Cold adaptation drives population genomic divergence in the ecological specialist, *Drosophila montana*

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ABSTRACT

Detecting signatures of ecological adaptation in comparative genomics is challenging, but analysing population samples with characterised geographic distributions, such as clinal variation, can help identify genes showing covariation with important ecological variation. Here we analysed patterns of geographic variation in the cold-adapted species *Drosophila montana* across phenotypes, genotypes and environmental conditions and tested for signatures of cold adaptation in population genomic divergence. We first derived the climatic variables associated with the geographic distribution of 24 populations across two continents to trace the scale of environmental variation experienced by the species, and measured variation in the cold tolerance of the flies of six populations from different geographic contexts. We then performed pooled whole genome sequencing of these six populations, and used Bayesian methods to identify SNPs where genetic differentiation is associated with both climatic variables and the population phenotypic measurements, while controlling for effects of demography and population structure. The top candidate SNPs were enriched on the X and 4th chromosomes, and they also lay near genes implicated in other studies of cold tolerance and population divergence in this species and its close relatives. We conclude that ecological adaptation has contributed to the divergence of *D. montana* populations throughout the genome and in particular on the X and 4th chromosomes, which also showed highest interpopulation F_{ST}. This study demonstrates that ecological selection can drive genomic divergence at different scales, from candidate genes to chromosome-wide effects.

INTRODUCTION

The geographic structure of a species is a result of its phylogeographic history, influenced by past and present dispersal, population demography and selection. Obtaining genome-wide data on genetic polymorphisms across multiple populations of a species is becoming relatively easy, but interpreting the patterns of geographic variation in such data and identifying genes which vary primarily due to selection remains challenging. Often simple 'outlier' approaches using genome scans which measure genetic differentiation such as F_{ST} or Dxy are adopted, but results are difficult to interpret due to confounding between selection, drift and population structure, or genomic features such as inversions and other causes of variation in recombination rate (Noor & Bennet, 2009; Cruickshank & Hahn, 2014; Wolf & Ellegren, 2016; Ravinet et al., 2017). If environmental data is available, we can use associations with such factors to help identify loci where genetic differentiation covaries with this environmental variation. Some genome scan methods can incorporate environmental variation and simultaneously fit effects for covariance with environmental factors, while controlling for effects of population demography (Foll & Gaggiotti

2008; de Villemereuil & Gaggiotti 2015). This approach has successfully identified genetic variation associated with altitude in humans, among other examples (Foll, Gaggiotti, Daub, Vatsiou, & Excoffier, 2014; de Villemereuil & Gaggiotti, 2015; Gautier, 2015) and has become a useful approach to investigate the ecological adaptations underlying population divergence.

Clinal patterns of variation in phenotypes or gene frequencies have a long history of being used to infer selection along ecotones, and analyses of cline shape can sometimes identify loci under direct selection from others showing clinal variation for other reasons such as phylogeographic history (Barton & Gale, 1993). Such studies can be very powerful, especially when independent parallel clines are available. For example, Kolaczkowski, Kern, Holloway & Begun (2011) sampled isofemale lines from extremes of a cline in Australian populations of *D. melanogaster*, and found many genes implicated in clinaly varying phenotypes to show highest differentiation. Also, Bergland, Behrman, O'Brien, Schmidt & Petrov (2014), and Kapun, Fabian, Goudet & Flatt (2016) sampled North American clines in *D. melanogaster* and *D. simulans* over several years and seasons to uncover clinal and seasonal variation at a genome scale. They found that many SNPs showed consistent seasonal fluctuations in allele frequencies throughout the clines, which indicates a regular response to seasonally varying selection pressures (Bergland et al., 2014). On the other hand, Machado et al. (2015) concluded that migration and gene flow play a greater role than adaptation in the overall clinality of genomic variants in *D. simulans* than *D. melanogaster*. While the two species share a significant proportion of the genes showing clinal variation, their differences in overwintering ability, migration and population bottlenecks probably act as additional drivers of differences in patterns of variation between them (Machado et al., 2015). Similar studies of clinal variation in phenotypes and allele frequencies have also been carried out in other insects (e.g. Paolucci, Salis, Vermeulen, Beukeboom, & van de Zande, 2016), plants (e.g. Chen et al., 2012; Bradbury, Smithson, & Krauss, 2013), mammals (e.g. Hoekstra, Drumm, & Nachman, 2004; Carneiro et al., 2013), fish (e.g. Vines et al., 2016), and other organisms (Endler, 1973; Endler, 1977; Takahashi, 2015). However, more studies are needed that simultaneously compare patterns of variation in allele frequencies and potentially causal environmental variation or ecologically important traits while controlling for population structure, as such studies are necessary to determine if adaptation to climate is directly driving patterns of genetic differentiation.

Here we investigated geographic variation at both the phenotypic and genetic levels in *Drosophila montana* samples from two continents. This species has spread around the northern hemisphere (Throckmorton, 1969) and both mtDNA and microsatellite data revealed genetically distinct Finnish and North American populations (Mirol et al., 2007). Moreover, more recent modelling of genome-wide SNP frequencies suggest that the Finnish-North American split happened around 1.75MYA and that of the North American populations shortly after that

90 (Garlovsky et al., 2020). It is one of the most cold-tolerant *Drosophila* species (Kellerman et al., 2012;) and the basic cold tolerance of *D. montana* flies can increase towards the cold seasons through two mechanisms, photoperiodic reproductive diapause (Vesala & Hoikkala, 2011) and cold-
93 acclimation induced by a decrease in day length and/or temperature (Vesala, Salminen, Laiho, Hoikkala, & Kankare, 2012; Kauranen et al., 2019). *D. montana* populations have been found to show clinal variation in the critical day length required for diapause induction (CDL; Tyukmaeva,
96 Salminen, Kankare, Knott, & Hoikkala 2011; Lankinen, Tyukmaeva, & Hoikkala 2013). There is also a correlation between CDL and latitudinally co-varying climatic factors such as the mean temperature of the coldest month (Tyukmaeva, Lankinen, Kinnunen, Kauranen, & Hoikkala, 2020).
99 In addition, *D. montana* populations from different geographic regions show variation in their courtship cues and mate choice (Routtu et al., 2007; Klappert, Mazzi, Hoikkala, & Ritchie, 2007), which has led to partial reproductive isolation between some distant populations (Jennings, Mazzi,
102 Ritchie, & Hoikkala, 2011; Jennings, Snook, & Hoikkala, 2014). At the genetic level, differential gene expression studies have identified candidate genes underlying diapause (Kankare, Salminen, Laiho, Vesala, & Hoikkala, 2010; Kankare, Parker, Merisalo, Salminen, & Hoikkala, 2016),
105 perception of day length (Parker, Ritchie, & Kankare, 2016), and cold acclimation (Parker et al., 2015). Furthermore, a quasi-natural selection experiment for shorter CDL, accompanied by a decrease in cold-tolerance, induced widespread changes in loci with potential roles with these traits
108 (Kauranen et al., 2019). Finally, population genomic analyses have identified several outlier loci when examining differentiation between North American and European populations (Parker et al., 2018). All this makes *D. montana* an interesting example of nascent speciation, potentially
111 influenced by ecological adaptation.

Here we sought to ask to what extent patterns in the genomic divergence of *D. montana* populations across two continents are correlated with climatic variation and phenotypic responses to
114 cold adaptation. We performed pooled whole-genome sequencing (pool-seq) on six different populations and used Bayesian methods to examine the association between genomic differentiation between populations and environmental variables across both continents. We also phenotyped
117 populations for two different cold tolerance measures; critical thermal minimum (CTmin), and chill coma recovery time (CCRT), and investigated the associations between them and the genetic and climatic data. Ultimately, we asked if the genomic loci showing an association between genetic and
120 environmental differentiation also showed association with population differentiation in cold tolerance phenotypes, and examined the possible overlap between the set of genes close to candidate SNPs with sets of candidate genes from previous studies of cold adaptation in *D.*
123 *montana*. If population differentiation is driven by ecological selection then we would predict the

extreme cold adaptation of *D montana* to have left a signature of genomic divergence associated with environmental and phenotypic differentiation across these loci.

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MATERIALS AND METHODS

Sample collections and DNA extraction

129 We collected samples of 49-50 wild-caught flies from six *D. montana* populations from a range of latitudes from 66°N to 38°N in the spring of 2013 or 2014. Four of these populations represented a range of latitudes in North America (N. A.), and two populations were from a range in Finland 132 (figure 1; table 1). Samples of wild-caught flies from the six populations were stored in ethanol (the male/female ratio varied across samples; table 1) and DNA of individual flies was extracted using CTAB solution and phenol-chloroform-isoamylalcohol purifications in 2016. Genomic DNA was 135 extracted from individual flies and quantified using Qubit (Thermo Fisher Scientific), and an equal amount of DNA from each individual (50 ng) was pooled into the final sample. Sequencing was performed at the Finnish Functional Genomics Centre in Turku, Finland (www.btk.fi/functional-138 genomics) on the Illumina HiSeq3000 platform (paired-end reads, read length = 150bp, estimated coverage ~121x).

141 **Phenotyping**

We measured the critical thermal minimum (CTmin) and chill coma recovery time (CCRT) of flies from six populations. Fly samples for these tests were collected for five populations (Seward, 144 Terrace, Ashford, Crested Butte and Korpilahti) from mass-bred populations that have been maintained in the lab since 2013-2014. For the Oulanka population, flies were collected from three isofemale strains (established in 2014), because the mass-bred population had been contaminated by 147 another species. The mass-bred populations were originally established from F4 progenies of 20 isofemale strains each (400 flies) and have been maintained in constant temperature (19 ± 1°C) and light (24h of light, to prevent the flies from entering diapause) regimes for about 20-25 generations 150 before the experiment. All flies were supplied with fresh malt medium in half-pint bottles every week (Lakovaara, 1969). The newly emerged flies were collected using light CO_2 anaesthesia within 24 hours after emergence, separated by sex and placed in malt-vials in the same conditions 153 until sexual maturity (20-21 days old) and were then used in CTmin and CCRT tests. The same individual flies were first assayed for CTmin and then for CCRT, the flies were not anaesthetised before these tests.

156 We assayed a total of 328 females and 302 males for CTmin and CCRT. These assays were done in batches of between 22 and 30 flies, and split evenly by sex (21 batches in total). Between 32 and 46 (mean 39) flies per population per sex were tested (for the Oulanka isofemale strains,

between 15 and 39 flies per strain per sex were used). CTmin tests are based on detecting the temperature (CTmin) at which flies lose neuromuscular function and enter reversible state of chill coma (Andersen et al., 2015). In these tests, the flies were placed into tubes sealed with parafilm and submerged into a 30% glycol-water mixture in Julabo F32-HL chamber. The temperature was decreased at the rate of 0.5°C per minute (from 19°C to -6°C) and CTmin was determined by eye, as the temperature at which a fly was unable to stand on its legs. Immediately after the Ctmin test, the temperature was set to -6°C and the flies were left in this temperature for 16 hours. Then vials were quickly taken out of the glycol-water bath and the flies' CCRT was determined as the time required for the flies to recover from chill coma and stand on their legs. The ambient room temperatures was recorded during trials but in an initial analysis including source population and room temperature there was no statistically significant effect of room temperature on CCRT ($F_{5,569} = 0.72$, $p = 0.4$), this variable was therefore left out of further analyses.

