Genomic Differentiation Between Temperate and Tropical Australian Populations of Drosophila melanogaster

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ABSTRACT

Determining the genetic basis of environmental adaptation is a central problem of evolutionary biology. This issue has been fruitfully addressed by examining genetic differentiation between populations that are recently separated and/or experience high rates of gene flow. A good example of this approach is the decades-long investigation of selection acting along latitudinal clines in Drosophila melanogaster. Here we use next-generation genome sequencing to reexamine the well-studied Australian D. melanogaster cline. We find evidence for extensive differentiation between temperate and tropical populations, with regulatory regions and unannotated regions showing particularly high levels of differentiation. Although the physical genomic scale of geographic differentiation is small—on the order of gene sized—we observed several larger highly differentiated regions. The region spanned by the cosmopolitan inversion polymorphism $In(3R)P$ shows higher levels of differentiation, consistent with the major difference in allele frequencies of Standard and $In(3R)P$ karyotypes in temperate vs. tropical Australian populations. Our analysis reveals evidence for spatially varying selection on a number of key biological processes, suggesting fundamental biological differences between flies from these two geographic regions.

ETERMINING the processes maintaining genetic variation within species is a basic goal of biological research and a central problem of evolutionary genetics. Indeed, the relative contributions to segregating variation of (1) low-frequency, unconditionally deleterious mutations, (2) intermediate-frequency, small-effect variants maintained by mutation and genetic drift, and (3) adaptive mutations maintained by positive selection e.g., spatially varying or negative frequency-dependent selection—remain unknown in any species. Thus, it is also unclear whether different processes predominate in different species, perhaps resulting from differences in population size, ecology, or genetics.

One approach for identifying adaptive variants segregating within species is to investigate systems in which there are major phenotypic variants likely influenced by natural selection and that have relatively simple genetics. This is what has traditionally been thought of as ecological genetics. For example, pigmentation variation in vertebrates (e.g., NACHMAN et al. 2003) is a good example of a trait for which the relatively small number of candidate genes allows the phenotypic effects of natural variants to be directly tested. For major phenotypic variants having a simple genetic basis but no candidate genes, genetic analysis can be used to isolate alternative alleles underlying the phenotypic difference. Examples include diapause variation and foraging behavior in *Drosophila melanogaster* (OSBORNE et al. 1997; SCHMIDT et al. 2008), traits relating to social behavior and copulatory plug formation in Caenorhabditis elegans (DE BONO and BARGMANN 1998; PALOPOLI et al. 2008), and several phenotypes in sticklebacks (COLOSIMO et al. 2004; MILLER et al. 2007; CHAN et al. 2010). Besides their simple genetics, such biological examples have the advantage that the targeted traits may have plausible connections to fitness variation in nature (though this is not always the case). In spite of the practical advantages associated with phenotypic variation resulting from simple genetics and alleles of large effect, such variation may not speak very strongly to the general properties of adaptive polymorphisms in natural populations, which may often be characterized by complex genetics or small-effect alleles.

A complementary approach uses population-genetic analysis to identify individual polymorphic variants/genes that may have been influenced by positive selection. This approach offers at least two advantages. First, it can be made genomic in scope and therefore may provide a less-biased view of the genes and phenotypes influenced by positive selection. There is no comparably comprehensive "omic" concept for phenotypic analysis, because

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the universe of phenotype space is difficult to define, difficult to measure, and highly dimensional (LEWONTIN 1974). Second, alleles having relatively small effects or effects not associated with easily defined phenotypes can be identified. A population-genetic approach is a particularly powerful discovery tool when joined with high-quality genome annotation, generating many new hypotheses about the genetic and phenotypic variation influenced by positive selection within species and providing vast opportunities for the downstream functional investigation of such variation.

One population-genetic approach for identifying positively selected polymorphisms is to search the genome for sites exhibiting large allele-frequency differences between recently separated populations or those experiencing high rates of gene flow (LEWONTIN and KRAKAUER 1975). Because even low levels of gene flow effectively homogenize neutral allele frequencies (WRIGHT 1931; MARUYAMA 1970; SLATKIN 1981), alleles under spatially varying selection are expected to appear as outliers with respect to allele-frequency differences across populations. This strategy may be particularly effective when allele frequencies change gradually along a cline, such as with latitude or altitude.

Some of the best-studied cases of latitudinal clines maintained by spatially varying selection are those of D. melanogaster. The majority of work on these clines has investigated various phenotypic traits, chromosome inversion polymorphisms, and enzyme-coding genes (SEZGIN $et \ al. 2004$), as well as several other genes harboring clinal variants (Costa et al. 1992; McCoLL and McKechnie 1999; Schmidt et al. 2000; Duvernell et al. 2003). The cline along the east coast of Australia has received considerable recent attention due to the efforts of Ary Hoffmann and collaborators (e.g., HOFFMANN and Weeks 2007). The fact that similar clines are often observed on different continents strongly implicates natural selection rather than demography as the cause of clinal variation (OAKESHOTT et al. 1981, 1983; SINGH and Rhomberg 1987; Singh 1989; Singh and Long 1992; Gockel et al. 2001; Kennington et al. 2003; Hoffmann and Weeks 2007). Importantly, although cosmopolitan chromosome inversion polymorphisms exhibit latitudinal clines (with inversion frequency increasing in more tropical populations), many observations convincingly show that inversions explain only a fraction of clinal variation, even for genes located in inverted regions (VOELKER et al. 1978; KNIBB 1982; SINGH and RHOMBERG 1987; FRYDENBERG et al. 2003; Umina et al. 2006). Indeed, many clinally varying genes are not physically near inversions (VOELKER et al. 1978; Singh and Rhomberg 1987; Sezgin et al. 2004; Turner et al. 2008).

We recently extended the genetic characterization of population differentiation from D. melanogaster clines by comparative genomic hybridization analysis of population samples from opposite ends of well-described clines

in Australia and North America (TURNER et al. 2008). That study generated new information on genomic differentiation, but the crude nature of the data limited the scope of the analysis and the strength of the conclusions that could be drawn. Here we revisit the issue of geographic differentiation between opposite ends of a known *D. melanogaster* cline, using next-generation sequencing to characterize genomic variation in flies from Queensland and Tasmania, Australia. These data are used to generate hypotheses regarding the biological differences between flies from these regions and to assess the population-genetic properties of sequence differentiation between these geographic regions.

MATERIALS AND METHODS

Sequencing, assembly, and data filtering: Population samples from the east coast of Australia were collected in 2004 (ANDERSON *et al.* 2005). Twenty isofemale lines from Queensland (Cairns, lat. 16.907, and Cooktown, lat. 15.476) and 19 isofemale lines from Tasmania (Hillwood, lat. 41.237, and Sorell, lat. 42.769) were used. Two females were collected from each Queensland line ($n = 40$ flies). These flies were pooled in a single tube and made into DNA. Similarly, two females were collected from each Tasmania line ($n = 38$ flies), pooled in a single tube, and made into DNA. Each of the two DNA samples was then sequenced using Solexa/Illumina technology (BENTLEY et al. 2008). Base calls and quality scores were determined using the Solexa GAPipeline v0.3.0. Output files were in fastq format. Reads were mapped against the D. melanogaster reference genome R5.8 (ADAMS et al. 2000), using Maq v0.6.8 (LI et al. 2008). Prior to mapping, we split fastq files into separate files with 1 million reads per file. The reads are available in the NCBI Sequence Read Archive under accession no. SRA012285.16.

Several Maq functions were used for data formatting. Solexa quality scores were converted to Sanger quality scores using Maq function sol2sanger and converted from fastq files to binary fastq (bfq) using the Maq function fastq2bfq. Bases 1–36 of each read were used; the expected heterozygosity parameter $(*-*m*")$ flag) was 0.005. Mapped reads were merged using mapmerge. The functions maq assemble and maq pileup were then used to produce pileup files. Finally, pileup files were split by chromosome arm for downstream analysis. Individual base calls with Maq quality scores ≤ 10 were excluded, as were positions with only a singleton variant in the entire Australian sample. We explored the value of increasing the Maq quality threshold to 20, but the reduction in coverage was too costly, given the amount of data. Because we excluded singletons and focused on genomic outliers, errors should not be an important factor with respect to our biological conclusions. We excluded genomic positions with $<$ 6 or $>$ 20 sequence reads in either population, because these sites are associated either with very low power to reject the null hypothesis or with the confounding phenomenon of differentiated copy-number variation.

