Dominance reversal protects large-effect resistance polymorphisms in temporally varying

environments

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Abstract

A central challenge in evolutionary biology is to uncover mechanisms maintaining functional genetic variation in heterogeneous environments[1,2]. Population genetics theory suggests that beneficial reversal of dominance, where alleles are dominant when beneficial and recessive when deleterious, can help maintain such variation in temporally varying environments[3,4]. However, empirical examples are scarce[5] due to difficulties in measuring dominance in fitness in field experiments[6]. Here we quantify the selective effects and dominance of large-effect insecticide-resistant alleles at the *Ace* enzymatic locus in *Drosophila melanogaster*[7]. In laboratory assays, we identify a beneficial reversal of dominance of the *Ace* alleles for fitness-associated phenotypes under selection in the presence and absence of malathion, a widely used organophosphate insecticide. Using highly replicated field mesocosms, we show that resistant *Ace* alleles fluctuate rapidly in response to a pulse of malathion, but are maintained in its absence. We show that this pattern is only consistent with beneficial reversal of dominance, where the resistant *Ace* alleles are dominant and beneficial for resistance and recessive and deleterious for enzymatic function. Moreover, we find that seasonally fluctuating selection due to insecticide resistance can generate fluctuating chromosome-scale genomic perturbations of allele frequencies. We propose an extension to Wright's physiological theory of dominance[8], arguing that under fluctuating selection the currently deleterious allele should often behave as loss-of-function and thus recessive to the currently beneficial allele. Overall, our results suggest that beneficial reversals of dominance can be common and can help both maintain genetic variation and allow for rapid evolutionary responses to environmental shifts.

Main text

The maintenance of functional additive genetic variation for fitness-related traits in populations, and specifically the portion that is due to the segregation of large-effect loci, has long posed a theoretical and empirical challenge[9,10]. Classical population genetics theory suggests that directional selection should erode such variation over time. However, the observed persistence of intermediate-frequency large-effect loci in natural populations implies that balancing selection mechanisms, including spatial or temporal environmental variation in selection pressures, may be a prevalent force acting on natural populations[11].

As one example, studies of seasonal dynamics in Drosophila revealed the presence of large-effect seasonal polymorphisms[12,13] that rapidly respond to environmental fluctuations, with the causal alleles shifting between advantageous to deleterious multiple times during a single seasonal cycle[14–16]. Some of these seasonal alleles have strong enough selective effects that they can change frequencies by tens of a percent per season, yet still remain polymorphic over hundreds of thousands or even millions of generations[12].

One mechanism proposed by theoretical models that can strongly stabilize genetic variation in the face of temporal fluctuations is beneficial reversal of dominance[3,4,17]. This phenomenon occurs when each allele is partially or completely dominant in environments in which it is favored and recessive in environments in which it is harmful. Such reversals of dominance act as a stabilizing mechanism by protecting recessive deleterious alleles from selection and precluding their loss. At the same time, it allows a rapid response to selection shifts, as adaptive alleles are always dominant, even when rare. Even modest beneficial reversal of dominance has been shown to help preserve variation under fluctuating selection in single- or multiple-locus models and to allow fluctuating selection to drive allele frequency fluctuations[4].

The central empirical questions are twofold: does beneficial reversal of dominance occur

for functional polymorphic large-effect loci across the genome, and does it naturally arise within

genetic systems? The overall scarcity of empirical examples[5] makes these questions difficult to

answer, as measuring fitness and the dominance of fitness effects in natural environments

remains a challenge[6].

To begin addressing this knowledge gap, here we investigate the dominance of large-

effect alleles conferring resistance to organophosphate insecticides at the *Ace* locus in natural

populations of *Drosophila melanogaster*. *Ace* encodes acetylcholinesterase (AChE), a key

enzyme in the insect nervous system responsible for breaking down acetylcholine[18].

Organophosphate insecticides, introduced in the 1950s and 1960s, act as irreversible inhibitors of

AChE, causing insect death by binding to its active site and preventing removal of acetylcholine

from the synapses upon firing[19]. These insecticides have imposed seasonally fluctuating selection

pressures on *D. melanogaster* populations, as seen in seasonal resistance fluctuations in field

studies[20,21]. This case is a compelling example of a large-effect polymorphism subject to

fluctuating selection, where the causal locus, the mechanistic basis of selection, and the

conditions that confer advantage to alternative alleles are well understood. Here we first analyze

genomic data from worldwide *D. melanogaster* populations to assess whether patterns of

resistant *Ace* allele frequencies are consistent with spatially and temporally variable insecticide

use. We then combine laboratory and outdoor mesocosm experiments to measure fitness effects

and dominance in the presence and absence of organophosphates, serving as proxies of the two

alternative environments.

Previous studies have identified several resistant *Ace* alleles in natural *D. melanogaster*

populations carrying resistance mutations at four conserved sites near the AChE active site

(I161V, G265A, F330Y, G368A), with those carrying the V̲GFG and V̲A̲YG resistance

haplotypes as the most common[7,22] (**Fig. 1a**). Our analysis of two inbred line panels, LNPA[14] and

DGRP[23], collected from a farmers market in Pennsylvania and an orchard in North Carolina,

respectively, confirmed these two as the most common resistant *Ace* alleles. Further, the LNPA

population also carries another resistance haplotype V̲GFA̲ at frequency ~13% (**Fig. 1a,**

Extended Data Fig. 1). Using the Drosophila Evolution Over Space and Time (DEST) dataset,

which sampled *D. melanogaster* populations worldwide across seasons and years[24], we tracked

the I161V mutation shared by all three resistant *Ace* alleles as a marker for resistance.

The I161V polymorphism displayed seasonal fluctuations of up to 33% per season (**Fig.**

1b) and its frequency varied from 1 to 85 % (**Fig. 1c**) in the 34 cases where we had paired

Spring and Fall samples from the same year at the same location in natural populations. The

variation of the frequency across all sampled populations in the Spring was more extreme

compared to the empirical null defined by studying matched control SNPs (ECDF test, p=

0.0018) (**Fig. 1d**). These findings support our notion that seasonally varying organophosphate

selection induces strong and rapidly fluctuating selection at the *Ace* locus.

Figure 1

Figure 1. Organophosphate-resistant *Ace* alleles display seasonal fluctuations and are present at intermediate frequencies in natural *Drosophila melanogaster* populations. a, Four widespread organophosphate resistance target site mutations in the *Ace* gene coding for acetylcholinesterase (AChE) in *D. melanogaster*. Frequencies of sensitive (S: IGFG) and common resistant *Ace* alleles with three different resistance haplotypes (R1: VGFG, R2: VGFA, R3: VAYG) in DGRP and LNPA panels of fully sequenced inbred lines (See also **Extended Data Figure 1**). **b-d,** Temporal and spatial dynamics of the shared organophosphate resistance polymorphism I161V present in common resistant *Ace* alleles in worldwide populations (data from the DEST database, see also **Methods**). Absolute allele frequency shift of I161V from Spring to Fall across populations (points for individual populations) (**b**), allele frequency map of I161V (**c**), and comparison of the variance of frequency of I161V (dashed orange line) to matched control SNPs across populations (log scale, ECDF test of SNP frequency variances, p = 0.0118) (**d**).

We next used a laboratory-based approach to assess the dominance of resistant *Ace*

alleles over their sensitive counterparts for fitness-associated phenotypes likely to be under

selection in organophosphate-rich and -free environments. The resistance mutations confer a

resistance benefit in the presence of insecticides by altering the shape of AChE's active site, thus

preventing insecticide binding[7]. However, these same mutations impair AChE activity and

stability[25], likely rendering them deleterious in the absence of insecticides[26].

Using the LNPA panel of inbred lines, which contains the sensitive and three resistant

Ace alleles (**Fig. 1a**, **Extended Data Fig. 1**), we generated recombinant populations with

homozygous sensitive, homozygous resistant, and heterozygous genotypes for each resistant

allele (S: IGFG, R1: <u>V</u>GFG, R2: <u>V</u>GF<u>A</u>, R3: <u>VAY</u>G) (see **Methods**). This approach[27] allowed us

to control for the genotype at the *Ace* locus while allowing variation in the rest of the genome.

This enabled us to measure effects specifically due to the *Ace* genotypes while reducing the

influence of unlinked genetic variation.

We first estimated resistance to organophosphates using malathion LD_{50} values (dose

causing 50% egg-to-adult mortality). For resistance conferred by insensitivity to malathion, the

level of dominance h of resistant alleles is measured by the ratio $(LD_{50}[RS] -$

$LD_{50}[SS])/(LD_{50}[RR]-LD_{50}[SS])$. The resistant R2 and R3 *Ace* alleles significantly increased

malathion LD_{50} by ~5.8x and ~7.8x respectively (p < 0.001 for both), and were highly dominant

over the sensitive S *Ace* allele, with dominance h 0.78 and 0.77 for R2 and R3, respectively (p <

0.001 for both). In contrast, the R1 *Ace* allele showed no significant increase in malathion

resistance (p = 0.646) and no clear dominance pattern (h = -1.29, p = 0.751) (**Fig. 2, Extended**

Data Fig. 2, Extended Data Table 1). The dominance of resistance is expected because

malathion covalently binds to and inactivates the sensitive S *Ace* allele, while the resistant alleles

remain functional. This pattern follows Wright's physiological theory of dominance[8], which

predicts that functional alleles are dominant over loss-of-function alleles, as even one copy of the

functional allele provides sufficient enzyme activity.

We next assessed the cost of resistance in the absence of organophosphates by

quantifying two key fitness-associated phenotypes, viability (egg to adult survival) and fecundity

(number of eggs laid by gravid females). All homozygous resistant genotypes exhibited lower

phenotypic fitness values compared to the homozygous sensitive genotype, for either or both of

these phenotypes, with viability reductions ranging from 12.4% to 16.9% (all $p < 0.001$) and

fecundity reductions from 16.2% (R2R2, $p = 0.37$) to 46.8% (R3R3, $p < 0.001$). The costs driven

by the three resistant alleles were either significantly recessive for at least one of the phenotypes

(viability R2: $h = 0.17$, $p = 0.027$, fecundity R3: $h = -0.02$, $p = 0.001$), or indistinguishable from

codominance (**Fig. 2g-l, Extended Data Tables 2-3**). Overall, the sensitive S *Ace* allele is

beneficial and dominant/codominant and never recessive towards its resistant counterparts in

terms of viability and fecundity in the absence of malathion.

