

Differential effects of conspecific and heterospecific density on the development of *Aedes aegypti* and *Aedes albopictus* larvae

Robert S Paton^{*1, 2}, Katherine Heath^{1, 3}, Anthony J Wilson⁴, and Michael B Bonsall^{1, 5}

¹Mathematical Ecology Research Group, Department of Zoology, University of Oxford, Oxford, OX1 3PS, UK

²Balliol College, Broad Street, Oxford, OX1 3BJ, UK

³New College, Holywell Street, Oxford, OX1 3BN, UK

⁴Integrative Entomology, The Pirbright Institute, Ash Road, Pirbright, Surrey, GU24 0NF, UK

⁵St. Peter's College, New Inn Hall Street, Oxford, OX1 2DL, UK

Draft to be submitted to the Journal of Animal Ecology July 2018

Abstract

1. Between-species competition shapes the distribution and abundance of populations. *Aedes aegypti* and *Ae. albopictus* are vectors of pathogens such as dengue and are known to compete at the larval stage.
2. The outcome of this inter-species competition has been found to be context dependent, with the strength and direction changing with resource availability and type. We were motivated by this uncertainty, and aimed to elucidate the magnitude and mechanism of competition.
3. We manipulated the larval density of mixed and single species cohorts of larvae, measuring the effects on survivorship and development time. Unlike other related studies, we adjusted the feeding regime so that the per-capita resource availability was kept constant across all density treatments, at a level sufficient for successful development. This ensured that each larvae at least had the opportunity to gain the requisite resources for pupation.
4. Our analysis found that *Ae. aegypti* suffered notably less mortality due to intra- and interspecific competition. For both species, intra- and interspecific competition led to the survival of faster developing individuals, with the exception that slower developing *Ae. albopictus* larvae survived when exposed a combination of both high con- and heterospecific densities.
5. These results show that the competition between *Ae. aegypti* and *Ae. albopictus* can still occur even when resources are theoretically adequate for development. This suggests that larvae can alter resource seeking and consumption parameters when exposed to high densities of conspecifics and heterospecifics, leading to contest competition. Evidence for resource-independent mechanisms of competition such as crowding are also found, as is evidence for the importance of demographic stochasticity in population processes.

Keywords: *Aedes*, competition, interspecific, intraspecific, mosquito, population regulation, Bayesian statistics, Gibbs variable selection, Product Space Method, Density-dependence

* Corresponding author: robert.paton@zoo.ox.ac.uk

1 Introduction

2 Studying the processes driving the occurrence and persistence of populations is central to the field of ecology
3 (Morin, 2011). Species with directly overlapping niches will compete for resources and space, just as they
4 do with conspecifics. These interactions between individuals of the same species (intraspecific) and different
5 species (interspecific) are crucial in shaping ecological communities and can help explain the abundance and
6 distribution of populations (Chesson, 2000; Morin, 2011). Theory predicts that species experiencing intraspecific
7 competition to a greater degree than interspecific competition can co-occur, whereas the opposite (interspecific
8 > intraspecific) will lead to competitive exclusion (Armstrong and McGehee, 1980). The extent of intra- and
9 interspecific interactions can change across gradients of biotic (e.g. predator abundance) and abiotic (e.g.
10 resource availability, constancy, type) variables, meaning both competitive exclusion and coexistence can occur
11 in heterogeneous environments or across landscapes and regions (Chamberlain, Bronstein, and Rudgers, 2014;
12 Amarasekare, 2003). For two species competing for the same resource, competition can be for the resource
13 directly and/or indirectly through interference. The former is simply the effect one species will have on the
14 other if it depletes an essential common resource. In the second case, one species inhibits the competitor
15 by using mechanical, signalling or chemical interference (Chesson, 2000). The effects of competition manifest
16 as penalties in life history parameters, such as survival, growth and development. Quantifying the direction,
17 magnitude and mechanism of intra- and interspecific competition has been the objective of a plethora of empirical
18 and theoretical studies (see Chesson (2000) and the references therein). Some opt to take a phenomenological
19 approach, describing the “net-outcomes” of competition, while others focus on finding mechanistic explanations.
20 Here, we are interested in a specific instance of inter-species competition; that between *Aedes* mosquitoes.

21 Mosquito-borne viruses are a significant cause of mortality and morbidity particularly in the developing
22 world (Bhatt et al., 2013). The recent Zika outbreak in Brazil and an estimated 100 million annual dengue
23 infections motivates the need for a concerted effort to curtail disease transmission (Yakob and Walker, 2016;
24 Bhatt et al., 2013). With the notable exception of yellow fever, vaccine efficacy is poor, and availability and
25 coverage continue to be a problem (Bhatt et al., 2013). This has led to a focus on controlling the *Aedes*
26 vectors of these diseases, with emphasis on releases of sterile, genetically-modified or *Wolbachia*-infected male
27 mosquitoes designed to suppress wild populations. The effectiveness of these strategies is contingent on a robust
28 understanding of the ecology of the principal disease vectors, *Aedes aegypti* and *Aedes albopictus*. Experimental
29 (Hancock et al., 2016) and theoretical (Yakob, Alphey, and Bonsall, 2008) work has highlighted the importance
30 of ecological processes - such as density-dependent competition - in determining the effectiveness of control.

31 *Aedes aegypti* originated in Africa, but has now become established in Asia and the Americas (Kraemer
32 et al., 2015; Brown et al., 2014). It is a primary vector of many arboviral diseases, such as dengue, chikungunya
33 and Zika (Black et al., 2002; Chouin-Carneiro et al., 2016). Female *Ae. aegypti* bite during the day and are
34 highly anthropophilic (Scott and Takken, 2012). This means that the bed-net based biting-prevention strategies
35 employed against malarial mosquitoes are ineffective against *Ae. aegypti*.

36 *Aedes albopictus* is a secondary vector of arboviruses originating from south-east Asia (Gratz, 2004). Invasive
37 in much of its range, *Ae. albopictus* is capable of occupying more temperate environments, with a range
38 extending northward to the USA and southern Europe (Kraemer et al., 2015). The range expansion of *Ae.*
39 *albopictus* was facilitated by international shipping, where its dormant eggs can survive in transit, often in old
40 tyres (Delatte et al., 2009; Simard et al., 2005). *Ae. albopictus* is generally considered to have a preference for

41 biting outdoors, only feeding opportunistically on humans (Paupy et al., 2009; Richards et al., 2006) (though
42 see Ponlawat and Harrington (2005) and Delatte et al. (2010) for examples of *Ae. albopictus* anthropophily).
43 Despite its host preferences, *Ae. albopictus* has still been implicated in several outbreaks, such as in Hawaii,
44 China and Japan (Paupy et al., 2009). Particularly relevant to this study is the finding that female *Ae.*
45 *albopictus* were more likely to become infected with dengue when they had experienced increased levels of intra-
46 and interspecific larval competition (Alto et al., 2008). This highlights its potential as a disease transmitter,
47 and has led to increasing concern that it could act as a maintenance or primary vector (Gratz, 2004; Paupy
48 et al., 2010).

49 Competing vectors

50 *Aedes aegypti* and *Ae. albopictus* are competent invasive species, both having established persistent populations
51 on new continents (Brady et al., 2014). The two species have increasingly come into contact as *Ae. albopictus*
52 expanded its range throughout the 20th century. These species are known to share larval habitats of ephemeral
53 freshwater pools. This direct niche overlap makes larval pools a forum for inter-species competition.

54 Historically, *Ae. aegypti* displaced *Ae. albopictus* from urban areas in Asia (Macdonald, 1956), such as in
55 Calcutta (Gilotra, Rozeboom, and Bhattacharya, 1967). Braks et al. (2003) and Simard et al. (2005) document
56 spatially segregated co-occurrence in Brazil and Cameroon respectively. The same segregation is documented
57 on some islands, such as in Hawaii (Winchester and Kapan, 2013) and Reunion (Bagny et al., 2009), though
58 declines (but not extinctions) of *Ae. aegypti* were also noted. More recent introductions of *Ae. albopictus*
59 into *Ae. aegypti* occupied areas has resulted in a rapid displacement of *Ae. aegypti*. In the mid-1980s, the
60 introduction of *Ae. albopictus* in Texas resulted in a rapid displacement of *Ae. aegypti* across the Southern
61 States, with it persisting only in select cities in Southern Florida (O'Meara et al., 1995). Habitat preference
62 studies suggest that *Ae. aegypti* seems better able to occupy urban environments, while *Ae. albopictus* has a
63 preference for more vegetated areas (Rey et al., 2006).

64 Several studies have attempted to determine which vector is the superior larval-stage competitor (reviewed in
65 Juliano (2009)). Results are mixed, with some early studies finding *Ae. aegypti* to be the superior competitor
66 (Moore and Whitacre, 1972; Moore and Fisher, 1969) and subsequent studies *Ae. albopictus* (Reiskin and
67 Lounibos, 2009; Juliano, Lounibos, and O'Meara, 2004; Braks et al., 2004). Most crucial is that the strength
68 and directions of inter-species competition was context dependent. For instance, competitive outcomes have been
69 found to change in response to different resource types (Barrera, 1996; Murrell and Juliano, 2008), temperatures
70 (Farjana, Tuno, and Higa, 2012) and habitat constancy (Costanzo, Kesavaraju, and Juliano, 2005). Moreover
71 it has also been shown that sympatric and allopatric populations of *Ae. aegypti* and *Ae. albopictus* can suffer
72 from and exert different levels of interspecific competition (Leisnham et al., 2009). Context-dependent variation
73 in the outcome of *Aedes* competition was corroborated by Juliano's 2010 meta-analysis of larval competition
74 studies. He concluded that *Ae. albopictus* suffered less interspecies competition than *Ae. aegypti* in habitats
75 with high-quality food, but that they were competitively equivalent in resource poor habitats. The fact that
76 *Aedes* mosquitoes compete across heterogeneous, fragmented habitats, further complicate findings. Across a
77 heterogeneous landscape, differences in competitive outcomes could allow for persistence in some areas but not
78 others (Juliano, 2009; Amarasekare, 2003).

79 Mechanisms of larval competition

80 Resource competition has long been considered the primary driver of intra- and interspecific larval competition
81 between *Aedes* mosquitoes (Dye, 1984a). Indeed this mechanism has been represented as density-dependent
82 competition in models of mosquito population dynamics (Dye, 1984b), including those aiming to inform optimal
83 disease interventions (Yakob, Alphey, and Bonsall, 2008; Bonsall et al., 2010). The functions describing intra-
84 and interspecific competition in such models can be parameterised by studies where single and mixed species
85 cohorts are reared in different densities and measure the effects on life history parameters.

86 However, Heath et al. (*In review*) highlight that many mosquitoes-focused empiricists conflate the effects
87 of larval resource availability with *all* density-dependant processes. That is to say that many studies hold
88 feeding regimes constant across density treatments (e.g. Reiskin and Lounibos (2009)), reducing the per-capita
89 resource availability (same resources, more individuals). The subsequent effects measured on survival/growth
90 rates/fecundity are all then treated as the result of resource-mediated competition, aggregating other mechanism
91 with it. This is important, as there are there are other mechanisms by which competition could occur. For
92 instance, evidence from Moore and Fisher (1969) and Moore and Whitacre (1972) demonstrated that the
93 development times of *Ae. albopictus* larvae in high-density mixed-species cohorts were significantly lengthened
94 by increased densities of *Ae. aegypti*. As the larvae were not resource-limited, the authors attribute this to
95 the production of a chemical compound termed a growth retardant factor (GFR), thought to be produced by
96 *Ae. aegypti* at high larval densities (though this result could not be repeated by Dye (1982)). Alternatively,
97 evidence from Dye (1984a) suggests that differences in development time could be attributed to the volume the
98 larvae were reared in. This could be due to mechanical interference reducing feeding efficiency, or by jostling to
99 reach the surface to breath.

100 We are motivated by the degree of uncertainty around the outcome of larval competition between *Ae. aegypti*
101 and *Ae. albopictus*, and the mechanism by which this competition occurs. In this study, we manipulated the
102 conspecific and heterospecific larval densities of *Ae. aegypti* and *Ae. albopictus*, and recorded the effect this
103 had on larval survivorship and development time. Crucially, unlike many *Aedes*-focused competition studies,
104 we adjusted the feeding regime so that the per-capita resource availability was kept constant across all density
105 treatments. We specifically chose a feeding regime under which each larvae *theoretically* had the necessary
106 resources to successfully develop. This allowed us to better isolate mechanistic aspects of larval competition,
107 and better observe what components of competition were attributed to direct resource-mediated or interference-
108 mediated competition.