Because a primary goal of our study was to generate biological, gene-centric hypotheses regarding the nature of selection, most analyses excluded regions of the genome adjacent to centromeres and telomeres associated with low heterozygosity, as determined from genome sequences of a Raleigh sample of inbred lines sequenced as part of the Drosophila Population Genomics Project (DPGP.org). These regions of reduced heterozygosity are expected to be associated with lower power to detect differentiation, and because

they experience reduced rates of crossing over, the physical scale of differentiation may be quite large, limiting opportunities for identifying potential targets of selection. The coordinates corresponding to regions of normal recombination used in our analyses are 2L, 844,225–19,946,732; 2R, 6,063,980–20,322,335; 3L, 447,386–18,392,988; 3R, 7,940,899– 27,237,549; and X, 1,036,552–20,902,578. The regions excluded are roughly consistent with the non- or low-recombining portions of the genome identified in prior studies (e.g., Singh et al. 2005).

Ancestral sequence reconstruction: For the purposes of unfolding the site frequency spectrum in our samples, ancestral states were inferred using maximum likelihood (ML) (Yang et al. 1995) [provided by PAML v4.3 (Yang 2007)], assuming the reference phylogeny (Drosophila 12 Genomes Consortium 2007), the HKY nucleotide substitution model (HASEGAWA et al. 1985), and gamma-distributed among-site rate variation (Yang 1996). ML reconstruction posterior probabilities were calculated using the empirical Bayesian approach described in Yang et al. (1995); the posterior probability of ancestral base b_i , given data x_i at alignment probability of ancestral base v_i , given data x_j at anguinerity
position j, is given by $P(b_i|x_j) = P(x_j|b_i)P(b_i)/\sum_{k=1}^{4} P(x_j|b_k)$ $P(b_k)$, where $P(x_j|b_i)$ is the probability of observing data x_j given base b_i in the ancestral sequence, and $P(b_i)$ is the frequency of base b_i in the data set. Positions with a ML reconstruction posterior probability < 0.9 were considered potentially unreliable and excluded from the analysis. The data for our ancestral sequence reconstruction were obtained from the MULTIZ 15 way insect alignment available for download from the UCSC genome browser (BLANCHETTE et al. 2004; HINRICHS et al. 2006).

Population genetic estimation of pooled sample reads: Although the pooling strategy provides an economical picture of sequence polymorphism, it is associated with atypical sampling properties. Here we provide results for bias-corrected estimators of heterozygosity and other canonical population genetic summary statistics.

Sequencing pooled DNA leads to an additional round of sampling with replacement, beyond the initial sampling of chromosomes from nature. Let p be the population frequency of an allele A_1 . Also consider the case where *n* chromosomes are sampled from nature and are sequenced to a depth m. We do not treat m as a random variable, although other authors have (FUTSCHIK and SCHLOTTERER 2010). The probability of sequencing $X = k$ from m reads of the A_1 allele, conditional upon the population frequency p and our pooled sample size n , is

$$
\text{Prob}\left(X = k \mid m, n, p\right) = \sum_{i=0}^{n} {m \choose k} \left(\frac{i}{n}\right)^{k} \left(1 - \frac{i}{n}\right)^{m-k} {n \choose i} p^{i} (1 - p)^{n-i}.
$$
 (1)

The expected value of the sample frequency, $E(k/m)$, should be unbiased with respect to the frequency in the population, as $E(k/m) = E(E(k/m|i/n)) = \sum_i E(k/m|i/n) \times \text{Prob}(i) = p.$ Deriving the second moment of the sample frequency is more involved and can be found in [supporting information,](http://www.genetics.org/cgi/data/genetics.110.123059/DC1/1) [File S1.](http://www.genetics.org/cgi/data/genetics.110.123059/DC1/9) The result is $E((k/m)^2) = p(1-p)(n-1+m)/nm + p^2$, which allows one to write down an unbiased estimator of heterozygosity $H = 2p(1-p)$. Under standard binomial sampling, the estimator H is biased and needs to be corrected by a factor of $n/(n-1)$ (NEI 1987). In the case of sequencing into pooled samples, the expectation of H is

$$
E(H) = E(2p(1-p)) = 2(E(p) - E(p^2))
$$

= 2p(1-p)\left(\frac{n-1}{n}\right)\left(\frac{m-1}{m}\right). (2)

The correction for the second round of sampling adds one term to the estimator of heterozygosity. The correction leads to our estimate of allele-frequency differentiation between Queensland and Tasmania, F_{ST} , which was calculated as

 $F_{\rm ST} = \frac{\Pi_{\rm total} - \Pi_{\rm within}}{\Pi}$

 $\frac{1}{\prod_{\text{total}}}$

where

$$
\Pi_{\text{total}} = H(P_{\text{total}})
$$
\n
$$
\Pi_{\text{within}} = \frac{(N_Q \times H(P_Q)) + (N_{\text{TAS}} \times H(P_{\text{TAS}}))}{N_Q + N_{\text{TAS}}}
$$
\n
$$
H(P) = 2p(1 - p)\frac{n}{n - 1m - 1}.
$$

Here N_Q and N_{TAS} are the sample sizes from Queensland and Tasmania populations, respectively, and P_{Q} and P_{TAS} are the corresponding allele frequencies. P_{total} is the allele frequency in the combined (i.e., Queensland and Tasmania) population sample. $H(P)$ is our corrected estimate of heterozygosity from Equation 2. In [File S1](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC9) we provide simulation results that demonstrate our corrected version of F_{st} is unbiased with respect to coverage.

Estimators of θ **:** As above in our treatment of heterozygosity, we need to correct estimators of the neutral mutation parameter $\theta = 4Nu$ for a pooled sampling strategy. Some recent work on this problem was done by FUTSCHIK and SCHLOTTERER (2010), who consider the case of pooled samples when the pool is large in comparison to sequence coverage. Here and in [File](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC9) [S1](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC9), we derive results for corrected estimators that are accurate in the case where coverage is of similar size to the pooled sample. Importantly, we can derive the expected site frequency spectrum of a pooled sequencing experiment.

The first result of interest is the probability of observing an allele segregating at frequency k from m in our sequenced sample, given a pooled sample size of n . This will differ from the quantity in Equation 1, because we sum over possible allele frequencies of the A_1 allele in the sample, i, in accordance with their expected probabilities under the standard neutral model. Thus the unconditional probability is

$$
\text{Prob}(k \mid m, n) = \sum_{i=1}^{n-1} \text{Prob}(k \mid m, n, i) \text{Prob}(i)
$$

$$
= \sum_{i=1}^{n-1} {m \choose k} \left(\frac{i}{n}\right)^k \left(1 - \frac{i}{n}\right)^{m-k} \left(\frac{1}{ia_n}\right), \qquad (3)
$$

where $a_n = \sum_{j=1}^{n-1} 1/j$. The last term in Equation 3 represents the probability of observing an allele segregating at frequency i from n chromosomes under the neutral model (Ewens 2004). Fu (1995) was able to derive the expected number of sites, X_i segregating at frequency *i* from *n* as $E\{X_i\} = \theta/i$. While Fu derived his result from modeling the genealogical process as a form of the Polya urn model, a simpler derivation comes by conditioning on the total number of segregating sites in a sample, S. Conditional on S, the X_i 's can be assumed to follow a multinomial distribution where the individual parameters reflect the expected frequencies of sites in the sample. Using this logic, $E\{X_i\} = E\{S\} \times \text{prob}(i) = \theta a_n \times 1/ia_n = \theta/\hat{i}$. Similarly we can write the expected counts of each frequency class in our sequenced sample Y_i ,

$$
E\{Y_k\} = E\{S\} \times \operatorname{Prob}(k \mid m, n)
$$

= $\theta a_n \sum_{i=1}^{n-1} {m \choose k} \left(\frac{i}{n}\right)^k \left(1 - \frac{i}{n}\right)^{m-k} \left(\frac{1}{ia_n}\right).$ (4)

We point the reader to [File S1](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC9) for simulation results confirming the accuracy of this expression. With the expected site frequency spectrum in hand, we can use the weighted linear combination of Achaz (2009) to write down estimators of θ given our sampling regime. In particular, given the high sequencing error rates inherent in these data, we want modified estimators of θ that exclude singletons.

