THE GENETIC BASIS OF INTER-ISLAND MATING BEHAVIOR DIVERGENCE

Running title: mating behavior genetics in *Laupala*

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AUTHOR CONTRIBUTIONS

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TB, KPO, and KLS conceived the study, KPO conducted the experiments, TB analyzed the data, and TB and KLS wrote the manuscript with input from KPO.

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DATA ACCESIBILITY

Scripts will be made available on github.com/thomasblankers/CerEukQTL. The transcriptome
and RNAseq reads will be made available on NCBI's GenBank under BioProject number
PRJNA429662. The Genotype-by-sequencing data will be made available under BioProject
number PRJNA429815. All other data that have not been attached in the supplementary material
will be made available in a Dryad repository.

ABSTRACT

Mating behavior divergence is a major source of reproductive isolation and an important force

driving speciation in various biogeographic contexts. However, the relationship between

biogeographic history, the tempo and mode of speciation, and the genetic architecture of

speciation phenotypes is poorly understood. Here, we use quantitative trait locus (QTL) mapping

to infer the number, distribution, and effect size of song rhythm variation in the crickets *Laupala*

eukolea and *L. cerasina*, which occur on different islands (Maui and Hawai'i). We then compare

these results with a similar study of an independently evolving species pair that diverged within

the same island. Pulse rate divergence is associated with a polygenic genetic architecture in both

the intra- and inter-island species pair. We find evidence consistent with parallel genetic

differentiation and a relationship between magnitude of phenotypic divergence and number of

causal loci. Functional annotation and GO enrichment showed that QTL regions identified here

are enriched for homologs of genes with known function in pathways that may be involved in

modulating cricket song rhythm. This is consistent with tightly-linked clusters of functionally

related genes in QTL regions and reveals several candidate genes that merit further study.

Keywords: speciation, sexual isolation, quantitative genetics, transcriptome, *Laupala*

INTRODUCTION

Behavioral (sexual) isolation is a major reproductive barrier in animals and an important force driving speciation (Mayr 1963; West-Eberhard 1983; Ritchie and Phillips 1998; Coyne and Orr 2004). However, the genetic mechanisms leading to sexual trait divergence, suppression of interspecific recombination, and ultimately the origin of new species remain poorly understood (Ritchie and Phillips 1998; Mackay 2001; Boake et al. 2002; Hoekstra 2010). We can make significant progress in understanding the speciation process by providing empirical insight into the genetic architecture of mating behavior divergence – the number, effect size, and genomic distribution of causal loci – as well as identifying the genes controlling divergent sexual behaviors.

The genetic architecture of phenotypes can be categorized as Type I (polygenic, additive) or Type II (oligogenic, epistatic) architectures (Templeton 1981). It has been argued that the type of genetic architecture can be informative about the tempo and mode of speciation (Carson and Templeton 1984; Harrison 1991). All else being equal, an oligogenic basis would allow for rapid phenotypic evolution, because the phenotypic effect of a single mutation is expected to be larger; theoretical models for sexual selection often assume such simple genetic architectures (Dieckmann and Doebeli 1999; Gourbiere 2004; Doorn et al. 2009; Servedio and Burger 2014). Moreover, it has also been suggested that oligogenic architectures may be lynch pins in radiations involving founder effects (Carson and Templeton 1984), such as those accompanying the colonization of archipelagos. In contrast, empirical studies show that divergent sexual traits are typically associated with Type I genetic architectures (Ritchie and Phillips 1998; Chenoweth and McGuigan 2010), without a disproportionate contribution from sex-linked loci (Ritchie and Phillips 1998; Qvarnström and Bailey 2009); although, the role of X-effects on the evolution of

secondary sexual characters remains somewhat contentious (e.g., Mittleman et al. 2017). A

polygenic architecture would allow for gradual (but not necessarily slow) and orchestrated

divergence of male and female sexual traits (Lande 1981; Shaw and Parsons 2002).

Another aspect of the genetic architecture that can greatly affect the rate of trait evolution is the

clustering of functionally related genes in specific genomic regions (also known as

"supergenes"). Fisher (1930) suggested that genes associated with the gradual adaptive change of

complex phenotypes become physically linked over time. He imagined this linkage would

maintain the identity of groups with complex phenotypic differences by reducing the disruptive

effects of recombination in the region with which the phenotype is associated. Indeed, linkage

disequilibrium within tightly linked clusters of quantitative trait loci (QTL) can be maintained by

low recombination (Noor et al. 2001).

The involvement of gene clusters has been implicated in the rapid evolution of (co)adaptive

phenotypes in plants and animals (Schwander et al. 2014), including courtship behavior (Gould

et al. 2010; Küpper et al. 2015; Lamichhaney et al. 2015; Tuttle et al. 2016). When functionally

relevant genes are closely linked (comprising co-adapted gene complexes), orchestrated adaptive

responses may be greatly facilitated: mutually beneficial and co-dependent alleles can segregate

as a single unit and recombination between forms rarely produces maladaptive allelic

combinations. This may be an important mechanism constraining natural variation in complex

traits, such as altruistic signals ('green beard', Dawkins 1976) or the interconnected properties of

the neural circuitry that control behaviors, including sex-specific mating behaviors, for which

male and female traits need to co-evolve within the population (Fisher 1930; Lande 1981;

Kirkpatrick and Ravigne 2002).

Here, we infer the number and distribution and predict the function of loci involved in sexual

trait divergence between two species of the endemic Hawaiian cricket genus *Laupala*.