109 **Methods**

110 **Routine colony maintenance**

111 Colony mosquitoes were kept at the Pirbright Institute in Surrey, UK. Rearing rooms were maintained at 25°C
112 ± 1°C with a 16:8 light:dark cycle. Pirbright's *Ae. aegypti* colony was established from a line at the Liverpool
113 School of Tropical Medicine, which was originally from West Africa (Macdonald, 1962). Eggs were placed
114 in 150ml of reverse-osmosis water and vacuum hatched for at least one hour. First instar larvae were then
115 transferred into bowls filled with approximately 1 litre of tap water, in densities of around 450 - 600 larvae per
116 bowl. Larvae were fed 0.15-0.2g desiccated beef liver powder (NOW Foods, Bloomingdale, IL, USA) every two
117 days, when the water was also changed. Pupated larvae were decanted into small 100ml tubs of water and placed
118 inside 40cm³ Bugdorm insect cages (MegaView Science, Taichung, Taiwan). Adults were maintained on room
119 temperature 10% sugar solution on a cotton disk, and females fed defibrinated horse blood (TCS Biosciences,
120 Buckingham, UK) using a Hemotek membrane feeding system (Hemotek Ltd., Great Harwood, Lancashire,
121 UK). Tubs lined with damp filter paper were put in each cage after blood feeding for egg-laying.

122 The *Ae. albopictus* line was Italian, and founded from the Rimini strain described in Dritsou et al. (2015).
123 The maintenance protocol was identical to the above, with the exception that *Ae. albopictus* eggs were hatched
124 in a medium of water and 0.3% dried active yeast (Youngs Home Brew Ltd., Bilston, West Midlands, UK).

125 **Experimental protocols**

126 Single and mixed species cohorts of *Ae. albopictus* and *Ae. aegypti* larvae were reared under different density
127 conditions. Seventh and eighth generation *Ae. aegypti* and *Ae. albopictus* were used, and were all from the
128 colonies described above. However, instead of hatching *Ae. albopictus* using yeast as per the routine protocol,
129 they were hatched in the same way as *Ae. aegypti*. This kept both the procedure the same across each species
130 and ensured that the yeast did not supplement the resources available to *Ae. albopictus*. As this method differed
131 from the standard hatching procedure for *Ae. albopictus*, the larvae were left in the vacuum for at least 3 hours
132 to ensure there was a sufficient yield of both species.

133 Egg papers were placed in reverse osmosis water and vacuum hatched overnight. Hatched first instar larvae
134 were counted into 50ml Falcon conical centrifuge tubes (Corning, New York, USA) tubes filled to 49ml with
135 water (1ml of food solution made this up to 50ml). The number of larvae in each tube corresponded to the
136 density combinations given in Table 1. The density scale was chosen to give roughly an even number of larvae
137 per treatment while also covering a biologically relevant range. Density was manipulated by changing the
138 number of individuals per tube while holding the volume of the tube constant (See Figure 1). Tubes for low
139 density treatments therefore contained fewer individuals than for high density treatments, reducing the sample
140 size. The lower-density tubes were therefore repeated so that the overall number of larvae experiencing each
141 density condition was around 50 (the number in the highest density treatment). The densities given in the
142 Table 1 were explored for each species in isolation (1:0), equal ratios of each species (1:1) and biased ratios (2:1
143 and 1:2, 1:3 and 3:1). The procedure described in Figure 1 was repeated twice for each ratio. For low-density,
144 mixed-species treatments some of ratios could not be achieved with number of individuals in the tube (e.g. 4:3
145 can not be configured from 6 larvae). The density of these treatments was therefore increased slightly in order
146 to allow for these configurations.

	Density Treatment				
	T1	T2	T3	T4	T5
Larvae per tube (La)	6	16	28	38	50
Density (La/ml)	0.12	0.32	0.56	0.76	1
Volume (ml)	50	50	50	50	50
Number of tubes	10	3	2	2	1
Food per larvae (mg/larvae/feed)	0.55	0.55	0.55	0.55	0.55
Food per tube (mg/tube/feed)	3.3	8.8	15.4	19.8	27.5
Ratios	1:0, 0:1, 1:1, 2:1, 1:2, 3:4, 4:3, 3:1, 1:3				

Table 1: A description of the density conditions (in larvae per millilitre, La/ml) explored in each treatment (T1 - 5). The quoted ratios are those of *Ae. aegypti* to *Ae. albopictus*. Each condition/ratio combination was repeated twice. Tubes are repeated so that there were approximately 50 larvae subjected to each of the density treatments. Food treatments are scaled to the number of larvae in each pot (milligrams per pot, mg/pot) from the amount decided on in the pilot study. In low-density treatments, 6 individuals were insufficient to achieve the required ratios. We therefore increased the number of larvae to the minimum amount needed to make the ratio, and adjusted the feeding regime accordingly.

147 A pilot study (see Appendix A) demonstrated that 0.55 mg of liver powder delivered on day 0, 2 and 4
 148 post-hatching supported the successful development of an individual larvae of either species in isolation. Liver
 149 powder was delivered as a dilution, mixed so that 1ml of food solution contained the correct concentration of
 150 food per-capita for each density treatment. When a larvae pupated, it was decanted to a separate container
 151 with a small amount of water until emergence. We recorded the number of survivors and the development time
 152 of these survivors. The species and gender of the emerged adult was then determined. We took the development
 153 time of a larvae to be from hatching to pupation. A summary of the experimental procedure is given in the
 154 Figure 1.

155 Analysis

156 We analysed the survival and development time data using Bayesian generalised additive (GAM) and gener-
 157 alised linear models (GLM). A total of 2435 larvae were analysed in the survival analysis, and 1489 larvae for
 158 development time (as only surviving larvae could be analysed). These statistical models were written and fit
 159 in JAGS (v4.3) (Plummer, 2003), a Bayesian inference package for the statistical software R (v3.4.2) (R Core
 160 Team, 2012). All models mentioned hereafter were run across four chains for a minimum of 2×10^5 iterations,
 161 with every second sample discarded to reduce autocorrelation. Chains were continued for additional iterations
 162 if they had not yet converged (until the potential scale reduction factor was < 1.02). For all models, parameters
 163 were given appropriately diffuse priors centred on zero, unless the pilot studies could be in some way informative
 164 (see appendix Table 4).

165 Survival

166 The survival data were modelled as either a binomial distribution or hierarchical beta-binomial distribution.
 167 The latter was included after initial inspection of the data showed that the proportions of larvae surviving in
 168 tubes undergoing the same density treatment varied. A beta distribution accounts for this variance, and could
 169 better explain the data. A binomial regression would model the number of survivors (S) from the total number
 170 (N) in the i^{th} tube as the outcome of a binomial distribution with a probability p

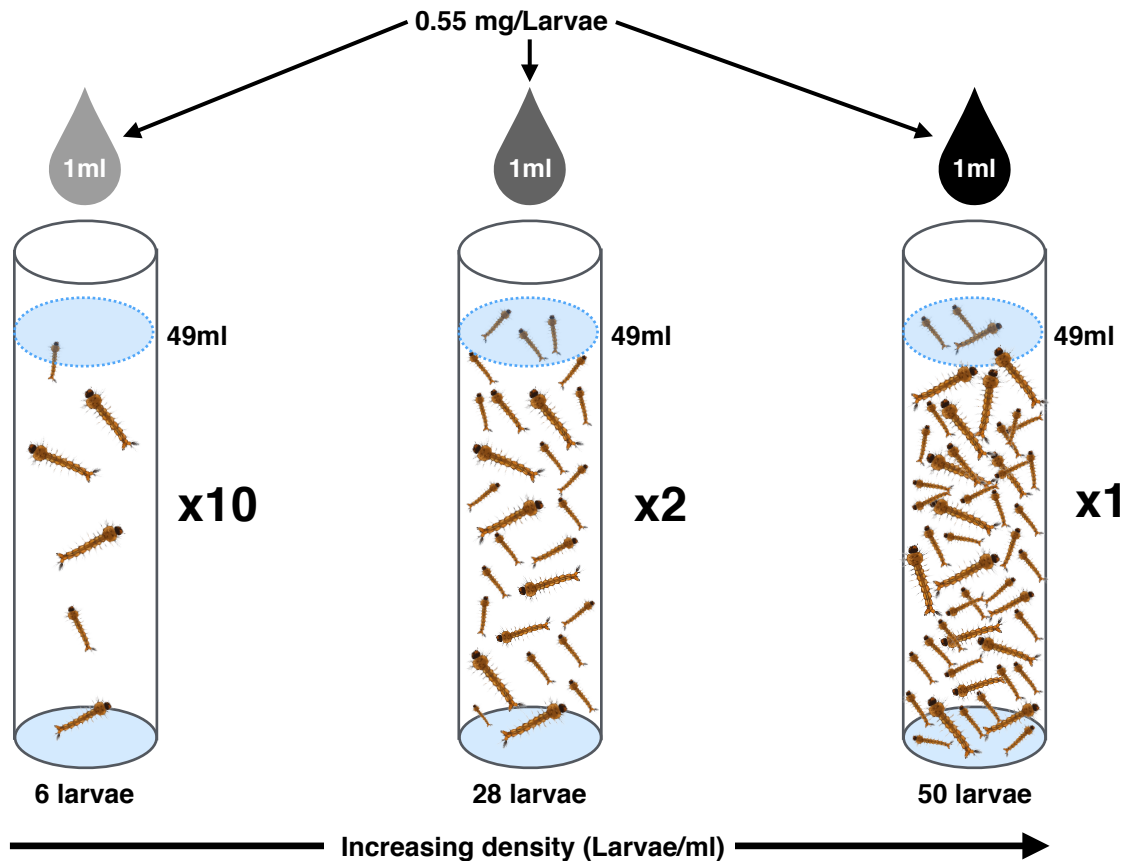


Figure 1: Summary schematic of the experimental design and procedure, shown for a 1:0 species ratio and 3 of the 5 density treatments tested. Falcon tubes were filled with reverse-osmosis water to 49ml, then made up with a final 1ml of a food dilution. Food dilutions were mixed so that 1ml held 0.55mg per larvae in suspension for each treatment (therefore a higher concentration was needed to cater for more larvae in higher density treatments). A further 1ml was added on day 2 and 4 of development. A number of larvae corresponding to one of the densities (6, 16, 28, 38 and 50 larvae for 0.12, 0.32, 0.56, 0.76 and 1 larvae per ml) were hatched and added to the falcons using a pipette. As the low density treatment contained only 6 individuals and the high density 50, it was necessary to repeat these tubes 10 times to achieve a similar sample size. All density treatments were repeated so that there were around 50 individuals experiencing each treatment. Pupated individuals were counted every day, and were removed and decanted to a small water filled tube until emergence. The emerged adults were sexed and identified to species level (for mixed species experiments). This procedure was repeated twice for each of the species ratios in Table 1.

$$S_i \sim \text{Binomial}(p, N_i)$$

171 The probability p is written as a function of explanatory variables (say a vector of predictors X) ($p = f(X)$).
172 A logit-link was used to bound p between zero and one ($\text{logit}(M) = f(X)$).

173 In the case of the beta-binomial distribution, the probability is given by a beta distribution with with two
174 shape parameters, s_1 and s_2

$$p \sim \text{Beta}(s_1, s_2)$$

175 This beta distribution is re-parametrised in terms of the mode of the distribution, for the following two reasons.
176 First, neither s_1 or s_2 describe a useful property of the beta distribution (e.g. mean, standard deviation) to
177 write as a function of covariates. Second, the mode is a far better description of skewed distributions than
178 other statistics such as the mean, which can be heavily influenced by “long tails”. The re-parametrisation is as
179 follows, with the mode M and a certainty parameter θ (Kruschke, 2015)

$$s_1 = M(\theta - 2) + 1$$

$$s_2 = (1 - M)(\theta - 2) + 1$$

180 In this case the mode M is written as as a function of the covariates ($M = f(X)$). A logit-link was used to
181 bound the mode between zero and one ($\text{logit}(M) = f(X)$).