These results are consistent with the beneficial reversal of dominance. They also suggest

that the response to organophosphates at the concentrations similar to the LD_{50} of the sensitive

homozygous genotype should induce a very rapid increase in the frequency of the resistant *Ace*

alleles and in the level of overall resistance, given that resistant *Ace* alleles are strongly

beneficial and dominant. We also expect that in the absence of insecticides, the resistant *Ace*

alleles should only show slow declines in frequency when rare given that they are recessive.

However, if previous insecticide exposure has caused these alleles to become common in the

population, their subsequent decline (when insecticides are removed) should occur much more

rapidly.

Figure 2

Figure 2. Beneficial reversal of dominance of organophosphate-resistant *Ace* alleles for fitness-associated phenotypes relevant to malathion-rich and -free environments. a-b, In a scenario of a beneficial reversal of dominance, the resistant R *Ace* alleles are beneficial and partially or completely dominant in malathion-rich environments, but deleterious and recessive in malathion-free environments. **c,** Selection (*s*) and dominance (*h*) coefficients for each fitness-associated phenotype are estimated based on the viability selection model. **d-l,** Comparison of malathion LD_{50} (**d, e, f**), egg-adult viability (n= 10 technical replicates, 50 eggs/replicate) (**g, h, i**), and fecundity (n= 8-10 technical replicates, 5 females/bottle/3 days) (**j, k , l**) among *Ace* genotypes. For calculation of malathion LD_{50} see **Methods** and **Extended Data Figure 2**. Egg-adult viability and fecundity data were analyzed with logistic and linear regression models. Points represent the mean ± s.e.m for each *Ace* genotype. Bootstrapping analysis was performed to assess whether the selection and dominance coefficients significantly differ from 0 and 0.5, respectively. The asterisks indicate significant differences (* <0.05, **< 0.01, ***<0.001). The color of the heterozygote for each *Ace* allele corresponds to its dominance based on the beneficial reversal of dominance model. Statistical tests in **Extended Data Table 1-3**.

To test these predictions, we directly investigated the population dynamics at the *Ace*

locus in an ecologically realistic environment by evolving replicate *Drosophila melanogaster*

populations in the presence and absence of seasonally fluctuating malathion in field mesocosms

at an experimental orchard in Pennsylvania (**Fig. 3a,** see **Methods**). We established 20 replicate

populations derived from a baseline population constructed from the LNPA panel of 76 inbred

lines used in our lab experiments (**Extended Data Figure 1**). These lines were outbred for 4

generations in large indoor cages before ~1000 males and females were used to seed each

outdoor cage (see **Methods** and Bitter and colleagues[28]). The initial frequencies of the resistant

Ace alleles in the field mesocosms likely reflect their frequencies in the local population from

which the LNPA lines were derived.

After the first ~4 weeks (3-4 generations) of untreated propagation, the 20 outdoor cages

were divided into ten malathion-treated and ten untreated cages. To mimic natural insecticide

exposure, we applied gradually increasing concentrations of commercial malathion (Southern Ag

Malathion 50% E.C.) in the growth media of the treated populations, 1.5-2.5 ppm from July 21

to August 24, 2021, followed by 7.5 ppm until September 6, 2021. These doses, based on our lab

LD_{50} measurements, exert strong selection against different *Ace* alleles, with lower doses

targeting the S and R1 alleles, and higher doses affecting the R2 and R3 alleles (**Extended Data**

Fig. 2). Following the malathion exposure, the experiment continued without pesticides in all 20

cages through December 22, 2021. Throughout the experiment, we tracked population dynamics,

malathion resistance, and genome-wide allele frequencies at eight timepoints (~every one to two

generations), focusing on trajectories of resistant *Ace* alleles and linked sites in response to

fluctuating malathion exposure (**Fig. 3a**).

Figure 3

Figure 3. Beneficial reversal of dominance of resistant *Ace* alleles for fitness in an ecologically realistic environment. a, Twenty field mesocosm cages were seeded with an outbred population of *D. melanogaster* generated via outcrossing for 4 generations 76 inbred lines carrying the sensitive S and resistant R1, R2, and R3 Ace alleles. Ten cages received a malathion pulse after the initial population establishment. Eight timepoints were sampled to track the evolution of malathion resistance and genome-wide allele in the treated and untreated populations. Malathion did not affect estimated adult fly population sizes (mean ± s.e.m.) in treated populations. **b,** The malathion pulse led to a significant increase and subsequent decline of resistance (LD_{50}, ppm) in the treated populations while resistance remained stable in the untreated populations. For LD_{50} calculations see **Methods** and **Extended Data Figure 3**. Light lines/points show individual populations (orange, treated; blue, untreated), dark lines/points represent mean ± s.e.m. (n=10 populations per treatment group). **c-d,** Trajectories of *Ace* alleles in treated (**c**) and untreated (**d**) populations. In treated populations, the malathion pulse led to a significant increase in the frequency of the resistant R2 and R3 *Ace* alleles, followed by a decline in the frequency of R3. *Ace* allele frequencies remained stable in the untreated populations. Light lines/points show individual allele trajectories, dark lines/points represent the mean ± s.e.m. (n = 10 populations per treatment group). (**continued on next page**)

Figure 3 (continued). e, Inferred selection (s) and dominance (h) coefficients from changes in the resistant *Ace* allele frequency. The colored ranges show the selection coefficients corresponding to the 0.95 confidence intervals of the slope distribution, obtained by bootstrapping cages within each treatment group. The overlap between the orange (treated cages) and dark blue (untreated cages) restricts the possible values of *s* and *h*. Within that overlap, lower values of *h* better explain both sets of data, as shown by higher values of the joint likelihood calculated from the bootstrap distributions (see **Methods**). All results of statistical tests can be found in **Extended Data Tables 4-6**.

Surprisingly, the seasonal population dynamics were qualitatively similar in both

malathion-treated and untreated cages (**Fig. 3a**). In all cages, population sizes increased through

the summer months until reaching maximum size and then slowly declined in late Fall as abiotic

conditions worsened. We interpret the unchanged seasonal population dynamics as an indication

that population dynamics in all cages are primarily determined by high levels of baseline egg,

larval, and pupal mortality that mask additional mortality imposed by malathion on the adult

census population.

To characterize malathion resistance, we tracked egg to adult survival on diets with 0-15

ppm malathion and estimated LD_{50} at each timepoint per population (see **Methods** and

Extended Data Fig. 3). In malathion-treated cages, resistance increased rapidly from ~2.2 ppm

to ~12.6 ppm during exposure (t = 24.26, p < 0.001), followed by a significant decline to ~10.6

ppm after removal of malathion (t = -3.96, p = 0.001) (**Fig. 3b, Extended Data Table 4.1**). In

contrast, resistance levels in untreated cages remained stable at ~2.2 ppm throughout the

experiment (t = 1.07, p = 0.288) (**Fig. 3b, Extended Data Table 4.2**).

Using a haplotype-aware method to analyze pooled sequencing data[29], we inferred the

frequency dynamics of the sensitive and resistant *Ace* alleles (see **Methods**). In treated cages,

resistant *Ace* alleles R2 and R3 increased significantly during malathion exposure (R2: t = 13.93,

p < 0.001; R3: t = 27.59, p < 0.001), with R3 subsequently declining post-exposure (t = -5.18, p

< 0.001) (**Fig. 3c, Extended Data Table 5**). The R1 allele showed muted responses, consistent

with our lab data showing that it confers no detectable malathion resistance (**Fig. 2c, Extended**

Data Table 5). In untreated populations, all resistant *Ace* allele frequencies remained stable (all

p > 0.05) (**Fig. 3d, Extended Data Table 6**).

To assess the contribution of the resistant *Ace* alleles to malathion resistance evolution in

the field mesocosms, we applied a viability selection model using lab-measured *Ace* genotype

viabilities (see **Methods**). This model closely recapitulated both the allele frequency trajectories

(**Extended Data Fig. 4a,b**) and the evolution of malathion resistance (**Extended Data Fig. 4c,d**)

observed in the field mesocosms. The agreement between model predictions and experimental

data provides compelling evidence that *Ace* was the major effect locus conferring malathion

resistance in the treated cages.

The results from the field mesocosms were qualitatively consistent with our expectations.

The *Ace* genetic system exhibited two key behaviors, rapid response to malathion exposure and

maintenance of resistance at low levels in its absence. In the malathion-treated cages, we

observed a significant decline of high-frequency resistant *Ace* alleles post malathion exposure,

indicating considerable fitness costs for resistant alleles when common. In contrast, untreated

cages showed fairly stable frequencies of low-frequency resistant alleles, suggesting low

selection coefficients (s) or dominance parameters (h) in the absence of malathion.

To obtain bounds on evolutionary parameters, we fit the allele frequency data of the

treated and untreated cages to a viability selection model where all resistant alleles share the

same fitness cost (see **Methods**). The model that fits both datasets best had low cost ($s \sim 2.5$ to

5%) and low dominance values ($h < 0.38$) (**Fig. 3e, Extended Data Fig. 5**). At higher values of

h, there is no single selection coefficient that can explain the patterns of allele frequency change

for both treated and untreated cages, and the likelihood of the data is higher the closer *h* is to

zero. Overall, the data are consistent with the fitness cost of organophosphate resistance being

recessive and low, allowing the resistant *Ace* alleles to persist at low frequencies for extended

periods of time.