Differentiation in acoustic sexual signaling behavior appears to play a central role in *Laupala*

speciation, a group with one of the highest speciation rates documented for arthropods

(Mendelson and Shaw 2005). Species are endemic to single islands and show striking

differentiation in male song and female (song) preference (Otte 1994; Mendelson and Shaw

2005). Like most other cricket species, the male produces a song by rubbing together its

specialized forewings. The songs of *Laupala* crickets are relatively simple and consist of trains

of pulses, each produced by a single closing movement of the wings. Evidence suggests that a

critical trait used in female mate choice is the repetition rate of these pulses, i.e. the pulse rate

(Alexander 1962; Otte 1992)*,* which is highly heritable and constitutes one of the major sources

of phenotypic divergence among *Laupala* species (Shaw 1996, 2000; Grace and Shaw 2011; Oh

et al. 2012; Oh and Shaw 2013).

The neurobiology of cricket song generation is generally well understood. The major structures

controlling the cricket song rhythm are the descending brain neurons and specialized motor

neurons in the thorax, called central pattern generators (Hennig and Otto 1996; Hedwig 2014;

Schöneich and Hedwig 2017). A wide variety of neurological cell types, ion channels,

neurotransmitters, and hormonal neuromodulators are expected to contribute to the rhythmic

properties of pattern generators (Marder and Bucher 2001) and to the song rhythm in crickets

(Gerhardt and Huber 2002; Hedwig 2014). So far, we have not been able to pin cricket song

rhythm variation down to individual genes, but other organisms with known genetic and

neurological pathways that drive sex-specific and (acoustic) courtship behaviors can shed light

on the potential mechanisms. In *Drosophila melanogaster*, sexual dimorphism in the nervous

115 system, which forms the basis of courtship song neurobiology, is controlled by the sex-specific

116 transcription factor *fruitless* in interaction with *doublesex* (Clyne and Miesenböck 2008;

117 Yamamoto and Koganezawa 2013). However, neither of these genes contributes to interspecific

118 differences in song rhythm (Cande et al. 2014). Two other genes, *slowpoke* and *cacophony*, have

119 been implicated in species and population differences across *Drosophila* species: these genes

120 control the properties of ion (calcium and potassium) channels at neuromuscular junctions

121 (Gleason 2005; Etges et al. 2007; Veltsos et al. 2015) and can transform the output of neuronal

122 networks including central pattern generators (Crocker et al. 2010). Therefore, we may expect

123 similar neuromodulators as well as genes involved in synaptic transmission at neuromuscular

124 junctions and rhythmic behavior to contribute to variation in song rhythm in crickets.

125 The first goal of this study is to illuminate the genetic architecture of sexual trait divergence in

126 the light of different geographical modes of speciation. There is evidence from a biometric study

127 that multiple genetic factors (~5) contribute to pulse rate variation in *L. cerasina* and *L. eukolea*

128 (Oh et al. 2012) despite rapid phenotypic divergence following colonization of a new island

129 (Mendelson et al. 2004). We thus hypothesize that pulse rate divergence is associated with a

130 polygenic architecture, independent of the biogeographic mode of speciation. Using quantitative

131 trait locus (QTL) mapping we examine the number, effect size, and genomic distribution of loci

132 contributing to interspecific pulse rate variation in *L. cerasina* and *L. eukolea*. We then discuss

133 these results in the light of an earlier study dissecting the genetic architecture of pulse rate

134 divergence in *L. kohalensis* and *L. paranigra* (Shaw et al. 2007), an independently evolving

135 species pair which has diverged within a single island (Hawai'i; Otte 1994; Mendelson and Shaw

136 2005).

The second aim of this study is to examine the genomic arrangement of the genes controlling

mating behavior divergence in this system. We test the hypothesis that the functionally related

genes are clustered in QTL regions. Using genome-wide, functional genetic data from both sexes,

and across ontogenetic stages and reproductive states, we annotate the genetic map and associate

the segregating loci with Gene Ontology terms. Based on theoretical predictions (Fisher 1930) as

well as empirical findings for mating behavior genetics in birds (Küpper et al. 2015;

Lamichhaney et al. 2015) and moths (Gould et al. 2010), we predict that QTL regions contain

multiple, functionally related genes. Given the involvement of genes controlling ion channels at

the neuromuscular junctions and other neuromodulators in song variation in *Drosophila*, we

expect QTL regions to be enriched for genes with putative functions in neuromuscular processes

associated with song production, rhythmic behaviors, or mating behavior. This would suggest

that functionally related genes cluster inside QTL regions (rather than that a QTL region harbors

a single gene driving the observed phenotypic effect).

MATERIAL & METHODS

All custom R scripts as well as all commands in Linux and Python used in the analyses described

above will be made available in the supplementary information.

Samples and interspecific crosses

Laupala eukolea nymphs were collected in 2012 in Kipahulu Valley on Maui at Ginger Camp

(20º 41' 60.000'' N; 156º 5' 18.000'' W) and Palikea Peak (20º 40' 20.640'' N; 156º 4' 5.160''

W); *L. cerasina* were collected in Kalopa State Park (20º 2' 13.200'' N; 155º 26' 36.960'' W) on

Hawai'i Island. Animals were kept in the lab in plastic cups under constant temperature (20º) and

humidity, and were provided cricket chow (Fluker Farms, LA) *ad libitum* as well as substrate to

lay eggs. Males and females were kept separately to ensure virginity of all animals. They were

phenotyped between two and ten weeks after the final molt, during which sexual receptivity is

maximized in *Laupala* (Grace and Shaw 2011). Two families of first generation interspecific

hybrids (HC1 & HC2) were each generated by mating a *L. cerasina* male with a *L. eukolea*

female. Several males and females from each family (14 full sib pairs from each of the families)

were used to obtain second generation hybrids following the breeding design in (Shaw 1996).