Modified versions of Tajima's nucleotide diversity $\hat{\theta}_{\pi}$ and Fay and Wu's $\hat{\theta}_H$ (Tajima 1983; Fay and Wu 2000) were computed as follows. Let Y_k represent the number of sites segregating in a region at derived frequency k from m reads, given a pool of n chromosomes. One can write an unbiased estimator of θ using arbitrary weights for each frequency class ω _i, such that

$$
\hat{\theta}_{\omega} = \frac{1}{a_n \sum_k \omega_k} \sum_{k=1}^{m-1} \omega_k Y_k \frac{1}{\text{Prob}(k \mid m, n)}.
$$
(5)

This result allows for generalized weighted estimators of θ given pooled sampling. We present simulation results in [File](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC9) [S1](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC9) that demonstrate our new estimators are accurate and unbiased with respect to coverage. In the present case, we are interested in two weighting schemes, one to create a modified $\hat{\theta}_{\pi}$ and the other for a modified $\hat{\theta}_{H}$ estimator. Let the associated weights be $\omega_{\pi,k}$ and $\omega_{H,k}$, respectively. Then

$$
\omega_{\pi,k} = \left\{ \begin{array}{ll} 0 \quad & k=1 \\ m-k \quad 1 \leq k \leq m-1 \end{array} \right.
$$

and

$$
\omega_{H,k} = \begin{cases} 0 & k = 1 \\ k & 1 < k \le m - 1. \end{cases}
$$

The modified Fay and Wu's H that excludes singleton sites is the difference between our two estimators. As our estimators are unbiased with respect to coverage, $\hat{\theta}$ over a region where m (coverage) varies is simply the sum of $\hat{\theta}$ at each m.

Outlier approach: The relative merit of a model-based inference from theory or simulations *an empirical genomic*based outlier approach for detecting targets of positive selection is an ongoing discussion in the literature (BEAUMONT and Nichols 1996; Akey et al. 2002; BEAUMONT and BALDING 2004; Teshima et al. 2006; Voight et al. 2006; Pickrell et al. 2009). For the following reasons, we chose to use an empirically based outlier approach for identifying candidate targets of selection: (1) the challenges associated with generating a realistic null model for our D. melanogaster cline are substantial, (2) we have relatively few data from which to estimate model parameters, (3) there is little doubt that many of the highly differentiated genomic regions from the east Australian cline result from selection, and (4) the empirical approach represents a simple, transparent treatment of the data. The many consistent biological signals we report here support the value of this approach, although they do not speak to its optimality.

Because the true length distribution of differentiated regions is unknown, two main approaches were used to identify such regions. Mean F_{ST} values were calculated for 1-kb nonoverlapping windows across the normally recombining regions of the genome. The top 1% or top 2.5% of these windows were considered "differentiated" for most analyses. For some analyses, the 5% tail was used (see [Figure S1a](http://www.genetics.org/cgi/data/genetics.110.123059/DC1/10) and results section below). To identify differentiation on a scale >1 kb, we aggregated 1-kb windows in our top 1% tail. We considered any region of at least five consecutive windows that were not in the top 10% of mean 1-kb F_{ST} as "undifferentiated'' between Queensland and Tasmania. Any region between two undifferentiated regions that had at least one

1-kb window in the top 1% F_{ST} was considered an independent differentiated region. We additionally investigated very smallscale differentiation by considering the top 0.1% of individualposition F_{ST} values not occurring in the top 10% 1-kb windows as potential outlier variants. Unless otherwise noted, all analyses were restricted to outliers occurring in normally recombining regions.

Genome annotations were taken from FlyBase R5.24 (TWEEDIE et al. 2009). Genome positions were annotated as coding sequence (CDS) , $3'$ - and $5'$ -UTR, intron, regulatory, and ''other.'' Because regulatory regions are underrepresented in the FlyBase annotation, additional regulatory annotations were retrieved from the OregAnno database (GRIFFITH et al. 2008) and a recent genome-wide scan for transcription-factor binding sites (MACARTHUR et al. 2009). Polymorphisms within coding sequence were additionally annotated as either nonsynonymous or synonymous.

Gene Ontology (GO) annotations (ASHBURNER et al. 2000) were obtained from FlyBase R5.24 (Tweenle et al. 2009). For each GO annotation, the number of genes within all 1-kb normally recombining windows with that annotation were identified. GO-category enrichment was determined using a hypergeometric test that compared the proportion of genes with a given GO annotation to the proportion of genes in the 2.5% most-differentiated 1-kb windows with that GO annotation. All GO categories with fewer than four genes were excluded, as four genes are the minimum number for which a significant hypergeometric result is possible at $\alpha = 0.05$. After controlling the false discovery rate using the method of Storey (2002), enriched GO categories with false discovery rate (FDR)-corrected P -values < 0.05 were determined. Similar GO-category enrichment analyses were performed using individual outlier genomic positions. Of course, differentiation at specific genes could have profound phenotypic consequences without leaving a statistically significant signature of GO enrichment.

Copy-number variation was evaluated by calculating the mean coverage for nonoverlapping 1-kb windows across Queensland and Tasmania genomes. For each window, we calculated the ratio of Queensland/Tasmania coverage and normalized these ratios by the mean coverage ratio across each chromosome arm. The top 1, 2.5, and 5% most-extreme windows were considered highly differentiated in copy number (see [Figure S1](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC10)b). Gene Ontology enrichment analyses were conducted as described above.

Structure prediction: RNA secondary structures were inferred using the Vienna RNA package v1.8.2 (HOFACKER 2003) with default parameters. Protein domain architecture was inferred using a sequence search of the PFam database (COGGILL et al. 2008; FINN et al. 2010). Homology-based 3D structural modeling was performed using MODELER 9v7 (Eswar et al. 2008). Structures were inferred for predicted proteins from a consensus sequence for Queensland and Tasmania genes Irc and NtR. Searching the Protein Data Bank (Berman et al. 2000) using melanogaster protein sequences returned structures 3ERH (SHEIKH et al. 2009) and 2QC1 (DELLISANTI et al. 2007) as the best matches to the predicted proteins of Irc and NtR, respectively. Queensland and Tasmania consensus protein sequences were aligned to each structural template using MAFFT v6.611 with the E-INS-i option (Катон et al. 2002; Катон and Тон 2008). Five structural models of each sequence were constructed and evaluated using the MODELER objective function as well as DOPE and GA341 assessment scores (Eramian et al. 2008). Results are shown for the best overall models. Sequence not alignable to the structural template was excluded.

FIGURE 1.—Genome-sequence coverage is equivalent across chromosome arms in normally recombining regions and more variable in lowrecombining regions. Mean sequencing coverage is plotted for Queensland (blue) and Tasmania (red) populations. Dark colors indicate regions of normal recombination; lighter colors indicate low-recombining centromeric and telomeric regions. Bars give standard error.

RESULTS

After filtering, the average genome coverage was $11.6\times$ in Queensland and $8.2\times$ in Tasmania. Coverage varied little across chromosome arms (Figure 1). The Queensland/ Tasmania coverage ratio was highly consistent, varying from 1.20 to 1.45 across all regions examined. In addition, coverage in normally recombining regions was nearly equivalent across chromosome arms: the X chromosome had the greatest coverage (11.3 and 8.0 in Queensland and Tasmania, respectively), while chromosome 2L had the lowest (10.4 and 7.3). After filtering, the mean coverage and mean number of SNPs per 1-kb window were 604.7 bp and 9.4, respectively.

Genomic patterns: Mean F_{ST} across the entire genome was $0.112 \pm 8.23 \times 10^{-5}$. The distribution of 1-kb window F_{ST} estimates has a long right tail (see [Figure](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC10) [S1](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC10)a); the 5, 2.5, and 1% thresholds for this tail are F_{ST} = $0.23, F_{ST} = 0.27, and F_{ST} = 0.32, respectively. Among-arm$ variation in F_{ST} was significantly heterogeneous (Kruskal– Wallis rank sum test: $P \leq 2.2 \times 10^{-16}$; see also [Table S1](http://www.genetics.org/cgi/data/genetics.110.123059/DC1/2)); the rank order of mean F_{ST} across chromosome arms was $3R(0.124) > 2L(0.116) > 3L(0.111) > 2R(0.107)$ X (0.097). Previous studies demonstrated that $In(3R)P$ vs. Standard represents a nearly fixed difference between Queensland and Tasmania (corresponding to F_{ST} close to 1.0), which is considerably greater differentiation than that observed for other cosmopolitan inversions in these populations (KNIBB et al. 1981). This suggests that the $In(3R)P$ cline is a main cause of the elevated F_{ST} for 3R. Two aspects of the data support this proposition. First, the region spanned by $In(3R)P$ was significantly more differentiated than the rest of 3R (0.129 vs. 0.113, Wilcoxon's rank sum test: $P \le 2.2 \times$ 10-16; see Figure 2c and [Figure S2\)](http://www.genetics.org/cgi/data/genetics.110.123059/DC1/11). Second, the physical scale of differentiation was significantly greater on chromosome arm 3R, which exhibited slightly fewer very small differentiated regions $(< 2$ kb) and significantly more large regions of high F_{ST} ($>$ 10 kb) compared to the other arms (Fisher's exact test, $P = 0.000378$, Figure 2b). Note that F_{ST} of nucleotide variation in the region spanned by $In(3R)P$ was dramatically lower than estimates of F_{ST} of the inversion itself, based on previous studies of these populations (KNIBB et al. 1981; KNIBB 1982; UMINA et al. 2005), suggesting extensive recombination in the history of this arrangement.