182 Exploration of the survival data showed some evidence that the survival probability could be changing as a
183 non-linear function of *Ae. aegypti* and *Ae. albopictus* density, and with some irregularity. Generalised additive
184 models (GAMs) use data-derived splines to fit smoothed non-linear responses to continuous explanatory variables
185 (Wood, 2006). As they are derived from the data, smoothed splines are not constrained in the same way higher
186 order self-interaction terms are in standard linear models. We therefore included smoothed responses in both the
187 binomial and beta-binomial models in addition to the linear terms. GAM terms can be estimated in a Bayesian
188 framework by modelling the smoothing parameters as random effects, where each smoothing parameter comes
189 from a the same normal distribution with an estimated standard deviation (Crainiceanu, Ruppert, and Wand,
190 2005). We used 5 knots for our splines, one per point on the density scale.

191 **Development time**

192 We modelled the development times as a gamma distribution (positive continuous values). As with the beta
193 distribution, the shape and rate parameters of the gamma distribution do not describe any useful property to
194 model as a function of the covariates. Additionally, when close to zero, the gamma distribution can be skewed.
195 We therefore re-expressed the shape (k) and rate (r) parameters of the gamma distribution in terms of the
196 mode, M , and standard deviation, σ (Kruschke, 2015)

$$r = \frac{M + \sqrt{(M^2 + 4\sigma^2)}}{2\sigma^2}$$

$$k = 1 + Mr$$

197 where the mode is written as a function of explanatory variables with a log-link, to ensure the mode is positive
198 ($\log(M) = f(X)$). The form of $f(X)$ was assumed to be a standard linear model, as there was no evidence of
199 non-linearity beyond that afforded by the link function.

200 Selecting predictors and model structures

201 Gibbs variable selection

202 Thoroughly exploring all biologically relevant combinations of predictors can be extremely time consuming,
203 particularly when dealing with multiple categorical interactions. In our case, development time can be explained
204 by two categorical variables, species and sex, and two continuous variables, *Ae. aegypti* and *Ae. albopictus*
205 density. To test the full model space, it would be necessary to explore all second and third order interactions
206 between these terms (this is similarly the case for survival, less the sex variable). We therefore opted to use
207 Gibbs variable selection (GVS), which combines variable selection and model estimation into the same step
208 (Tenan et al., 2014).

209 In brief, GVS adds a set of binary variables to the model, which are capable of turning individual parameters
210 on and off during optimisation. As an example, we could write a generic response variable y as being predicted
211 by p predictors. This model could be written in matrix form, using a vector of parameters β (length p) and a
212 design matrix, \mathbf{X}

$$y = \sum_{j=1}^p \beta_j \mathbf{X}_j$$

213 In the case of GVS, a column vector of binary indicator variables, γ is added, where $\gamma \in \{0, 1\}$. Each each
214 element of γ corresponds to a parameter in β .

$$y = \sum_{j=1}^p \gamma_j \beta_j \mathbf{X}_j$$

215 The state of each of element of γ is denotes whether predictor should to be included in the model (1), or excluded
216 (0). Each element of γ is assigned an unbiased 50:50 *Bernoulli* prior (i.e. there is a prior probability of 0.5 of
217 any one parameter being included). The frequency with which combinations of model variables are activated
218 can then interpreted as the preference for including predictors.

219 In our case, this procedure is complicated by the inclusion of two and three way categorical interactions with
220 hereditary constraints (the constituent, lower-order terms of an interaction must also be included in a model).
221 The priors for the γ terms of the interactions were therefore written as the multiple of the states of the lower
222 order terms ($\gamma_i \sim \text{Bernoulli}(\gamma_j \pi_i)$, where j denoted a lower order term on which the higher order term, i ,
223 depends). This ensured that the state of the interaction indicator could only be one ($\gamma_i = 1$) if the lower order
224 terms were also active ($\gamma_j = 1$). This does however make higher order interactions inherently less likely to be
225 included (Kruschke, 2015), though this is not necessarily undesirable for high order interactions terms should
226 only be included with strong support.

227 Our implementation of GVS also makes use of pseudo priors, as suggested by Dellaportas, Forster, and
228 Ntzoufras (2000). Pseudo priors are priors which are do not affect the posterior distribution of the estimated
229 parameters, instead they are designed to improve the performance of the MCMC sampler itself. Pseudo priors

230 were taken from an initial model run where all indicator variables were set to 1. This model was therefore
231 the “full model”, with a posterior estimates obtained for each parameter. These posteriors are then used as
232 pseudo priors, where they are only active when $\gamma_j = 0$. Otherwise (i.e. when the parameter is active and being
233 optimised) the standard prior is used. This can be written, for a normally distributed parameter, with the mean
234 and standard deviation either given as pseudo priors from an initial model run ($\bar{\mu}$ and $\bar{\sigma}$) or as the actual priors
235 (μ and σ) depending on the state of γ

$$p(\beta_j | \gamma_j) \sim \mathcal{N}(\gamma_j \bar{\mu}_j + (1 - \gamma_j) \mu_j, \gamma_j \bar{\sigma}_j + (1 - \gamma_j) \sigma_j)$$

236 Where β_j is an element of the parameter vector, and γ_j the corresponding element of the vector of binary
237 variables. The motivation for using pseudo priors is to encourage the sampler to frequently turn model param-
238 eters on and off, as only if the full model space is thoroughly explored can adequate parameter estimates be
239 obtained, and the inference be trusted. Pseudo priors achieve this by sampling from the posterior estimate of
240 the a parameter (the pseudo prior) when it is inactive, encouraging it to switch the parameter on (the posterior
241 will clearly be more likely than the prior). Turning the parameter back on, the prior returns to the true values
242 and the model is estimated as normal.

243 **Product space method**

244 GVS is useful for selecting predictors as the full model space does not need to be explicitly specified, saving time
245 and effort. It is however not suited to the comparison of model different model *structures* and *distributions* (such
246 as the binomial and beta-binomial being compared for the survival data). Bayes factor can be used to compare
247 the likelihood of the data under two statistical models, even when they are not nested. Models are assessed on
248 the prior-weighted average of how well they fit the data, over the whole parameter space (Lodewyckx et al.,
249 2011). Complexity is implicitly penalised by this averaging, as models with many poorly fitting parameters will
250 perform worse in aggregate than a model with a few well fitting parameters. The product space method (PSM)
251 is a way of obtaining a Bayes factor to compare between model structures.

252 Lodewyckx et al. (2011) explain how the PSM can yield the Bayes factor for multiple models. They suggest
253 that all models should be fit simultaneously as part of an aggregate model, with a stochastic categorical dis-
254 tribution coded to select which model is active. The frequencies with which each model is selected to explain
255 the data is then a measure of the Bayes factor. The use of pseudo priors is suggested in order to promote
256 switching, and they operate in the same way as those in GVS. Pseudo priors are obtained by optimising each
257 model separately, obtaining posteriors for each. As before, the pseudo priors do not affect the likelihood, and
258 there therefore do not influence the posterior directly. They are included solely to improve the performance of
259 the sampler itself, and promote frequent switches. Other checks recommended in (Lodewyckx et al., 2011) were
260 also carried out to ensure that Bayes factor estimates were robust. A preferred model was chosen based on the
261 thresholds given in Raftery (1995).

262 All parameter estimates and predictions are presented as medians, with 95% highest density intervals (HDI's)
263 as a measure of uncertainly. We elected to use HDI's as they are less misleading than symmetric quantiles when
264 describing skewed sample distributions, as can be produced by MCMC methods (Kruschke, 2015). HDI's
265 correspond to a range across which 95% of the probability mass of a sample falls, and is therefore an intuitive
266 metric of uncertainty.

267 Results

268 Survival

269 GVS selection yielded optimal predictor combinations for the two candidate model structures (the binomial and
270 the beta-binomial). These GVS results are reported in full in appendix Tables 5 and 6. The two best models
271 from the GVS were then compared using the product space method. This yielded a log Bayes factor strongly in
272 favour of the beta-binomial model ($\log(BF_{12}) = -36.54$). The hierarchical beta-binomial model was therefore
273 selected as the best model.

274 This model included a species-specific intercept, a species-specific response to *Ae. aegypti* density and a
275 species-agnostic response to *Ae. albopictus* density. Notably, none of the non-linear responses were included in
276 the final model, implying that the process could adequately be captured by a linear response. This combination
277 of predictors was selected in 33.51% of 4×10^6 iterations, with the next nearest parameter combination at 24.20%
278 (see Table 6 for full GVS results). Parameters estimates for this model are given in Table 2 and shown in
279 Appendix C Figure 8.

280 In the lowest density single-species treatments, *Ae. aegypti* was 6.58% [0.76, 15.89] more likely to survive
281 than *Ae. albopictus*. *Ae. albopictus* survivorship declined in response to *Ae. aegypti* density, and did so more
282 severely than *Ae. aegypti*. Across the density range, the estimated intraspecific response of *Ae. aegypti* was a
283 reduction in survival probability of 17.36% [5.69, 29.33], while the interspecific response of *Ae. albopictus* was a
284 reduction of 37.99% [21.67, 52.01]. The species did not differ in how they responded to *Ae. albopictus* density,
285 with the intraspecific response of *Ae. albopictus* and interspecific response of *Ae. aegypti* being a 22.81%
286 [10.98, 34.65] reduction in survival probability. Figure 2 shows the effect of conspecific density on the survival
287 probability of both species (intraspecific competition), while Figure 3 shows the effect of both conspecific and
288 heterospecific density (intraspecific *and* intraspecific).

289

290

291 Development Time

292 The most frequently selected model during GVS was one including a species- and sex-specific adjustment to the
293 intercept as well as species-specific response to *Ae. aegypti* density, *Ae. albopictus* density and the *interaction*
294 between these two densities. This model was selected in 22.92% of 4×10^6 iterations, with the next nearest model
295 at 21.95% (8.70% after that). The full GVS results are given in appendix Table 7. This next nearest model
296 excluded the interaction term and the species-specific response to either density, meaning it was nested in the
297 former. As these two models were selected with a comparable frequency and therefore had similar support, we
298 compared these two models using the product space method to further assess the performance of each model.
299 The Bayes factor supported the more complex model ($\log(BF_{12}) = -0.795$), which included the species specific
300 effects and interaction.

301 Parameter estimates are given in Table 3 (and shown in appendix Figure 9). The development times of *Ae.*
302 *aegypti* in the lowest density treatment were 15.52% [11.84, 19.30] faster than those of *Ae. albopictus*. Females
303 of both species took 7.85% [5.86, 10.01] longer to develop than males. Increasing densities of conspecifics led to

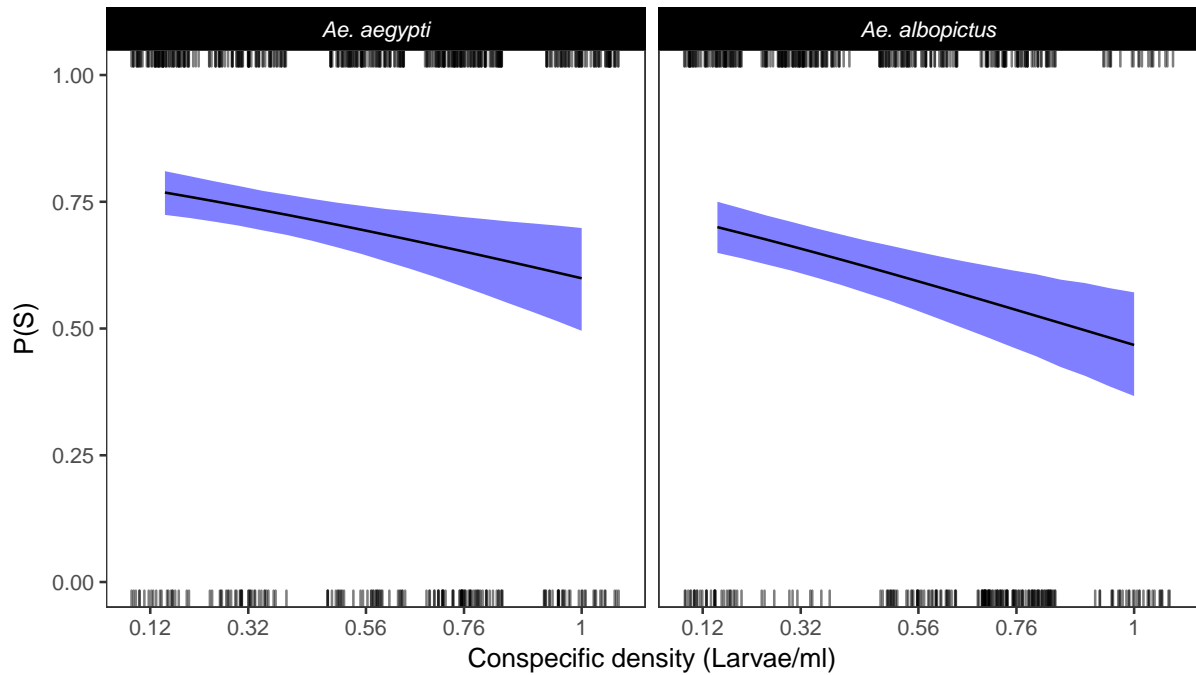


Figure 2: Model fit for the beta-binomial model of the survival data. Data are shown as jittered tick marks on the floor (deaths) and ceiling (survivors). Both species respond linearly to conspecific density (as no non-linear generalised additive model terms were retained through GVS). *Ae. albopictus* responds more strongly to conspecific density than *Ae. aegypti* (17.36% [5.69, 29.33] reduction versus 22.81% [10.98, 34.65]).