The rapid frequency fluctuations of large-effect alleles are expected to generate long-

range allele frequency perturbations. However, in most situations these effects are difficult to

quantify as the patterns of linkage of common large-effect variants are complex. Our system

presents a rare opportunity to do this as we have the information of starting haplotypes and thus

at least the starting patterns of linkage of SNPs genome-wide with the Ace alleles. Using a two-

step approach (see **Methods** for details), we first employed quasibinomial logistic regression to

estimate allele frequency changes (effect sizes) for genome-wide SNPs during malathion

exposure (July 26 to September 21, 2022) and post-exposure (September 21 to December 22,

2021). Second, we identified the SNPs tightly linked (Ace-linked) and loosely linked (control) to

the sweeping R2 and R3 *Ace* alleles across the genome, based on patterns of linkage in our

inbred lines. This approach allowed us to quantify the extent of both the forward *Ace* sweep

during malathion exposure and the reverse *Ace* sweep post-exposure.

During the malathion exposure, we observed a large selective sweep (~4-10 Mbp) on the

3R chromosome arm driven by the *Ace* resistant alleles in the malathion-treated populations. The

effect sizes of linked variation were consistently elevated above the control baseline (**Fig. 4a**).

Additionally, peaks on arms 2R and 3L were elevated equally for both Ace-linked and control

sites, suggesting the presence of two additional resistance loci (**Fig. 4a**). In untreated

populations, the frequencies of the R2 and R3 *Ace* alleles remained stable (**Fig. 3c**). As expected,

Ace-linked sites in untreated populations did not show any changes in frequency (**Fig. 4b**).

Figure 4

Figure 4. **Strong fluctuating selection of resistant *Ace* alleles caused chromosome-scale forward and reverse sweeps during and after malathion treatment, respectively. a-b,** Median allele frequency change (effect size) estimated via quasibinomial logistic regression modeling for Ace-linked and unlinked control SNPs in 500kb windows across the genome in malathion-treated (**a**) and untreated (**b**) populations during malathion treatment. The shaded areas represent 95% bootstrap confidence intervals. Sweep width was estimated with bootstrap and is represented with red rectangles on panel a (dark red, middle red, and light red rectangles correspond to 2.5%, 50%, and 97.5% bootstrap quantiles for sweep width, respectively. **c-d,** Comparison of effect size for Ace-linked (top) and unlinked control (bottom) SNPs during (y-axis) and after malathion treatment (x-axis) in malathion-treated (**c**) and untreated populations (**d**). SNPs on chromosomal arm 3R (left) while SNPs on chromosomes 2, X, and the 3L arm (right). Ace-linked and unlinked control SNPs are color-coded by distance from *Ace* locus(dark to light orange, malathion-treated; dark to light blue: untreated).

After the malathion exposure, we observed a reverse sweep driven by the *Ace* resistant

alleles in the malathion-treated populations. Ace-linked SNPs on the 3R chromosome showed a

negative association between frequency changes during and after malathion exposure, with

stronger reversals closer to the *Ace* locus compared to less-linked control SNPs (**Fig. 4c,** left top

and bottom). We did not observe significant patterns of reversal for either Ace-linked or control

SNPs on other chromosomes with treatment (**Fig. 4c,** right top and bottom) or in untreated

populations (**Fig. 4d)**. Overall, our analysis confirmed that strong fluctuating selection on

resistant *Ace* alleles caused long-range, almost chromosome-scale allele frequency perturbations.

Here we provide compelling laboratory evidence for beneficial reversal of dominance at a

locus subject to strong, temporally fluctuating selection. Based on these measurements we

predicted the rapid increase in frequency of the resistant *Ace* alleles in the presence of

organophosphates and the relative stability in their absence. A large-scale highly replicated field

mesocosm experiment confirmed our predictions and revealed genome-wide fluctuating sweeps

driven by the resistant *Ace* allele. A viability-selection model suggests that the cost of resistance

is likely recessive, as only a recessive cost is consistent with the observed stability when rare and

the reduction in frequency when common.

These results allow us to speculate as to the likely mechanistic reasons for the dominance

reversals in fitness we observe. Consistently with previous studies, resistance is beneficial in the

presence of organophosphates[7] and costly in its absence[25]. We reasoned that in the presence of

organophosphates the benefit should be dominant because loss of function in one copy of the

protein will be compensated by the sufficient function of the resistant copy. This follows

Wright's physiological theory of dominance[8] that argues that reduction in enzymatic activity by

one half should have only a small effect on fitness. Similarly, in the absence of

organophosphates the cost should be recessive since the sensitive allele maintains normal

function and the logic of the physiological model of dominance applies again.

This beneficial reversal of dominance extends Wright's model of dominance as the

identity of the dominant beneficial allele changes with the environment. This model also

suggests that beneficial reversal of dominance may be a general feature of balanced allelic

arrangements where alternative alleles lose their functional capacities across environments due to

tradeoffs. One can easily imagine that such scenarios are common and generic and do not require

special fine-tuning between fitness and dominance. For example, loci involved in resistance to

synthetic insecticides and host plant toxins, which are under temporally varying selection, likely

exhibit similar dominance patterns[30,31].

An important implication of beneficial reversal of dominance is the capacity to help

maintain very large-effect polymorphism and allow for rapid evolutionary responses to

environmental change. As we observed in our experiment, fluctuating selection acting on such

loci will result in large-scale perturbations of allele frequencies at the causal loci as well as at

linked loci at long genomic scales. These perturbations would be hard to detect without knowing

the exact linkage structure[32], because the signatures left in the genomic sequences are complex

and are unlike what one expects with selective sweeps by *de novo* mutation. However, if the

genome contains even a modest number of large effect allele displaying dominance reversal in

response to fluctuating selection this by itself can maintain genome-wide functional

polymorphisms on long time-scales.

To conclude, our work demonstrates that beneficial reversal of dominance operates at

least at some loci of large fitness effect, facilitating both rapid responses to shifting selection

pressures and the long-term maintenance of polymorphism. We present arguments for why such

reversals should arise commonly and naturally as a simple consequence of the less active (nearly

loss-of-function) alleles being recessive as suggested by Wright's theory of dominance. We also

introduce a way to quantify dominance in fitness by measuring allele trajectories under selection

starting at different frequencies. This approach can be used to assess the presence of beneficial

reversal of dominance for loci of large effect segregating in populations across a range of taxa.

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responsible for formal analysis, visualization, and writing-review and editing; M.B. was

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visualization; S.G. was responsible for formal analysis; A.H., CT, and Z.K.M. were responsible

for investigation; P.S. and D.A.P. jointly supervised the research. P.S. was responsible for

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responsible for conceptualization, formal analysis, writing-review and editing, and funding

acquisition.

Methods

Population genomic analysis for variation of organophosphate-resistant *Ace* alleles over space and time

We first conducted a literature review to compile all known naturally segregating target site resistance mutations in the acetylcholinesterase (*Ace* gene) protein of *D. melanogaster* that confer resistance to organophosphates. Mutero and colleagues in 1994[33] first identified the resistance mutations F115S, I199V, I199T, G303A and F368Y, and numbered them based on the precursor acetylcholinesterase (AChE) protein. Menozzi and colleagues in 2004[7] identified combinations of the resistance mutations I161(199)V, G265(303)A, F330(368)Y and G368(406)A in worldwide organophosphate-resistant *D. melanogaster* strains and numbered them based on the mature AChE protein (numbers in the brackets refer to the precursor AChE protein). They did not identify the resistance mutation F77(115)S. At position 77, the mutation TTC to TCC changes phenylalanine to serine (Chr3R: 9,070,101, v5.39). At position 161, the mutation ATC to GTC changes the isoleucine to valine (Chr3R:9,069,721, v5.39). At position 265, the mutation GGC to GCC changes the glycine to alanine (Chr3R:9,069,408 , v5.39). At position 330, the mutation TTT to TAT changes the phenylalanine to tyrosine (Chr3R:9,069,054 , v5.39). At position 368, the mutation GGC to GCC/GCT changes the glycine to alanine (Chr3R: 9,063,921 , v5.39). The AChE protein's numbering changed between the studies after its crystallization in 2000, which defined the N-terminal signal peptide and the C-terminal sequence[34]. The mutation G368A was misannotated in the study on adaptation of *D. melanogaster* to organophosphate insecticides by Karasov and colleagues[22].

Organophosphate-resistant *Ace* alleles in DGRP and LNPA inbred lines

We characterized the presence of organophosphate-resistant *Ace* alleles in two fully

sequenced inbred line panels, the Drosophila Genetic Reference Panel (DGRP) and our LNPA

panel of inbred lines. The DGRP panel consists of 205 inbred lines derived from wild-caught

females collected at the Raleigh, North Carolina Farmers Market in 2003[23]. The LNPA panel

consists of 76 inbred lines derived from wild-caught individuals collected in Spring and Fall

from Linvilla Orchards, Media PA USA[14]. Both panels contain the two common resistant *Ace*

alleles (Ace-R1: <u>V</u>GF<u>G</u> and Ace-R3: <u>VA</u>Y<u>G</u>) at high frequency, the sensitive *Ace* allele (Ace-S:

IGFG), and other rare resistant alleles. The LNPA panel also contains the resistant *Ace* allele

Ace-R2: <u>V</u>GF<u>A</u> at high frequency. We used the LNPA panel for our lab and field mesocosm

experiments.

<u>Seasonal and spatial variation of organophosphate-resistant *Ace* alleles in natural *Drosophila*</u>

<u>*melanogaster* populations</u>

We used the DEST (Drosophila Evolution Over Space and Time) database to characterize

variation in resistant *Ace* allele frequencies between Spring and Fall and across populations. Our

analysis focused on the resistant *Ace* allele coding for I161V, a marker for common resistant

alleles, as it is shared among them. We selected paired samples of wild-caught populations from

locations with both spring/summer (March-August) and fall/winter (September-December) data

within the same year, retaining the earliest Spring/Summer and latest Fall/Winter sample for

each location-year combination. Based on these criteria, we ended up with 34 paired samples

collected between 2012 and 2016.

To analyze temporal variation, we calculated the absolute frequency shift of the I161V

allele from Spring to Fall for each population per year. For spatial variation, we calculated I161V

average frequency at each population in Spring samples across available years and visualized its

spatial distribution in an allele frequency map.