 $In(2L)t$ also shows clinal variation, though not as steep as that of $In(3R)P$ (KNIBB *et al.* 1981). There was also a significant difference in F_{ST} for the region spanned by $In(2L)t$ (0.116) vs. the rest of the arm (0.109) (Wilcoxon's rank sum test: $P \le 2.2 \times 10^{-16}$); however, it appears that most of the difference is explained by the region of low differentiation in the uninverted region adjacent to the centromere (see [Figure S2\)](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC11). The other two autosomal arms similarly showed only very slightly higher F_{ST} (3L) or no difference in F_{ST} (2R) for regions spanned by cosmopolitan inversions (there is no such inversion on the X chromosome). Much of the difference between standard and inverted regions for arms other than $3R$ is explained by reduced heterozygosity and differentiation in centromere-proximal regions that are not included in the inversions (see [Figure S2\)](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC11).

Despite the filtering of regions corresponding to reduced heterozygosity as defined by DPGP, we observed that regions near centromeres (and some telomeres) showed low levels of differentiation, which corresponds to regions of reduced heterozygosity (see [Figure S2](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC11)). This suggests that some centromere- and telomere-proximal euchromatic sequence experiencing reduced crossing over may remain in our filtered data. However, the physical scale of differentiated regions was similar in normally vs. lowrecombining regions of the genome (Figure 2a).

We detected significant heterogeneity in levels of nucleotide diversity $(\hat{\theta}_{\pi})$ among chromosome arms

FIGURE 2.—Size of differentiated regions is similar in areas of normal and low recombination and larger on chromosome 3R. We calculated mean F_{ST} in nonoverlapping 1-kb windows across the *D. melanogaster* genome. Groups of windows in the top 1% tail of the F_{ST} distribution were grouped together into larger differentiated regions separated from one another by at least five consecutive windows with mean F_{ST} in the bottom 90% tail (see MATERIALS AND METHODS). (a) We plot the size distribution of these differentiated regions for normally recombining (blue) and low-recombining (gray) areas of the genome. Bars indicate standard error. (b) We plot the size distribution of differentiated regions found in normally recombining regions of chromosome 3R (blue) and the size distribution of differentiated regions in normally recombining regions of other chromosome arms (gray). (c) We plot mean F_{ST} (bottom) and mean polymorphism (π , top) across chromosome \mathcal{R} . Blue lines indicate average values over 25-kb windows slid every 10 kb; red lines show 200-kb windows slid 50 kb at a time. The gray box indicates the location of the cosmopolitan 3R-Payne inversion.

(Kruskal–Wallis rank sum test: $P \le 2.2 \times 10^{-16}$; see also [Table S1](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC2)), with the X chromosome showing the lowest diversity. We also detected systematic differences in nucleotide diversity between population samples, with the Tasmanian population showing consistently lower heterozygosity than the Queensland sample (see [Table](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC2) [S1](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC2)). Additionally, Fay and Wu's H statistic was significantly more negative for Tasmania than for Queensland both in the genome as a whole (Wilcoxon's rank sum test: $P < 2.2 \times 10^{-16}$; see [Figure S3](http://www.genetics.org/cgi/data/genetics.110.123059/DC1/12)) and in the normally recombining portion of the genome (Wilcoxon's rank sum test: $P < 2.2 \times 10^{-16}$). One explanation for the more negative Fay and Wu's H statistic in Tasmania is recent strong selection in this temperate population (Fay and Wu 2000). Consistent with this explanation, we found that the 1-kb regions that were very highly differentiated also exhibited considerably more negative values of H in Tasmania compared to Queensland, relative to the rest of the genome (Wilcoxon's rank sum tests: 5% tail, $P < 2.2 \times 10^{-16}$; 2.5% tail, $P < 2.2 \times 10^{-16}$; 1% tail, $P < 2.2 \times 10^{-16}$).

The largest differentiated euchromatic region spanned 854 kb at the tip of the X chromosome (Figure 3a), a region of low heterozygosity documented in several studies (AGUADE et al. 1989; BEGUN and AQUADRO 1995; LANGLEY et al. 2000). Interestingly, previous studies suggested that the scale of linkage disequilibrium in this region of the genome is not dramatically reduced, in spite of reduced levels of crossing over (BEGUN and AQUADRO 1995; LANGLEY et al. 2000). This suggests that differentiation at the tip of the X region corresponds to a mosaic linkage-disequilibrium structure of relatively low small-scale linkage disequilibrium interspersed with scattered large-scale linkage disequilibrium. The largest differentiated segment in the middle of a chromosome arm was a 752-kb region of chromosome 2R (Figure 3b). Interestingly, Cyp6g1, an insecticide resistance gene (DABORN et al. 2002; SCHMIDT et al. 2010) known to be under recent strong selection, is located in this region and is an excellent candidate for the observed differentiation. Other areas of extended differentiation were observed in the euchromatic portion of the X chromosome (a 245-kb region from 18,055 to 18,300 kb) and toward the proximal end of chromosome 2L (a 131-kb region from 20,172 to 20,303 kb).

The majority of differentiation between the Queensland and Tasmania populations occurs on a small physical scale (see Figure 2, a and b, and [Table S1](http://www.genetics.org/cgi/content/full/genetics.110.123059/DC2)). In fact, F_{ST} outlier regions (see materials and methods) were defined by single 1-kb windows in most cases, and most such windows localize to single genes. This small-scale differentiation facilitates effective identification of candidate genes influenced by spatially varying selection. Figure 4 shows one example in which a 1-kb windows in the top 2.5% F_{ST} tail localizes to *Sfmbt*, a chromatin-binding protein involved in gene regulation (GRIMM et al. 2009).

Figure 3.—Largest highly differentiated regions occurred at the tip of the X chromosome \overline{a} (a) and in the middle of chromosome $2R$ (b). Highly differentiated regions are indicated in gray. We plot mean F_{ST} across each chromosomal region, blue lines indicating 10-kb windows with 1-kb slides and red lines indicating 50-kb windows with 20-kb slides. Annotated genes are drawn across the top of each panel.

Differentiation in this gene is primarily attributable to two fixed substitutions in the middle of the gene. Interestingly, Sfmbt has been shown through yeast two-hybrid studies to physically interact with seven other genes (Yu et al. 2008), two of which—CG33275 and CG17018—are also highly differentiated between Queensland and Tasmania (1-kb $F_{ST} = 0.26$ and 0.45, respectively). Two additional genes predicted to interact with Sfmbt on the basis of known interactions between human homologs— Hdac3 and Stam—are also highly differentiated (1-kb) $F_{ST} = 0.28$ and 0.33, respectively).

A genome browser displaying 1-kb windows and their associated F_{ST} estimates is available at [http://](http://altair.dartmouth.edu/ucsc/index.html) [altair.dartmouth.edu/ucsc/index.html.](http://altair.dartmouth.edu/ucsc/index.html) Significantly differentiated regions showed substantial overlap with outlier regions previously identified in similar Australian samples, using comparative genomic hybridization (TURNER et al. 2008). For example, the proportions of Turner et al.'s outlier regions at $FDR = 0.001$ that overlap at least one 1-kb window in our 2.5 or 5% F_{ST} tail were 34 and 58%, respectively.

Differentiation across genome annotations: Among CDS, intron, 5'-UTR, 3'-UTR, regulatory, and unannotated parts of the genome, mean F_{ST} was highest for 3'-UTR (Fisher's exact test, $P = 0.0007346$), in spite of the lower power associated with the small size of the UTR sequence. Moreover, 3'-UTRs were consistently overrepresented in the tail of highly differentiated 1-kb windows (Figure 5). In contrast, coding sequence and introns were consistently underrepresented in the mostdifferentiated genomic regions. Regions not annotated as either genic or regulatory were also highly enriched in the most-differentiated regions, although less so than 3'-UTRs. Interestingly, regulatory regions and 5'-UTRs were moderately overrepresented in highly differentiated autosomal regions but underrepresented on the X chromosome.

To investigate general biological patterns associated with the observed 3'-UTR differentiation, F_{ST} was calculated for each 3'-UTR, which was followed by a Gene Ontology enrichment analysis for the genes associated with the top 1% most-differentiated 3'-UTRs. This analysis revealed no significant enrichments, which was not unexpected given the limited functional annotations associated with most of the genes. However, a number of highly differentiated 3'-UTRs were associated with either transcriptional regulators or genes involved in protein phosphorylation, supporting an important role for regulatory evolution in Queensland vs. Tasmania differentiation. Other genes with highly differentiated 3'-UTRs

FIGURE 4.-Regions of high population differentiation localize within the *Sfmbt* gene on chromosome 2L. We plot individual-position F_{ST} (blue) and mean F_{ST} within 1-kb windows (red) across the chromosome. The red dotted line indicates F_{ST} cutoff for the top 2.5% of 1-kb windows. Individual genes are drawn across the top (black); exons are in blue, 3'-UTRs in light gray, and 5'-UTRs in dark gray.