Phenotyping

Male songs were recorded following the methods in (Shaw, 1996). A single recording for each

individual (*L. cerasina*, n = 24; *L. eukolea*, n = 16; F2, n = 230) was made between 10 A.M. and

4 P.M. Virgin, adult males were recorded individually in a plastic container with screen covers in

an anechoic and temperature-controlled chamber using a SONY Pro Walkman cassette recorder

and SONY microphone. Songs were then digitized using SOUNDSCOPE∕16 (GWI Instruments,

Cambridge, MA, USA) at 44.1 kHz to generate an oscillogram displaying trains of pulses

(singing bouts). We estimated the pulse rate by averaging the inverse of five pulse periods

(measured from the onset of a pulse to the onset on the next pulse) measured from a single

singing bout.

Genotyping

We extracted DNA from whole adult crickets using the DNeasy Blood & Tissue Kits (Qiagen,

Valencia, CA, USA). Genotype-by-Sequencing library preparation and sequencing were done in

2014 at the Genomic Diversity Facility at Cornell University following Elshire et al. (2011). The

Pst I restriction enzyme was used for sequence digestion and DNA was sequenced on the Illumina

HiSeq 2000 platform (Illumina Inc., USA) with 100 bp single end reads.

Reads were trimmed and demultiplexed using Flexbar (Dodt et al. 2012) and then mapped to the

L. kohalensis de novo draft genome using Bowtie2 (Langmead and Salzberg 2012) with default

parameters. We then called SNPs using two different pipelines: The Genome Analysis Toolkit

(GATK; DePristo *et al.* 2011; Van der Auwera *et al.* 2013) and FreeBayes (Garrison and Marth

2012). For GATK we used individual BAM files to generate gVCF files using 'HaplotypeCaller'

followed by the joint genotyping step 'GenotypeGVCF'. We then evaluated variation in SNP

quality across all genotypes using custom R scripts to determine appropriate settings for hard

filtering based on the following metrics (based on the recommendations for hard filtering section

"Understanding and adapting the generic hard-filtering recommendations" at

https://software.broadinstitute.org/gatk/ accessed on 28 February 2017): quality-by-depth, Phred-

scaled *P*-value using Fisher's Exact Test to detect strand bias, root mean square of the mapping

quality of the reads, u-based z-approximation from the Mann-Whitney Rank Sum Test for

mapping qualities, u-based z-approximation from the Mann-Whitney Rank Sum Test for the

distance from the end of the read for reads with the alternate allele. For FreeBayes we called

variants from a merged BAM file using standard filters. After variant calling we filtered the

SNPs using 'vcffilter', a Perl library part of the VCFtools package (Danecek et al. 2011) based

on the following metrics: quality (> 30), depth of coverage (> 10), and strand bias for the

alternative and reference alleles (SAP and SRP, both > 0.0001). Finally, the variant files from the

GATK pipeline and the FreeBayes pipeline were filtered to only contain biallelic SNPs with less

than 10% missing genotypes using VCFtools. We retained all SNPs that had identical genotype

calls between the two variant discovery pipelines. We then pruned our data further to contain

only ancestry informative markers (i.e. grandparents are homozygous for alternative alleles), one

SNP per scaffold, markers with no or only limited segregation distortion (χ^2- square associated q-

value ≤ 0.05, i.e. a 5% false discovery rate [Benjamini & Hochberg, 1995]), and markers with

fewer than 99% of their genotypes in common with other marker loci (i.e. exclude one of each

pair of marker loci with identical genotypes for all individuals).

Linkage mapping

To infer the genetic architecture, we first performed a QTL scan to detect the number, effect size

and any possible interactions of the regions associated with variation in pulse rate. For each of

the hybrid cross families, HC1 and HC2, we created linkage maps separately using MapMaker

(Lander et al. 1987). Map construction followed four steps. First, markers were grouped into

linkage groups using the 'group' command with the 'default linkage criteria' set to 4.0 (LOD)

and 35 (cM). Second, for each group, a subset of the marker passing a series of quality criteria,

i.e. informative, well-spaced markers, were ordered using the 'order' command. Markers were

considered informative if they had no missing genotypes and well-spaced if they were more than

2.0 cM apart from other markers. Third, remaining markers were added with the 'build'

command and the order was verified using the 'ripple' command. Markers were first added to the

map satisfying a log-likelihood threshold of 4.0 for the positioning of the marker (i.e., the

assigned marker position is 10,000 x more likely than all other positions), then adding remaining

markers at a log-likelihood threshold of 3.0, followed by a final step with log-likelihood

threshold set to 2.0. Markers not incorporated into the map at this stage were discarded. To

determine the final marker order we used the 'ripple' command with a window size of 6 markers

and a log-likelihood threshold of 2.0. Arbitrary orders in marker dense regions (i.e., orders with

similar likelihoods) were resolved using information from both HC1 and HC2 maps, choosing

the order that maximized the likelihood and minimized the map length (measured in cM) for

both cross families.

Fourth, and finally, the linkage maps were merged using the R package LPmerge (Endelman and

Plomion 2014). LPmerge uses linear programming to combine two maps from independent

populations based on the similarities in marker order. Incongruent marker orders between HC1

and HC2, i.e. linear inequalities, were solved based on the weight assigned to each independent

linkage map. The solution also depended on the size of the interval, K, in which conflicting

markers were detected and re-ordered (or removed if no solution was found and removing a

constraining marker improved the linear equality). For each linkage group separately, we varied

the weighting of the two linkage maps and the interval in which the linear inequality was

resolved (K) to find the consensus map associated with the lowest mean and variance of the root-

mean-squared error between the consensus map and the original maps.