To further assess the spatial variability of the resistance polymorphism I161V, we

compared the I161V allele variance to matched control single nucleotide polymorphisms (SNPs)

in the Spring samples across locations. We selected 1000 matched control SNPs based on the

following criteria: (1) located within 2Mb from 100kb away from *Ace* to avoid linked SNPs, (2)

within the ln(3R)K cosmopolitan inversion to match inversion status, and (3) average frequency

across all Spring samples within 4% of the median frequency of the I161V resistance mutation.

Finally, we used the cumulative distribution function (CDF) to quantify how extreme the I161V

variance was compared to the control SNPs.

Lab experiments to estimate dominance of resistant *Ace* alleles for fitness-associated

phenotypes in presence and absence of malathion

To assess whether the dominance of each resistant *Ace* allele (Ace-R1: <u>V</u>GFG, Ace-R2: <u>V</u>GF<u>A</u>,

Ace-R3: <u>VA</u>Y<u>G</u>) over their sensitive counterpart (Ace-S: IGFG) reverses for fitness-associated

phenotypes that are primarily under selection in organophosphate-rich and -free environments,

we first used our LNPA panel of inbred lines to generate recombinant populations with

homozygous sensitive, homozygous resistant, and heterozygous *Ace* genotypes for each *Ace*

allele. This step was meant to bring potential deleterious, recessive mutations in the inbred lines

into heterozygosity. We then measured malathion resistance, viability and fecundity in

homozygous and heterozygous populations for each *Ace* genotype.

<u>Generation of recombinant populations with homozygous sensitive, homozygous resistant, and</u>

<u>heterozygous *Ace* genotypes</u>

To generate recombinant populations for each *Ace* allele, we first intercrossed 2-3 inbred

lines with the same *Ace* allele using a round robin cross scheme (e.g., Line_1 SS x Line_2 SS,

Line_2 SS x Line_3 SS, Line_3 SS x Line_1 SS) to bring all founders with the same *Ace* allele

together (10 non-mated females x 10 males per round robin cross). We then combined 16 F1

flies (8 non-mated females and 8 males) from each of the round robin crosses per *Ace* allele to

establish the next generation. Subsequently, we maintained the homozygous populations in vials

and allowed them to recombine for four generations until we performed the phenotype

measurements. We used lines 12LN6-70_(B33), 12LN6-92_(B3), LNPA-3 for the sensitive *Ace*

allele (Ace-S: IGFG), lines 12LN6-86_(B29) and LNPA-53 for the R1 resistant *Ace* allele (Ace-

R1: <u>V</u>GFG), lines LNPA-14, LNPA-17 and LNPA-87 for the R2 resistant *Ace* allele (Ace-R2:

<u>V</u>GF<u>A</u>), and lines 12LN6-45_(B26), 12LN6-82_(B4), and 12LN6-94_(B19) for the R3 resistant

Ace allele (Ace-R3: <u>VAY</u>G).

<u>Measurements of fitness-associated phenotypes</u>

For all experiments, we first set up breeding cages with ~ 500 4-to-7-day-old flies of

homozygous or heterozygous populations for the sensitive and the resistant *Ace* alleles. To

generate the heterozygous recombinant populations, we crossed SS non-mated females with

homozygous males of each resistant allele (R1R1, R2R2, R3R3).

To compare the level of malathion resistance among the different alleles, we measured

egg-to-adult viability on diets that ranged in malathion concentration from 0 ppm to 30 ppm. For

this, we collected eggs of each population that were laid within a period of 24 hours and then

introduced 50 eggs of each population into narrow vials containing approximately 7 ml of

Drosophila growth media supplemented with the respective malathion concentration. We tested

each of the malathion concentrations in duplicate vials. We used commercial malathion of 50%

strength (Southern Ag Malathion 50% E.C.) and dissolved it in the Drosophila growth media.

This medium was kept overnight at 4°C and used the next day for the assay. We monitored adult

eclosion every evening over a period of 10 days until all adult flies had enclosed.

To compare viability among the different genotypes, we introduced 50 eggs of each

population into narrow vials containing ~7 ml of Drosophila growth media. Each of the

genotypes were tested in 10 replicate vials. We monitored adult eclosion every evening over a

period of 7 days until all adult flies had enclosed.

To compare fecundity among the different genotypes, we used density-controlled (~50

eggs/vial) adult female progeny of each population. We introduced five 3-day-old females of

each genotype in egg-laying bottles fitted with egg-laying caps filled with Drosophila growth

media. Each day over a period of 3 days we counted the number of eggs laid. Each of the

genotypes were tested in 8-10 replicate egg-laying bottles. The egg-laying caps were examined

under a stereoscope where we counted the eggs laid each day over the 3-day period.

<u>Statistical analysis of fitness-associated phenotypes</u>

We analyzed fecundity, viability, and malathion resistance for the three genotypes (SS,

SR, RR) of each *Ace* allele (R1, R2, R3) using R (version 4.2.2). For fecundity and viability, we

fitted linear and logistic regression models, respectively, calculating estimated marginal means

and performing pairwise comparisons adjusted for multiple testing using the Benjamini-

Hochberg procedure. We then implemented a bootstrap procedure (1,000 resamples) to estimate

deviation from additivity, selection coefficient, and dominance coefficient. Deviation from

additivity was calculated as W[SR] - (W[SS] + W[RR]) / 2, where W represents fitness

(fecundity or viability) for each genotype. The selection coefficient s was computed as (W[RR] –

W[SS]) / W[SS], indicating the relative fitness of the resistant genotype compared to the

sensitive genotype. The dominance coefficient h was calculated as (W[SR] – W[SS]) / (W[RR] –

W[SS]), measuring the degree to which the heterozygote phenotype is closer to either

homozygote. Significance was assessed by testing whether results differed from zero (additivity

and selection) or 0.5 (dominance). For malathion resistance, we estimated LD_{50} values for each

genotype using four-parameter logistic dose-response models $f(x) = c + (d-c) / (1 + e^{\wedge}(b(x-e)))$,

where e is $LD_{50,}$ d (upper limit) = 100%, c (lower limit) = 0%, and b is the relative slope around

e. For this, we used the L.4() function in the drc package (version 3.0.1)[35] in R (version 4.2.2)

with egg to adult viability at the range of malathion concentrations as the response variable. We

then used a bootstrap procedure (1,000 resamples) to compare LD_{50} values between genotypes

and calculate the same coefficients, substituting LD_{50} values for W in the formulas. For all

analyses, bootstrap resampling was used to calculate confidence intervals and p-values, with

significance assessed against null hypotheses of 0 (additivity and selection) and 0.5 (dominance).

Field mesocosm experiments to track evolution of malathion resistance and genome-wide

allele frequencies in the presence and absence of fluctuating malathion selection

Experimental orchard and field mesocosm cages

To mimic the natural surroundings and weather conditions that flies are exposed to in nature, we

conducted the study in an experimental orchard at the University of Pennsylvania in

Philadelphia. The orchard consisted of cleared land with walk-in mesocosm cages (2m x 2m x

2m) constructed of fine mesh and built around metal frames (BioQuip PO 1406C). We planted a

dwarf peach tree in each mesocosm cage to provide flies with shade. All peaches were removed

before ripening to prevent flies from feeding or laying eggs on them. To provide flies with a

feeding and breeding substrate, we added 1.5lb aluminum loaf pans with 400ml Drosophila

growth media every two days during the experiment. To avoid an overcrowded developmental

environment for the eggs, each loaf pan was covered with a screen mesh lid every two days

during the experiment, and eggs were allowed to develop until eclosion ceased, at which point

adult flies were released into the general population. The loaf pans were placed on a shelving

unit oriented away from direct sunlight to protect them from rain and direct sun.

Establishment of experimental *D. melanogaster* populations in field mesocosm cages

To construct the baseline *D. melanogaster* population for the experiment, we crossed the

76 fully sequenced LNPA inbred lines from Pennsylvania. We used inbred lines to facilitate the

use of haplotype inference to attain high effective sequencing coverage[29]. To initiate the baseline

population, we combined 10 females and 10 males from each line into a single breeding cage.

After 4 generations of mating and density-controlled rearing in laboratory conditions, we

introduced 500 females and 500 males of a single age cohort into each mesocosm cage on June

21, 2021.

Malathion treatment over the course of the experiment

A diagram of the experimental design is shown in **Fig. 3a**. In the first step (*Establishment*

phase: June 21 to July 20, 2021), we established 20 replicate populations in mesocosm cages and

allowed them to expand in the absence of interventions. After establishment, the populations

were split into ten malathion-treated and ten malathion-untreated populations. To mimic the

insecticide exposure of flies in nature, the malathion-treated populations were exposed to

malathion in summer. In nature, insecticides are mainly applied during summer for pest control

and their application ceases in the fall[36]. During the malathion treatment phase of the experiment,

we sequentially exposed the populations to gradually increasing concentrations of malathion, 1.5

- 2.5ppm malathion (July 21 to August 24, 2021) and. 7.5ppm malathion (August 25 to

September 6, 2021). We used commercially available malathion grade of 50% strength (Southern

Ag Malathion 50% E.C.) and dissolved it in the *Drosophila* growth media. We selected

malathion doses based on the Malathion 50% E.C. label instructions to control small insect pests

in the field and a previous long-term selection experiment for malathion resistance in *D.*

melanogaster[37]. The medium supplemented with malathion was prepared once a week to avoid

malathion degradation. After the malathion treatment, the experiment lasted until early winter

(September 7 to December 22, 2021). Over the course of the experiment, we performed high-

resolution temporal sampling (~ bi-weekly sampling during summer and monthly during fall) to

track evolution of malathion resistance and genome-wide allele frequencies.

Track population size in the field mesocosms over time

To make relative comparisons of population sizes between the malathion-treated and untreated

cages, we took photographs of 4 equal size quadrats of the ceiling in each cage at dusk

(approximately 2.5% of the ceiling for each quadrat). To count the number of adult flies in each

photograph, we designed and validated an algorithm for the semi-automated processing of the

photographs. The number of adult flies in each of the 4 photographs was multiplied by 40 to

correct for total surface area and obtain 4 population size estimates per cage.