FIGURE 5.—3'-UTRs and unannotated regions are overrepresented in the most-differentiated genomic regions. We calculated the enrichment for each annotation type in the 1% (a), 2.5% (b), and 5% (c) tail of 1-kb F_{ST} regions, relative to each type's distribution across all 1-kb windows in the normally recombining portion of the genome. Results are shown separately for autosomes and the X chromosome. An enrichment score of 1.0 (indicated by a solid vertical line) indicates no enrichment or depletion; values >1 indicate an overabundance of that type in the F_{ST} tail, whereas values <1 indicate underabundance.

code for proteins involved in energy metabolism, development, or seminal fluid (see [Table S2\)](http://www.genetics.org/cgi/data/genetics.110.123059/DC1/3).

An example of a gene exhibiting highly localized 3'-UTR differentiation is Hex-t2, a testis-specific hexokinase (Duvernell and Eanes 2000). Figure 6 shows that there is a small region of elevated differentiation toward the $3'$ end of Hex-t2, with peak differentiation occurring in the 3'-UTR. Within this differentiated region are two polymorphic sites in the Queensland population (a U/A polymorphism at position 75 in the UTR and an A/G polymorphism at position 55) that are fixed for the minor allele in Tasmania. Computational prediction of the RNA secondary structure of this $3'$ -UTR suggests that the Tasmania fixations induce a marked change in RNA secondary structure, consistent with potential functional importance.

Protein-coding differentiation: Despite the fact that many outlier F_{ST} windows fall within exons, coding sequence was not overrepresented in the 1-kb window F_{ST} tail. However, because the windowing analysis does not account for the possibility of different physical scales of selection in DNA sequence space and protein space, alternative methods of characterizing protein differentiation were explored. First, mean F_{ST} for nonsynonymous variants in each gene in the normally recombining portion of the genome was calculated, with the top 1% of individual-gene nonsynonymous F_{ST} considered as coding for highly differentiated proteins. This analysis favors smaller genes/proteins, for which differentiation is likely to be gene/protein-wide. Alternatively, large multidomain proteins might show significant differentiation only in specific functional domains. To investigate this possibility, the PFam database (Finn et al. 2010) was used to annotate known functional domains for all D. melanogaster genes. Mean nonsynonymous F_{ST} was calculated separately for each domain in a gene, with the maximum domain F_{ST} being recorded for each gene.

[Table S3](http://www.genetics.org/cgi/data/genetics.110.123059/DC1/4) and [Table S4](http://www.genetics.org/cgi/data/genetics.110.123059/DC1/5) list the top candidate genes from these analyses, which suggest a number of interesting protein-coding genes for further study. For example, Figure 7a shows elevated differentiation around a fixed amino acid difference at position 47 in the disulfide oxidoreductase gene Txl. A threonine residue in Tasmania that is conserved throughout Drosophila has changed to alanine in Queensland, leading to elevated F_{ST} throughout the first exon. The alanine allele has also been observed in African *melanogaster* populations (DPGP.org). This may represent a more unusual case of recent selection in tropical populations (Queensland and Africa) rather than temperate adaptation.

We also observed elevated F_{ST} around a nonsynonymous fixed substitution in Irc (Figure 7b), an immunerelated catalase required to protect flies from microbial infection (Ha et al. 2005a,b). Although the observed V317I substitution in Tasmania is conservative and occurs in a disordered loop region, this position is in direct ligand contact in the protein structure, suggesting a potential functional role in modulating molecular interactions (Figure 7c). Alternatively, these changes could be affecting pre-mRNA processing. The two fixed substitutions in Tasmanian Irc are the nonsynonymous V317I change at the 5' end of exon 6 and a synonymous $G \rightarrow A$ substitution 11 bases downstream. These changes could be involved in splicing regulation, as RNA secondary structure prediction suggests that they could produce a radical reorganization of pre-mRNA structure (see [Figure](http://www.genetics.org/cgi/data/genetics.110.123059/DC1/13) [S4](http://www.genetics.org/cgi/data/genetics.110.123059/DC1/13)).

FIGURE 6.-Elevated differentiation between Queensland and Tasmania populations localizes to the 3'-UTR of the Hex-t2 gene. We plot the F_{ST} of individual genomic positions against the structure of the Hex-t2 gene. Exons are drawn in black, the $5'$ -UTR is dark gray, and the $3'$ -UTR is light gray. The bottom panel shows predicted secondary structures of Queensland and Tasmania 3'-UTR regions. Queensland positions indicated by arrows are polymorphic, with the major allele at left; corresponding positions in Tasmania are fixed for what is the minor allele in Queensland.

One of the most differentiated protein domains in the genome is the ligand-binding domain of the NtR gene, an extracellular ligand-gated ion channel. Figure 8a shows a large number of polymorphisms across NtR, along with a cluster of three amino acid variants in the ligand-binding domain. The most differentiated of these variants is an I/V polymorphism for which the major allele in Queensland (I, frequency $= 0.73$) is the minor allele in Tasmania (frequency 0.1); F_{ST} for this site is 0.51. The remaining amino acid polymorphisms in this domain are an L/F polymorphism ($F_{ST} = 0.14$) and an E/D polymorphism $(F_{ST} = 0.19)$. While L is the major allele in both populations at the first position, the E/D Queensland polymorphism is fixed for D in Tasmania. Structural homology modeling suggests that this E/D polymorphism occurs in the main immunogenic region (MIR) of the protein (Figure 8b). This region constitutes a loop sandwiched between β 2 and β 3 that binds autoimmune antibodies in myasthenia gravis patients in the homologous human muscle acetylcholine receptor (TSOULOUFIS et al. 2000; DELLISANTI et al. 2007). The fact that the I/V polymorphism is found in close proximity to

FIGURE 7.—Elevated nonsynonymous F_{ST} in two melanogaster protein-coding genes. We plot individual-position F_{ST} along the gene structure. Exons are drawn in black, the 5'-UTR is dark gray, and the 3'-UTR is light gray. Nonsynonymous polymorphisms are shown in red; synonymous and noncoding polymorphisms are shown in blue. (a) A nonsynonymous fixed difference between Queensland and Tasmania is associated with elevated F_{ST} at the txl gene. (b) Elevated F_{ST} at a fixed protein-coding change in Irc. (c) Structural homology models of Queensland (orange) and Tasmania (turquoise) Irc ; the V317I substitution is potentially involved in direct ligand interaction.

this region suggests the possibility that differentiation at NtR could affect interactions with other molecules, possibly those relating to the immune system.

Biological patterns underlying genic differentiation: The extensive genetic interactions and pleiotropic effects of laboratory mutations in Drosophila genes make it challenging to reliably infer from differentiated genes the phenotypes that may be targets of selection. Nevertheless, the small physical scale of differentiation makes it worthwhile to explore general patterns in the data as a means of generating hypotheses regarding pathways and phenotypes that might experience spatially varying selection in Australian melanogaster populations. Our approach was to test for enrichment of GO terms among the genes that overlapped a 1-kb window in the upper 2.5% tail of the distribution, which

Figure 8.—Elevated nonsynonymous differentiation in NtR localizes to the major immunogenic region (MIR) of the ligandbinding domain (LBD). (a) We plot positional F_{ST} across gene structure, with exons drawn in black, 5'-UTR in dark gray, and 3'-UTR in light gray; methyltransferase and ligand-binding domains are indicated by green and red, respectively. Nonsynony-

mous polymorphisms are shown by red circles. (b) We plot highly differentiated E/D and I/V polymorphisms on the predicted 3D structure of the NtR LBD. In both cases, the major allele in Queensland (E, I) is shown in orange, and the major allele in Tasmania (D, V) is shown in turquoise.

corresponds to F_{ST} > 0.27. These analyses were supplemented by inspection of genetic interactions annotated in FlyBase. We also point to plausible candidates in the 5% tail where appropriate.