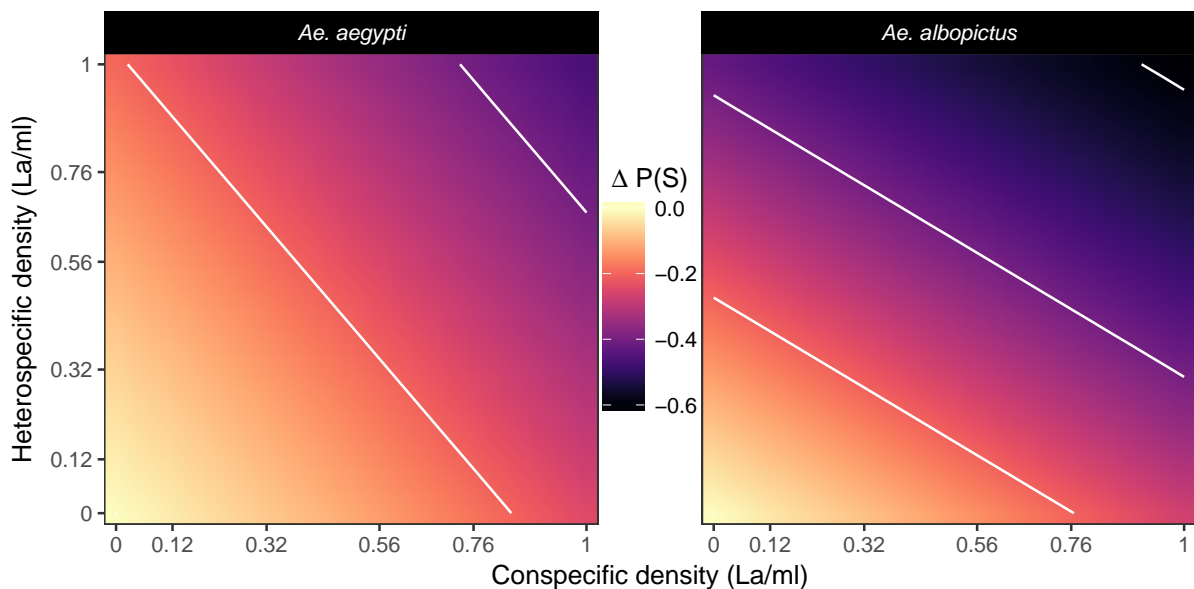


Figure 3: Changes in the survivorship predicted by the beta-binomial survival model across the combinations of density conditions outlined in Table 1. The intraspecific responses run along the x-axis and the interspecific response along the y-axis. Off-axis values are the additive combinations of inter- and intraspecific competition. Values are expressed as the difference from the baseline survival probability ($\Delta P(S)$), which is the probability associated with the bottom left hand corner in each panel. Contour lines delineate 20% decreases in survival probability, with colder colours indicating decreases in survival.

Parameter	Median	Lower 95% - Upper 95%
<i>Ae. aegypti</i>		
Intercept	1.34	1.04 to 1.65
Intraspecific	-0.94	-1.55 to -0.33
<i>Ae. albopictus</i>		
Intercept	1.02	0.73 to 1.31
Interspecific	-1.83	-2.71 to -0.96
Both species		
<i>Ae. albopictus</i> density	-1.15	-1.70 to -0.60
θ (certainty parameter)	22.94	16.57 to 30.86

Table 2: Parameter estimates for the beta-binomial model of the survival data, after GVS. Values are quoted as the medians, with the 95% highest density intervals also given. Values are given for each species if there was species specific response included in the final model. Note these values are on a logit scale. Note that the value for *Ae. albopictus* density is the intraspecific density for *Ae. albopictus* and interspecific competition for *Ae. aegypti*.

304 faster development times for both species, but far less so for *Ae. aegypti*. Across the density range intraspecific
305 competition reduced development times by 8.37 % [4.00, 12.61] for *Ae. aegypti* and 16.14 % [11.19, 20.72] for
306 *Ae. albopictus*. Interspecific competition reduced development times by 10.86% [0.53, 20.30] for *Ae. aegypti* and
307 25.39% [14.98, 34.92] for *Ae. albopictus*. The intraspecific effects are illustrated in Figure 4, and the combined
308 intra- and interspecific effects in Figure 5.

309 Interestingly, the interactive effect of density for *Ae. aegypti* was estimated as being tightly centred on zero
310 (-0.01 [-0.06, 0.03], log scale), meaning that it did not respond differently to combined higher densities of both
311 species. In contrast, the interactive response of *Ae. albopictus* was strongly positive (0.11 [0.06, 0.16], log scale).
312 The model predicted that at the maximum *combined* densities of both species, surviving *Ae. albopictus* would
313 take 59.11 % [11.03, 109.54] *longer* to develop compared to the lowest density treatment. This is contrary to
314 the faster development time observed when responding to conspecific and heterospecific density in isolation.
315 The interactive effect is observable in Figure 5, towards the back right corner of the *Ae. albopictus* panels.

316

317

318

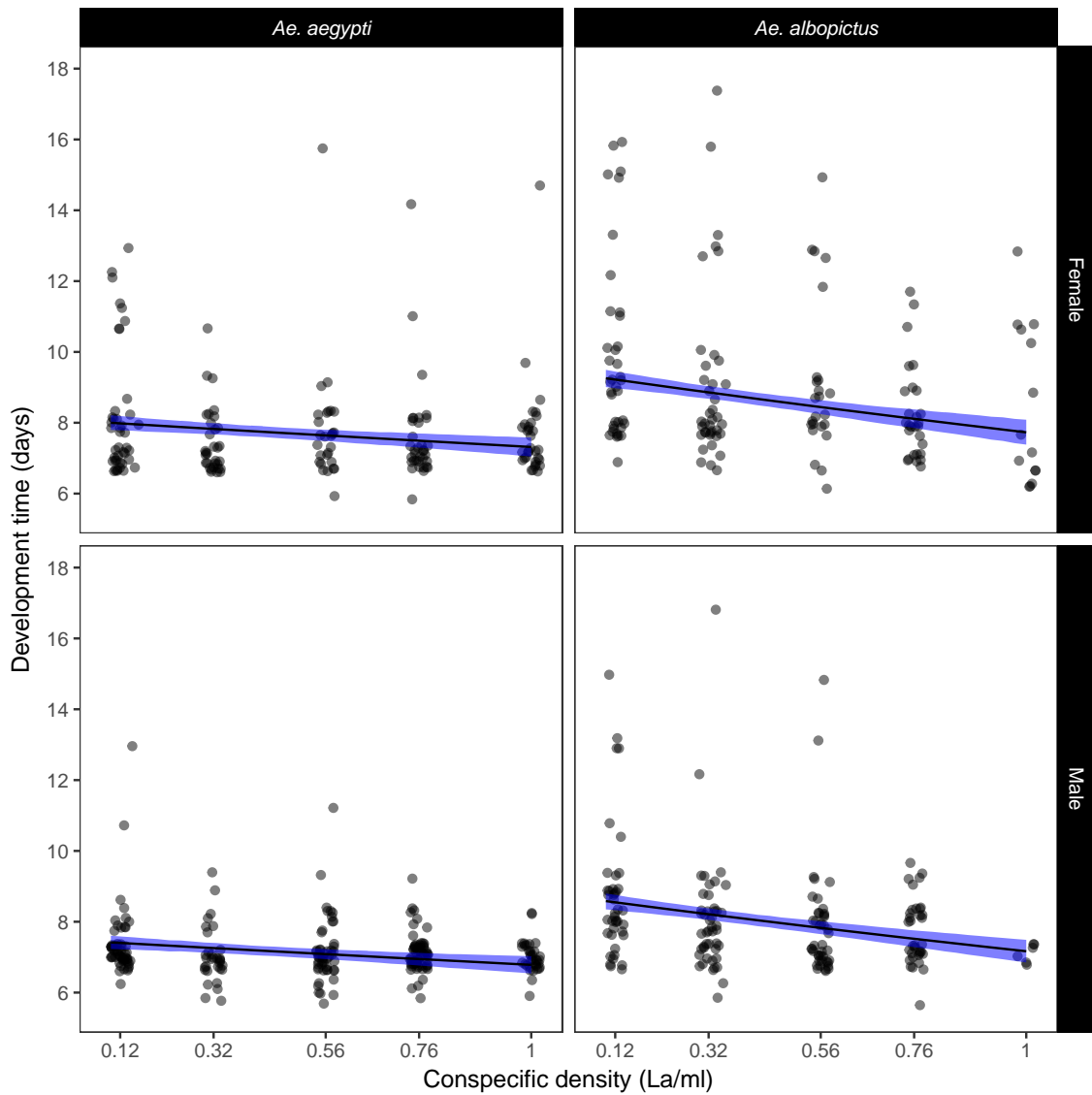


Figure 4: Model fit for the gamma-distributed model of the development time data. This figure shows intraspecific competition for both species. Evident is the slower baseline development time of *Ae. albopictus* (15.52 % [11.84, 19.30] slower), and marginally slower development of females for both species (7.86 % [5.86, 10.01]). Note that there is no sex-specific gradient, only an adjustment to the intercept. Across the range of densities, development times are reduced by 8.37 % [4.00, 12.61] for *Ae. aegypti* and by 16.14 % [11.19, 20.72] for *Ae. albopictus*.