QTL mapping

We used multiple-QTL models in the R/qtl (Broman et al. 2003) package to detect and locate

QTL and calculate effect sizes. For HC1 and HC2 independently, and for the merged (consensus)

map, we first performed a single QTL scan using the scanone function with the multiple

imputation method (Sen and Churchill 2001) and the Haley-Knot" regression (Haley and Knott

1992). We then performed a two-dimensional QTL scan using the Haley-Knott regression to

detect pairs of QTL and interaction effects among QTL. We then permutated the two-

dimensional QTL to establish penalized likelihood criteria for main and interaction effects. We

subsequently built a multiple QTL model, starting with the QTL with the highest LOD (log of

odds) score, refining the position using 'refineqtl', and then scanning for additional QTL. We

continued adding QTL (followed by refining their position) until an additional QTL did not

improve the LOD score of the model beyond the penalized LOD score threshold for main effects

at the alpha = 0.05 level. After the addition of each QTL, we checked for potential QTL

interactions that would improve the multiple QTL model beyond the (heavy) penalized LOD

score threshold for interaction effects at the alpha = 0.05 level. Finally, we estimated effect sizes

by fitting the QTL model and using the drop-one-term analysis. In the merged map, we included

cross type as a covariate in all steps described above. For comparison, we also used composite

interval mapping (CIM) to scan for QTL while using the markers under the QTL peaks identified

in the multiple QTL models as covariates and dropping those covariates if they were within a 20

cM window surrounding the tested region.

To estimate the true number of genetic loci underlying pulse rate variation based on the QTL

results, we use the method of Otto and Jones (2000). We first solved equation 11 (Otto and

Jones 2000) for zero, specifying a_{min} as the smallest QTL effect we detected in the QTL scan (for

HC1, HC2, or for the combined map) to calculate the threshold of the smallest QTL effect we

could detect. We then used equation 6 (Otto and Jones 2000) to estimate the true number of loci.

The calculations were done using custom function in R, which is available upon request and in

the Github repository associated with the manuscript.

Transcriptome assembly

To look for candidate genes in QTL regions and test for enrichment of specific gene functions

we first assembled the transcriptome to obtain information about putative gene function of the

loci within regions of interest. The *L. cerasina* individuals used for RNA-sequencing and

transcriptome assembly were first generation lab-reared offspring. A total of ten samples were

stored in RNAlater following the manufacturers recommendations (Qiagen, Germany) and

pooled by sex prior to sequencing: four adult males (two sampled in the morning and two

sampled in the evening, one of which was sampled immediately *after* mating a female), four

adult females (as with the males, two were sampled in the morning and the two were sampled in

the evening, one being collected immediately *after* mating), and a juvenile male and female. The

tissue was homogenized using sterilized forceps in RNAlater. RNA was extracted using the

RNAeasy kit (Qiagen, Germany). A quality check was done using a NanoDrop

spectrophotometer (Thermoscientific, Wilmington, DE, USA) and the Agilent Bioanalyzer 2100

(de Goor 2003). The samples were then sequenced on a single lane on the Illumina HiSeq 2000

platform with 50 bp paired end reads.

Reads were processed using Fastq-mcf from the Ea-Utils package (Aronesty 2011) with the

parameters -q 30 (trim nucleotides from the extremes of the read with qscore below 30) and -l 30

(discard reads with lengths below 30 bp). Read duplications were removed using PrinSeq

(Schmieder and Edwards 2011) and reads were corrected using Musket with the default

parameters (Liu et al. 2013).

We assembled the *L. cerasina* transcriptome using Trinity's (Haas et al. 2013) genome-guided

assembly pipline. We used the *Laupala kohalensis* reference genome (Blankers et al. 2017) and a

maximum intron size cut-off of 5000 bp. We first created a HISAT (Kim et al. 2015) index of the

genome and then aligned the male and female paired-end reads to the genome using default

settings. We sorted the resulting alignment SAM file and converted it to BAM format using

samtools (Li et al. 2009). We then did the genome-guided assembly using Trinity and checked

the quality of the assembly by calculating N50 statistics, mapping the male and female reads

back to the transcriptome using bowtie2 (Langmead and Salzberg 2012), and searching for

conserved eukaryote and arthropod genes from the BUSCO database (Simão et al. 2015). We

then mapped the reads back to the transcriptome using GMAP (Wu and Watanabe 2005) and

BLAT (Kent 2002), and used custom R scripts to retain a single best hit scaffold for each

transcript based on the coverage, identity, and number of matched bases.

Transcriptome annotation

We checked for contamination using NCBI's VecScreen, using the UniVec Core database and

the recommended blastn parameter values (https://www.ncbi.nlm.nih.gov/tools/vecscreen/about/,

accessed July 20 2017). We then functionally annotated the transcripts in three steps using

BLAST (Altschul et al. 1990; Camacho et al. 2009): first we matched our transcripts against the

Drosophila melanogaster proteome using an e-value cut-off of 1e-5. Any transcripts that were

not annotated in the first step were matched (at the same threshold) with the Uniprot/Swissprot

data base (The UniProt Consortium 2017), limiting our search to arthropod proteins. Finally, we

matched the remaining transcripts against the non-redundant protein database at NCBI, with an

e-value cut-off of 1e-5 and limiting our search to animal proteins.

We then used hmmer2go (https://github.com/sestaton/HMMER2GO) to estimate Open Reading

Frames (ORFs) and translated only a single, longest ORF per transcript. We annotated the

retained protein sequences using InterProScan (Zdobnov and Apweiler 2001; Jones et al. 2014).

We imported the transcriptome FASTA file, the XML output from the BLAST searches, and the

InterPro results into Blast2Go (Conesa et al. 2005). We recovered the original BLAST best hit,

and ran the Gene Ontology mapping using default settings. We then merged all these results and

ran the Annotation tool.

Gene Ontology

We tested the hypothesis that genes residing in QTL regions are functionally enriched for

biological processes potentially involved in cricket courtship behavior and song production. We

first used topGO from R's BioConductor environment (Alexa and Rahnenfuhrer 2016) to do

gene set enrichment analysis. We combined all the transcripts matching scaffolds within the

LOD 1 interval of the seven QTL peaks in the consensus linkage map (i.e. scaffolds with a

marker that explained pulse rate variation within a 1 LOD score significance level of the highest

LOD score for a given QTL). We then used the parent-child p-value correction (Grossmann et al.