<u>Statistical analysis of population data</u>

To assess the effects of time and malathion treatment on population size, we fitted a linear mixed

effect model with the population size estimate as the response variable. We defined our model to

investigate the quadratic relationship of time with population size and to account for the random

effects attributable to differences in cages. The regression analysis was performed in R (version

4.2.2) using lme4 (version 1.1.33).

Track malathion resistance in the field mesocosms over time

To characterize the rate and direction of evolution of malathion resistance in the malathion-

treated and untreated populations, we repeatedly assayed the evolving populations. Prior to the

malathion resistance assay, we collected F1 eggs from each mesocosm cage and transferred them

in 2 groups of 200 eggs to bottles with media (i.e., density controlled) in a constant common

garden environment (25˚C, 12L:12D, 50% humidity) in the laboratory to distinguish evolution

from phenotypic plasticity. We then performed the malathion resistance assay with density and

age-controlled individuals from each mesocosm cage in the F2 generation (25˚C, 12L:12D, 50%

humidity). The common garden experiment for assaying malathion resistance took place at

Stanford University with F1 eggs in bottles with media shipped overnight from the University of

Pennsylvania.

Malathion resistance measurements

To characterize the level of malathion resistance in the malathion-treated and untreated

populations, we tracked egg to adult survival in the F2 generation on diets that ranged in

malathion concentration from 0 ppm to 15 ppm over the course of the experiment. For the

collection of F2 eggs, we placed ~ 400 4-to-7-day-old F1 individuals in breeding cages with egg

lay caps for 5-7 hours. We then introduced 50 F2 eggs in a narrow vial containing ~7ml of

Drosophila growth media supplemented with the range of malathion concentration. We tested

each of the malathion concentrations in duplicate vials. We used commercial malathion of 50%

strength (Southern Ag Malathion 50% E.C.) and dissolved it in the Drosophila growth media.

This medium was kept overnight at 4°C and used the next day for the assay. We monitored adult

eclosion every evening over a period of 10 days until all adult flies had eclosed.

Statistical analysis of malathion resistance data

To assess the temporal dynamics of malathion resistance in both malathion-treated and untreated

cages, we fitted separate linear mixed-effects models using the lmer() function in the R package

lme4 (version 1.1.33). The response variable in these models was malathion resistance, measured

as the LD_{50} value, the dose that causes 50% egg-to-adult mortality. For the malathion-treated

cages, we modeled resistance changes over two distinct time periods: (1) from July 26, 2021, to

September 21, 2021, when populations were evolving under malathion exposure, and (2) from

September 21, 2021, to December 22, 2021, after malathion treatment had ceased. In contrast,

for the malathion-untreated cages, we assessed resistance changes over the full experimental

period, from July 26, 2021, to December 22, 2021. To avoid biases, we excluded data from July

13, 2021, because the LD_{50} estimate from this time point was underestimated due to a technical

error. In each model, we included time point as fixed effect, while a random intercept was

included for each cage to account for between-cage variability. The main outcome measure of

malathion resistance for each cage at each time point was the mean of 1–2 technical replicate

LD_{50} measurements. To estimate LD_{50} for each technical replicate per cage per time point, we

fitted four-parameter logistic dose-response models using the L.4() function in the drc package

(version 3.0.1) in R (version 4.2.2) with egg to adult viability at the range of malathion

concentrations as the response variable.

Track genome-wide allele frequencies in the field mesocosms over time

To track the trajectories of the resistant and sensitive *Ace* alleles and characterize the extent of

the sweep caused by the *Ace* alleles, we tracked genome-wide allele frequencies of the evolving

populations across the experiment using the software tool HAF-pipe. HAF-pipe estimates

genome-wide allele frequencies in the evolving populations via inference of known founder

haplotypes from low-coverage pooled sequencing data [29]. As part of our experimental design, we

performed whole-genome, low-coverage pooled sequencing of 100 randomly selected F1

females from each of the 20 evolving populations at eight time points through the experiment. To

measure biological and technical variation, we performed whole-genome, low-coverage pooled

sequencing of different sets of 100 randomly selected F1 females from the 20 evolving

populations at two time points collected at Stanford (biological replicates) and of same samples

of 100 randomly selected F1 females but processed independently (technical replicates). Last, to

evaluate the accuracy of HAF-pipe, we performed whole-genome, high-coverage pooled

sequencing of four biological replicate samples from the baseline population and for the evolving

populations at an early and a late time point. The data for the untreated cages were also used for

a recent independent study from Bitter and colleagues [16].

Sample collection, DNA extraction, library preparation, and sequencing

We collected samples from each population approximately every two generations during

the summer phase and every generation during the fall phase. To collect the samples, we placed a

new loaf pan with Drosophila growth media in each mesocosm cage one day before collection.

The next day, we transferred five groups of 200 F1 eggs to bottles with media, where we

controlled the density and maintained them in a constant laboratory environment of 25°C,

12L:12D, and 50% humidity. Three bottles with F1 eggs were kept at UPenn and two bottles

with F1 eggs were shipped overnight to Stanford. At Stanford, F1 adults were allowed to lay

eggs, and 200 F2 eggs were placed in vials for density control. For both the F1 and F2

generation, we harvested 4-to-7-day-old individuals after eclosion and preserved them in 100%

ethanol in 1.5ml vials at -20°C until further processing.

For each sample, we prepared genomic DNA from pools of 100 ethanol-preserved

females. We first submerged the samples twice in a rehydration buffer (400 mM NaCl, 20 mM

Tris-HCl pH 8.0, 30 mM EDTA) for 15 min at room temperature and then isolated genomic

DNA using the Monarch Genomic DNA purification kit (Cat No. 3010L, New England Biolabs).

The manufacturer's protocol was modified to include a step for tissue homogenization with two

3mm glass beads (Cat No. 11-312C, Fisher Scientific) in a bead beater for five minutes to ensure

complete homogenization of the flies so that the genomic DNA from each fly was equally

represented in the genomic DNA pool. We quantified the genomic DNA using the Qubit dsDNA

BR (Broad-Range) Assay kit (Cat No. Q32853, Life Technologies) on a Qubit

spectrophotometer and estimated its purity on a NanoDrop spectrophotometer.

We then prepared sequencing libraries using the Illumina DNA prep, (M) Tagmentation

kit (Cat No. 20018705, Illumina Inc.) and the Illumina UD Indexes sets (Cat No 20027123,

20027214, 20042666, 20042667, Illumina Inc.) for unique dual indexing. We modified the

manufacturer's protocol by preparing libraries in 1/5 of the recommended reaction volume to

maximize kit efficiency and pooling equimolarly amplified libraries in sets of eight after the

library amplification step. After the cleanup, we quantified the pooled libraries using a Qubit

spectrophotometer and an Agilent Bioanalyzer. Finally, the pooled libraries were 150bp paired-

end sequenced on the NovaSeq 6000 S2 platform at the Sequencing Service Center at the

Stanford Genomics Center and on a NovaSeq 6000 SP platform at Admera. All sequences will

be deposited in SRA.

<u>Processing of DNA sequencing data for genome-wide allele frequency estimation</u>

We trimmed the raw sequencing reads of adapter sequences and bases with quality score

< 20. We then mapped the trimmed reads to the *D. melanogaster* reference genome (v5.39) using

bwa and default parameters [38], and aligned reads were deduplicated using Picard tools. We

randomly sampled reads from the aligned bams to obtain an equivalent, genome-wide coverage

of 8x across all samples. We computed haplotype-derived allele frequency (HAF) estimates

using HAF pipe. Briefly, after using an expectation-maximization algorithm to estimate

haplotype frequencies in overlapping genomic windows from mapped sequence reads (originally

developed by Kessner and colleagues [39]) at each site previously identified as polymorphic in the

inbred reference panel, we summed the estimated frequencies of haplotypes carrying the

alternate allele to obtain HAFs . We conducted haplotype inference in window sizes that varied

proportionally to the expected length of un-recombined haplotype blocks, which varied as a

function of the estimated number of generations since the original outbreeding. HAFs were

compiled to only include those sites with an average minor allele frequency (MAF) > 0.02 in the

baseline population, and present in at least one evolved sample at a MAF > 0.01.

Track trajectories of sensitive and resistant *Ace* alleles in the evolving populations over

time

We first estimated the frequency of each of the 76 founder haplotypes in the *Ace* region

(Chr3R:9,063,921-9,069,721) in each of the malathion-treated and malathion-untreated

populations at each time point, focusing on the founders containing the four known resistance

mutations . To obtain an accurate measure of the frequency of each haplotype, we calculated the

mean frequency across the 10 overlapping genomic windows that included each site within the

region of interest.

We then estimated the relative frequency of each *Ace* allele, defined by the combination

of the four known resistance mutations, in each population at each time point. Given our

knowledge of the resistance mutation combinations for each founder, we computed the relative

frequency of each *Ace* allele (Ace-S: IGFG, Ace-R1: VGFG, Ace-R2: VGFA, Ace-R3: VAYG,

Ace-R4:IGFA, Ace-R5:IGYG, Ace-R6:VAFG, Ace-R7: VAYA) by summing the frequencies of

the haplotype blocks from the 76 founders that shared the same *Ace* allele. For founders

heterozygous for the *Ace* alleles, we divided the contributions of their haplotype block evenly

between the two corresponding *Ace* allele frequencies. *Ace* alleles with a frequency < 0.01%

(Ace-R4:IGFA, Ace-R5:IGYG, Ace-R6:VAFG, Ace-R7: VAYA) in the evolving populations

were excluded from further analysis.

Statistical analysis of *Ace* allele frequency data

To assess the temporal dynamics of *Ace* allele frequencies (Ace-S: IGFG, Ace-R1:

VGFG, Ace-R2: VGFA, Ace-R3: VAYG), we fitted separate linear mixed-effects models using

the lmer() function in the R package lme4 (version 1.1.33). The response variables in these

models were the frequencies of each *Ace* allele. For the malathion-treated cages, we modeled *Ace*

allele frequency changes over two distinct time periods: (1) from July 26, 2021, to September 21,

2021, when populations were evolving under malathion exposure, and (2) from September 21,

2021, to December 22, 2021, after malathion treatment had ceased. In contrast, for the

malathion-untreated cages, we assessed *Ace* allele frequency changes from the beginning of the

treatment to the end of the experiment, from July 26, 2021 to December 22, 2021.