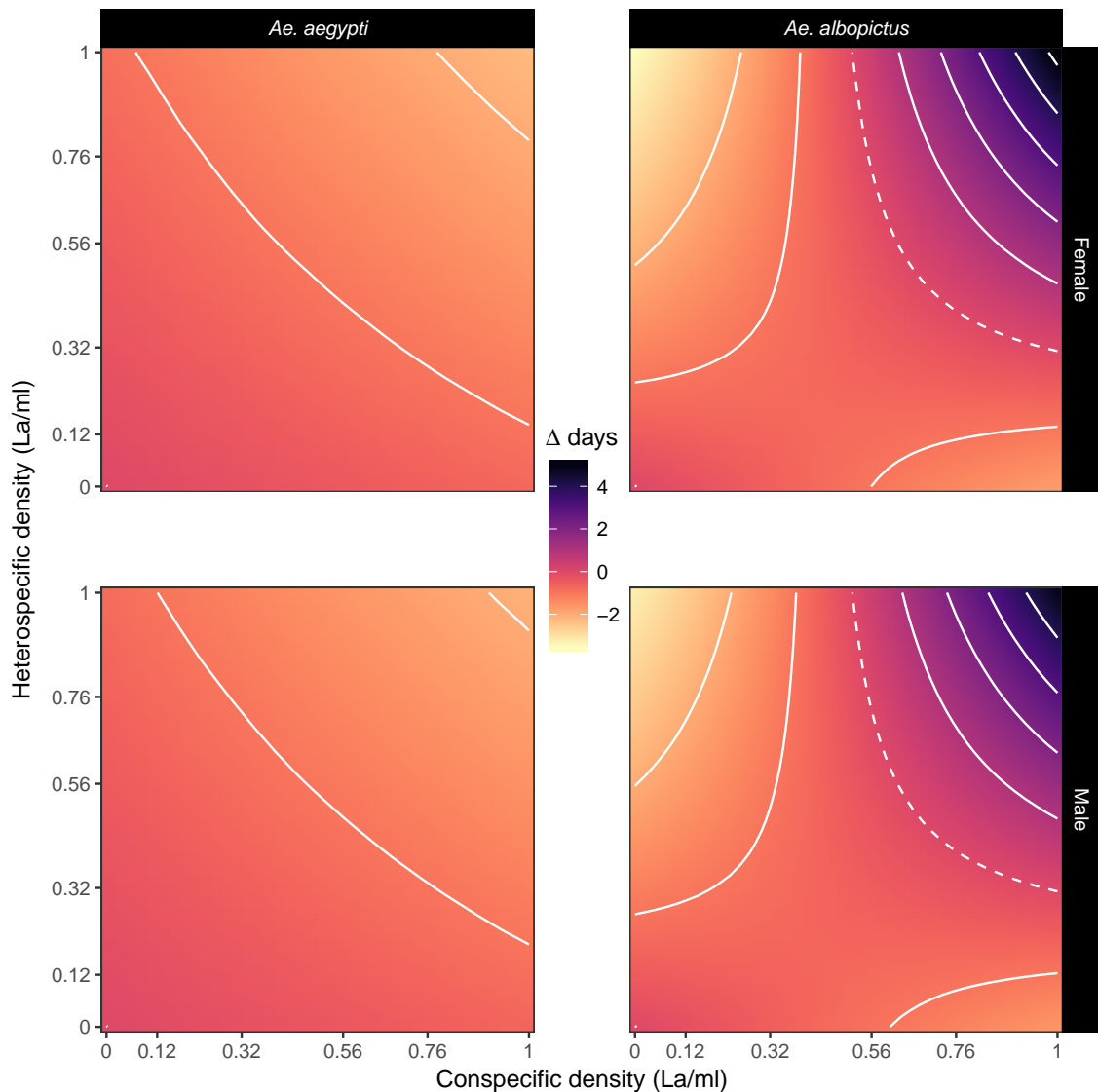


Figure 5: Changes in the predicted development time (Δ days) across the combinations of density conditions outlined in Table 1. Within-species competition is shown along the x-axis and between-species on the y-axis. Values are expressed as the differences from the intercept development time in each panel (the development time associated with the bottom left hand corner of each panel). Colours warmer than the zero mark in the legend indicate decreases in development time, while colder colours indicate increases in development time (compared to the bottom left-hand value). Contour lines delineate changes of 2 days, with the dashed contour the zero mark. There is notably little change in the development time of *Ae. aegypti* across the surface (smaller effect sizes), with no interactive effects of density. In contrast, *Ae. albopictus* speeds up its development time in response to hetero- and conspecific density, albeit to a greater extent for heterospecifics. However, the positive interactive effects of density on *Ae. albopictus* development time means the model predicts slower development when densities of conspecifics and heterospecifics are high. Differences between males and females are minor, and determined only by the shift in the intercept (there were no sex-specific responses to density).

Parameter	Median	Lower 95% - Upper 95%
<i>Ae. aegypti</i> males		
Intercept	2.01	1.98 to 2.04
Intraspecific density	-0.10	-0.15 to -0.05
Interspecific density †	-0.12	-0.29 to 0.05
Density interaction †	-0.01	-0.06 to 0.03
<i>Ae. albopictus</i> males		
Intercept	2.17	2.14 to 2.20
Intraspecific density	-0.20	-0.27 to -0.14
Interspecific density	-0.47	-0.68 to -0.26
Density interaction	0.11	0.06 to 0.16
Both species		
Sex (female)	0.08	0.06 to 0.10
σ (standard deviation)	1.48	1.42 to 1.53

Table 3: Parameter estimates for the gamma-distributed GLM for development time, following GVS and comparison by the PSM. Values are quoted as the medians, with the 95% highest density intervals also given. Values are given for each species where there are species specific responses. All values are on a log scale. The predictor for the interaction term was multiplied by 10 to keep it on the same scale as the two independent densities, so the effect size is directly comparable. † symbols denote parameters with intervals that cross zero. These have been retained due to hereditary constraints in predictor selection.

Discussion

As vectors of diseases such as dengue and Zika, the ecology of *Aedes* mosquitoes is of the utmost importance for predicting vector occurrence, disease incidence and the efficacy of interventions. Our study aimed to quantify the effects of inter- and intraspecific competition on the survivorship and development time of larvae under a particular per-capita feeding regime. We find that *Ae. aegypti* suffered intra- and interspecific competition to a lesser extent than *Ae. albopictus*. Indeed, effect sizes were very small for *Ae. aegypti* (particularly for development time) whereas *Ae. albopictus* suffered higher mortality and took longer to develop when in high conspecific and heterospecific densities. However, the fact we observe any effect is of note, as the larvae were fed per-capita, and at a level which *could* have supported the successful development of all larvae.

The higher baseline survivorship of *Ae. aegypti* is consistent with historic lab studies (Macdonald, 1962) and studies using a similar food resource (Barrera, 1996), but not other studies using other food types (Juliano, Lounibos, and O’Meara, 2004). There was no support for a species-specific response of survivorship to *Ae. albopictus* density, indicating that the strength of intraspecific competition in *Ae. albopictus* is equal to the effect of interspecific competition on *Ae. aegypti*. The same is not true for the response to *Ae. aegypti* density, where there is a greater effect of interspecific competition on *Ae. albopictus* than intraspecific competition on *Ae. aegypti*. The findings for survivorship run somewhat contrary to other competition studies, where the effects of on interspecific competition are usually greater for *Ae. aegypti* (Juliano, Lounibos, and O’Meara, 2004; Reiskin and Lounibos, 2009) or neutral (Black et al., 1989). This could be explained by the use of liver powder as our choice of larval resource, as this has been known to favour *Ae. aegypti* (Barrera, 1996). Alternatively, this could be the result of strain-specific properties (Dye, 1984a).

The superiority of the beta-binomial model structure in explaining the survivorship data tells us that an ad-

ditional second-level process was required to account for the variance in larval survival between tube replicates. This variance could either be “true” demographic variance in survival or “error” variance caused by our experimental setup across tubes and replicates (miscounts of larvae, food dilutions). Should it be the former, this is indicative of interesting features of larval demographic variation. In low-density treatments there were fewer individuals, a difference which we accounted for by repeating these tubes (so that the numbers per treatment were the same). However, we could not control for the demographic make-up of mosquitoes in each tubes, and therefore the dynamics in low-density tubes will be effected by the sample of larval phenotypes expressed in this relatively small sample of larvae. For instance, if each larvae has a certain capacity to respond to conspecific and heterospecific density (e.g. increased resource uptake), then in a small cohort a *single* larva capable of outperforming the others would have a profound effect on the density effects observed in the tube. Individual phenotypes are known to generate the population dynamics we observe (Sumpter and Broomhead, 2001), and it is of note that in smaller cohorts of mosquitoes variation in processes such as survival could shape the observed patterns of persistence and abundance. This evidence points to the importance of demographic processes in the overall dynamics of mosquito populations.

Across the combinations of densities, surviving *Ae. aegypti* larvae developed more quickly than *Ae. albopictus*. In response to conspecific density, the surviving larvae of both species were those that developed quickly. This suggests that the surviving larvae either accrued the necessary resources to pupate faster than competitors, or had a lower resource threshold for pupation. *Ae. aegypti* development times changed only marginally, whereas *Ae. albopictus* did so to a far greater extent.

Of most interest is the observation that *Ae. albopictus* larvae which survived in treatments with high densities of conspecifics and heterospecifics developed more slowly. This is the opposite of its response to intraspecific competition, where it sped up development time. It could be the case that slowly developing individuals are able to cannibalise deceased larvae which break down over time (dead larvae were not removed during counts). It is known that invertebrate carcasses can be a food source for larva (Daugherty, Alto, and Juliano, 2000), so perhaps some *Ae. albopictus* larvae are “playing the long-game”, and benefiting from the delayed release of this additional resource. The longest development times for *Ae. albopictus* also occur under conditions where the mortality of both species is highest, meaning the number of carcasses would also be highest. This fits with evidence that *Ae. albopictus* is better able to survive periods of starvation (Barrera, 1996). While the chemical retardant hypothesis (Moore and Fisher, 1969; Moore and Whitacre, 1972) has received little recent attention, it is worth mentioning that this mechanism could also account for the delayed development time observed in *Ae. albopictus*.

Our study is novel in that our feeding regime was adjusted for each density treatment so that the per-capita resource availability was the same. From our pilot studies we knew that this amount was sufficient for a larvae of either species to pupate. Despite the larvae of both species feasibly being able to pupate on the available resources, many did not, especially for *Ae. albopictus* at high densities. The implication is that non-pupating larvae were not getting the threshold resources required to become pupae. This could be attributed to conspecifics and heterospecifics taking more than the “allotted” 0.55mg per larvae. Interestingly, this points to the rate and degree of resource uptake being mediated by the density of other larvae - both of the same and different species. It would seem that *Ae. aegypti* is better able to alter these resource seeking/uptake parameters than *Ae. albopictus*, as it suffers fewer deaths as a result of competition. Had our study provided even more food

380 per-capita, it is possible that the effects of competition would have been ameliorated. This is because there
381 may come a level of food availability where even significant changes in the rate and extent of uptake by larvae
382 would not be enough to inhibit competitors. Repeating this experiment at a greater range of per-capita feeding
383 regimes is certainly an avenue worth pursuing.

384 This is therefore a manifestation of contest competition, whereby the uptake of resources by the faster
385 developing larvae results in the death of slower developing larvae who never gain the requisite resources for
386 pupation. In contrast, if all larvae expressed the same resource seeking and accruing behaviours that they had
387 in isolation, there would have been sufficient food for all to pupate.

388 It is noteworthy that in a single-species example (using only *Ae. aegypti*), Heath et al. (*In review*) did not
389 find an effect of conspecific density on either survival and development time using this exact feeding regime. The
390 only difference between the experiments was the type and volume of containers used to rear the larvae. This
391 may allude to an effect of habitat volume and surface area, with individuals potentially competing for space,
392 and access to the surface to breathe. Smaller containers with smaller surface areas may amplify the behavioural
393 responses, leading to the outcomes described above. Such mechanisms have been suggested in the past (Dye,
394 1984b), and further emphasise the extent to which habitat properties can alter competitive outcomes.

395 Conclusion

396 When seeking a consensus from competition experiments between *Ae. aegypti* and *Ae. albopictus*, Juliano
397 (2009) and others found that competition was context dependent. Outcomes varied across gradients of habitat
398 resource availability, temperature and constancy. It was therefore never the case that any one study could
399 *fully* explain the competition between these two species. However, our study contributes a unique insight
400 into the consequences of competition under this specific feeding regime. The results show how these larvae
401 could potentially alter the rate and extent of resource uptake to the detriment of their peers. We also provide
402 evidence of an interactive effect on *Ae. albopictus* development time, which we suggest could be mediated by
403 mechanisms other than resource uptake, such as cannibalism or chemical interference. Our model selection
404 revealed that our survival data were overdispersed, which highlights the importance of demographic processes
405 in driving variation in population-level processes. We add to the broader understanding of how within and
406 between species competition can be driven by both resource mediated and resource independent processes, and
407 give insight into the degree to which even relatively simple organisms can display a diverse range of responses
408 to increased densities of competitors.

409 **Acknowledgements**

410 We would like to thank Jo Stoner, Sanjay Basu and Derek Au, who supported RSP and KH with the experiments.
411 Comments and advice from Chris Terry were appreciated.

412 RP was supported by a NERC studentship (NE/L002612/1) and is a CASE student with the Pirbright
413 Institute. KH was supported by a BBSRC studentship (BB/M011224/1).