To investigate population differences in CTmin and CCRT phenotypes we fit General Additive Mixed Models (GAMMs) in R (v. 3.6.3; R Development Core Team, 2020) using the "mgcv" R package (Wood, 2004). The full model included altitude, latitude, and sex as fixed effects and experimental batch as a random effect. We used a cubic regression spline as the basis smoothing function for both altitude and latitude. The full models are given in the Supplementary Materials.

Bioclimatic variables and population geography

We obtained representative climate data from the WorldClim database (Hijmans, Cameron, Parra, Jones, & Jarvis, 2005) for each *D. montana* population sampled for the pool-seq (see above), as well as for 18 additional populations of this species (Tyukmaeva et al., 2020). We downloaded the climate data and extracted the values corresponding to population coordinates using the R package "raster" (v. 2.5-8; Hijmans et al., 2016). In total this amounts to 55 bioclimatic variables for each population (table S1). To reduce the number of variables in the dataset a principle components analysis (PCA) was performed using the "PCA()" function from the R package "FactoMineR" (v. 1.28; Lê, Josse, & Husson, 2008). Principle components were kept for further analysis if their eigenvalues were > 1. PCA scores for each population were z-transformed using the "scale()" function in base R. Additionally, CTmin and CCRT were summarised to a mean value for each population. In total, this gives four "environmental" variables measured for each population (PC1, PC2, CTmin, and CCRT).

Mapping, SNP calling and genomic analysis

Quality of raw reads was checked with FASTQC (v. 0.11.5) (Andrews, 2015) and reads were trimmed using trimmomatic (v. 0.32; Bolger, Lohse, & Usadel, 2014; see Supplementary Materials for full trimming parameters). Trimmed reads were mapped to the *D. montana* reference genome (Parker et al., 2018) using BWA mem (v. 0.7.7; Li, 2013) with the default options but keeping only alignments with a mapping quality of > 20 following best practice guidelines for pool-seq (Schlötterer, Tobler, Kofler, & Nolte, 2014). Duplicate alignments were removed with samtools rmdup (v 1.3.1; Li et al., 2009) and regions around indels were re-aligned using picard (v. 1.118, Broad Institute), GATK (v. 3.2-2, McKenna et al., 2010) and samtools. Separate .bam files for each of the sequenced populations were finally merged using bamtools (v. 2.4.0; Barnett, Garrison, Quinlan, Strömberg, & Marth, 2011).

Over 80% of reads were properly mapped and retained in all samples. The mean coverage for Seward samples was nearly twice that of the other samples (figure S1 and figure S2). To remove the potential for this difference to cause artefacts in downstream analyses, the .bam files for Seward were down-sampled to contain 94.1 million reads (the average across the 5 remaining populations). Median empirical coverage was between ~62 and 88x (table S2; figure S1) and much less variable among the populations, allowing common maximum and minimum thresholds to be set based on the aggregate distribution (figure S3). Allele counts for each population at each genomic position were obtained with samtools mpileup (v. 1.3.1; Li et al., 2009) using options to skip indel calling as well as ignoring reads with a mapping quality < 20 and sites with a base quality < 15. This was followed by the heuristic SNP calling software PoolSNP using a minimum count of 5 to call an allele, and a minimum coverage of 37 and a maximum coverage < 95th percentile of the scaffold-wide coverage distribution to call a SNP (Kapun et al., 2019). Even if all these filters were passed, an allele was not considered if its frequency was < 0.001. Finally, we only considered SNPs on scaffolds > 10kb in length. The final set consisted of 2,190,511 biallelic SNPs that could be placed on scaffolds ordered along the chromosomes and were used in downstream analyses (table 2).

To test for an association between the four environmental variables and genetic differentiation we used BayeScEnv (v. 1.1; Foll & Gaggiotti, 2008; de Villemereuil & Gaggiotti, 2015). BayeScEnv fits a model of F_{ST} to population differentiation for each locus, incorporating environmental differentiation as a predictor (included as the parameter *g*) while fitting two locus-specific effects, one for environmental selection, and the other for other processes (demography, other types of selection). It therefore controls for confounding effects of population structure/relatedness in testing for an association with environmental variables. BayeScEnv was run with five pilot runs of 1000 iterations each, followed by a main chain of 4,000 iterations of which 2,000 were discarded as burn-in. Four MCMC chains were run for each analysis to evaluate convergence of the chains to common parameter estimates. Because of the unbalanced number of

228 males (and the resulting variation in ratios of X:Y chromosomes) in the pools, BayeScEnv analyses were performed separately on SNPs that could be assigned to the autosomal linkage groups (chromosomes) and the X chromosome. Raw count data were used for the autosomal data. For X
231 linked SNPs, allele count data were scaled to the known number of X chromosomes in the pool using n_{eff}, the effective sample size taking into account the multiple rounds of binomial sampling inherent to a pool-seq design (Kolaczkowski et al., 2011; Feder, Petrov, & Bergland, 2012). N_{eff}
234 scaled the allele counts at each SNP downwards based on the known number of chromosomes in the pool (see table 1).

Chains were assessed for convergence with the "coda" R package (v. 0.19-1; Plummer, Best,
237 Cowles, & Vines, 2006). Convergence was reached across the four chains for most analyses and parameters (potential scale reduction factors (PSRFs) of ~1 in a Gelman-Rubin diagnostic test; figures S4-S7), except for analyses of autosomal SNPs and PC2 as the environmental variable
240 which showed mild convergence problems (PSRF = 1.71), although parameter estimates agreed well with the other chains. Thus, this first chain (black line in figures S4-S7) was discounted for all parameters and only estimates from the remaining 3 chains were used. The union of significant
243 SNPs (q-value for the g parameter < 0.05) across these chains were taken as the final candidate SNPs.

Finally, population genetic statistics (π, and Tajima's D) were computed in windows of 10kb
246 with a step size of 5kb using methods implemented for pool-seq data (Kapun et al., 2019). Windows contained a mean of 488.2 SNPs (SE ±1.2). These statistics were only computed for scaffolds with a length > 50kb. F_{ST} was computed for each population with the R package "poolfstat" (v. 1.1.1;
249 Hivert, Leblois, Petit, Gautier, & Vitalis, 2018) by first computing all pairwise values, and then deriving population specific F_{ST} values by averaging across all pairwise values where a population was included. See the supplementary material for pseudocode commands of the key pipeline steps.

252 We performed GO term enrichment analyses with DAVID (v. 6.8; Huang et al., 2009a, b) and GOwinda (v. 1.12; Kofler & Schlötterer), which accounts for differences in gene length. For DAVID, since the *D. montana* annotation contains information about orthologs in *D. virilis,* we
255 extracted all genes within 10kb of a candidate SNP with an ortholog in *D. virilis* and submitted them to DAVID. For analyses with GOwinda, because the gene-sets need to be given manually, we obtained gene-sets from FuncAssociate3 (Berriz, Beaver, Cenik, Tasan & Roth 2009). As above, we
258 considered SNPs within 10kb of a gene (--gene-definition updownstream10000) and performed 1 million simulations to obtain the empirical p-value distribution. Regulatory elements, such as enhancers, and transcription factor binding sites, can occur up to 1Mb up- or downstream from a
261 target gene in other species (e.g. Maston, Evans & Green. 2006; Chan et al., 2010; Werner, Koshikawa, Williams & Carroll 2010; Pennacchio, Bickmore, Dean, Nobrega, & Bejerano 2013)

but generally lie within 2kb of a gene region in *D. melanogaster* (Arnosti, 2003), thus 10kb represents a compromise.

RESULTS

Cold tolerance measures, bioclimatic variables and population geography

Across individuals, there was no evidence of an association between minimum critical temperature (CTmin; pooled across sexes) and the chill coma recovery time (CCRT; cor = 0.08, p = 0.07). CTmin and CCRT varied among populations according to sex, latitude, and altitude. CTmin was significantly different between sexes (t = 3.14, p = 0.002). Latitude also had a strong effect on CTmin, and the Effective Degrees of Freedom (edf = 1), suggested this was largely a linear effect after accounting for altitude (F = 40.4, p < 0.001; figure 2A). Altitude had a more complex effect (edf = 1.262, F = 24.0, p < 0.001), but with a strong altitude outlier in Crested Butte (table 1), this result should be taken with some caution. Moreover, the overall adjusted R-squared was low at only 0.09. For CCRT, only latitude had a significant effect (edf = 1, F = 17.2, p < 0.001; figure 2B). Taken together, CTmin was lower for populations at higher latitudes as well as for populations at higher altitudes (figure 2A). As one would expect, CTmin showed on average lower values (figure 2A), and CCRTs were shorter (figure 2B), at higher latitudes, meaning that more northern and higher altitude populations show higher cold tolerance.

We performed a Principal Component Analysis (PCA) of the WorldClim climate data for a total of 24 *D. montana* populations, from which we had collected samples and where climate data were available. We wanted to examine whether the populations chosen for the cold tolerance tests and genome sequencing were representative of the range of environmental variation experienced by the species. These analyses identified four Principal Components (PCs) that together explained about 98% of the variation (figure 3A; figure S8). The first two PCs separated the populations roughly by a measure of distance from the coast (PC1) and then by latitude (or altitude) (PC2). PC1 explained ~54% of the variation (figure 3A and B) and loaded heavily on climate and biological variables associated with precipitation and temperature such as “Mean Temperature of Coldest Quarter”, “Precipitation of Wettest Month”, “Annual Precipitation” (see figure S8 and table S3). Meanwhile, PC2 explained ~23% of the variation (figure 3A and C) and loaded heavily on biological variables that are associated with latitudinal clinality, e.g. “Mean Diurnal [Temperature] Range,” and “Isothermality” which is the diurnal range divided by the mean “Annual [Temperature] Range”. The remaining PCs (PC3 and PC4) explained about 11.5 and 5% of the variation, respectively and did not capture as much of the climatic variation, and were therefore not considered further. Latitude (Spearman’s Rank Correlation: rho = -0.50, p = 0.01) but not altitude (rho = -0.19, p = 0.39) correlated significantly with PC1. However, both altitude (rho = -0.50, p = 0.02) and latitude (rho =

-0.59, p = 0.003) correlated with PC2 (see also figure 3C). Importantly, all these patterns also held if PCA was performed using only the six populations for which genomic data were collected. This
300 suggests that environmental variation across the six populations selected for sequencing reflects variation experienced by all 24 populations. Thus, any relationship between environmental variables and genetic differentiation in the samples selected for pool-seq is likely to reflect true
303 patterns across populations of *D. montana*. For all subsequent analyses, we used the results of the PCA using all 24 populations, and to examine the association between climate and phenotype, we compared these across the six populations. CTmin was positively correlated with PC1 (Pearson's
306 correlation coefficient (cor) = 0.94, p < 0.01) and had a marginally non-significant association with PC2 (cor = 0.75, p = 0.09). However, CCRT showed no relationship with either PC1 (cor = 0.09, p = 0.87) or PC2 (cor = -0.46, p = 0.36) although the small sample sizes (N = 6 in all cases) makes
309 reliable conclusions difficult (see figure S9).

Genomic analyses

312 The number of SNPs with a significant (q-value < 0.05) association between population-based F_{ST}, the two cold tolerance measures (CCRT and CTmin), and the two PCs of the bioclimatic data varied from 312 (chromosome 3, CCRT) to 2,480 (chromosome 4, PC2) across the chromosomes
315 (table 2). Using PC1 as an environmental variable with BayeScEnv gave a total of 2,976 and 1,528 SNPs with a q-value < 0.05 on the autosomes and on the X chromosome, respectively. Interestingly, the distribution across the chromosomes was not random. Using the distribution of all SNPs to
318 obtain expected counts, there was a significant deviation from expectation (X^2 = 2,906.4, d.f. = 4, p < 0.001). There were many more SNPs than expected on chromosome 4 (1,432 vs. 954) and on the X chromosome (1,528 vs. 526). Results were similar for PC2 with 6,607 and 1,861 SNPs with a q-
321 value < 0.05 on the autosomes and X chromosomes, respectively. Again, there was a significant deviation from the expected distribution of SNPs across the chromosomes (X^2 = 1,681.9, d.f. = 4, p < 0.001) with an overrepresentation on the 4th (2,480 vs. 1,794) and the X chromosomes (1,861 vs.
324 989). Manhattan plots of the distribution of SNPs across chromosomes are given in figures S10-S13.