Several high- F_{ST} windows overlapped genes functioning in central Drosophila signaling pathways, including the JAK-STAT pathway, the torso pathway, the EGFR pathway, and the TGF- β pathway. In the JAK-STAT pathway the ligand μ *pd2* (1-kb $F_{ST} = 0.70$) and STAT (Stat92E, 1-kb $F_{ST} = 0.32$) both showed elevated F_{ST} , as did CycE (1-kb $F_{ST} = 0.25$) and Ptp61F (1-kb $F_{ST} = 0.28$), which regulate that pathway. Other modifiers of *JAK*- $STAT$ signaling that overlapped high- F_{ST} windows included crb (1-kb $F_{ST} = 0.35$), tkv (1-kb $F_{ST} = 0.39$), Mad (1-kb $F_{ST} = 0.35$), and *Stam* (1-kb $F_{ST} = 0.33$). Highly differentiated genes in the torso signaling pathway (which regulates several processes, including metamorphosis and body size) included tup (1-kb $F_{ST} = 0.41$), Gap1 (1-kb $F_{ST} = 0.26$), pnt (1-kb $F_{ST} = 0.60$), tld (1-kb $F_{ST} = 0.25$), and csw (1-kb $F_{ST} = 0.26$). Differentiated genes in the $EGFR$ signaling pathway included vn (1-kb) $F_{ST} = 0.27$, argos (1-kb $F_{ST} = 0.23$), sprouty (1-kb $F_{ST} =$ 0.29), Star (1-kb $F_{ST} = 0.29$), and ed (1-kb $F_{ST} = 0.30$). Genes in the $TGF- β pathway were also overrepresented$ among high- F_{ST} windows and included *dally* (1-kb F_{ST} = 0.39), Mad, and tkv (1-kb $F_{ST} = 0.39$). The gene dpp, which is centrally located in this pathway, also contained a region of high differentiation (1-kb $F_{ST} = 0.24$). Finally, the hypothesis that ecdysone signaling experiences spatially varying selection is supported by highly differentiated windows overlapping the ecdysone receptor, EcR (1-kb $F_{ST} = 0.25$); the eclosion hormone gene *Eh* (1-kb $F_{ST} = 0.33$); *Moses* (1-kb $F_{ST} = 0.41$); *taiman* (1-kb $F_{ST} = 0.37$); and the ecdysone-induced protein-coding genes $Eip63E$ (1-kb $F_{ST} = 0.33$), $Eip74EF$ (1-kb $F_{ST} = 0.31$), $Eip75B$ (1-kb $F_{ST} = 0.30$), and $Eip93F$ (1-kb $F_{ST} = 0.44$). It is worth noting that substantial crosstalk exists between some of these pathways and that other genes associated with key pathways such as Notch show evidence of differentiation in our data.

These results support the existence of pervasive spatially varying selection acting at key genes throughout multiple Drosophila signaling pathways. It is highly plausible that several candidates influence clinal variation in body size, metabolism, and additional important life history traits (see [Table S5](http://www.genetics.org/cgi/data/genetics.110.123059/DC1/6) for a complete list of enriched GO terms). Many genes implicated in bodysize variation were highly differentiated, including InR [1-kb $F_{ST} = 0.26$ (PAABY *et al.* 2010)], *dally* (1-kb $F_{ST} =$ 0.39), Orct2, and Pi3K21B at the tip of 2L, which contains a highly differentiated 1-kb window ($F_{ST} = 0.28$) but was not included in most of our analyses because of its location at the distal end of the chromosome arm. Interestingly, many body-size candidate genes revealed by our analysis are located on chromosome arm 3R, which is consistent with previous genetic analyses showing that most of the body-size variation associated with the Australian cline is inseparable from $In(3R)P$ in mapping crosses (RAKO et al. 2006, 2007). Our dataincluding evidence of extensive recombination between standard and $In(3R)P$ arrangements—suggest that the differentiated genes that are located on 3R are particularly promising targets for investigating the genetic basis of body-size variation in D. melanogaster.

A large number of GO terms related to developmental processes are enriched for F_{ST} outliers. The associated genes contribute to many phenotypes, including external morphology $(e.g.,$ wing and eye), nervous system development, ovarian follicle development, larval development, and embryonic development. The Toll signaling pathway, which contains a number of immune system genes, is enriched. The immunity gene sick is also in the 5% tail of F_{ST} windows. Olfactory behavior and olfactory learning are enriched in 1-kb outlier tails. In addition, a number of F_{ST} -outlier nonsynonymous SNPs not located in outlier windows are found in olfactory or gustatory receptors or odorant-binding proteins. Several ionotropic receptors, a new class of odorant receptors, appear in the 5% F_{ST} tail of 1-kb windows. It is interesting to note the evidence that thermal stress disrupts odor learning in flies (Wang et al. 2007) via developmental effects on the mushroom body, in light of the observation that ''mushroom body development'' is among the enriched GO terms in our analysis. A number of ion channel-related genes appear among the outlier 1-kb windows, leading to enrichment of GO categories:

FIGURE 9.-Coordinated differentiation in *norpA* (a) and the 3'-UTR of per (b) , a known target of norpA splicing regulation. We plot individual-position F_{ST} along the gene structure. Exons are drawn in black, the $5'$ -UTR is dark gray, and the 3'-UTR is light gray.

calcium-, potassium-, and sodium-ion transport. ''Calcium ion binding'' is the second most significantly enriched molecular function and includes several Cadherins as well as Calmodulin. Selection associated with variation in the visual environment between Queensland and Tasmania is suggested by the enrichment of GO terms such as ''phototransduction.''

Although circadian rhythm genes are not overrepresented among the F_{ST} outliers, several genes relating to circadian biology are found among the most differentiated 1-kb windows. The cryptochrome gene, which regulates circadian rhythm, is highly differentiated (F_{ST} = 0.30), as are *couch potato* (F_{ST} = 0.23) and *timeless* (F_{ST} = 0.20), which have already been implicated in spatially varying selection in D . *melanogaster* (SANDRELLI et al. 2007; TAUBER et al. 2007; SCHMIDT et al. 2008). Another interesting candidate is norpA, a phospholipase C gene required for thermal synchronization of the circadian clock (Glaser and Stanewsky 2005). This gene is in the 2.5% F_{ST} tail and highly differentiated across its entire length (see Figure 9a). Four of its seven interacting partners annotated in FlyBase are also in the 2.5% tail (see [Table S7\)](http://www.genetics.org/cgi/data/genetics.110.123059/DC1/8). Additionally, norpA is known to regulate splicing in the 3'-UTR of per, a central circadianclock gene in Drosophila (COLLINS et al. 2004; МАЈЕRСАК et al. 2004) that shows a highly localzed 3'-UTR elevation in F_{ST} in our data (Figure 9b). Together, these results strongly suggest a cluster of correlated differentiation occurring across several genes at the interface between thermal and light entrainment of the circadian clock.

Finally, transcription and chromatin regulation appear to be under widespread selection, as seven related biological process GO terms are enriched among the F_{ST} outlier windows. Additionally, "transcription factor" is

the second most significantly enriched GO molecular function term. Particularly interesting differentiated genes include Trl, HDAC4, additional sex combs, Enhancer of polycomb, histoneacetlytransferase Tip60, Ino80, JIL-1, 14-3-3e, and Sfmbt.

Copy-number variation: Differences in copy number between Queensland and Tasmania were investigated using an outlier approach analogous to that used for F_{ST} . The normalized ratio of Queensland/Tasmania coverage for 1-kb nonoverlapping windows was calculated across the genome (see materials and methods), with the top 1% most-extreme estimates considered highly differentiated regions. Note that frequency variation and ploidy-level variation are confounded in this analysis. Relative to the genome-wide average of copynumber differentiation, slightly more than half (55%) of the 1-kb windows had more coverage in the Queensland population. However, significantly more (62.5%) of the highly differentiated windows showed increased copy number in the Tasmania population ($P = 2.2 \times$ 10-16), suggesting that duplication events could be important for local adaptation in Tasmania.

The largest region exhibiting significant copy-number variation (CNV) is a 107-kb region of chromosome 3R (Figure 10), which spans a small number of proteincoding genes including the last few exons of timeout and the entire Ace gene. Ace codes for an acetylcholinesterase associated with pesticide resistance (Menozzi et al. 2004), which was previously identified as a differentiated CNV between these populations (TURNER et al. 2008). Interestingly, Ace expression has been shown to vary over the circadian cycle (Hooven et al. 2009), and acetylcholinesterase levels are highly correlated with pesticide resistance (CHARPENTIER and FOURNIER 2001).

Gene Ontology enrichment analysis of genes found in highly differentiated CNV regions revealed categories similar to those observed for our F_{ST} enrichment analysis (see [Table S6](http://www.genetics.org/cgi/data/genetics.110.123059/DC1/7)), including transcription factors and ion-channel genes. Across both GO-enrichment analyses, 185 unique GO terms were enriched, 66 of which (36%) were found in both analyses. Interestingly, despite the large degree of overlap between GO enrichment terms in the F_{ST} and CNV analyses, the specific genes associated with each enriched GO category did not overlap to a large degree. Of the 719 genes in the copynumber 1% outlier set and the 551 genes in the corresponding F_{ST} outlier set, only 72 (6%) were found in both (as expected given the upper bound of coverage included in the F_{ST} analysis). This suggests the possibility that selection may often result in recruitment of alleles resulting from both nucleotide and copy-number differences. Several terms enriched in the CNV GO analysis did not appear in the F_{ST} GO enrichment, including "circadian rhythm," "sex determination," "courtship and mating behavior," "female meiosis chromosome segregation,'' and ''chorion-containing eggshell formation'' (which was also detected by TURNER et al. 2008).