2007) to test for GO term enrichment relative to the *L. cerasina* transcriptome. We did an

additional false discovery rate correction using the Benajamini & Hochberg algorithm

(Benjamini and Hochberg 1995) with the p.adjust function in R and considered any GO term

enriched within the QTL region at a false discovery rate of 10% or less. We also manually

inspected putative gene function in QTL regions by examining experimentally proven biological

and molecular functions for the highest ranked BLAST annotations on FlyBase (Gramates et al.

2017).

RESULTS

Linkage mapping

We mapped a total of 298 and 416 markers for HC1 (n=94) and HC2 (n=136), respectively (Fig

S1) to 8 linkage groups corresponding to the seven autosomes and the X chromosome in

Laupala. The map lengths were 821.2 cM and 734.1 cM corresponding to 2.72 marker/cM and

1.76 marker/cM, respectively. Merging the maps resulted in 508 unique markers at a total map

length of 776 cM (1.52 cM/marker).

QTL mapping

Laupala cerasina and *L. eukolea* males have non-overlapping, normally distributed pulse rate

distributions (Fig 1). The average pulse rate difference was 1.66 pulses per second (Table 1). The

F_2 song phenotype was normally distributed, the means of the HC1 and HC2 progeny did not

differ significantly ($P = 0.0724$), and the joint F2 distribution encompassed the parental species'

phenotypic distributions (Table 1, Fig 1).

We detected two moderate effect (~10% of the species difference) QTL in both the HC1 and

HC2 mapping populations on linkage group (LG) 1 and LG3 (Fig 2, Table 2). In HC2, we

additionally detected three smaller effect QTL (< 5%) on LG5, LG7, and LGX. Merging the

maps and combining the sample sizes also revealed a small effect QTL on LG2 and LG4 (Table

3). All (haploid) QTL effects were significantly larger than zero ($P < 0.05$) and of the same sign

(Table 2, Table 3). Together, the seven QTL for the combined HC1 and HC2 mapping

populations explained 38.73% (or 0.64 pps) of the phenotypic difference between the parental

lines (Table 3; 20.18% and 32.07% for HC1 and HC2, respectively, Table 2). None of the QTL

had significant dominant effects (Table S1) and no interactions of additive QTL were detected.

The QTL on LG1 and LG3 mapped to approximately the same location in HC1 and HC2, with

the marker nearest to the peak in HC2 directly flanking the peak marker in HC1 (Fig 2, Table

S2). Note that the genetic map of LG1 is substantially larger, indicating higher recombination

rates in that region, in HC1 compared to HC2 and the combined map, but that this does not result

in a different marker order. In general, the marker order on the linkage maps and mapped QTL

intervals were highly concordant among the HC1, HC2, and combined map (Fig S1).

Based on the results for HC1 and HC2 and using the method in (Otto and Jones 2000) we

estimated the true number of loci to be 9.41 (95% confidence interval = [1.57-29.02]; detection

threshold, theta = 0.069 pps) and 8.84 (95% CI = [3.18-19.03]; theta = 0.018), respectively.

Using all 230 F2 individuals, we estimated the true number of loci at 13.59 ((95% CI = [5.83-

26.23]; theta = 0.025). The estimated amount of variation that remains undetected was ([true #

loci – detected # loci] x average effect size of undetected): [9-2] x 0.03 = 0.21 for HC1, [9-5] x

0.01 = 0.04 for HC2, and [14-7] x 0.01 = 0.07 for the combined map, respectively.

Transcriptome

We used the genome-guided assembly from the Trinity (Haas et al. 2013) pipeline to assemble

the transcriptome. Of the 50,148,157 reads after filtering (52,980,661 prior to filtering) that were

used to assemble the transcriptome, 90.58% mapped to the reference genome. The assembly had

a total length of 53,928,392 bp, the median contig length was 397 bp, and the contig N50 was

1,805 bp. Mean coverage was 49.9x and 40.8x for female and male reads, respectively. The male

and female reads mapped back to the transcriptome with high confidence, at mapping rates of

92.05% and 92.26%, respectively. The BUSCO analysis indicated that we captured a large

amount of conserved eukaryote and arthropod genes with 97.4% and 95.2% complete BUSCO

hits, respectively. Using the *D. melanogaster* proteome, the arthropod specific Uniprot/Swissprot

database and NCBI's non-redundant database of animal proteins, we successfully annotated

19,713 transcripts (32.2% of all transcripts) at a combined length of 32,039,513 bp (59% of the

full assembly). A total of 17,577 transcripts have a Gene Ontology (GO) annotation.

Gene Ontology

There were 179 scaffolds within 1 LOD of the QTL peaks combined. We mapped a total of

2,270 transcripts against 171 of the 179 scaffolds. We first tested whether QTL regions were

significantly enriched for genes involved in neurogenesis, ion channels, courtship behavior, and

neuromuscular development (Table S3). Testing the GO terms in the LOD1 intervals around the

QTL peaks across the 7 linkage groups with a significant QTL resulted in several enriched

biological processes. The ten most strongly enriched categories were related to locomotion

behavior, brain morphogenesis, metabolism, neuromuscular processes, and photoreceptor cell

specialization (Table S4, Fig S2). Among the other significantly (5% FDR) enriched categories

were calcium ion channel and ion transport regulation, peripheral nervous system development,

neuron differentiation, and neurotransmitter secretion, although these are just a few of the many

significantly enriched biological processes (Table S3). Testing each of the seven QTL region

separately, we found that all categories were enriched for several GO terms, including those

related to neuromuscular development (LG1, LG4), development, maintenance, and transmission

at synapses (LG1, LG3, LG5, LGX), rhythmic and locomotor behaviors (LG4, LG7), mating

behavior (LG3), hormone and pheromone production (LG2), and nervous system development

(LG4, LGX; Table S5).