414 **Author contributions**

415 RSP and KH designed the experiments and developed the concept and ideas, with advice from MBB and AJW.

416 RSP and KH carried out the experiments. RSP designed and conducted the analysis, and wrote the manuscript.

417 KH, MBB and AJW reviewed the manuscript, and contributed to the final document.

418 References

- 419 Alto, Barry W. et al. (2008). “Larval competition alters susceptibility of adult *Aedes* mosquitoes to dengue
420 infection”. In: *Proceedings of the Royal Society B: Biological Sciences* 275.1633, pp. 463–471.
- 421 Amarasekare, Priyanga (2003). “Competitive coexistence in spatially structured environments: a synthesis”. In:
422 *Ecology Letters* 6.12, pp. 1109–1122.
- 423 Armstrong, Robert A. and Richard McGehee (1980). “Competitive Exclusion”. In: *The American Naturalist*
424 115.2, pp. 151–170.
- 425 Bagny, Leïla et al. (2009). “Progressive Decrease in *Aedes aegypti* Distribution in Reunion Island Since the
426 1900s”. In: *Journal of medical entomology* 46.6, pp. 1541–1545.
- 427 Barrera, Roberto (1996). “Competition and resistance to starvation in larvae of container-inhabiting *Aedes*
428 mosquitoes”. In: *Ecological Entomology* 21.2, pp. 117–127.
- 429 Bhatt, Samir et al. (2013). “The global distribution and burden of dengue”. In: *Nature* 496.7446, pp. 504–507.
- 430 Black, I V William C et al. (1989). “Laboratory Study of Competition Between United States Strains of *Aedes*
431 albopictus and *Aedes aegypti* (Diptera: Culicidae)”. In: *Journal of Medical Entomology* 26.4, pp. 260–271.
- 432 Black, William C. et al. (2002). “Flavivirus Susceptibility in *Aedes aegypti*”. In: *Archives of Medical Research*
433 33.4, pp. 379–388.
- 434 Bonsall, Michael B. et al. (2010). “Transgenic Control of Vectors: The Effects of Interspecific Interactions”. In:
435 *Israel Journal of Ecology & Evolution* 56.3-4, pp. 353–370.
- 436 Brady, Oliver J. et al. (2014). “Global temperature constraints on *Aedes aegypti* and *Ae. albopictus* persistence
437 and competence for dengue virus transmission”. In: *Parasites and Vectors* 7.1, p. 338.
- 438 Braks, M. A. H. et al. (2004). “Interspecific competition between two invasive species of container mosquitoes,
439 *Aedes aegypti* and *Aedes albopictus* (Diptera: Culicidae), in Brazil”. In: *Annals of the Entomological Society*
440 *of America* 97.1995, pp. 130–139.
- 441 Braks, Marieta a H et al. (2003). “Convergent habitat segregation of *Aedes aegypti* and *Aedes albopictus*
442 (Diptera: Culicidae) in southeastern Brazil and Florida.” In: *Journal of medical entomology* 40.Juliano 1998,
443 pp. 785–794.
- 444 Brown, Julia E. et al. (2014). “Human impacts have shaped historical and recent evolution in *Aedes aegypti*,
445 the dengue and yellow fever mosquito”. In: *Evolution* 68.2, pp. 514–525.
- 446 Chamberlain, Scott A., Judith L. Bronstein, and Jennifer A. Rudgers (2014). “How context dependent are
447 species interactions?” In: *Ecology Letters* 17.7, pp. 881–890.
- 448 Chesson, Peter (2000). “Mechanisms of Maintenance of Species Diversity”. In: *Annual Review of Ecology and*
449 *Systematics* 31.1, pp. 343–366.
- 450 Chouin-Carneiro, Thais et al. (2016). “Differential Susceptibilities of *Aedes aegypti* and *Aedes albopictus* from
451 the Americas to Zika Virus”. In: *PLOS Neglected Tropical Diseases* 10.3. Ed. by Michael J Turell, e0004543.
- 452 Costanzo, Katie S., Banugopan Kesavaraju, and Steven a. Juliano (2005). “Condition-specific competition in
453 container mosquitoes: The role of noncompeting life-history stages”. In: *Ecology* 86.12, pp. 3289–3295.
- 454 Crainiceanu, Ciprian M, David Ruppert, and Matthew P Wand (2005). “Bayesian analysis for penalized spline
455 regression using WinBUGS”. In: *Journal of Statistical Software* 14.14, pp. 1–24.
- 456 Daugherty, M P, B W Alto, and S Juliano (2000). “Invertebrate carcasses as a resource for competing *Aedes*
457 albopictus and *Aedes aegypti* (Diptera: Culicidae).” In: *Journal of medical entomology* 37.3, pp. 364–372.

- 458 Delatte, H. et al. (2009). “Influence of Temperature on Immature Development, Survival, Longevity, Fecundity,
459 and Gonotrophic Cycles of *Ae. albopictus*, Vector of Chikungunya and Dengue in the Indian Ocean”. In:
460 *Journal of Medical Entomology* 46.1, pp. 33–41.
- 461 Delatte, Helene et al. (2010). “Blood-Feeding Behavior of *Aedes albopictus*, a Vector of Chikungunya on La
462 Réunion”. In: *Vector-Borne and Zoonotic Diseases* 10.3, pp. 249–258.
- 463 Dellaportas, P., J.J. Forster, and Ioannis Ntzoufras (2000). “Bayesian variable selection using the Gibbs sam-
464 pler”. In: *Generalized linear models: a Bayesian perspective*. Ed. by B. Dey, D., Ghosh, S., Mallick. 5th ed.
465 Vol. 5. New York: Marcel Dekker, Inc., pp. 273–286.
- 466 Dritsou, Vicky et al. (2015). “A draft genome sequence of an invasive mosquito: an Italian *Aedes albopictus*”.
467 In: *Pathogens and Global Health* 109.5, pp. 207–220.
- 468 Dye, Christopher (1982). “Intraspecific competition amongst larval *Aedes aegypti*: food exploitation or chemical
469 interference?” In: *Ecological Entomology* 7.1, pp. 39–46.
- 470 — (1984a). “Competition amongst larval *Aedes aegypti*: the role of interference”. In: *Ecological Entomology*
471 9.3, pp. 355–357.
- 472 — (1984b). “Models for the Population Dynamics of the Yellow Fever Mosquito, *Aedes aegypti*”. In: *British*
473 *Ecological Society* 53.1, pp. 247–268.
- 474 Farjana, T., N. Tuno, and Y. Higa (2012). “Effects of temperature and diet on development and interspecies
475 competition in *Aedes aegypti* and *Aedes albopictus*”. In: *Medical and Veterinary Entomology* 26.2, pp. 210–
476 217.
- 477 Gilotra, S. K., L. E. Rozeboom, and N. C. Bhattacharya (1967). “Observations on possible competitive displace-
478 ment between populations of *Aedes aegypti* Linnaeus and *Aedes albopictus* Skuse in Calcutta.” In: *Bulletin*
479 *of the World Health Organization* 37.3, pp. 437–446.
- 480 Gratz, N. G. (2004). “Critical review of the vector status of *Aedes albopictus*”. In: *Medical and Veterinary*
481 *Entomology* 18.3, pp. 215–227.
- 482 Hancock, Penelope A. et al. (2016). “Density-dependent population dynamics in *Aedes aegypti* slow the spread
483 of wMel Wolbachia”. In: *Journal of Applied Ecology* 53.3, pp. 785–793.
- 484 Heath, Katherine et al. (2018). “Resource availability, larval demographics and density-dependence in *Aedes*
485 *aegypti*”. In: *In review*.
- 486 Juliano, Steven A. (2009). “Species Interactions Among Larval Mosquitoes: Context Dependence Across Habitat
487 Gradients”. In: *Annual Review of Entomology* 54.1, pp. 37–56.
- 488 — (2010). “Coexistence, Exclusion, or Neutrality? A Meta-Analysis of Competition between *Aedes Albopictus*
489 and Resident Mosquitoes”. In: *Israel Journal of Ecology and Evolution* 56.3-4, pp. 325–351.
- 490 Juliano, Steven A., L. Philip Lounibos, and George F. O’Meara (2004). “A field test for competitive effects of
491 *Aedes albopictus* on *A. aegypti* in South Florida: Differences between sites of coexistence and exclusion?”
492 In: *Oecologia* 139.4, pp. 583–593.
- 493 Kraemer, Moritz U.G. et al. (2015). “The global distribution of the arbovirus vectors *Aedes aegypti* and *Ae.*
494 *albopictus*”. In: *eLife* 4, pp. 1–18.
- 495 Kruschke, John K (2015). “Doing Bayesian Data Analysis”. In: *Doing Bayesian Data Analysis (Second Edition)*.
496 Ed. by John K Kruschke. Second Edi. Boston: Academic Press, pp. 265–296.
- 497 Leisnham, P. T. et al. (2009). “Interpopulation divergence in competitive interactions of the mosquito *Aedes*
498 *albopictus*”. In: *Ecology* 90.9, pp. 2405–2413.

- 499 Lodewyckx, Tom et al. (2011). “A tutorial on Bayes factor estimation with the product space method”. In:
500 *Journal of Mathematical Psychology* 55.5, pp. 331–347.
- 501 Macdonald, W W (1956). “Aedes Aegypti in Malaya”. In: *Annals of Tropical Medicine Parasitology* 50.4,
502 pp. 399–414.
- 503 — (1962). “The Selection of a Strain of Aedes egypti Susceptible to Infection with Semi-Periodic Brugia Malayi”.
504 In: *Annals of Tropical Medicine & Parasitology* 56.3, pp. 368–372.
- 505 Moore, C. G. and B. R. Fisher (1969). “Competition in mosquitoes. Density and species ratio effects on growth,
506 mortality, fecundity, and production of growth retardant.” In: *Annals of the Entomological Society of America*
507 62.6, pp. 1325–1331.
- 508 Moore, C G and D M Whitacre (1972). “Competition in mosquitoes. 2. Production of Aedes aegypti larval growth
509 retardant at various densities and nutrition levels”. In: *Annals of the Entomological Society of America* 65.4,
510 pp. 915–918.
- 511 Morin, Peter J. (2011). *Community Ecology*. 2nd Editio. Chichester, UK: John Wiley Sons, Ltd.
- 512 Murrell, Ebony G and Steven A Juliano (2008). “Detritus Type Alters the Outcome of Interspecific Competition
513 Between Aedes aegypti and Aedes albopictus (Diptera: Culicidae)”. In: *Journal of Medical Entomology* 45.3,
514 pp. 375–383.
- 515 O’Meara, George F et al. (1995). “Spread of Aedes albopictus and Decline of Ae. aegypti (Diptera: Culicidae)
516 in Florida”. In: *Journal of Medical Entomology* 32.4, pp. 554–562.
- 517 Paupy, C. et al. (2009). “Aedes albopictus, an arbovirus vector: From the darkness to the light”. In: *Microbes
518 and Infection* 11.14-15, pp. 1177–1185.
- 519 Paupy, Christophe et al. (2010). “Comparative Role of Aedes albopictus and Aedes aegypti in the Emergence
520 of Dengue and Chikungunya in Central Africa”. In: *Vector-Borne and Zoonotic Diseases* 10.3, pp. 259–266.
- 521 Plummer, M. (2003). “JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling”. In:
522 *Proceedings of the 3rd International Workshop on Distributed Statistical Computing (DSC 2003)*, pp. 20–22.
- 523 Ponlawat, Alongkot and Laura C. Harrington (2005). “Blood Feeding Patterns of Aedes aegypti and Aedes
524 albopictus in Thailand”. In: *Journal of Medical Entomology* 42.5, pp. 844–849.
- 525 R Core Team (2012). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical
526 Computing. Vienna, Austria.
- 527 Raftery, Adrian E (1995). “Bayesian Model Selection in Social Research”. In: *American Sociological Association
528* 25, pp. 111–163.
- 529 Reiskin, M. H. and L. P. Lounibos (2009). “Effects of intraspecific larval competition on adult longevity in the
530 mosquitoes Aedes aegypti and Aedes albopictus”. In: *Medical and Veterinary Entomology* 23.1, pp. 62–68.
- 531 Rey, Jorge R et al. (2006). “Habitat segregation of mosquito arbovirus vectors in south Florida.” In: *Journal of
532 medical entomology* 43.6, pp. 1134–41.
- 533 Richards, Stephanie L et al. (2006). “Host-Feeding Patterns of Aedes albopictus (Diptera: Culicidae) in Relation
534 to Availability of Human and Domestic Animals in Suburban Landscapes of Central North Carolina”. In:
535 *Journal of Medical Entomology* 43.3, pp. 543–551.
- 536 Scott, Thomas W. and Willem Takken (2012). “Feeding strategies of anthropophilic mosquitoes result in in-
537 creased risk of pathogen transmission”. In: *Trends in Parasitology* 28.3, pp. 114–121.