FIGURE 10.—A large region of increased copy number in Queensland occurs on chromosome 3R. We plot the average number of sequence reads for each 1-kb window across this region, both for the Queensland (blue) and for the Tasmania (red) populations. Genes in this region are drawn across the top. The gray box indicates the inferred region of increased copy number in Queensland.

DISCUSSION

A large body of evidence supports the idea that much of the phenotypic and genetic differentiation along the Australian *D. melanogaster* latitudinal cline is driven by spatially varying selection (OAKESHOTT et al. 1981, 1983; Singh and Rhomberg 1987; Singh 1989; Singh and LONG 1992; GOCKEL et al. 2001; KENNINGTON et al. 2003; Hoffmann and Weeks 2007). Here we have presented the first genome-sequence-based analysis of population differentiation associated with this cline. Although our analysis included only populations from each end of the cline, it is likely that the set of highly differentiated genomic regions between these cline endpoints is considerably enriched for targets of spatially varying selection. Indeed, the fact that the most highly differentiated genomic regions show much more negative Fay and Wu's H estimates in Tasmania is consistent with the hypothesis that the observed differentiation is associated with recent strong selection in temperate populations (SEZGIN et al. 2004). The dramatic enrichment of several GO terms among the genes overlapping differentiated regions also supports the notion that selection plays a major role, because it is difficult to envision a neutral demographic process that could result in such enrichment patterns.

Two main lines of evidence support the proposition that gene regulation is an important target of spatially varying selection in these populations. First, 3'-UTRs and unannotated sequence are the most overrepresented sequence classes among the outlier 1-kb F_{ST} windows. 3'-UTRs, which exhibit the strongest enrichment in our analysis, play an important role in gene regulation (LAI 2002; KUERSTEN and GOODWIN 2003; DE MOOR et al. 2005; STARK et al. 2005; CHATTERJEE and PAL 2009; MANGONE et al. 2010). Recent studies have found substantial *cis*-acting effects on regulatory variation in Drosophila (HUGHES et al. 2006; LAWNICZAK et al. 2008; Lemos et al. 2008; Graze et al. 2009; McManus et al. 2010); our results raise the intriguing possibility that variation in $3'$ -UTRs may make a significant contribution to adaptive cis-acting regulatory variation. The overrepresentation of noncoding DNA among F_{ST} outlier windows is consistent with previous population genetic results supporting the importance of noncoding sequence for adaptive divergence over longer timescales in *D. melanogaster* (ANDOLFATTO 2005). It will be interesting to investigate these currently unannotated regions in the context of ongoing efforts to improve the annotation of the *D. melanogaster* genome (CELNIKER et al. 2009). The second line of evidence supporting the importance of selection on gene regulation along the cline is the finding that transcription- and chromatinrelated genes are among the most differentiated in the genome, which is consistent with previous analyses of these populations (Levine and Begun 2008; Turner et al. 2008) and with genomic inferences on the importance of recurrent directional selection on proteins regulating chromatin and transcription in D. simulans (Begun et al. 2007).

Although the protein-coding sequence was underrepresented among the most extremely differentiated 1-kb windows, one should not conclude that amino acid variants are unimportant for selection along the cline, as a large number of outlier windows overlap coding sequence. It is interesting to consider possible populationgenetic explanations for why CDS is underrepresented. The timescale of differentiation between Queensland and Tasmanian populations is very small, perhaps on the order of 1000 generations (HOFFMANN and WEEKS 2007). Because the mutation rate per base pair is small, much of the selective response during the initial colonization of Australia was likely the result of frequency changes of alleles already segregating in ancestral populations rather than from invasion into the populations of new mutations that occurred subsequent to colonization. Whole-genome surveys of polymorphism in Drosophila suggest that nonsynonymous sites are severalfold less polymorphic than synonymous or noncoding sites (e.g., BEGUN et al. 2007; SACKTON et al. 2009). Thus, on a per-site basis compared to noncoding variants, amino acid variants are considerably less available to selection on standing variation following a radical change of the environment. The physical scale

of differentiation predicted under the selection-onstanding-variation model depends on the amount of linkage disequilibrium associated with the site destined to experience selection after the environment changes. Surveys of linkage disequilibrium in normally recombining regions from large samples of cosmopolitan D. melanogaster consistently find that sites in strong linkage disequilibrium tend to be within 2 kb of each other (MIYASHITA and LANGLEY 1988; PALSSON et al. 2004; MACDONALD et al. 2005). This is consistent with the scale of geographic differentiation observed in our data and with the hypothesis that much of the observed differentiation between temperate and tropical populations is the result of recent strong selection on standing variants. Genomic data on the frequency distribution of variation and the scale of linkage disequilbrium from populations along the Australian cline and from African and European populations should provide the resources necessary for addressing issues relating to the geographic origins, frequencies, and fitnesses of variants experiencing selection in Australia.

One of the general findings from our analysis is that many genes and pathways centrally important to Drosophila biology appear to experience spatially varying selection. The fact that laboratory mutations in these genes and pathways tend to be highly pleiotropic is, in the conventional thinking, associated with reduced mutation rate to beneficial alleles. It is important to realize, however, that it is the individual mutation— rather than the gene—that is more or less pleiotropic. The distribution of pleiotropic effects of natural variants is likely to be quite different and dramatically smaller than those of laboratory mutations. Moreover, the large population sizes of Drosophila suggest that drift may be relatively unimportant and that variants that reach appreciable frequencies may have special genetic and population-genetic properties. Thus, the candidate variants identified here may have very small pleiotropic effects, in spite of the fundamental biological roles of the corresponding genes. Alternatively, natural alleles that were pleiotropic along the axes favored by correlated natural selection would be strongly favored, and these too could constitute a considerable fraction of the variants in fundamental signaling pathways that show differentiation between these populations.

The genomic results regarding the dramatic biological differences between these fly populations raise the obvious question—unanswerable with these data—as to the phenotypic and fitness effects of the selected mutations and how the distribution of such effects may vary across biological functions and positions in genetic pathways. For example, one class of selected mutations may contribute to phenotypic differences between temperate and tropical flies, while a second—potentially larger—class exhibiting genotype \times environment interactions may exhibit latitudinal clines, because different genotypes are required to produce a single optimal

phenotype in different environments (e.g., LEVINE et al. 2011). Larger genomic data sets and functional analyses should produce much sharper inferences regarding the specific polymorphisms, pathways, and biological functions that have diverged under selection between temperate and tropical populations and further reveal the genetic and population-genetic principles of adaptation in this model species.

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GENETICS

Supporting Information

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Genomic Differentiation Between Temperate and Tropical Australian Populations of Drosophila melanogaster

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FIGURE S1: Upper-tail F_{ST} and copy-number ratio cutoffs used in this study. We bin honoverlapping the genome windows of F_{ST} (a) and copy-number ratio (b) and plot the number of windows in each bin. Tail cutoffs of 1, non-lapping 1kb genomic windows of FST (a) and plot the FST (a) and plot the FST (b) and plot the plot th FIGURE S1.—Upper-tail *FST* and copy-number ratio cutoffs used in this study. We bin nonoverlapping 1kb genomic windows each panel.

FIGURE S2.—We plot *F_{ST}* for standard and inverted regions of each chromosome arm. Inverted regions are indicated by gray norizontal lines. Blue series indicate average FST values over 25Kb willdows shu every TOKD, fed lines show 200Kb willdows shu
50kb at a time. Overall *F_{ST}* across each region (standardvs. inverted) is also indicated in inversion on the X chromosome. horizontal lines. Blue series indicate average *FST* values over 25kb windows slid every 10kb; red lines show 200kb windows slid

FIGURE S3.—A comparison of the distributions of H statistics computed in 1kb windows in both the Queensland and the Tasmanian samples. This is a modified version of Fay and Wu's H which exludes singleton variants. See main text for details. The medians of these distributions are significantly different from one another in a Wilcoxon rank sum test $(p< 2.2 \times 10^{-16})$.

Computationally-inferred secondary structure of *Irc* pre-mRNA is shown for Queensland and Tasmania alleles. FIGURE S4.—Fixed differences between Queensland and Tasmania at the *Irc* gene radically alter pre-mRNA structure.

We report average polymorphism per 1kb (π) and Fay and Wu's *H* for each

population, as well as mean *FST* **and size of highly-differentiated genomic regions for the normally-**

recombining portion of each chromosome arm.

Genes in the top 2.5% of 3'UTR differentiation.

We calculated the mean F_{ST} of each gene's 3'UTR region and list the top 2.5%.

