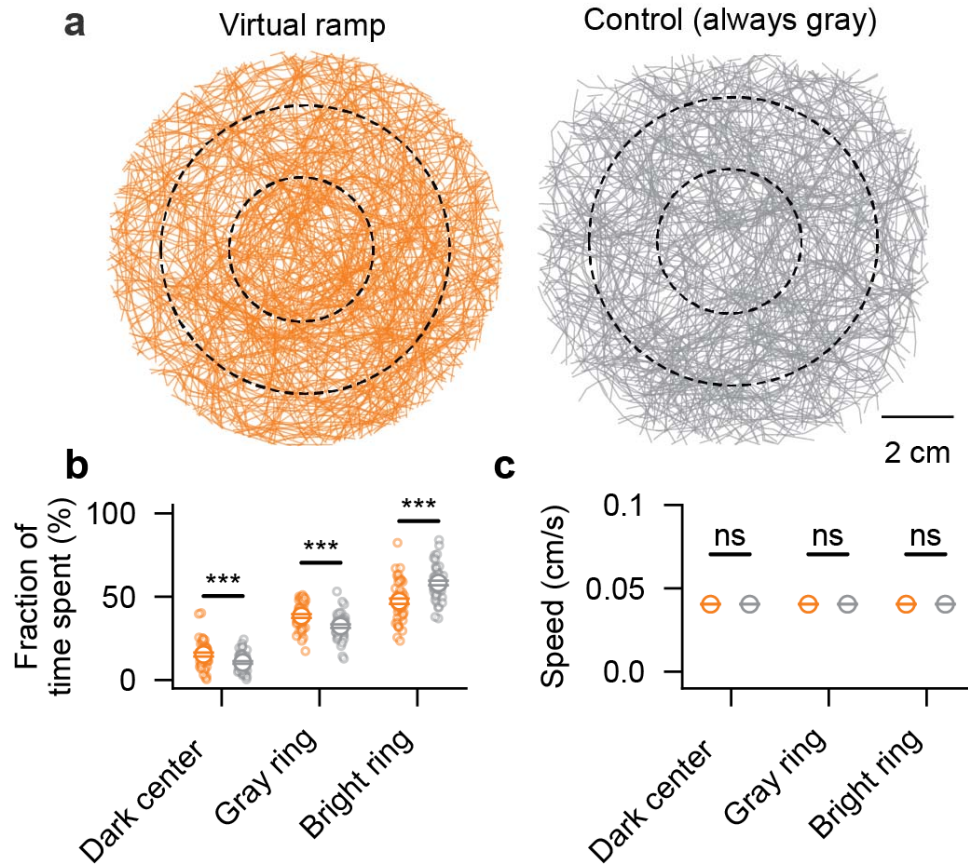
436 **(A)** Fraction of time larvae spend in the different regions for finer radial bin size (left to right: $p = 0.264$, $p = 0.060$, $p = 0.002$, $p = 0.009$, $p = 0.310$, $p < 0.001$; two-sided t-tests). **(B)** Fraction of time spent in the
 437 different regions, analyzed in 10 min time bins (left to right: $p = 0.360$, $p = 0.481$, $p = 0.256$ for first period;
 438 $p = 0.053$, $p < 0.001$, $p < 0.001$ for second period; $p = 0.616$, $p = 0.002$, $p = 0.011$ for third period; $p =$
 439 0.054 , $p = 0.044$, $p = 0.022$ for third period; two-sided t-tests). **(C)** Whole-field luminance as function of
 440 larval position for the “Ramp” stimulus and the “Control” stimulus. **(D)** Raw trajectories. Dashed circles
 441 delineate the “Dark” center, the “Gray” ring, and the “Bright” ring. **(E)** Fraction of time spent in each region
 442 (left to right: $p = 0.009$, $p = 0.484$, $p = 0.051$; two-sided t-tests). **(F)** Crawling speed in each region (left to
 443 right: $p = 0.200$, $p = 0.479$, $p = 0.770$; two-sided t-tests). Error bars in **(A–F)** represent mean \pm SEM. Blue
 444 dots in **(A,B)** indicate “Valley” stimulus larvae; Orange dots and lines in **(C–F)** indicate “Ramp” stimulus
 445 larvae; Gray dots and lines in **(A–F)** indicate “Constant” stimulus larvae. $N = 27$, $N = 26$, and $N = 27$
 446 larvae for the “Valley” stimulus, the “Ramp” stimulus, and the “Constant” stimulus, respectively. Open
 447 circles represent individual animals.
 448

449



450

451 **Supplementary Figure 2 | Regression analysis on individual turn events. (A,B)** Absolute turn angle
452 as function of instantaneous luminance (A) and as function of luminance change since the previous turn
453 (B) for “Valley” stimulus larvae (blue) and “Constant” stimulus larvae (gray). Small dots represent
454 individual turns ($n = 3153$ and $n = 2981$ events, respectively, from $N = 27$ larvae for each group). Bigger
455 dots represent binned data, which were used for the linear regression. 15 Lux bins in (A) and 20 Lux bins
456 in (B).



457

458 **Supplementary Figure 3 | Simulated larvae navigating the “Ramp” stimulus.** (A) Raw trajectories for
459 model larvae navigating the “Ramp” stimulus (orange) and the “Constant” stimulus (gray). Dashed circles
460 delineate the “Dark” center, the “Gray” ring, and the “Bright” ring (as in Fig. S1D). (B,C) Fraction of time
461 simulated larvae spend in the different regions and respective crawling speeds (as in Fig. S1E,F); left to
462 right: $p < 0.001$, $p < 0.001$, $p < 0.001$ in (B) and $p = 0.296$, $p = 0.677$, $p = 0.213$ in (C). $N = 50$ simulated
463 larvae in both groups. Model parameters are the same as used in Fig. 3B–I. Error bars represent mean \pm
464 SEM.

465