We also used average CTmin values per population in similar analyses and found a total of
327 2,668 and 1,272 SNPs with a q-value < 0.05 on the autosomes and X chromosomes, respectively. The pattern of significant deviations from expected distributions (X^2 = 2,526.2, d.f. = 4, p < 0.001) was also due to an excess on the 4th (1,383 vs. 835) and the X chromosomes (1,272 vs. 460). Similar
330 results were found for CCRT with a total of 2,240 and 1,228 SNPs with a q-value < 0.05, respectively. Once again, there was a significant deviation from the expected distribution of SNPs

(X^2 = 2,825.6, d.f. = 3, $p < 0.001$) with and excess on the 4th (1,252 vs. 735) and the X
333 chromosomes (1,228 vs. 405).

To more closely examine the loci implicated in the four BayScEnv analyses, we identified genes containing or nearby (within 10kb) the candidate SNPs (table S4). Overall, there is quite a
336 large overlap among these genes with ~39% (1,102 in total) of them being shared by all the four analyses (table S4, figure 4). Some (147, ~13%) of these common genes are novel to *D. montana* (i.e. not annotated in *D. virilis* or in other *Drosophila* spp.) and therefore have no annotation, but
339 955 have an identifiable *D. virilis* ortholog (table S4). The second largest set are those genes unique to the analysis of PC2 as an environmental covariate (figure 4). We performed functional enrichment analyses with DAVID keeping all annotation clusters with an enrichment score > 1.3
342 (corresponding to an average corrected p-value of 0.05). This revealed several common categories of genes associated with the climatic variables and population phenotypes (table S5). For example, terms associated with membrane and transmembrane structures, immunoglobulins, HAD hydrolase
345 and nucleotide binding were enriched in most of the variables (table S5). Interestingly, there were also several gene ontology categories that were only enriched in one of the variables, such as glycoside and ATPase hydrolase in CCRT and ion channels and transport, as well as metal binding
348 in PC1 (table S4, table S5). GOwinda analyses revealed significant enrichment of GO terms (after accounting for variation in gene lengths and correcting for multiple testing) only for genes near SNPs associated with variation in CCRT across populations. Interestingly, the term "carbohydrate
351 derivative binding" was identified among the most enriched terms (table S6), which agrees closely with some terms identified using DAVID for the same variables (table S5). Similarly, for PC2, "nucleotide binding" was among the top scoring enriched terms in both GOwinda and DAVID
354 analyses, though this was not significant after controlling for multiple testing in GOwinda (table S5, table S6)

We then compared these loci with genes implicated in previous studies of climatic adaptation in
357 *D. montana* including gene expression studies of traits connected to diapause and cold-tolerance (Kankare et al., 2010; 2016; Parker et al., 2015; 2016). Additionally, several candidate genes have been identified near the most significantly differentiated SNPs among *D. montana* populations from
360 Oulanka (Finland), and from North American populations in Colorado and Vancouver (Parker et al., 2018). Finally, quasi-natural selection experiments identified several genes within 10kb of SNPs responding to selection for a shorter CDL for diapause induction (Kauranen et al., 2019). We tested
363 for an overlap between the total set of genes within 10kb of outlier SNPs from all of the BayScEnv runs (N = 2,694) and the candidate gene sets identified in earlier studies (see table S7 for the gene sets and studies used). We computed a bootstrap distribution of overlaps by sampling 2,694 random
366 genes from the *D. montana* annotation (N = 13,683). For each of the gene sets from previous

studies this was done 100 times and the distribution compared to the empirical overlap. Results are given in figure S10. In all the cases the empirical overlap was greater than expected by chance with empirical p-values < 0.05 (ranging from < 0.001 to 0.014; figure S14). The only gene that was found in all five of the previous studies used and in the comparison here is called *sidestep II* (*side-II*; table S8). Unfortunately, there is no information available about the biological processes or molecular functions connected to it. Moreover, from 44 other genes that were common to four of our previous studies and this study (table S8) most (27) have an ortholog in *D. melanogaster*. These genes have molecular functions such as transmembrane signaling or transporter, acetylcholinesterase, ATP binding, protein serine/threonine kinase, carboxylic ester hydrolase, or Rho guanyl-nucleotide exchange factor activity (Thurmond et al., 2019). Many of the genes are also connected to metal ion, nucleid acid or zinc ion binding (table S8). After identifying information on molecular or biological function and Interpro domains, eventually only five genes remained for which there was no information available (table S8).

Examination of population genetic parameters identified the Crested Butte population as anomalous. The distribution of Tajima's D is centered close to zero in most populations, being slightly more negative in North American populations (figure S15). However, Crested Butte is an outlier with a greatly reduced genome-wide Tajima's D (figure S15). Similarly, diversity (π) is also lower in this population than in other populations. There is no overall relationship between latitude and π (Spearman's rho = 0.14, N = 6, p = 0.8; figure S15) but there is a strong correlation between latitude and Tajima's D which is influenced by this population (with Crested Butte: rho = 0.88, N = 6, p = 0.03; without Crested Butte: rho = 0.8, N = 5, p = 0.13). Although Crested Butte occurs at a much higher altitude (>2800 meters) than other populations neither Tajima's D nor π correlated significantly with altitude (Tajima's D: rho = -0.6, N = 6, p = 0.24, π: rho = -0.6, N = 6, p = 0.24). Furthermore, F_{ST} was similar across all populations and chromosomes with the exception of Crested Butte which remained an outlier with clearly high F_{ST} (table 3). Finally, F_{ST} was always highest on chromosome 4 and the X chromosome, complementing the results seen in BayeScEnv analyses (table 3 *c.f.* table 2) and as expected if ecological selection is influencing genomic divergence.

DISCUSSION

Detecting genomic signatures of climatic adaptation is an important, but challenging, task. Here we use multiple sources of evidence to study ecological adaptation and population divergence in a highly cold tolerant species of *Drosophila*, *D. montana*. This species is characterised by a wide circumpolar distribution extending to high latitudes both in North America and Europe, and to high altitudes in the southern part of its range in the Rocky Mountains of North America. These habitats impose extreme seasonal and climatic selective pressure. We collected bio-climatic data from 24

402 populations along a latitudinal gradient of about 2,900 km in North America, and six populations from a gradient of 720 km in Finland. We characterised population level cold-tolerance for six populations from these ranges using two methods, critical thermal minimum (CTmin) and chill
405 coma recovery time (CCRT) and show that CTmin were lower and CCRT shorter in higher latitude populations, as one would expect. Thus, northern populations are more cold-tolerant. Finally, we performed pool-seq of these six populations to investigate the association between genomic and
408 environmental differentiation.

The two methods examining cold tolerance gave somewhat different results, as CTmin, but not CCRT, differed significantly between sexes, with females having lower CTmin than males. In an
411 earlier study investigating seasonal changes in *D. montana* CCRTs, only one out of six comparisons showed a significant difference between sexes (Vesala, Salminen, Kostal, Zahradnickova, & Hoikkala, 2012) and Gibert, Moreteau, Petavy, Karan & David (2001) did not detect sex-specific
414 differences in CCRT in any of 84 *Drosophila* species they studied. However, several studies of *D. melanogaster* have detected shorter CCRT in females than in males, suggesting that females are more cold tolerant than males (David et al., 1998; Andersen et al., 2015; Bauerfeind, Kellermann,
417 Moghadam, Loeschcke, & Fischer, 2014), perhaps related to their greater body mass (e.g. Wilder et al., 2010). Consequently, the extent and adaptive significance of sex-specific differences in CCRT in *Drosophila* remains unclear.

420 We derived principal components to summarise WorldClim climatic variables using data from all the 24 populations. The first principal component (PC1) separated populations roughly by a measure of "distance inland" and loaded heavily on climate and variables associated with
423 precipitation and temperature. These results follow the geographic distribution of the populations, for example, the population with highest values for PC1 is Ashford, which is on the Pacific coast and receives most rain, but also experiences warm summers and mild winters. Principal component
426 2 (PC2), loaded heavily on bioclimatic variables associated with latitudinal clinality, which also mapped onto the populations intuitively as those with higher values on PC2 also occurred at higher latitudes. Interestingly, CTmin values were positively correlated with PC1, but not with PC2, while
429 CCRT showed no relationship with either of these components. This suggests that CTmin and CCRT measure at least slightly different biochemical or physiological mechanisms (see e.g. MacMillan, Williams, Staples, & Sinclair, 2012; Findsen, Pedersen, Petersen, Nielsen & Overgaard
432 2013), and could hence be correlated with different climatic variables and also show relatively weak correlation to each other (Andersen et al., 2015). It is also interesting to note that high altitude populations have very similar values on PC1 and PC2 to high latitude populations, most likely
435 reflecting the similar climates in these populations. These similarities in climate are likely also

underlying the similarities in CTmin between the high altitude population (Crested Butte) and the high latitude populations from Finland.

438 The Bayesian analysis identified SNPs showing an association of genetic differentiation with climatic and phenotypic variation. The extent to which the loci associated with the phenotypes and adaptations to different climatic conditions are shared indicates that these are closely associated in 441 influencing genome evolution. We found that genes near SNPs showing a significant association between genetic and climatic differentiation overlapped to a large extent with genetic and phenotypic differentiation among populations. The largest intersection set, containing 1,102 genes, 444 was the one containing genes near SNPs associated with all the four variables examined (PC1, PC2, CTmin and CCRT). However, PC2 loads heavily on bioclimatic variables relating to latitude, and our analysis using PC2 as a covariate has a large number of private genes (see figure 4), suggesting 447 that there is also a substantial amount of genetic variation underlying adaptations to latitude unrelated to the phenotypic measures we have quantified. Our study is an excellent example of how strong ecological selection may be detected in genomic studies. In particular, because the Bayesian 450 methods examining both ecological variables and relevant phenotypes gave significant overlap amongst the associated loci, and that these are further associated with more broad genomic differentiation between populations, gives confidence that we are consistently identifying genes 453 associated with ecological selection.

Analyses of the functional annotation of these genes strengthens our conclusions that climate driven adaptation is important. Regions near SNPs associated with climatic variables were enriched 456 for genes previously identified as candidates related to cold tolerance, diapause and responses to changes in day length in *D. montana* (Kankare et al., 2010; 2016; Parker et al., 2015; 2016). Thus, genetic variation across populations of these flies may be largely shaped by differences in 459 ecological and climatic variation. This ecological specialisation may have also contributed to the divergence of *D. montana* from its relatives. Parker et al., (2018) surveyed the rates of molecular evolution in eleven cold tolerant and non-cold tolerant species of Drosophila. The genes found to be 462 evolving at faster rates in cold-tolerant species were enriched for many of the same functional categories as in our current study, including e.g. membrane and transmembrane proteins and immunoglobulins (Parker et al., 2018).