DISCUSSION

Behavioral isolation is an important barrier to gene flow in the earliest stages of animal

speciation, but we know little about the number and distribution of underlying genetic loci and

their relationships with the tempo and mode of evolution. In island systems where founder

effects have been hypothesized in the history of species radiations, shifts in the phenotypic and

genetic environments due to genetic drift may enable speciation (Carson and Templeton 1984;

Templeton 2008), in particular for traits involved in sexual isolation (Van Oosterhout et al. 2003;

Templeton 2008; Bolund et al. 2010). In such a scenario, the genetic architecture has been

considered a lynch pin that can become reorganized upon disruption during the genetic upheaval

following the founder event. For this to occur, a type II genetic architecture (epistatic, major

gene/modifier) must underlie speciation phenotypes (Shaw and Mullen 2011; Mullen and Shaw

2014), such as those involved in sexual signaling. Conversely, it has been argued that a Type I

(additive, polygenic) genetic architecture, often underlies mating behavior divergence (Ritchie

and Phillips 1998). Here, we examine the genetic basis of interspecific variation in the song

rhythm between two swordtail cricket species that are isolated sexually (song and preference

behavior; Oh et al. 2012) and geographically (occupying different islands; Otte 1994; Mendelson

and Shaw 2005). We also provide compelling preliminary evidence that functional loci cluster in

specific regions associated with quantitative sexual traits and discuss some interesting homologs

of genes implicated in *Drosophila melanogaster* courtship behavior and in various

neurophysiological processes that can be tied to cricket song rhythm found within these regions.

The genetic architecture of inter-island sexual trait divergence

As opposed to documenting a contrast between the genetics of intra- versus inter-island

speciation events, we find significant parallels in QTL number, location, effect size, and

interaction between this study and an independently diverged intra-island species pair (Shaw et

al. 2007). We detected six moderate to small effect QTL for pulse rate variation on the seven

autosomes in *Laupala* and an additional small effect X-linked QTL. Based on our estimates of

the missing variation and number of undetected loci (Otto and Jones 2000), we conclude that the

true number of loci controlling pulse rate variation in *L. cerasina* and *L. eukolea* is likely more

than ten. Moreover, we found no detectable interaction effects among the identified QTL. Thus,

pulse rate divergence between these species most likely has a polygenic (Type I) genetic

architecture, rather than a Type II architecture, as has been hypothesized for speciation

phenotypes that interact with founder induced interisland speciation (Carson and Templeton

1984). These findings support earlier biometric evidence for both *L. kohalensis* by *L. paranigra*

and *L. cerasina* by *L. eukolea* species crosses (Shaw 1996; Oh et al. 2012). These results are

significant in that *Laupala* has one of the fastest rates of speciation known, yet a type I genetic

architecture underlies the interspecific genetics of an important speciation phenotype in this

radiation, independent of the biogeographic context. Other phenotypes may or may not follow

this pattern (e.g., Mullen et al. 2008) and merit further investigation.

Contrasting the results for *L. cerasina* and *L. eukolea* with those for *L. kohalensis* and *L.*

paranigra (Shaw et al. 2007) also uncovers that genetic differentiation in replicate *Laupala*

species pairs shows substantial parallelism. While the Shaw et al. (2007) study was based on

AFLP markers and the present study utilizes GBS markers, making precise comparisons of QTL

location challenging, some general comparisons between homologous linkage groups are

possible. Two major QTL on LG1 and LG3 explain around 12% and 8% of the average

phenotypic difference between *L. eukolea* and *L. cerasina*. The homologous linkage groups in

the genetic map of *L. kohalensis* and *L. paranigra* (linkage group numbers are the same, see also

Blankers et al. 2017 for linkage group homology) have QTL explaining around 9% and 10% of

the parental difference, respectively. Likewise, both the present study and *L. kohalensis* x *L.*

paranigra study find QTL effects on LG 4, LG5 and the X chromosome (the latter in line with

prior findings from biometric studies revealing a significant phenotypic difference in first

generation reciprocal hybrids (Shaw 1996; Oh et al. 2012)). Moreover, phenotype associations

on LG6 and LG7 were very weak or absent in both studies. Finally, all QTL allelic effects

estimated in this study and in Shaw et al. (2007) have directionality consistent with a hypothesis

of directional selection (Orr 1998; i.e., an allele originating from the fast (or slow) species

increases (or decreases) the pulse rate in hybrids).

There were also some differences between the two species pairs. While the QTL effects on LG4

and LG5 are present in both species pairs, they are larger in the *L. kohalensis* x *L. paranigra*

cross than in the current study (~0.14 and ~0.29 pps in the 2007 study, 0.05 and 0.07 pps in this

study). Additionally, we did not find evidence for secondary peaks on LG1 and LG3 (both had

small second peaks in the 2007 study) and detect only seven instead of eight QTL, despite

similar sample sizes and much denser genotype sampling (GBS SNP markers instead of AFLPs

used in the 2007 study). Estimates of the true number of loci also differs between the species

pairs, although both fit a polygenic architecture better than an oligogenic or major effect/epistasis

architecture (n = 14 (95% CI = [6-26]; at an estimated detection threshold of 0.025 pps) for this

study and n = 30 (95% CI = [15-55]; threshold = 0.040 pps) for Shaw et al. (2007), data from

table 2).