Model *Ace* allele frequency evolution

We simulated the evolution of *Ace* allele frequencies and malathion resistance in our mesocosm

experiments using a viability selection model[40]. Additionally, based on the changes in *Ace* allele

frequencies in malathion-free environments across both sets of cages, we estimated the possible

ranges for the fitness costs of and dominance of malathion resistance.

<u>The impact of viability on *Ace* allele frequency dynamics and malathion resistance in the field</u>

<u>mesocosm experiment</u>

We investigated whether selection acting on viability recapitulates the allele frequency

and malathion resistance dynamics observed in the field. We focused on viability as it is a key

fitness-related trait in both malathion-rich and malathion-free environments. Furthermore, we

had laboratory measurements of viabilities for *Ace* genotypes across ranges of malathion

concentrations, allowing us to parametrize our model and test its predictions.

Within our model, the population frequencies of the *Ace* alleles change only due to selection that

acts on viability. We assumed that the effects of other forces (mutation, recombination, and

genetic drift) were negligible in comparison over the timescales that we considered (~10

generations). Under these assumptions, the frequency dynamics of the sensitive (f_0) and resistant

(f_1, f_2, f_3) *Ace* alleles follow from

662
$$f_i(t+1) = \frac{f_i(t)\sum_j w_{ij}f_j(t)}{\bar{w}(t)},$$

663   where t is time measured in generations, w_{ij} is viability of individuals carrying both i and j

664   alleles, and $\bar{w}$ is the mean population viability defined as

665
$$\bar{w}(t) = \sum_{i,j} f_i(t)f_j(t)w_{ij}.$$

We used laboratory measurements to determine individual viabilities w_{ij} in the absence

and presence of malathion (at 2.5 and 7.5 ppm). We used the marginal mean values from the

linear model for viability for each genotype and the predicted viability values from the dose-

response analysis (see previous section on 'Statistical analysis of fitness-associated phenotypes').

Due to the lack of measurements for heterozygous resistant genotypes, we assumed that

combinations of resistant alleles are codominant, i.e. that $w_{12} = 0.5 \cdot w_{11} + 0.5 \cdot w_{22}$; $w_{13} = 0.5 \cdot$

$w_{11} + 0.5 \cdot w_{33}$; $w_{23} = 0.5 \cdot w_{22} + 0.5 \cdot w_{33}$. The initial *Ace* allele frequencies, $f_i(0)$, were

estimated as the median values from the first sampling time point (July 13, 2021) for each

treatment group.

To estimate *D. melanogaster* generation times at our eight sampling time points, we used

a degree-day model based on Behrman and Schmidt[41]. This model assumes *D. melanogaster*

requires 112 degree-days to complete one generation, with development occurring between 12°C

and 29°C. We calculated daily degree-days as [(daily max. temp. + daily min. temp.) / 2] - 12°C,

adjusting temperatures outside the 12-29°C range to these limits. Cumulative degree-days were

tracked, with each 112 degree-day accumulation marking a new generation. This allowed us to

estimate generations at each sampling time point throughout the experiment.

We then calculated the population resistance R as a weighted sum,

683
$$R(t) = \sum_{i,j} g_{ij}(t)w_{ij},$$

684 where $g_{ij}(t)$ are genotype frequencies and w_{ij} are the corresponding viabilities. The initial

685 genotype frequencies were estimated from the initial allele frequencies, assuming Hardy-

686 Weinberg equilibrium:

687
$$g_{ij}(0) = f_i(0)f_j(0).$$
688 The consequent genotype frequencies followed from the viability selection model,

690
$$g_{ij}(t) = \begin{cases} \dfrac{2f_i(t)f_j(t)w_{ij}}{\overline{w}}, i \neq j, \\ \dfrac{f_i(t)f_j(t)w_{ij}}{\overline{w}}, i = j. \end{cases}$$

<u>Inferring the ranges of possible fitness costs and dominance coefficients from empirical allele</u>

<u>frequency trajectories</u>

To estimate the fitness cost and dominance of malathion resistance in the malathion-free

environment, we analyzed the empirical frequency trajectories of these alleles in both the

untreated and treated populations after the removal of malathion. This approach allowed us to

constrain the range of possible parameters that could explain the observed frequencies of the

resistant alleles in both the treated and untreated populations. Assuming the resistant alleles share

the same selection (s) and dominance (h) coefficients, and further that the cost of resistance is

small (s<<1), the frequency dynamics follow

701
$$\partial_t f = s(f \cdot (1 - f) \cdot (f + h(1 - 2f))),$$
allowing us to find s that would be consistent with the observed slope $\partial_t f$ of the frequency

trajectory for a given h[42].

To do that, we first bootstrapped the combined frequency trajectories of resistant alleles

in individual cages within each treatment group 10,000 times. For each set of bootstrapped

trajectories, we used linear regression (LinearRegression().fit function from the scikit-learn

Python library[43] to infer their slope. For a range of $h \in [0,1]$, we then calculated the bounds on s

by finding the values that correspond to the lower and upper bound of the 95% confidence

interval of the bootstrap distribution. To further constrain the range of possible parameters, we

similarly inferred the full distribution of s for each set of cages, and evaluated their overlap by

computing the joint likelihood function,

$$\mathcal{L} = \prod p(s),$$

where $p(s)$ is the probability density corresponding to a fixed value of s. Larger values of L

therefore correspond to more likely combinations of h and s given the observed frequency

dynamics.

Characterize extent of forward and reverse sweep caused by *Ace* resistant alleles

To assess how fluctuating organophosphate selection on the R2 and R3 *Ace* resistant alleles

affected genome-wide frequency trajectories of linked SNPs during and post-malathion

treatment, we employed a two-step approach. First, we used quasibinomial logistic regression to

estimate allele frequency shifts for genome-wide SNPs during malathion treatment (July 26 to

September 21, 2022) and post-treatment (September 21 to December 22, 2021). Second, we

developed a linked SNP selection procedure using linkage information from the inbred lines to

identify SNPs tightly linked (Ace-linked) and loosely linked (control) to the sweeping R2 and R3

Ace alleles across the genome. We used these sets of SNPs to quantify the extent of both the

forward *Ace* sweep during malathion treatment and the reverse *Ace* sweep post-treatment.

Quasi-binomial logistic regression to estimate allele frequency differences in malathion-treated

and untreated populations during and after the malathion treatment

To quantify allele frequency changes during malathion treatment (July 26 to September

21, 2022) and post-treatment (September 21 to December 22, 2021) in both treated and untreated

populations, we used a quasibinomial logistic regression approach[14,44]. This method models the

number of reads mapped to the alternative allele 'α' (relative to the reference allele 'A') at each

biallelic SNP for each pooled sample. To account for both the expected accuracy of HAFs as

well as pseudo-replication due to a fixed number of individuals in each sample [45], we estimated

an effective read depth reads (at each biallelic SNP for each pooled sample per population using

738
$$n_{eff} = \frac{((2 \times N \times EC) - 1)}{2 \times N + EC}$$

740   where N is the number of individuals per sample (100) and EC is the expected effective read

741   coverage based on the accuracy of HAF-pipe.

742   We then used a logit link implemented in a quasi-binomial logistic regression to model the

743   counts of the alternative allele 'α' ($C_a = HAF * neff$) and reference allele 'A' ($C_A = (1 -$

744    $HAF) * neff$) as a function of time in the malathion-treated and -untreated populations

746
$$logit(p_a) = log\left(\frac{p_a}{1 - p_a}\right) = b_0 + b_1 \times time + e$$

747   where p_a is probability of observing the allele 'α', while the coefficients b_0 and b_1 correspond to

748   the intercept and the effect of time, respectively. We fitted the model using the glm() function in

749   R (version 4.2.2) with family = 'quasibinomial'. To compute the allele frequency change (effect

750   size) between two time points (x_1 and x_2), we calculated

751
$$\Delta p = p_2 - p_1 = \frac{e^{(b_0 + b_1 \times x_2)}}{1 + e^{(b_0 + b_1 \times x_2)}} - \frac{e^{(b_0 + b_1 \times x_1)}}{1 + e^{(b_0 + b_1 \times x_1)}}$$

753   <u>Analysis of allele frequency changes of Ace-linked SNPs</u>

754   To quantify the extent of the forward *Ace* sweep during malathion treatment, we

identified SNPs linked to the sweeping R2 and R3 *Ace* alleles, as well as unlinked (control)

SNPs, using whole genome data from the 76 sequenced Pennsylvania inbred lines (LNPA). First,

we labeled R2 and R3 *Ace* alleles as "R" and the remaining alleles (R1 and S) as "S", creating a

binary "R"/"S" *Ace* locus across the inbred lines. Among the inbred lines, 54 were homozygous

"S", 5 heterozygous "R/S", and 17 homozygous "R". To select linked SNPs, we used the inbred

lines data to compute r2 between the binary "R"/"S" *Ace* locus and every reported biallelic SNP

in the inbred LNPA lines as the squared correlation coefficient of allelic indicator variables[46].

We initially retained SNPs with r2 > 0.03, a threshold frequency previously used to deem two

loci highly linked[16]. However, to avoid issues with low-frequency SNPs in finite populations, we

added an allele count condition. We selected SNPs with r2 > 0.03 that also have an allele present

in ≥60% of "R/R" lines and in ≤40% of "S/S" and "S/R" lines. This ensures selection of high-

frequency, well-assorted SNPs between "R" and "S" lines, which are more informative for sweep

analysis. This approach yielded 5672 Ace-linked SNPs across chromosomes 2, 3, and X. The

60% threshold was chosen as the highest value providing enough Ace-linked SNPs to uniformly

cover the genome, with consistent results when varied. Finally, for each Ace-linked SNP, we

selected an unlinked control SNP with r2 < 0.01 with the binary "R"/"S" *Ace* locus. To ensure

comparable initial conditions, unlinked control SNPs were chosen within 500kb of their linked

counterpart and had an allele frequency within 0.05 of the Ace-linked SNP at the start of

malathion treatment in each cage. This process yielded 4793 matched unlinked control SNPs,

fewer than the linked SNPs due to the stringent matching criteria. To visualize the results, we

aggregated SNPs into 500kb windows along the genome and used bootstrap resampling to

compute median GLM-estimated effect sizes and confidence intervals for Ace-linked and

unlinked control SNPs separately. To statistically characterize the width of the forward sweep,

for each of the 100,000 bootstrap samples, we have identified the range of windows on the 3R

arm on which the median for linked SNPs is larger than the median for the control SNPs, and

recorded the width of the positive range, resulting in a bootstrap sample of sweep widths.