465 The fact that many of the same annotation terms are enriched in clusters for all environmental variables in DAVID analyses, suggests that similar genes or biochemical pathways are involved in these adaptations. Membrane proteins and lipids are an important determinant of 468 membrane and cuticular permeability at different temperatures, which in turn has an effect on the resistance to desiccation stress in insects (Gibbs, 2002; Stanziano, Sové, Rundle, & Sinclair, 2015). Importantly, there is evidence for a close link between the desiccation stress response and cold

471 tolerance across species and in *Drosophila* in particular, suggesting an overlap in some of the mechanisms involved (Sinclair, Nelson, Nilson, Roberts, & Gibbs, 2007). Cold-hardy lines of *D. melanogaster* are known to exhibit elevated lipid metabolism, perhaps in order to allow rapid lipid
474 membrane modification (Williams et al., 2016) in different environmental conditions. Pleckstrin homology (PH) domain was one of the functional clusters found in both the current study and in the species comparison of Parker et al., (2018). This domain is a flexible module of 100-120 amino
477 acids which interacts with a variety of different ligands, composing a protein-protein interaction platform (Scheffzek & Welti, 2012). As changes in the membrane lipid biochemistry form an integral part of the cold tolerance response, genes associated with PH may assist in homeoviscous
480 adaptation i.e. alteration of membrane phospholipid composition to maintain fluidity at low temperatures (Sinensky, 1974). Interestingly, the only gene found in all five of our previous studies of cold tolerance in *D. montana* was *sidestep II* (*side-II*). Unfortunately, there is no information
483 available for the biological processes or molecular functions associated with this gene, but *side-II* has protein features including immunoglobulin and immunoglobulin-like domain superfamily (Thurmond et al., 2019) and could be involved in immunological processes during cold response of
486 the flies (Parker et al., 2021). Insects are known to produce a diverse range of antimicrobial peptides and proteins as part of their immune activity against viruses, bacteria, fungi and parasites (Mylonakis, Podsiadlowski, Muhammed, & Vilcinskas, 2016) and hence immune responses could
489 be part of a general stress response in cold tolerance (Sinclair, Ferguson, Salehipour-shirazi, & MacMillan, 2013; Ferguson, Heinrichs, & Sinclair, 2016). We also find confirmation of some enriched GO terms in GOwinda analyses that control for variation in gene length, although overlap
492 is not substantial. In sum, our results indicate that some of the same biochemical processes that are targeted by selection on larger evolutionary scales (i.e. across species), are also involved in local adaptation for different populations within a species, providing a rare bridge between the processes
495 of population differentiation and speciation.

At the chromosomal level, we found an over-representation of loci associated with ecological selection on chromosomes X (which corresponds to chromosome 2L in *D. melanogaster*) and 4. It
498 is well-known that X chromosomes can generally evolve quickly due to selection on semi-recessive advantageous loci in the hemizygous sex, and smaller effective population size (Charlesworth, Coyne, & Barton, 1987) and are often most divergent between closely related species (Abbott,
501 Norden, & Hansson, 2017; Ellegren et al., 2012). However, there is no obvious reason to expect faster divergence in chromosome 4. *Drosophila montana* populations have considerable chromosomal polymorphism (e.g. Patterson and Stone, 1952; Stone, Guest, & Wilson, 1960;
504 Morales-Hojas, Päällysaho, Vieira, Hoikkala, & Vieira, 2007) and American populations have been classified into several chromosomal forms on the basis of their geographical origin, size and

chromosome structure (Throckmorton, 1982). Moreover, both the X chromosome and chromosome 4 of *D. montana* are known to harbour polymorphic inversions (Stone et al., 1960; Morales-Hojas et al., 2007) and such inversions have often been found to vary clinally (e.g. Kolaczkowski et al., 2011; Cheng et al., 2012; Kapun et al., 2016). Recent genomic data confirms that there are several inversions in both chromosomes X and 4, but we do not yet have any detailed information on their distributions within populations (Poikela et al., unpublished). The reduced recombination within inversions can independently capture advantageous alleles under selection (Kirkpatrick & Barton, 2006) and divergence is often greater in chromosomes carrying inverted regions and non-colinear regions (Lohse, Clarke, Ritchie, & Etges, 2015) and such regions may divergence more quickly during speciation with gene flow. Indeed, here we found that the X chromosome and chromosome 4 always have the highest levels of F_{ST} across all populations, as expected if the ecological selection on loci on these chromosomes influenced overall patterns of genomic diversion, perhaps due to hitchhiking.

Finally, our findings include intriguing result regarding the Crested Butte population which shows reduced genetic variability and a substantial reduction of Tajima's D relative to the other populations. This population occurs at a very high altitude (>2800 m) and also shows reproductive incompatibilities with other populations (Jennings et al., 2014). It may have also been bottlenecked during its adaptation to this high altitude, so population expansion or selected sweeps could be prevalent within this population (Garlovsky et al., 2020). Whether ecological specialisation is associated with the spread of incompatibilities is an intriguing possibility.

CONCLUSION

Identifying the genetic variation that underlies population divergence and ultimately speciation remains a challenge. Detecting associations between genetic and environmental differentiation at loci across populations has become a popular approach. Here we apply Bayesian methods to detect such loci across populations of *Drosophila montana*, which is an extremely cold-tolerant *Drosophila* species where we expect strong ecological selection. We identify many genes that are associated with both climate variables and population-level cold-tolerance phenotypes. These genes overlap with candidate genes from other studies of variation in cold-tolerance in *D. montana* and were also over-represented on chromosomes X and 4 which may be associated with inversion polymorphisms known to be present in these chromosomes. Our study thus provides a clear example of how strong ecological selection can be detected in genome studies, using Bayesian methods to detect local adaptation in combination with studies of ecologically important variables and phenotypes.

Data Availability

Raw reads have been deposited with NCBI (https://www.ncbi.nlm.nih.gov) under the BioProject accession PRJNA588720.

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Author contributions

AH, MGR, and MK conceived the study. VT performed the phenotyping experiments. RAWW performed all analyses. RAWW, MK and MGR led the writing of the MS. All authors contributed to the final form of the manuscript.

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840 **Tables, Figures, and Figure Legends**

Table 1. The sources of genomic samples (coordinates and the name of the nearest town), altitude
843 of the sampling site, the year in which sampling was performed, and the number of males and females sampled (M/F) for each pool.

Source	**Sampling Site**	**Year**	**M/F**
USA, Alaska	Seward 60°9'N; 149°27'W Altitude 35 m	2013	30/20
Canada, British Columbia	Terrace 54°27'N; 128°34'W Altitude 217 m	2014	22/27
USA, Washington	Ashford, 46°45'N; 121°57'W Altitude 573 m	2013	16/34
USA, Colorado	Crested Butte 38°54'N; 106°57'W Altitude 2900 m	2013	36/13
Finland	Oulanka 66°40'N; 29°20'E Altitude 337 m	2013	25/25
Finland	Korpilahti 62°20'N; 25°34'E Altitude 133 m	2013	27/23

846

Table 2. Number of SNPs with a q-value < 0.05 for the g parameter on each linkage group (chromosomes) and each environmental variable (see Methods). The total number of SNPs on each linkage group are given in the bottom row.

Environmental Variable	**LG2**	**LG3**	**LG4**	**LG5**	**Autosomes Total**	**X**	**Overall Total**
PC1	561	485	1,432	498	2,976	1,528	4,504
PC2	1,639	1,191	2,480	1,297	6,607	1,861	8,468
CTmin	502	399	1,383	384	2,668	1,272	3,940
CCRT	360	312	1,252	316	2,240	1,228	3,468
Total	441,381	613,952	463,965	415,312	441,381	255,901	2,190,511

Table 3. Mean (SD) F_{ST} values for each linkage group (chromosome) and population

Chromosome	Oulanka	Korpilahti	Ashford	Seward	Crested Butte	Terrace
LG2	0.12 (0.16)	0.12 (0.16)	0.10 (0.15)	0.10 (0.15)	0.15 (0.21)	0.11 (0.16)
LG3	0.11 (0.16)	0.11 (0.16)	0.09 (0.14)	0.09 (0.14)	0.15 (0.21)	0.10 (0.14)
LG4	0.15 (0.18)	0.15 (0.18)	0.14 (0.18)	0.13 (0.17)	0.19 (0.23)	0.13 (0.17)
LG5	0.12 (0.17)	0.13 (0.17)	0.11 (0.15)	0.11 (0.15)	0.16 (0.22)	0.11 (0.16)
X	0.16 (0.21)	0.16 (0.21)	0.14 (0.20)	0.15 (0.20)	0.19 (0.24)	0.14 (0.19)

852

Figure 1. Maps of all *D. montana* populations in this study. Panels show population locations from
855 **A** Finland and **B** North America showing the locations of all populations sampled. Labelled, blue circles give the locations of populations sampled for phenotyping and sequencing.

858 **Figure 2.** Population phenotypes. **A** and **B** show the variation in CTmin and CCRT across populations and latitude, respectively. Solid and dashed lines show the predicted values from the partial effect of latitude from the best model (see Results) for males and females, respectively. In **B**,
861 although the points are plotted separately for males and females, the best model only included latitude as a covariate. In both panels the points and error bars give the mean and standard errors, respectively.

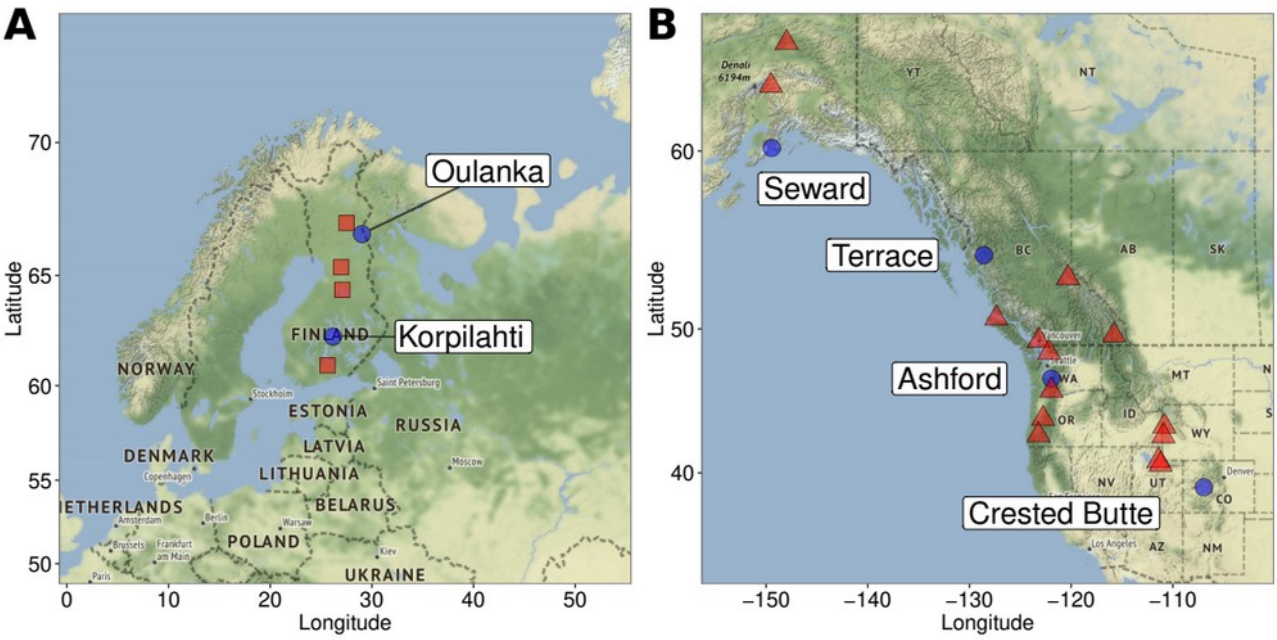
864

Figure 3. Principle Components Analysis. **A** The distribution of all populations along the two first PC axes. The loadings of variables on each axis can be found in table S3. Blue circles give the
867 populations that have been pool-sequenced for this study, red squares and triangles give the other Finnish and North American populations, respectively. **B** and **C** give PCs 1 and 2 as a function of latitude and altitude, respectively. The legend for altitude in both **B** and **C** is given in **C**.