Together, our findings indicate that there is substantial genetic parallelism across species pairs,

that QTL on the same linkage groups largely have similar effect sizes, but that, by our estimates,

the number of causal loci differs. Morphological (Otte 1994) and molecular evidence

(Mendelson and Shaw 2005) place the two species pairs in independent species groups. Based on

records of island's geological history (Carson and Clague 1995), and the island endemism of *L.*

kohalensis, L. paranigra and *L. cerasina*, both species pairs have likely diverged in the last

500,000 years (Mendelson and Shaw 2005). Both groups show significant, conspicuous

differentiation in male and female sexual traits, but *L. kohalensis* and *L. paranigra* have diverged

to a greater degree (~ 3 pulses per second difference, versus ~ 1.6 pps for *L. eukolea* and *L.*

cerasina). Interestingly, this aligns well with the 2-fold difference in the estimated true number

of loci. Further comparative work is needed to probe the generality of these findings to better

illuminate the relationship between biogeography, magnitude of phenotypic divergence, and

genetic architecture of speciation.

As with any experiment, linkage mapping and QTL analyses are vulnerable to estimation error

(e.g., map order errors and false positive QTL) and an important way to mitigate this error, is

through replication. Here, we first studied the genetic architecture in two independent mapping

populations separately (mapping families HC1 and HC2), before combining the data to

maximize our sample size. The family-specific linkage maps are collinear, while the order was

determined independently for each map initially, providing support for the inferred marker order.

The major QTL on LG1 and LG3 have similar effect sizes and map to the same location in both

mapping populations. There are additional, smaller effect QTL that we detected in the larger

mapping population (HC2) only, likely a consequence of a larger sample size (similar to Shaw et

al. 2007). There are also QTL on LG2 and LG4 that were only detected after combining the two

mapping families. Thus, there is some corroboration of the results, which rules out

environmental sources of genotype-phenotype association and we also reveal some limitations to

detect small-effect QTL at lower sample sizes.

Behavioral gene clusters

Our results support the hypothesis that functionally related genes are clustered in specific

genomic regions. This is important because it suggests that QTL regions likely contain several

closely linked (and thus co-segregating) functionally related genes. Gene clusters reflect a

potential adaptation to overcome constraints associated with behavioral evolution that requires

coordinated change in several loci controlling complex neurophysiological traits. Close linkage

would reduce interspecific and intraspecific recombination and facilitate adaptation (Noor et al.

2001). It has been associated with several traits that are important in reproductive isolation

(Gould et al. 2010; Lowry and Willis 2010), speciation (Hermann et al. 2013), and mating

behavior variation (Küpper et al. 2015; Lamichhaney et al. 2015; Tuttle et al. 2016), specifically

in the light of trait-preference co-evolution (Lande 1981; Kirkpatrick 1982; Shaw et al. 2011;

Singh and Shaw 2012). In *Laupala* there is evidence for co-localization of male song and female

preference QTL (Shaw and Lesnick 2009; Wiley et al. 2012) and for male song QTL falling in

regions of low interspecific recombination, which might facilitate coordinated divergence among

genes underlying male song behavior and/or between male and female traits (Blankers et al.

2017). Additional fine-mapping approaches are necessary to see if any closely linked QTL can

be detected once more recombination events can be observed (at higher sample sizes).

Our results also shed light on the potential genetic mechanisms that control mating behavior

variation in *Laupala*. The main enriched biological processes among the predicted gene products

in QTL regions can be tied to potential modulators of central pattern generators (rhythmic

behaviors) and to sex-specific expression in nervous system development pathways in fruit flies:

various neuromuscular processes, nervous system development, neurotransmitter secretion, and

other neurological processes. These findings were in part driven by potential homologs of *lola* (6

cM away from the peak at LG4), *semaphorin* (directly flanking the peak at LG7), and

roundabout (1.5 cM away from the peak at LG1). All three of these genes are affected by sex-

specific transcription of *fruitless* (which itself is located on LG2) in *D. melanogaster* and

contribute to sexual dimorphism in the nervous system (Moran and Kyriacou 2009; Dauwalder

2011; Nojima et al. 2014).

In addition to these sex specific receptor proteins, we find receptors for serotonin, GABA,

dopamine, and acetylcholine, all known neuromodulators of central pattern generators in insects

(Marder and Bucher 2001; Gerhardt and Huber 2002; Katz 2016). We also identify several ion

channel genes such as *cadherin* (flanking the QTL peak marker on LG3), *cacophony* (16 cM

from the peak on LG4, which has a functional role in the inter-pulse interval in *D. melanogaster*

Peixoto and Hall 1998), *KCNQ potassium channel* (1.5 cM from peak marker on LG3), and

sandman (1.9 cM from the peak at LG5). We acknowledge that without functional genetic

experiments (e.g. knockout experiments) and tissue specific expression screens (to check if

expression of these genes is sex-specific and/or if they are active in the mesothorax where the

central pattern generators are located) there is no conclusive evidence that these genes are

involved in modulation of the central pattern generator or song rhythm in *Laupala*. Overall,

however, QTL regions are significantly enriched for a variety of processes related to

neuromodulation and nervous system development and multiple QTL harbor interesting

candidate loci for central pattern generator modulation and courtship behavior, which merit

follow-up analyses and functional validation.

Together, this study presents rare comparative insights into the polygenic genetic architecture

associated with sexual trait divergence during speciation in different biogeographic contexts.

Clearly, rapid quantitative trait differentiation associated with speciation can occur under a Type

I genetic architecture, where many genes diverge in concert to produce a conspicuous species

difference. We show that the genetic architecture of male song rhythm divergence in closely

related *Laupala* species is remarkably similar among two independently originated species pairs,

despite their different geographic histories. Through this study, we further identify several

potential candidate genes controlling this highly divergent and isolating behavioral phenotype.

We show that the QTL regions underlying song pulse rate divergence identified in this study are

enriched for a variety of neuromuscular processes that may contribute to modulating the central

pattern generators that control the song rhythm. This finding suggests potential clustering of

functionally related loci in small genomic regions, which warrant additional research.

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TABLES

Table 1. Phenotypic distributions. The mean, standard deviation, and sample size of the pulse rate (pulses per

second) are shown for the parental species and the F2 generation (both cross types, HC1 and HC2).