- 538 Simard, Frédéric et al. (2005). “Geographic distribution and breeding site preference of *Aedes albopictus* and
539 *Aedes aegypti* (Diptera: culicidae) in Cameroon, Central Africa.” In: *Journal of medical entomology* 42.5,
540 pp. 726–731.
- 541 Sumpter, D. J. T. and D. S. Broomhead (2001). “Relating individual behaviour to population dynamics”. In:
542 *Proceedings of the Royal Society B: Biological Sciences* 268.1470, pp. 925–932.
- 543 Tenan, Simone et al. (2014). “Bayesian model selection: The steepest mountain to climb”. In: *Ecological Mod-*
544 *elling* 283, pp. 62–69.
- 545 Winchester, Jonathan C. and Durrell D. Kapan (2013). “History of *Aedes* Mosquitoes in Hawaii”. In: *Journal*
546 *of the American Mosquito Control Association* 29.2, pp. 154–163.
- 547 Wood, Simon N (2006). *Generalized Additive Models: An Introduction with R*. Vol. 170. 1, p. 388.
- 548 Yakob, Laith, Luke Alphey, and Michael B. Bonsall (2008). “*Aedes aegypti* control: The concomitant role of
549 competition, space and transgenic technologies”. In: *Journal of Applied Ecology* 45.4, pp. 1258–1265.
- 550 Yakob, Laith and Thomas Walker (2016). “Zika virus outbreak in the Americas: The need for novel mosquito
551 control methods”. In: *The Lancet Global Health* 4.3, e148–e149.

552 **A Pilot study**

553 In order to choose an appropriate feeding regime for the main experiments, it was necessary to find the baseline
554 per-capita nutritional requirements of both species. We therefore explored, on a per-capita basis, how much
555 liver powder was required for a larvae to successfully develop.

556 **Procedure**

557 Eggs of each species were vacuum hatched for approximately 1.5 hours in tap water, which ensured all larvae
558 were the same age. The wells of a 6-well-plate were filled with 9ml RO filtered water. A single larvae was placed
559 into each well of a six well plate. A dilution of liver powder corresponding to 0.05, 0.2, 0.35, 0.5, 0.65 and 0.8
560 mg per larvae was added to each well, bringing the total volume to 10ml. The larvae were fed again with 1ml
561 of this solution on the 2nd and 4th day after hatching (evaporation was thought to maintain the volume at
562 ~ 10 ml). Each day the larvae were checked to see if they had pupated or died. Larvae were given a three
563 weeks to develop, after which time they were assumed dead. This process was repeated for each species, across
564 3 replicates.

565 A binomially distributed logit-link generalised linear model was used to analyse the survival data, and a
566 step-wise down model selection procedure using log-likelihood ratio tests (LRT) was used to determine the
567 optimal set of predictors.

568 **Results**

569 Food treatment had a significant (LRT: $\Delta df = 1$, $p = 2.1 \times 10^{-16}$) positive effect (0.0143 ± 0.0025 , logit scale)
570 on survivorship, but the effect did not significantly differ between species (LRT: $\Delta df = 1$, $p = 0.1299$). The
571 relationship is shown in Figure 6.

572 **Conclusions**

573 Both species responded to the availability to the liver power in the same way. The estimated probability of
574 survival asymptotically approached 1 from approximately 0.5mg/La. We therefore elected to set our feeding
575 regime at 0.55mg/La, to ensure that there were adequate food resources to maintain all larvae in the population.

576

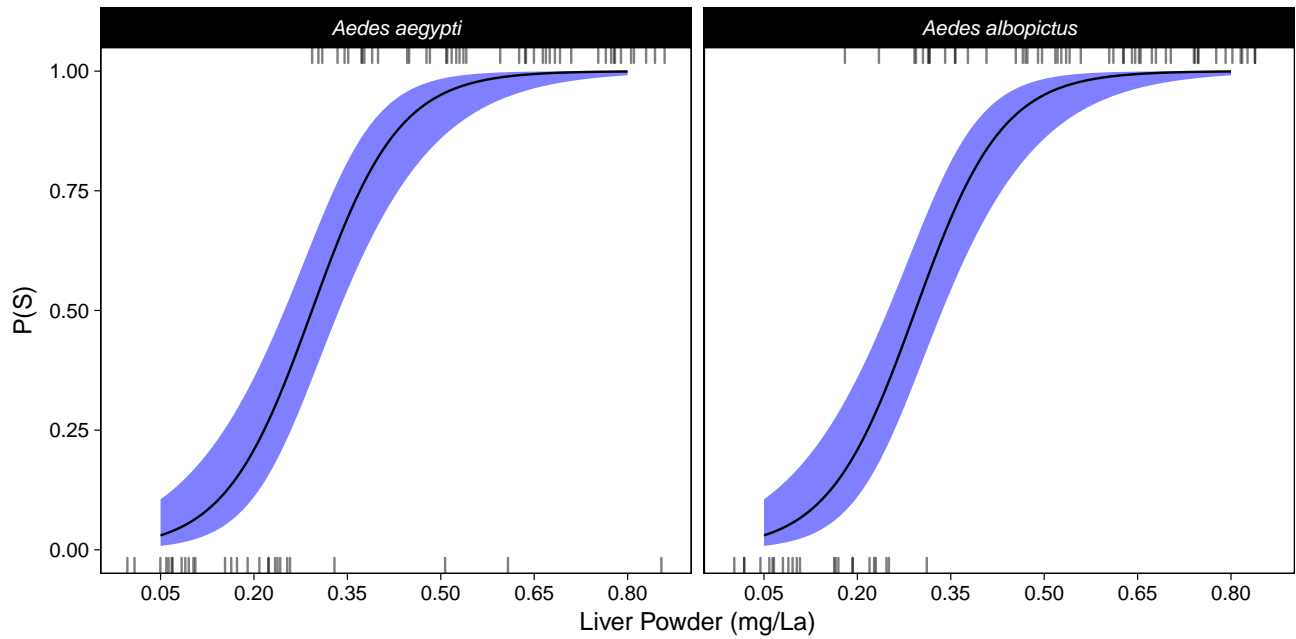


Figure 6: Experimental data for the pilot studies examining the development time and survivorship of *Ae. aegypti* and *Ae. albopictus*. Points show the per-replicate proportion of larvae that survived each food treatment, while the rugs show the raw survival data. Note that there is a positive effect of food availability on survivorship, that it is consistent across both species.

577 B Priors

Survival Models		Development Time Model	
Variable(s)	Distribution	Variable(s)	Distribution
Intercept	$\mathcal{N}(2.7, 1)$	Intercept	$\mathcal{N}(2.079, 1)$
Linear predictors	$\mathcal{N}(0, 1)$	Linear predictors	$\mathcal{N}(0, 0.3)$
Smoothing parameters	$\Gamma(1, 0.001)$	Standard deviation	$\Gamma(1.28, 0.23)$
Certainty, θ (beta-binomial)	$\Gamma(1, 1000)$	-	-

Table 4: Priors used for fitting the binomial, beta binomial and development time models. Both intercepts were taken from pilot runs of the experiment, as was the standard deviation for development time.

578 C Gibbs Variable Selection (GVS)

579 Results for the GVS procedure are reported for the two survivorship model structures (binomial in Table 5 and
 580 beta-binomial in Table 6), and the gamma model of development times (Table 7). The frequencies with which
 581 predictor combinations are reported, along with the absolute number of iterations. Parameter combinations
 582 selected less than 1% of the iterations are not included in the tables. The fits corresponding to each of the best
 583 fitting model are given in Figures 7 and 8 for the two survival models, and 9 for the development time model.

Binomial model of larval survival

Rank	Predictor combinations	N	%
1	$Int + Sp + D_{aeg} + D_{alb} + Sp : D_{alb} + f(D_{aeg})$	633723	15.84
2	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb} + Sp : D_{alb} + f(D_{aeg})$	402459	10.06
3	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb} + D_{aeg} : D_{aeg} + f(D_{aeg})$	326178	8.15
4	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb}$	295250	7.38
5	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb} + Sp : D_{alb}$	240442	6.01
6	$Int + Sp + D_{aeg} + D_{alb} + D_{aeg} : D_{aeg} + f(D_{aeg})$	213651	5.34
7	$Int + Sp + D_{aeg} + D_{alb} + f(D_{aeg})$	212110	5.30
8	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb} + Sp : D_{alb} + D_{aeg} : D_{aeg} + f(D_{aeg})$	202547	5.06
9	$Int + Sp + D_{aeg} + D_{alb} + Sp : D_{alb} + D_{aeg} : D_{aeg} + f(D_{aeg})$	179147	4.48
10	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb} + Sp : D_{alb} + Sp : D_{aeg} : D_{alb} + f(D_{aeg})$	173728	4.34
11	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb} + f(D_{aeg})$	152175	3.80
12	$Int + Sp + D_{aeg} + D_{alb} + Sp : D_{alb} + Sp : D_{aeg} : D_{alb} + f(D_{aeg})$	107058	2.68
13	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb} + D_{aeg} : D_{aeg} + Sp : D_{aeg} : D_{alb} + f(D_{aeg})$	57074	1.43
14	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb} + Sp : D_{alb} + Sp : D_{aeg} : D_{alb}$	53330	1.33
15	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb} + Sp : D_{aeg} : D_{alb}$	53317	1.33
16	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb} + Sp : D_{alb} + D_{aeg} : D_{aeg} + Sp : D_{aeg} : D_{alb} + f(D_{aeg})$	48099	1.20
17	$Int + Sp + D_{aeg} + D_{alb} + D_{aeg} : D_{aeg} + Sp : D_{aeg} : D_{alb} + f(D_{aeg})$	46015	1.15

Table 5: Frequencies with which combinations of predictors were selected for the binomial model during GVS. N denotes for how many samples particular variable combinations were active, and the percentages calculated as N divided by the total number of iterations (4×10^6). Int is the intercept, Sp the species, D_{aeg} the density of *Ae. aegypti* and D_{alb} the density of *Ae. albopictus*. Interactions between variables are denoted by :, while $f()$ denotes that the term is a smooth function of the predictor in brackets. Each smooth functions had 5 knots. The most frequently selected model is given in row 1, and included a species-specific intercept, a linear species specific response to *Ae. albopictus* density and a linear and smooth term for *Ae. aegypti* density.

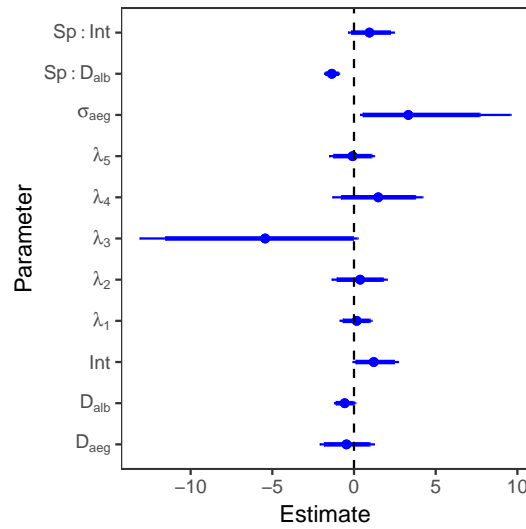


Figure 7: Parameter estimates for the binomial model, after the predictors had been selected by GVS. Dots denote medians, thick lines the 90% HDIs and thin lines the 95% HDIs. In this model, σ_{aeg} is the standard deviation of the normal distribution used to estimate the smoothing parameters (λ_{1-5}) of the 5-knot smooth function of *Ae. aegypti* density (Crainiceanu, Ruppert, and Wand, 2005). Colons denote interactions, “Sp” the intercept change for *Ae. albopictus* and “Int” the intercept. D_{aeg} and D_{alb} are the densities of *Ae. aegypti* and *Ae. albopictus* respectively. This model was compared to the beta-binomial model (Figure 8).

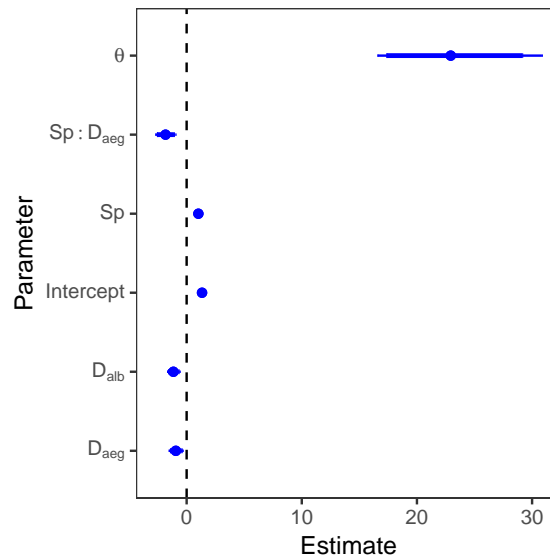


Figure 8: Parameter estimates for the beta-binomial model, after the predictors have been selected by GVS. Dots denote medians, thick lines the 90% HDIs, and thin lines the 95% HDIs. In this model, θ is the certainty parameter, as mentioned in the re-parametrisation of the beta distribution in (Kruschke, 2015). Colons denote interactions, “Sp” the intercept change for *Ae. albopictus* and “Int” the intercept. D_{aeg} and D_{alb} are the densities of *Ae. aegypti* and *Ae. albopictus* respectively. This model was compared to the beta-binomial model (Figure 7). These estimates are also given in Table 2 in the main text.