870

Figure 4. Overlap of genes within 10kb of top SNPs from BayeScEnv analyses for PC1, PC2 CTmin, and CCRT. The total number of genes near significant SNPs for each variable are given by
873 the bars in the bottom left (x-axis labelled "Set Size"). The overlaps are depicted by points connected by lines along the *x*-axis and the height of the bars indicate the number of genes in common (intersection) to the variables connected by dots and lines.

Figure 1


A
Oulanka
Korpilahti
NORWAY
FINLAND
ESTONIA
RUSSIA
LATVIA
DENMARK
LITHUANIA
BELARUS
POLAND
UKRAINE
Latitude
Longitude
B
Seward
Terrace
Ashford
Crested Butte
Denali 6194m
YT
NT
BC
AB
SK
MT
WA
OR
ID
WY
NV
UT
CO
AZ
NM
Latitude
Longitude

879 **Figure 2**

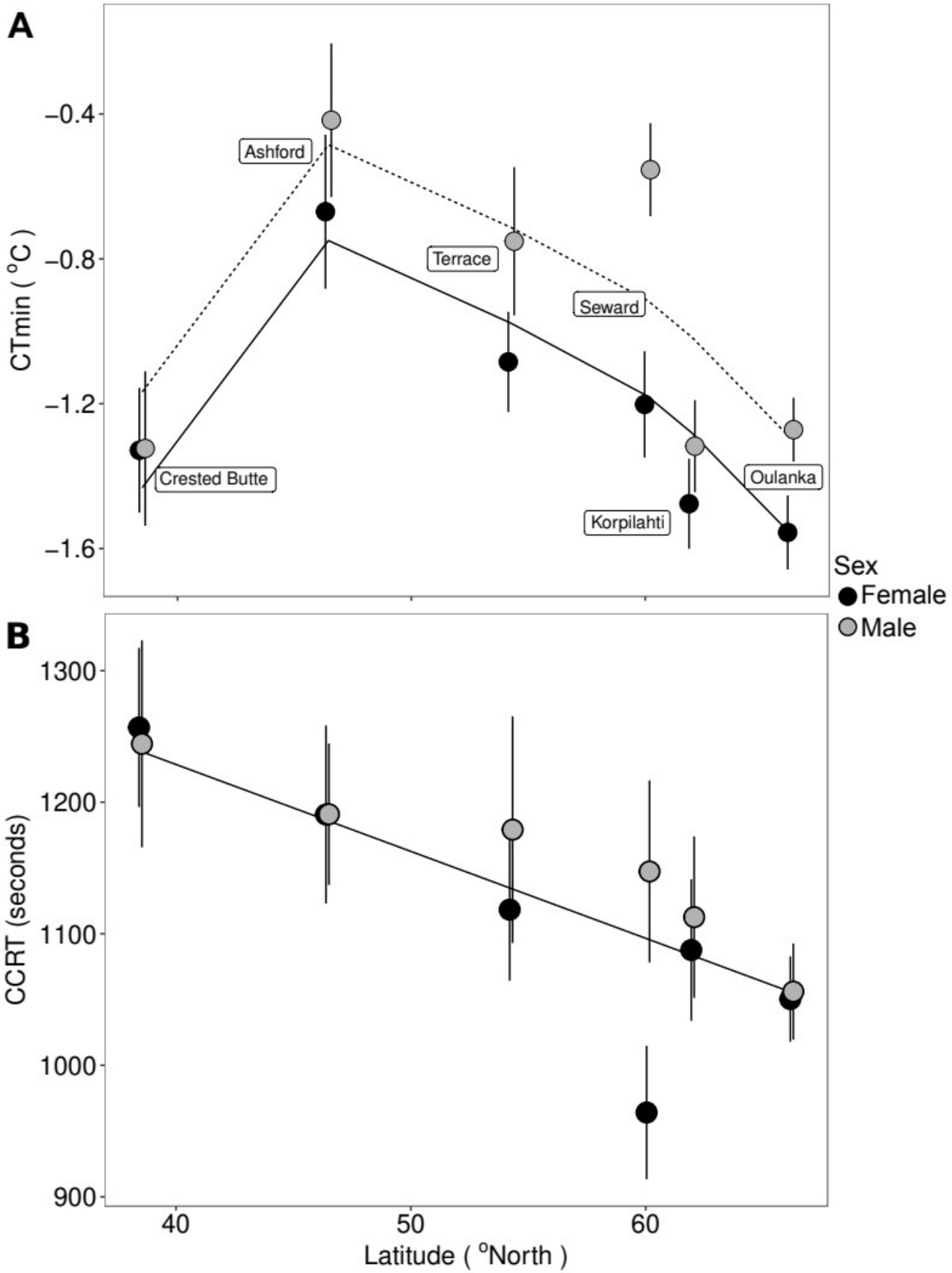

A
−0.4
−0.8
−1.2
−1.6
CTmin (°C)
Ashford
Terrace
Seward
Crested Butte
Korpilahti
Oulanka
Sex
Female
Male
B
1300
1200
1100
1000
900
CCRT (seconds)
40
50
60
Latitude (°North)

Figure 3.

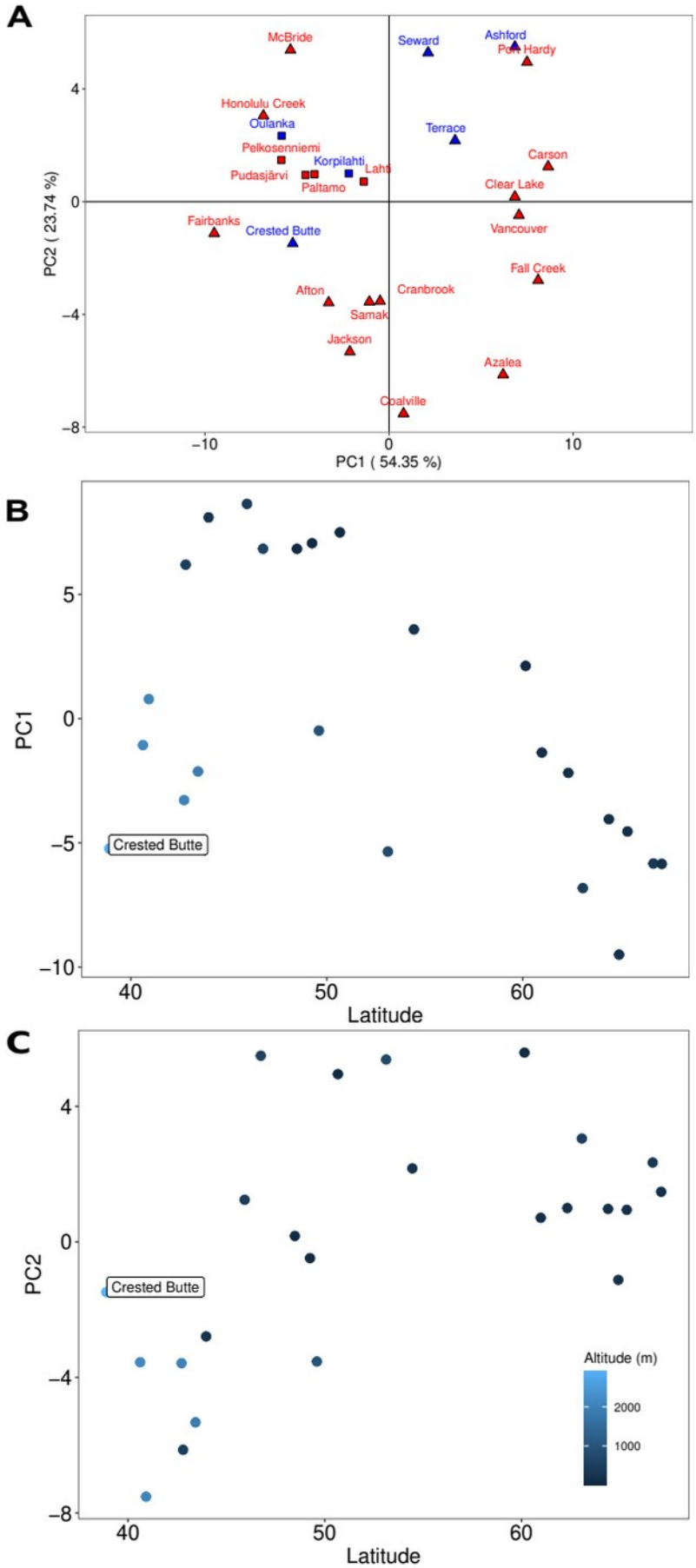
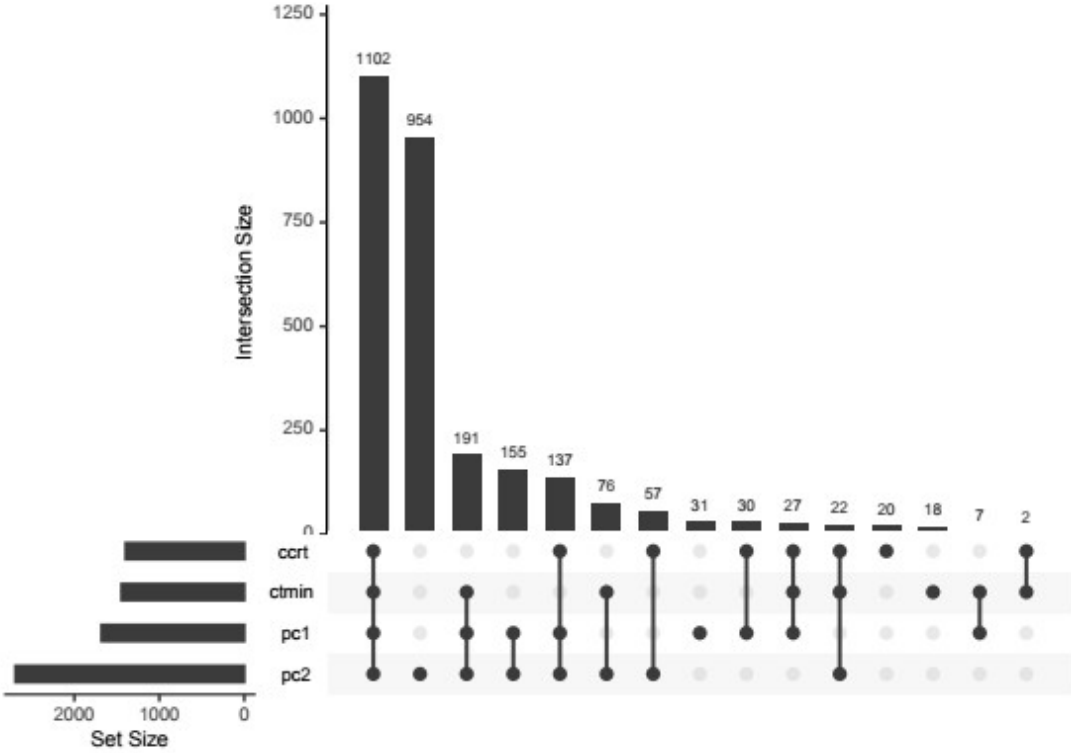

A
McBride
Seward
Ashford
Port Hardy
Honolulu Creek
Oulanka
Terrace
Pelkosenniemi
Korpilahti
Carson
Pudasjärvi
Lahti
Paltamo
Clear Lake
Fairbanks
Crested Butte
Vancouver
Fall Creek
Afton
Cranbrook
Samak
Jackson
Azalea
Coalville
PC2 (23.74 %)
PC1 (54.35 %)
B
PC1
Crested Butte
Latitude
C
PC2
Crested Butte
Altitude (m)
2000
1000
Latitude

Figure 4.