	Mean (pps)	sd	n
L. cerasina	2.33	0.07	24
L. eukolea	3.99	0.12	16
Environmental Variance*	0.02	0.13	
F2 HC1	3.11	0.20	94
F2 HC2	3.16	0.23	136
F2 mean	3.14	0.22	230

792 *Environmental variance was calculate following (Fishman et al. 2002); "mean" in this context refers to the

793 environmental variance, while "sd" is the square root of that variance.

Table 2. QTL results from HC1 and HC2. QTL were mapped using the maps for the 94 HC1 and 136 HC2 F2 individuals. LOD: log-of-odds. A and B alleles denote *L. cerasina* and *L. eukolea* alleles, respectively. All QTL effects are significantly different from zero (* P < 0.05; † P < 0.01; ‡ P < 0.001). ESD: environmental standard deviation.

| Linkage group | QTL location (cM) | LOD | Nearest scaffold | Marker location | Phenotypic Value | | | QTL effect (pps +/- SD) | QTL effect (% parental difference) | QTL effect (#ESDs) | % F2 variance explained |
					AA	AB	BB				
HC1											
1	119	17.81	S004794	119.4	2.88	3.14	3.31	0.220 +/- 0.021†	13.23	1.75	50.60
3	71.3	7.04	S001552	71.3	2.95	3.13	3.16	0.116 +/- 0.020‡	6.95	0.92	14.96
HC2											
1	57.0	23.85	S002490	56.9	2.90	3.18	3.31	0.216 +/- 0.017†	13.03	1.72	37.05
3	67.1	12.98	S000355	67.1	3.03	3.17	3.28	0.136 +/- 0.016†	8.18	1.08	16.46
5	48.9	5.38	S001294	48.9	3.04	3.17	3.25	0.076 +/- 0.015*	4.55	0.60	5.96
7	56.0	2.63	S001482	56.1	3.10	3.14	3.29	0.056 +/- 0.017*	3.38	0.44	2.78
X	32.0	3.74	S000108	29.7	3.13	3.19	3.13	0.049 +/- 0.012*	2.93	0.39	4.03

801 Table 3. QTL results from the combined map. QTL were mapped using the consensus map for the 230 F2

802 individuals. LOD: log-of-odds. A and B alleles denote *L. cerasina* and *L. eukolea* alleles, respectively. All QTL

803 effects are significantly different from zero (* P < 0.05; † P < 0.01; ‡ P < 0.001). ESD: environmental standard

804 deviation.

Linkage group	QTL location (cM)	LOD	Nearest scaffold	Marker location	Phenotypic value			QTL effect (pps +/- SD)	QTL effect (% parental difference)	QTL effect (#ESDs)	% F2 variance explained
					AA	AB	BB				
1	59.0	40.73	S001131	58.8	2.89	3.17	3.31	0.203 +/- 0.013	12.25	1.61	36.39
2	71.0	4.78	S001921	69.1	3.05	3.15	3.18	0.055 +/- 0.013	3.31	0.44	2.90
3	79.9	21.28	S000385	79.9	3.02	3.14	3.23	0.123 +/- 0.012	7.42	0.98	15.34
4	59.8	3.97	S016452	59.0	3.10	3.12	3.23	0.053 +/- 0.013	3.20	0.42	2.39
5	36.9	8.32	S002445	36.9	3.05	3.16	3.19	0.068 +/- 0.012	4.09	0.54	5.23
7	5.0	3.51	S007011	9.8	3.08	3.14	3.20	0.045 +/- 0.013	2.69	0.35	2.10
X	38.0	5.46	S003132	37.2	3.10	3.17	3.10	0.041 +/- 0.009	2.46	0.32	3.34
cross	-	2.24	-	-	-	-	-	0.055 +/- 0.018	3.31	0.44	1.33

 FIGURE LEGENDS

Figure 1. Phenotypic distributions for the parental lines and first and second-generation hybrid

offspring. The data from the F1 hybrids in the top panel are from Oh et al. 2012 and shown to

illustrate F1 distributions as well as the maternal bias in pulse rate inheritance. The F2 data are

split by family/mapping population (HC1 and HC2).

Figure 2. Results from the multiple QTL models (black solid lines, only for linkage groups with

significant QTL) and composite interval mapping (grey solid lines). The vertical dotted line

shows the 5% significance threshold for the composite interval mapping. The horizontal dotted

lines connect homologous markers nearby QTL peaks in HC1 and HC2 to illustrate the overlap

between the QTL scans in the different mapping populations. The panels on the far right show

the effect size of each of the QTL as the pulse rate mean +/- standard error for each of the

genotype categories AA (left), AB (center), BB (right).

Figure S1. Linkage map and multivariate QTL model results. The horizontal black bars show the

position of the SNP markers in the HC1, combined, and HC2 map, respectively. The black dots

and solid lines connect homologous scaffolds between adjacent linkage groups. The scale

indicates the position along the linkage group in cM. The red vertical bars and error bars show

the 1-LOD and 2-LOD interval around the QTL peaks, respectively. QTL were calculated using

a multivariate model and significance was inferred using penalized LOD scores.

Figure S2. Enriched Gene Ontology network. The 10 most strongly enriched biological processes

(squares) and their relationship (arrows) as well as associated parental terms (ellipses) are shown.

The colors correlate with the parent-child algorithm corrected P values (not with FDR corrected

q-values). Warmer colors (more red) indicate lower P values.

Figure 1. Phenotypic distributions for the parental lines and first and second-generation hybrid offspring. The data from the F1 hybrids in the top panel is from Oh et al. 2012 and shown to illustrate F1 distributions as well as the maternal bias in pulse rate inheritance. The F2 data is split by family/mapping population (HC1 and HC2).

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