To quantify the reverse *Ace* sweep post-malathion treatment, we analyzed allele

frequency changes for the same Ace-linked and unlinked control SNPs during the post-treatment

period (September 21 to December 22, 2021). We compared post-treatment to during-treatment

frequency changes, plotting them against each other while considering genomic distance from

the *Ace* locus on chromosome 3R. To quantify this relationship, we analyzed the correlation

between these changes as a function of distance from *Ace*. We used 500kb windows and

bootstrap resampling to compute median effect sizes and confidence intervals for Ace-linked and

unlinked control SNPs, consistent with our forward sweep analysis approach.

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Extended Data Figure 1

b

Ace haplotype	LNPA relative frequency (%)	DGRP relative frequency (%)
IGFG	63.16	54.15
VGFA	13.16	0.49
VAYG	12.50	30.73
VGFG	7.89	12.20
IGYG	1.32	0.98
IGFA	0.66	NA
VAFG	0.66	NA
VAYA	0.66	NA
IAFG	NA	1.46

Extended Data Figure 1. Sensitive and resistant *Ace* alleles in the panel of LNPA and DGRP inbred lines. a, Heatmap showing clustering of seventy-six *D. melanogaster* isogenic lines in the LNPA panel based on the sensitive or resistant *Ace* allele they carry (Ace-S: IGFG, Ace-R1: VGFG, Ace-R2: VGFA, Ace-R3: VAYG). The x-axis in the heatmap shows the genomic position on chromosome 3R around the *Ace* locus. Each row represents the *Ace* haplotype information of one isogenic line. Each column represents one biallelic exonic SNP at the *Ace* locus. Reference alleles are colored in dark grey, alternative alleles are colored in light grey, heterozygotes in medium grey. For the resistance mutations, alleles coding for the resistance mutations are colored in orange, alternative in grey, and heterozygotes in yellow. **b,** Table showing frequency of the sensitive and each of the resistant *Ace* alleles carrying different resistance haplotypes in the panels of LNPA and DGRP inbred lines.

Extended Data Figure 2

a

b

Dose response curve analysis for each Ace genotype

Genotype	LD50	std.error	statistic	p.value
SS	1.39	0.18	7.79	3.7768e-12
R1R1	1.56	0.20	7.68	6.3407e-12
R2R2	8.16	0.40	20.41	7.7563e-40
R3R3	10.81	0.45	23.96	3.3625e-46
SR1	2.34	0.19	12.49	3.0000e-23
SR2	6.80	0.26	25.89	2.1374e-49
SR3	8.84	0.30	29.95	1.3764e-55

Extended Data Figure 2. Comparison of malathion resistance among the *Ace* genotypes. a, Lab measurements of egg to adult viability in recombinant populations carrying different *Ace* genotypes on standard Drosophila media with a range of malathion concentrations (n= 2 technical replicates per genotype for each malathion doses, 50 eggs per replicate). Four-parameter logistic models fitted to data of each *Ace* genotype. The shaded areas highlight viability of each genotype at malathion doses (2.5ppm and 7.5 ppm) applied in the field mesocosm experiment. **b,** Table with estimated LD_{50} values for each *Ace* genotype from four-parameter logistic dose-response model (see also **Methods**).

Extended Data Figure 3

Extended Data Figure 3. Tracking evolution of malathion resistance in the field mesocosm experiment. Egg-adult survival on diets with a range of malathion concentrations as measured after two generations of common garden rearing throughout the field mesocosm experiment. Light lines and points show the mean egg-adult survival for individual malathion-treated (orange) and untreated (blue) populations (n = 2 technical replicates, 50 eggs per replicate). Dark lines and points represent the mean ± s.e.m. from all populations for each treatment group (n = 10 populations per treatment group). Further information on experimental design can be found in **Methods**.

Extended Data Figure 4

Extended Data Figure 4. **Modeling the impact of viability selection on *Ace* allele frequency dynamics and malathion resistance in the field mesocosm experiment**. **a-b,** Comparison between the observed *Ace* allele frequency trajectories over 10 generations in the malathion-treated (**a**) and untreated (**b**) populations from the field mesocosm experiment (mean ± s.e.m.) and the expected trajectories from simulations based on a viability selection model using laboratory-derived parameters. See **Methods** for details about the viability selection model. **c-d,** Comparison between the observed egg-to-adult survival across a range of malathion concentrations (**c**) and the evolution of malathion resistance (LD_{50}, ppm) (**d**) over 10 generations in the field mesocosm experiment (mean ± s.e.m.), and the expected results from the same model simulations. Dashed lines represent the expected values from the viability selection model, while solid lines represent the observed data from the field experiment. Generations were estimated based on a degree-day model starting from the first sampling point (July 13, 2021). In all plots, points correspond to each generation and estimated time point, and are connected by lines for visualization.

Extended Data Figure 5

Extended Data Figure 5. **Modeling the cost of resistant *Ace* alleles in malathion-free environment.**
a, Inferred values of the fitness effect of resistance (*s*) and the dominance coefficients (*h*) from the
change in mutant allele frequencies in treated (orange) and untreated (blue) populations under a
viability selection model (see **Methods**). The solid lines correspond to the values of *s* and *h* inferred
from the mean slope of frequency trajectories, obtained by bootstrapping cages 10,000 times, and the
shaded regions denote the values of *s* and *h* that lie within the 0.95 confidence region of the bootstrap
distribution. All mutants were assumed to share the fitness cost and the dominance coefficient. **b,** The
distribution of the slopes of resistant allele frequency trajectories in treated (orange) and untreated
(blue) populations, obtained by bootstrapping cages 10,000 times. For each bootstrap realization, the
slope was inferred using linear regression. The vertical lines denote the means of the distributions, and
the shaded regions correspond to 0.95 confidence intervals.

Extended Data Figure 6

Extended Data Figure 6. Characterization of the forward sweep during malathion treatment. a,b, Difference in absolute glm-estimated effect sizes between Ace-linked and unlinked control SNPs in malathion-treated (**a**) and untreated (**b**) cages. Shared areas on the plots represent 95% bootstrap confidence intervals of the difference computed by sampling SNPs in 500kb windows. **c,** Bootstrap sampling distribution of forward sweep width on the 3R arm in the malathion-treated population.

Extendend Data Table 1

Effect estimates from linear model analysis for LD50

Parameter	LD50	Std.Error	P.value
SS mean	1.39	0.19	-
SR1 mean	2.34	0.13	-
R1R1 mean	1.56	0.14	-
SS vs. SR1	-0.93	0.34	0.0063
SS vs. R1R1	-0.17	0.37	0.646
SR1 vs. R1R1	0.76	0.39	0.0516
SR1 - (SS + R1R1)/2 (additivity)	0.76	0.32	1e-16
(R1R1 - SS) / R1R1 (selection, s)	-0.25	0.29	0.751
(SR1 - SS) / (R1R1 - SS) (dominance, h)	-1.29	5.10	0.751
SR2 mean	6.80	0.24	-
R2R2 mean	8.16	0.36	-
SS vs. SR2	-5.38	0.36	0
SS vs. R2R2	-6.72	0.42	0
SR2 vs. R2R2	-1.34	0.45	0.003
SR2 - (SS + R2R2)/2 (additivity)	1.87	0.35	1e-16
(R2R2 - SS) / R2R2 (selection, s)	3.83	1.05	1e-16
(SR2 - SS) / (R2R2 - SS) (dominance, h)	0.78	0.06	1e-16
SR3 mean	8.84	0.32	-
R3R3 mean	10.81	0.49	-
SS vs. SR3	-7.41	0.36	0
SS vs. R3R3	-9.37	0.79	0
SR3 vs. R3R3	-1.96	0.80	0.0145
SR3 - (SS + R3R3)/2 (additivity)	2.59	0.48	1e-16
(R3R3 - SS) / R3R3 (selection, s)	5.64	1.45	1e-16
(SR3 - SS) / (R3R3 - SS) (dominance, h)	0.77	0.07	1e-16

Extendend Data Table 2

Effect estimates from logistic model analysis for viability

Parameter	Viability	Std.Error	Lower.CI	Upper.CI	P.value
SS mean	0.89	0.01	-	-	-
SR1 mean	0.86	0.02	-	-	-
R1R1 mean	0.76	0.02	-	-	-
SS vs. SR1	1.42	0.27	-	-	0.0702
SS vs. R1R1	2.61	0.47	-	-	<.0001
SR1 vs. R1R1	1.84	0.30	-	-	4e-04
SR1 - (SS + R1R1)/2 (additivity)	0.03	0.02	-0.02	0.07	0.214
(R1R1 - SS) / R1R1 (selection, s)	-0.15	0.03	-0.2	-0.09	0.001
(SR1 - SS) / (R1R1 - SS) (dominance, h)	0.29	0.20	-0.15	0.64	0.214
SR2 mean	0.87	0.02	-	-	-
R2R2 mean	0.74	0.02	-	-	-
SS vs. SR2	1.28	0.25	-	-	0.205
SS vs. R2R2	2.96	0.53	-	-	<.0001
SR2 vs. R2R2	2.31	0.39	-	-	<.0001
SR2 - (SS + R2R2)/2 (additivity)	0.05	0.02	0.01	0.1	0.027
(R2R2 - SS) / R2R2 (selection, s)	-0.17	0.05	-0.28	-0.09	0.001
(SR2 - SS) / (R2R2 - SS) (dominance, h)	0.17	0.15	-0.15	0.45	0.027
SR3 mean	0.86	0.02	-	-	-
R3R3 mean	0.78	0.02	-	-	-
SS vs. SR3	1.42	0.27	-	-	0.0702
SS vs. R3R3	2.43	0.44	-	-	<.0001
SR3 vs. R3R3	1.72	0.29	-	-	0.0018
SR3 - (SS + R3R3)/2 (additivity)	0.02	0.02	-0.02	0.06	0.286
(R3R3 - SS) / R3R3 (selection, s)	-0.13	0.02	-0.18	-0.08	0.001
(SR3 - SS) / (R3R3 - SS) (dominance, h)	0.32	0.19	-0.15	0.67	0.286