Intersection Size
1250
1000
750
500
250
0
1102
954
191
155
137
76
57
31
30
27
22
20
18
7
2
ccrt
ctmin
pc1
pc2
2000
1000
0
Set Size

Supplementary Information for

Cold adaptation drives population genomic divergence in the ecological specialist, *Drosophila montana*

Wiberg et al.

Pseudocode bioinformatic pipeline with model commands:

1. Trimming

```
java -jar Trimmomatic.jar PE -phred33 *_R1_001.fastq.gz *_R2_001.fastq.gz *_tqc_R1_pe.fq.gz *_ftqc_R1_se.fq.gz *_tqc_R2_pe.fq.gz *_ftqc_R2_se.fq.gz ILLUMINACLIP:TruSeq3-PE.fa:2:30:10:8:TRUE CROP:145 LEADING:20 TRAILING:20 SLIDINGWINDOW:5:20 MINLEN:100;
```

2. Mapping

```
bwa mem -t 5  D_montana_genome_freeze_v1.4.fa *_R1_pe.fq.gz *_R2_pe.fq.gz | samtools view -Sb -q 30 -f 0x02 - > *.bam

samtools rmdup *_srt.bam *_srt_rmdup.bam

java -Xmx2g -jar $gatk -T RealignerTargetCreator -R D_montana_genome_freeze_v1.4.fa -I *_srt_rmdup_srt_rdgrp.bam -o *_srt_rmdup_srt_rdgrp.intervals

java -Xmx4g -jar $gatk -T IndelRealigner -R D_montana_genome_freeze_v1.4.fa -I *_srt_rmdup_srt_rdgrp.bam -targetIntervals *_srt_rmdup_srt_rdgrp.intervals -o *_srt_rmdup_srt_rdgrp_indraln.bam
```

3. Subsample Seward sample

```
XX=94100000

cat <(samtools view -H Seward_srt.bam) <(samtools view Seward_srt.bam | shuf -n ${XX}) > Seward_subs.sam

samtools view -bS Seward_subs.sam -o Seward_subs.bam
```

4. SNP calling

```
samtools mpileup --max-depth 1000000 --skip-indels --min-MQ 20 --min-BQ 15 --fasta-ref
D_montana_genome_freeze_v1.4.fa Oulanka.bam Korpilahti.bam Ashford.bam Seward.bam
Crested_Butte.bamTerrace.bam > montana_clines.mpileup

PoolSNP.sh mpileup=montana_clines.mpileup output=montana_clines
reference=D_montana_genome_freeze_v1.4.fa
names=Oulanka,Korpilahti,Ashford,Seward,Crested_Butte,Terrace min-cov=37 max-cov=0.95
min-count=5 min-freq=0.001 miss-frac=0.01 base-quality=15 jobs=10
```

5. BayeScEnv

```
bayescenv *_all_bscanin.txt -burn 2000 -pilot 1000 -npb 5 -n 2000 -env *.txt -od *_bscanout
```

6. Gowinda

```
gowinda --output-file *_topsnps_gowinda.tab --gene-definition updownstream10000 --simulations
1000000 --mode gene --gene-set-file funcassociate_go_associations.txt  --snp-file  all_snps.tab --
candidate-snp-file *_candidate_snps_file.tab --annotation-file
D_montana_genome_freeze_v1.4_dmel.gtf
```

Final models of population phenotypes

```
gamm(
        Ctmin ~ s(latitude, bs="cr", k=5) + s(altitude, bs="cr", k=5) + sex ,
        random = list(exp_batch=~1),
        data=cold_pop_dat
)

gamm(
        CCRT ~ s(latitude, bs="cr", k=5),
        random = list(exp_batch=~1),
        data=cold_pop_dat
)
```

where the term *exp_batch* was the experimental batch random effect.

Supplementary Tables, Figures and Legends

Table S1. See supplementary .tsv file

Table S2. Mapping statistics from merged .bam files. Statistics for Seward samples are given after downsampling of reads.

Sample	**Number of reads**	**Median coverage**
Oulanka	78,261,294	62x
Korpilahti	88,285,498	71x
Ashford	82,318,578	66x
Crested Butte	97,443,044	80x
Seward	92,743,585	76x
Terrace	109,266,003	88x

Table S3. Loadings (correlation coefficients) of the 55 bioclimatic variables on principal components (PCs) 1-4. Correlation coefficients > 0.9 are highlighted in bold

Variable	Variable Name	Dim.1	Dim.2	Dim.3	Dim.4
bio1	Annual Mean Temperature	**0.95**	-0.26	0.15	-0.12
bio2	Mean Diurnal Range (Mean of monthly (max temp - min temp))	-0.11	-0.81	-0.56	0
bio3	Isothermality (BIO2/BIO7) (* 100)	0.62	-0.49	-0.56	-0.05
bio4	Temperature Seasonality (standard deviation *100)	-0.9	-0.17	0.2	0.29
bio5	Max Temperature of Warmest Month	0.33	**-0.92**	0.01	0.13
bio6	Min Temperature of Coldest Month	**0.97**	0.08	0.1	-0.13
bio7	Temperature Annual Range (BIO5-BIO6)	-0.8	-0.53	-0.1	0.19
bio8	Mean Temperature of Wettest Quarter	-0.33	-0.07	0.71	0.21
bio9	Mean Temperature of Driest Quarter	0.85	-0.24	-0.26	-0.14
bio10	Mean Temperature of Warmest Quarter	0.55	-0.62	0.51	0.14
bio11	Mean Temperature of Coldest Quarter	**0.97**	-0.06	0	-0.19
bio12	Annual Precipitation	0.81	0.49	-0.21	0.25
bio13	Precipitation of Wettest Month	0.81	0.44	-0.14	0.35
bio14	Precipitation of Driest Month	0.29	0.66	-0.2	-0.56
bio15	Precipitation Seasonality (Coefficient of Variation)	0.55	0.22	0.28	0.63
bio16	Precipitation of Wettest Quarter	0.81	0.43	-0.16	0.36
bio17	Precipitation of Driest Quarter	0.51	0.66	-0.35	-0.33
bio18	Precipitation of Warmest Quarter	-0.23	**0.92**	0.14	-0.12
bio19	Precipitation of Coldest Quarter	0.84	0.35	-0.25	0.33
tmin1	Minimum Temperature – January	**0.97**	0.08	0.11	-0.13
tmin2	Minimum Temperature – February	**0.97**	0.06	0.07	-0.12
tmin3	Minimum Temperature – March	**0.97**	-0.01	0.18	-0.13
tmin4	Minimum Temperature – April	0.91	-0.02	0.37	-0.1
tmin5	Minimum Temperature – May	0.71	0.02	0.68	0.02
tmin6	Minimum Temperature – June	0.39	0.1	0.9	0.12
tmin7	Minimum Temperature – July	0.36	0.08	0.91	0.06
tmin8	Minimum Temperature – August	0.61	0.13	0.77	0
tmin9	Minimum Temperature – September	0.81	0.19	0.55	-0.04
tmin10	Minimum Temperature – October	0.88	0.15	0.35	-0.18
tmin11	Minimum Temperature – November	**0.93**	0.05	0.23	-0.2

tmin12	Minimum Temperature – December	**0.96**	0.11	0.18	-0.15
tmax1	Maximum Temperature – January	**0.91**	-0.21	-0.15	-0.25
tmax2	Maximum Temperature – February	**0.92**	-0.27	-0.18	-0.19
tmax3	Maximum Temperature – March	**0.91**	-0.38	-0.04	-0.12
tmax4	Maximum Temperature – April	0.82	-0.54	0.08	-0.05
tmax5	Maximum Temperature – May	0.58	-0.73	0.25	0.08
tmax6	Maximum Temperature – June	0.25	-0.89	0.26	0.19
tmax7	Maximum Temperature – July	0.31	**-0.92**	0.01	0.12
tmax8	Maximum Temperature – August	0.5	-0.84	-0.09	0.07
tmax9	Maximum Temperature – September	0.68	-0.7	-0.18	0.02
tmax10	Maximum Temperature – October	0.77	-0.57	-0.23	-0.14
tmax11	Maximum Temperature – November	0.86	-0.36	-0.12	-0.26
tmax12	Maximum Temperature – December	0.91	-0.19	-0.09	-0.28
prec1	Precipitation – January	0.83	0.33	-0.26	0.35
prec2	Precipitation – February	0.83	0.35	-0.27	0.32
prec3	Precipitation – March	0.83	0.29	-0.31	0.34
prec4	Precipitation – April	0.85	0.33	-0.3	0.22
prec5	Precipitation – May	0.78	0.36	-0.35	0.06
prec6	Precipitation – June	0.22	0.78	-0.14	0.11
prec7	Precipitation – July	-0.6	0.7	0.21	-0.18
prec8	Precipitation – August	-0.35	0.82	0.25	-0.15
prec9	Precipitation – September	0.37	0.74	0	-0.18
prec10	Precipitation – October	0.72	0.57	-0.02	0.01
prec11	Precipitation – November	0.86	0.36	-0.18	0.3
prec12	Precipitation – December	0.85	0.35	-0.22	0.31

Table S4. See supplementary .xls format spreadsheet (bscan top SNPs)

Table S5. See supplementary .xls format spreadsheet (DAVID results)

Table S6. See supplementary .xls format spreadsheet (GOwinda results)

Table S7. Previous studies to which the results from the current study are compared.