Genes in the top 2.5% of whole-gene nonsynonymous F_{ST} differentiation.

We calculated the mean nonsynonymous F_{ST} of each gene and list the top 2.5%

Genes in the top 2.5% of individual-domain nonsynonymous *FST* **differentiation.**

We calculated the mean nonsynonymous F_{ST} of each PFam domain in each gene We calculated the mean nonsymonymous FST of each PFam domain in each gene and took the most-differentiated domain as that gene's representative domain. We list list the top 2.5% of individual-domain differentiated genes.

Significantly-enriched Gene Ontology categories in top 2.5% 1kb F_{ST} regions.

Reported P-values are corrected for a false-discovery rate of 0.05.

Signficantly-enriched Gene Ontology categories in top 1% 1kb copy-number

variable (CNV) regions.

Biological Process

Molecular Function
GO accession P-value Description

i.

Reported P-values are corrected for a false-discovery rate of 0.05.

The highly-differentiated circadian-regulation gene *norpA* **and its known**

genetic-interaction partners.

Asterisks (*) indicate that the gene is in the top 2.5% of 1kb F_{ST} windows.

FILE S1

Corrections for pooled sampling

The nature of our experimental design creates additional noise that we must correct for in our population genetic estimates. In particular, the pooled DNA sequencing design of this manuscript creates a second level of binomial sampling, beyond what is associated with the "normal" population genetic survey. Throughout we assume that a sample of size n chromosomes is taken from nature and pooled for sequencing. This sequencing is performed to depth m which may be variable among loci/sites. Conditioning on a population frequency of the A_1 allele p, the probability of sampling i out of n A_1 alleles in our initial sample is simply binomial with parameters n and p . Thus the expected value of the sample frequency $E(i/n) = p$ and the second moment is $E((i/n)^2) = \frac{p(1-p)}{n} + p^2$.

We will first derive similar results for the pooled sampling design, and then move on to estimation of population genetic statistics. The probability of sampling $k A_1$ alleles out of m in our pooled sequences conditional upon having sampled i out of n in our initial sampling is again binomial, this time with parameters m and i/n . Thus the probability of sequencing k out of m reads of the A_1 allele conditional upon the population allele frequency is

$$
Prob(X = k|m, n, p) = \sum_{i=0}^{n} {m \choose k} (i/n)^{k} (1 - i/n)^{m-k} {n \choose i} p^{i} (1-p)^{n-i}.
$$
 (1)

The expected value of the frequency of the allele in our sequenced sample, k/m , can then

be easily found through the use of conditional expectations

$$
E{k/m} = E{E{k/m|i/n}}
$$

=
$$
\sum_{i=0}^{n} E{k/m|i/n} \times Prob(i)
$$

=
$$
\sum_{i=0}^{n} \frac{m(i/n)}{m} {n \choose i} p^{i} (1-p)^{n-i} = p
$$
 (2)

We can find the second moment through similar means

$$
E\{(k/m)^2\} = E\{E\{(k/m)^2|i/n\}\}\
$$

=
$$
\sum_{i=0}^{n} E\{(k/m)^2|i/n\} \times Prob(i)
$$

=
$$
\sum_{i=0}^{n} \left\{\frac{(i/n)(1-i/n)}{m} + (i/n)^2\right\} \times Prob(i)
$$

=
$$
\sum_{i=0}^{n} \frac{(i/n)(1-i/n)}{m} \times Prob(i) + \sum_{i=0}^{n} (i/n)^2 \times Prob(i)
$$
 (3)

There are two terms in equation 3. This second term is immediately recognizable as the second moment that we examined above (i.e. $\frac{p(1-p)}{n} + p^2$). The first term after a bit of algebra turns into

$$
\frac{1}{m}\{p(1-p)-\frac{p(1-p)}{n})\}
$$

putting it all together, the expectation of the second moment, conditional upon the population allele frequency is

$$
E\{(k/m)^2\} = p(1-p)/m - p(1-p)/mn + p(1-p)/n
$$

With that result in hand we are now ready to write down the expectation of heterozygosity $(H = 2p(1-p))$ given our population allele frequency

$$
E\{H\} = E\{2p(1-p)\} = 2(E\{p\} - E\{p^2\})
$$

= 2(p - p(1 - p)/m + p(1 - p)/mn - p(1 - p)/n)
= 2p(1 - p)((n - 1)/n)((m - 1)/m) (4)

This leads to a simple bias correction on our estimates of heterozygosity which is $n/(n 1 \times m/(m-1)$. Figure S7 shows coalescent simulation results, where we generated samples from the standard coalescent model, and then resampled chromosomes with replacement to a coverage depth m . We then applied both the "double" correction derived here and the standard single correction. As can be seen in that figure, we do indeed have an unbiased estimator of heterozygosity if we correct for both the original size of our pooled sample and the coverage.

FIGURE S5.—Simulation results showing the corrected heterozygosity (eqn 4) is effective across a range of coverages used in this manuscript

Estimating θ

Of interest to us is coming up with an unbiased estimator of $\theta = 4Nu$ in the face of our pooled sampling strategy. Recently (Futschik and Schlotterer 2010) have done quite a bit of work on this problem, and they were able to come up with corrected estimators for $\theta_p i$ and θ_w . Here we derive ostensibly similar results through different means, and arrive at a generalized correction for pooled sampling which allows for construction of arbitrary estimators of θ as linear combinations of the site frequency spectrum using the system of (Achaz 2008).

We start by generalizing equation 1 of the supplement across the sample site frequency spectrum (SFS) expected under the standard neutral model. The probability of observing an allele segregating at frequency i out of n in a standard sample is $Prob(i|n) = 1/ia_n$, where $a_n = \sum_{i=1}^{n-1} 1/i$ (Ewens 2004). Thus the probability of observing an allele at frequency k out of m reads in our pooled sequence sample unconditional on the population

frequency is

$$
Prob(k|m, n) = \sum_{i=1}^{n-1} Prob(K|m, n, i) Prob(i)
$$

=
$$
\sum_{i=1}^{n-1} {m \choose k} (i/n)^{k} (1 - i/n)^{m-k} (1/ia_n)
$$
 (5)

This expression allows us to write down the expected number of sites segregating at frequency k out of m, call it Y_k as a function of the mutation rate θ . Conditioning on the expected number of segregating sites S in our initial sample of size n allows us to write down the expected values of the Y_k s as

$$
E\{Y_k\} = E\{S\} \times Prob(k|m, n)
$$

= $\theta a_n \sum_{i=1}^{n-1} {m \choose k} (i/n)^k (1 - i/n)^{m-k} (1/ia_n)$ (6)

To check the accuracy of this expression we performed coalescent simulations with a specified sample size n and mutation rate θ . The initial site frequency spectrum was recorded and then transformed to mimic our pooled sequencing by sampling alleles at each segregating site with replacement. This yields a transformed SFS Y – see figure S6.

Given the accuracy of our correction for the SFS we move on to derive a bias corrected estimation scheme for θ . In particular we note that rearrangement of equation 6 suggests a moment estimator of the type derived in Fu (1995),

$$
\hat{\theta} = \frac{Y_i}{a_n} \frac{1}{Prob(k|m, n)}
$$

Achaz (2009) noted that linear combinations of the SFS can be used to derive new estimators of θ given some arbitrary weighting scheme. In this context we can write down the bias corrected version of Achaz's generic estimator as

$$
\hat{\theta}_{\omega} = \frac{1}{a_n \sum_k \omega_k} \sum_{k=1}^{m-1} \omega_k Y_k \frac{1}{Prob(k|m, n)}.
$$
\n⁽⁷⁾

In this manuscript we focus attention on Tajima's nucleotide diversity $(\hat{\theta}_{\pi})$ and Fay and Wu's (θ_H) (Tajima 1983; Fay and Wu 2000). To show the potential generality of our correction scheme we present coalescent simulation results as before where we have estimated θ using six different weighting schemes: $\omega_{\pi,i}$, $\omega_{H,i}$, and $\omega_{W,i}$, each with and without use of singletons

In the case where singletons are ignored each of the
$$
\omega_1 = 0
$$
. As can be seen in Figure S7 our bias corrected estimates are quite accurate, thus the framework we have introduced here should be general.

FIGURE S6.—Simulation results showing the correspondence between the observed and expected site frequency spectrum as *m* the sequencing depth changes. 1000 coalescent simulations were run with $n=10$ and $\theta=10$. The expected values in red are derived from equation 6. Shown for comparison in blue are the expectations under the standard neutral model.

Corrected Estimators

FIGURE S7.—Simulation results showing the performance of our bias corrected estimators of θ . 1000 coalescent simulations were run with $n = 40$ and $\theta = 10$. Uncorrected estimates are shown in black.

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