Beta-binomial model of larval survival

Rank	Predictor combinations	N	%
1	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb}$	1340494	33.51
2	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb} + Sp : D_{alb}$	968011	24.20
3	$Int + Sp + D_{aeg} + D_{alb}$	533692	13.34
4	$Int + Sp + D_{aeg} + D_{alb} + Sp : D_{alb}$	355619	8.89
5	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb} + D_{aeg} : D_{alb}$	184094	4.60
6	$Int + Sp + D_{aeg} + D_{alb} + Sp : D_{alb} + D_{aeg} : D_{alb}$	116732	2.92
7	$Int + Sp + D_{aeg} + D_{alb} + D_{aeg} : D_{alb}$	97547	2.44
8	$Int + Sp + D_{aeg} + Sp : D_{aeg} + D_{alb} + Sp : D_{alb} + D_{aeg} : D_{alb}$	81131	2.03
9	$Int + Sp + D_{aeg} + D_{alb} + Sp : D_{alb} + f(D_{aeg})$	42801	1.07
10	$Int + D_{aeg} + D_{alb}$	41163	1.03

Table 6: Frequencies with which combinations of predictors were selected for the beta-binomial model during GVS. N denotes for how many samples particular variable combinations were active, and the percentages calculated as N divided by the total number of iterations (4×10^6). Int is the intercept, Sp the species, D_{aeg} the density of *Ae. aegypti* and D_{alb} the density of *Ae. albopictus*. Interactions between variables are denoted by :, while $f()$ denotes that the term is a smooth function of the predictor in brackets. Each smooth functions had 5 knots. The most frequently selected model is given in row 1, and included a species-specific intercept, a linear species-specific response to *Ae. aegypti* density and a linear *Ae. albopictus* density.

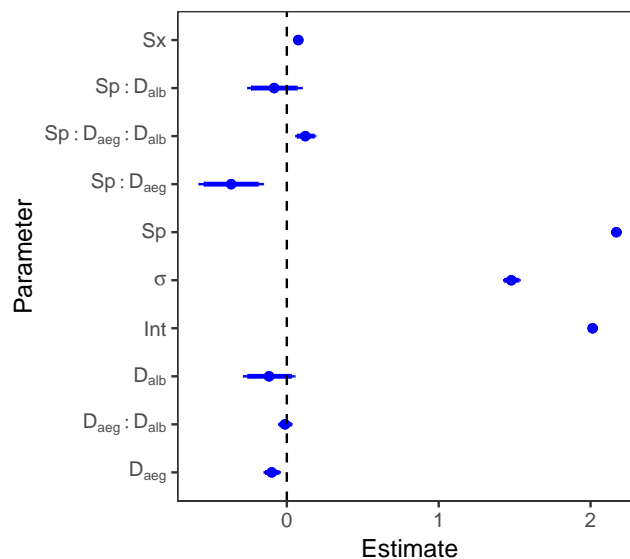


Figure 9: Parameter estimates for the development time model after the predictors have been selected by GVS. Dots denote medians, thick lines the 90% HDIs, and thin lines the 95% HDIs. Colons denote interactions, “Sp” the intercept change for *Ae. albopictus* and “Int” the intercept. D_{aeg} and D_{alb} are the densities of *Ae. aegypti* and *Ae. albopictus* respectively. These four models were then compared using the PSM to decide on the best structure.

Gamma distributed model of development time

Rank	Predictor combinations	N	%
1	$Int + Sp + Sx + D_{aeg} + D_{alb} + D_{aeg} : D_{alb} + Sp : D_{aeg} + Sp : D_{alb} + Sp : D_{aeg} : D_{alb}$	916754	22.92
2	$Int + Sp + Sx + D_{aeg} + D_{alb}$	877931	21.95
3	$Int + Sp + Sx + D_{aeg} + D_{alb} + D_{aeg} : D_{alb} + Sp : D_{aeg} + Sp : D_{alb} + Sx : D_{alb} + Sp : D_{aeg} : D_{alb}$	347898	8.70
4	$Int + Sp + Sx + D_{aeg} + D_{alb} + Sx : D_{alb}$	340935	8.52
5	$Int + Sp + Sx + D_{aeg} + D_{alb} + Sp : D_{aeg}$	173395	4.33
6	$Int + Sp + Sx + D_{aeg} + D_{alb} + D_{aeg} : D_{alb} + Sp : D_{aeg} + Sx : D_{aeg} + Sp : D_{alb} + Sp : D_{aeg} : D_{alb}$	154349	3.86
7	$Int + Sp + Sx + D_{aeg} + D_{alb} + Sp : D_{alb}$	153422	3.84
8	$Int + Sp + Sx + D_{aeg} + D_{alb} + Sx : D_{aeg}$	145638	3.64
9	$Int + Sp + Sx + Sp : Sx + D_{aeg} + D_{alb}$	92416	2.31
10	$Int + Sp + Sx + Sp : Sx + D_{aeg} + D_{alb} + D_{aeg} : D_{alb} + Sp : D_{aeg} + Sp : D_{alb} + Sp : D_{aeg} : D_{alb}$	88255	2.21
11	$Int + Sp + Sx + D_{aeg} + D_{alb} + D_{aeg} : D_{alb}$	79092	1.98
12	$Int + Sp + Sx + D_{aeg} + D_{alb} + Sp : D_{aeg} + Sx : D_{alb}$	66902	1.67
13	$Int + Sp + Sx + D_{aeg} + D_{alb} + Sp : D_{alb} + Sx : D_{alb}$	58694	1.47
14	$Int + Sp + Sx + D_{aeg} + D_{alb} + D_{aeg} : D_{alb} + Sp : D_{alb}$	47654	1.19
15	$Int + Sp + Sx + D_{aeg} + D_{alb} + Sx : D_{aeg} + Sx : D_{alb}$	46270	1.16

Table 7: Frequencies with which combinations of predictors were selected for the gamma GLM during GVS. N denotes for how many samples particular variable combinations were active, and the percentages are N divided by the total number of iterations (4×10^6). Int is the Intercept, Sp the species (categorical), Sx the sex (categorical), D_{aeg} the density of *Ae. aegypti* and D_{alb} the density of *Ae. albopictus*. Interactions between variables are denoted by colon. The most selected model is given in the first row, and included a sex-specific intercept, as well as

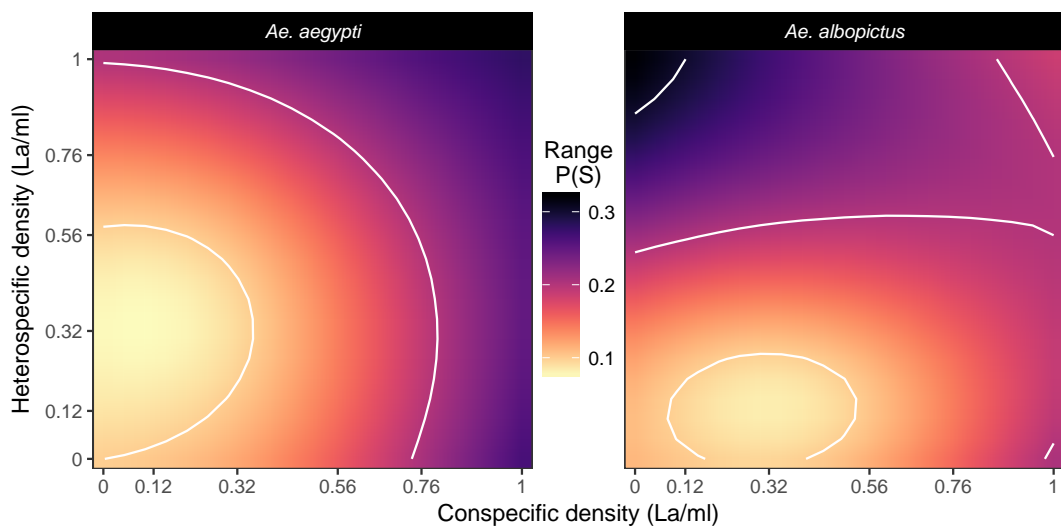


Figure 10: Plot showing the distribution of uncertainty (as a range in survival probability) across the predicted response surfaces in Figure 3.

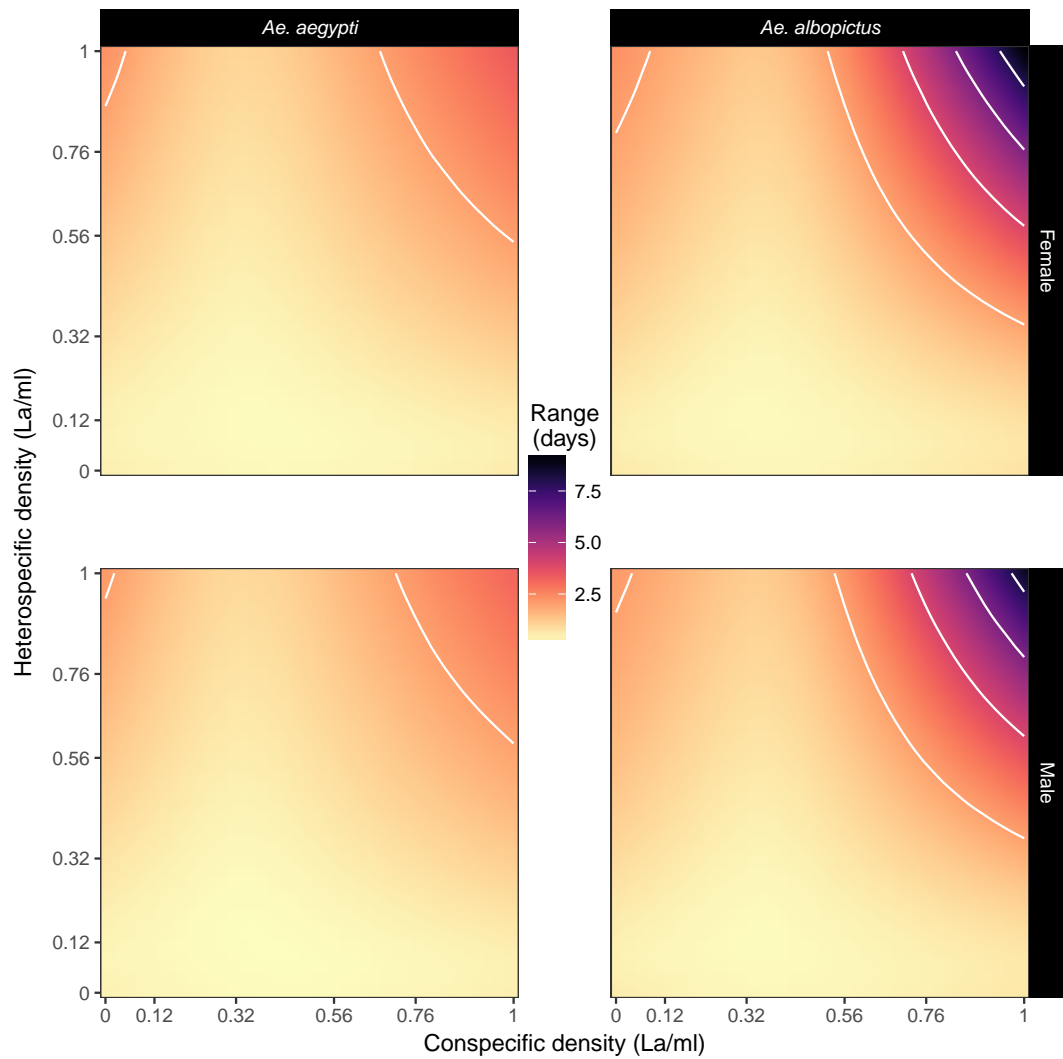


Figure 11: Plot showing the distribution of uncertainty (as a range in days) across the predicted response surfaces in Figure 5.