Reference	**Study**	**Geneset being compared**
Kankare et al., 2010	Gene expression change during diapause	Genes that significantly changed their expression in response to diapause
Parker et al., 2015	Gene expression response to cold acclimation	Genes that were DE in either *D. montana* or in both *D. montana* and *D. virilis* in response to cold acclimation
Parker et al., 2016	Gene expression response to different day lengths	Genes that responded in expression to day length in either diapausing or non-diapausing flies.
Kankare et al., 2016	Gene expression differences in diapuasing and non-diapausing females	Genes that were either upregulated or downregulated in diapausing compared to non-diapausing females.
Parker et al., 2018	*D. montana* genome: population differentiation among three populations.	Genes that were within 1kb of outlier SNPs in any of three pairwise Fst outlier scans.
Kauranen et al., 2019	Quasinatural selection under shorter day lengths.	Genes within 10kb of a SNP that changed in allele frequency

Table S8. See supplementary .xls format spreadsheet (genes/overlap between studies)

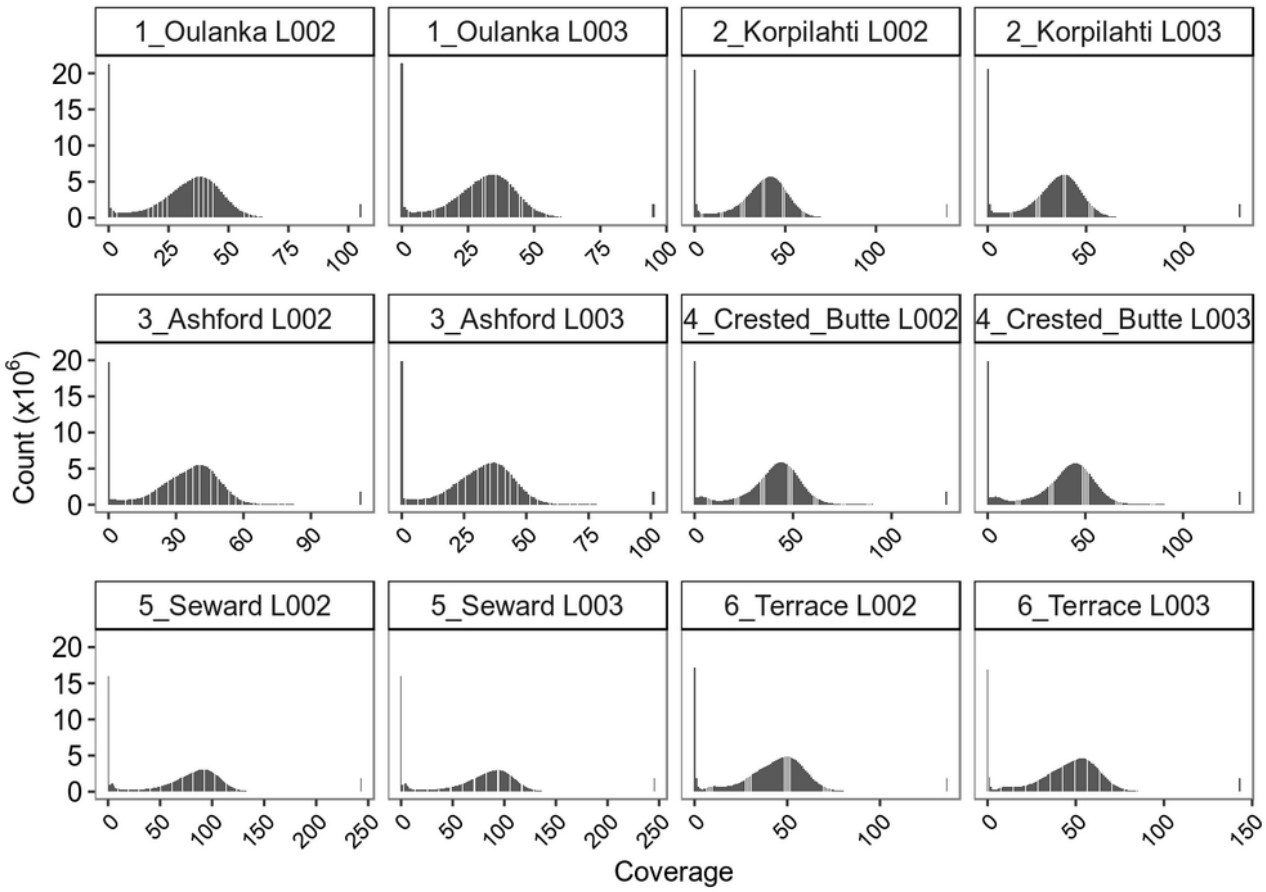


Figure S1. Coverage distributions of all samples before downsampling of Seward data. Note the different scales of the X-axes.

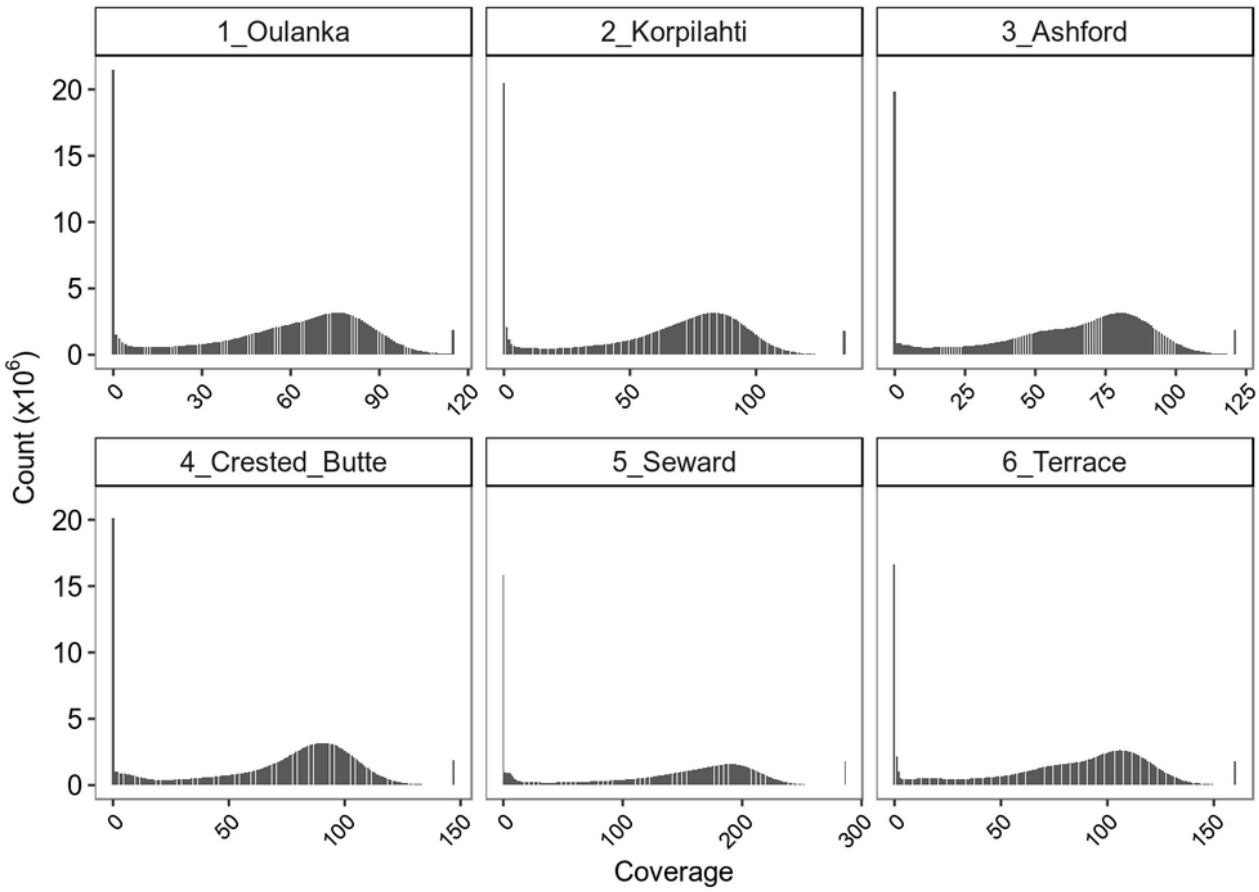


Figure S2. Coverage distributions of merged samples before downsampling of Seward data. Note the different scales of the X-axes.

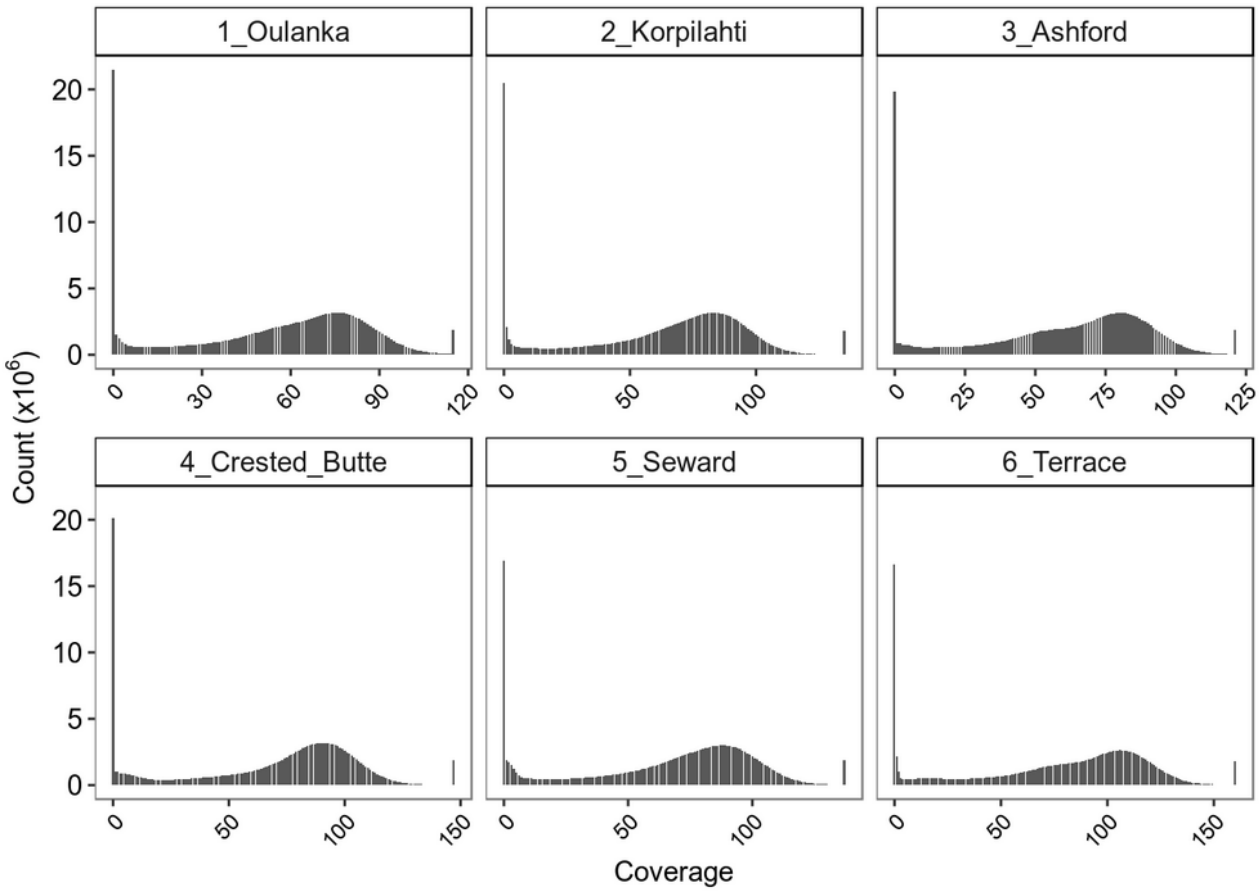


Figure S3. Coverage distributions of merged samples after downsampling of Seward data. Note the different scales of the X-axes.

Figure S4. Diagnostic gelman and trace plots for BayeScEnv MCMC chains with CTmin as the environmental variable. Analyses were split into **A** autosomal SNPs and **B** X chromosome SNPs. Gelman plots show the Gelman-Rubin shrink factors that summarise variation in parameter estimates across chains. Only data from the three chosen MCMC chains are included in these plots. Trace plots show parameter values across iterations of MCMC chains. These plots show data from all four chains that were run. See supplementary .pdf files.

Figure S5. Diagnostic plots for BayeScEnv MCMC chains with CCRT as the environmental variable. Analyses were split into **A** autosomal SNPs and **B** X chromosome SNPs. Gelman plots show the Gelman-Rubin shrink factors that summarise variation in parameter estimates across chains. Only data from the three chosen MCMC chains are included in these plots. Trace plots show parameter values across iterations of MCMC chains. These plots show data from all four chains that were run. See supplementary .pdf files.

Figure S6. Diagnostic plots for BayeScEnv MCMC chains with PC1 of the bioclimatic PCA as the environmental variable. Analyses were split into **A** autosomal SNPs and **B** X chromosome SNPs. Gelman plots show the Gelman-Rubin shrink factors that summarise variation in parameter estimates across chains. Only data from the three chosen MCMC chains are included in these plots. Trace plots show parameter values across iterations of MCMC chains. These plots show data from all four chains that were run. See supplementary .pdf files.