Extendend Data Table 3

Effect estimates from linear model analysis for fecundity

Parameter	Fecundity	Std.Error	Lower.CI	Upper.CI	P.value
SS mean	200.22	11.99	-	-	-
SR1 mean	165.33	14.01	-	-	-
R1R1 mean	136.50	14.86	-	-	-
SS vs. SR1	34.89	19.81	-	-	0.14
SS vs. R1R1	63.72	20.42	-	-	0.01
SR1 vs. R1R1	28.83	20.42	-	-	0.17
SR1 - (SS + R1R1)/2 (additivity)	-3.03	17.26	-36.62	31.59	0.879
(R1R1 - SS) / R1R1 (selection, s)	-0.32	0.09	-0.48	-0.12	0.003
(SR1 - SS) / (R1R1 - SS) (dominance, h)	0.55	0.40	-0.07	1.32	0.881
SR2 mean	187.60	13.64	-	-	-
R2R2 mean	167.78	14.37	-	-	-
SS vs. SR2	12.62	19.81	-	-	0.53
SS vs. R2R2	32.44	20.33	-	-	0.37
SR2 vs. R2R2	19.82	19.81	-	-	0.49
SR2 - (SS + R2R2)/2 (additivity)	3.60	18.42	-33.15	43.16	0.834
(R2R2 - SS) / R2R2 (selection, s)	-0.16	0.09	-0.33	0.03	0.093
(SR2 - SS) / (R2R2 - SS) (dominance, h)	0.39	4.09	-2.3	3.23	0.842
SR3 mean	202.00	12.71	-	-	-
R3R3 mean	106.44	11.99	-	-	-
SS vs. SR3	-1.78	17.47	-	-	0.92
SS vs. R3R3	93.78	16.95	-	-	<.0001
SR3 vs. R3R3	95.56	17.47	-	-	<.0001
SR3 - (SS + R3R3)/2 (additivity)	48.67	12.84	22.41	73.56	1e-16
(R3R3 - SS) / R3R3 (selection, s)	-0.47	0.07	-0.59	-0.31	0.001
(SR3 - SS) / (R3R3 - SS) (dominance, h)	-0.02	0.19	-0.48	0.29	0.001

Extendend Data Table 4

Extended Data Table 4.1 Effect of time on malathion resistance (LD50) in treated cages

Predictors	During treatment				After treatment			
	Estimates	std. Error	Statistic	p	Estimates	std. Error	Statistic	p
Intercept	-3.02 ***	0.46	-6.58	**<0.001**	15.56 ***	1.09	14.29	**<0.001**
Time	2.48 ***	0.10	24.26	**<0.001**	-0.57 ***	0.14	-3.96	**0.001**
Random Effects								
σ^2		0.91				0.98		
τ_{00}		0.00 Treatment_Cage				0.24 Treatment_Cage		
ICC						0.20		
N		10 Treatment_Cage				10 Treatment_Cage		
Observations		40				30		
Marginal R^2 / Conditional R^2		0.938 / NA				0.302 / 0.441		
AIC		122.513				101.066		

* p<0.05   ** p<0.01   *** p<0.001

Extended Data Table 4.2 Effect of time on malathion resistance (LD50) in untreated cages

Predictors	Beginning of treatment to end of experiment			
	Estimates	std. Error	Statistic	p
Intercept	2.27 ***	0.15	14.91	**<0.001**
Time	0.03	0.02	1.07	0.288
Random Effects				
σ^2		0.16		
τ_{00} Treatment_Cage		0.03		
ICC		0.15		
N Treatment_Cage		10		
Observations		59		
Marginal R^2 / Conditional R^2		0.017 / 0.166		
AIC		83.651		

* p<0.05   ** p<0.01   *** p<0.001

Extendend Data Table 5

Extended Data Table 5.1 Effect of time on S (IGFG) frequency in treated cages

Predictors	During treatment				After treatment			
	Estimates	std. Error	Statistic	p	Estimates	std. Error	Statistic	p
Intercept	0.88 ***	0.02	49.15	**<0.001**	0.04	0.05	0.74	0.468
Time	-0.13 ***	0.00	-30.81	**<0.001**	0.02 *	0.01	2.64	**0.014**
Random Effects								
σ^2	0.00				0.00			
τ_{00}	0.00 cage				0.00 cage			
N	10 cage				10 cage			
Observations	50				30			
Marginal R^2 / Conditional R^2	0.951 / NA				0.194 / NA			
AIC	-148.876				-97.774			

*p<0.05   ** p<0.01   *** p<0.001*

Extended Data Table 5.2 Effect of time on R1 (VGFG) frequency in treated cages

Predictors	During treatment				After treatment			
	Estimates	std. Error	Statistic	p	Estimates	std. Error	Statistic	p
Intercept	0.08 ***	0.00	16.13	**<0.001**	0.04 **	0.01	3.09	**0.005**
Time	-0.00 ***	0.00	-4.05	**<0.001**	0.00	0.00	0.46	0.651
Random Effects								
σ^2	0.00				0.00			
τ_{00}	0.00 cage				0.00 cage			
ICC					0.25			
N	10 cage				10 cage			
Observations	50				30			
Marginal R^2 / Conditional R^2	0.251 / NA				0.005 / 0.250			
AIC	-276.043				-162.492			

*p<0.05   ** p<0.01   *** p<0.001*

Extended Data Table 5.3 Effect of time on R2 (VGFA) frequency in treated cages

Predictors	During treatment				After treatment			
	Estimates	std. Error	Statistic	p	Estimates	std. Error	Statistic	p
Intercept	0.01	0.01	0.93	0.356	0.14 **	0.04	3.39	**0.002**
Time	0.04 ***	0.00	13.93	**<0.001**	0.02 **	0.01	3.03	**0.006**
Random Effects								
σ^2	0.00				0.00			
τ_{00}	0.00 cage				0.00 cage			
N	10 cage				10 cage			
Observations	50				30			
Marginal R^2 / Conditional R^2	0.798 / NA				0.240 / NA			
AIC	-178.169				-107.043			

*p<0.05   ** p<0.01   *** p<0.001*

Extended Data Table 5.4 Effect of time on R3 (VAYG) frequency in treated cages

Predictors	During treatment				After treatment			
	Estimates	std. Error	Statistic	p	Estimates	std. Error	Statistic	p
Intercept	0.03	0.01	1.88	0.067	0.78 ***	0.05	15.18	**<0.001**
Time	0.09 ***	0.00	27.59	**<0.001**	-0.04 ***	0.01	-5.18	**<0.001**
Random Effects								
σ^2	0.00				0.00			
τ_{00}	0.00 cage				0.00 cage			
ICC	0.04							
N	10 cage				10 cage			
Observations	50				30			
Marginal R^2 / Conditional R^2	0.937 / 0.940				0.481 / NA			
AIC	-170.172				-96.128			

*p<0.05   ** p<0.01   *** p<0.001*

Extendend Data Table 6

Extended Data Table 6.1 Effect of time on S (IGFG) haplotype frequency in untreated cages

Predictors	Estimates	std. Error	Statistic	p
		Beginning of treatment to end of experiment		
Intercept	0.63 ***	0.02	39.49	**<0.001**
Time	0.00	0.00	0.21	0.838
Random Effects				
σ^2		0.00		
$\tau_{00\ cage}$		0.00		
ICC		0.03		
N_{cage}		10		
Observations		69		
Marginal R^2 / Conditional R^2		0.001 / 0.032		
AIC		-196.762		

* p<0.05   ** p<0.01   *** p<0.001

Extended Data Table 6.2 Effect of time on R1 (VGFG) haplotype frequency in untreated cages

Predictors	Estimates	std. Error	Statistic	p
		Beginning of treatment to end of experiment		
Intercept	0.06 ***	0.00	14.68	**<0.001**
Time	0.00	0.00	1.91	0.061
Random Effects				
σ^2		0.00		
$\tau_{00\ cage}$		0.00		
N_{cage}		10		
Observations		69		
Marginal R^2 / Conditional R^2		0.051 / NA		
AIC		-370.061		

* p<0.05   ** p<0.01   *** p<0.001

Extended Data Table 6.3 Effect of time on R2 (VGFA) haplotype frequency in untreated cages

Predictors	Estimates	std. Error	Statistic	p
		Beginning of treatment to end of experiment		
Intercept	0.07 ***	0.01	9.08	**<0.001**
Time	-0.00	0.00	-0.02	0.985
Random Effects				
σ^2		0.00		
$\tau_{00\ cage}$		0.00		
ICC		0.02		
N_{cage}		10		
Observations		69		
Marginal R^2 / Conditional R^2		0.000 / 0.024		
AIC		-285.686		

* p<0.05   ** p<0.01   *** p<0.001

Extended Data Table 6.4 Effect of time on R3 (VAYG) haplotype frequency in untreated cages

Predictors	Estimates	std. Error	Statistic	p
		Beginning of treatment to end of experiment		
Intercept	0.24 ***	0.01	17.99	**<0.001**
Time	-0.00	0.00	-0.86	0.392
Random Effects				
σ^2		0.00		
$\tau_{00\ cage}$		0.00		
ICC		0.05		
N_{cage}		10		
Observations		69		
Marginal R^2 / Conditional R^2		0.010 / 0.064		
AIC		-222.940		

* p<0.05   ** p<0.01   *** p<0.001