Figure S7. Diagnostic plots for BayeScEnv MCMC chains with PC2 of the bioclimatic PCA as the environmental variable. Analyses were split into **A** autosomal SNPs and **B** X chromosome SNPs. Gelman plots show the Gelman-Rubin shrink factors that summarise variation in parameter estimates across chains. Only data from the three chosen MCMC chains are included in these plots. Trace plots show parameter values across iterations of MCMC chains. These plots show data from all four chains that were run. See supplementary .pdf files.

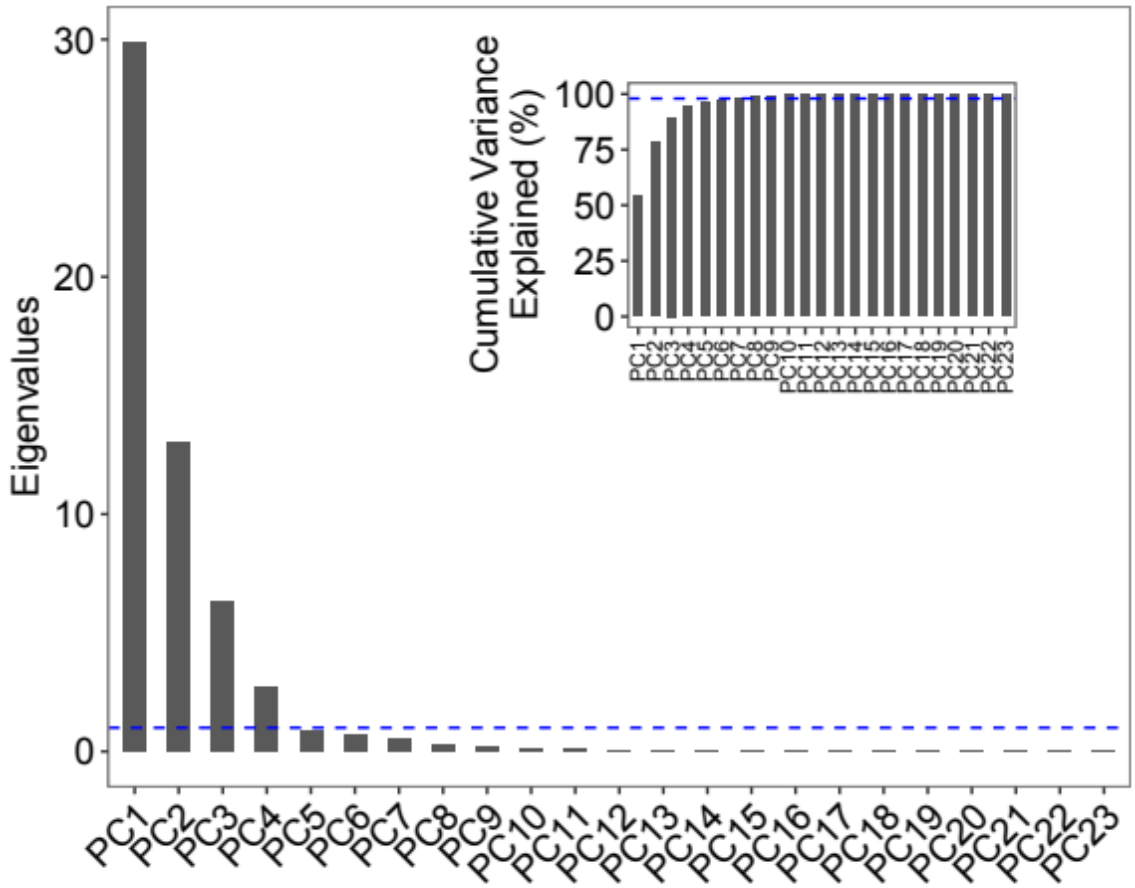


Figure S8. "Scree plot" of principal components 1-23 from a Principle Components Analysis of the 55 bioclimatic variables. Main plot shows the eigenvalues of the principal components, the horizontal dashed line shows the eigenvalue threshold of 1. The inset figure shows the cumulative amount of variance explained by the principal components. The horizontal dashed line gives 98% of the cumulative variance.

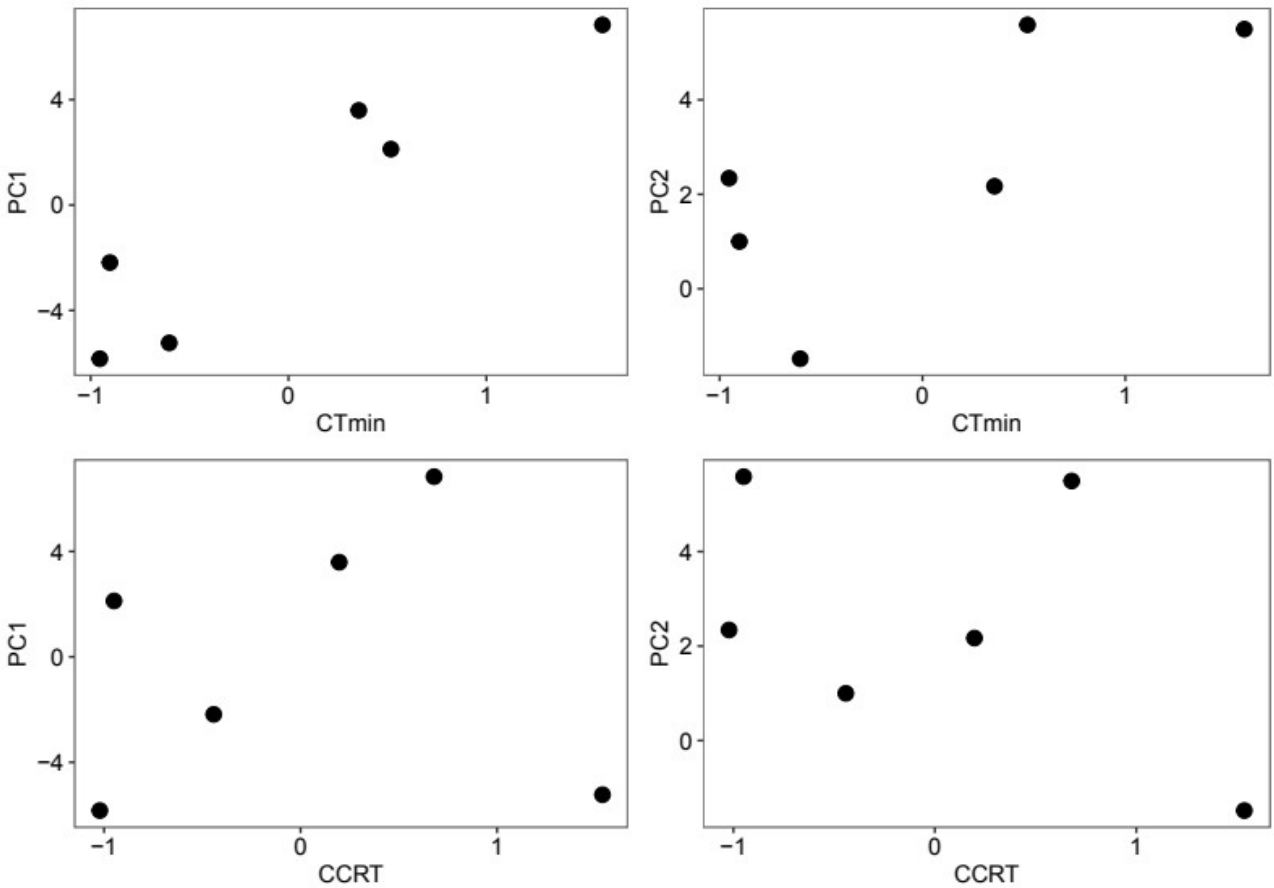


Figure S9. Scatter plots of the relationship between the population phenotypes (CTmin and CCRT) and the two chosen principal components (PC1 and PC2). PC values and phenotype values have been z-transformed.

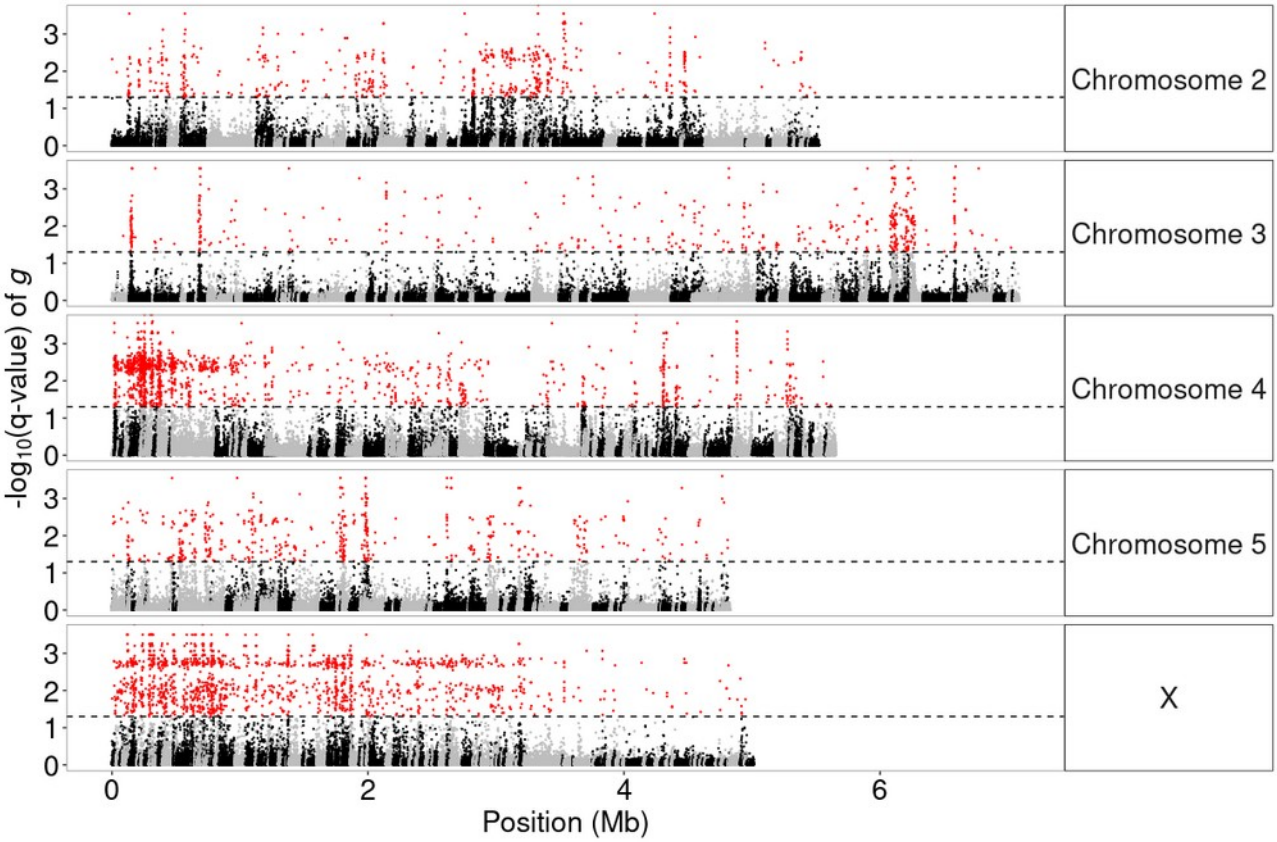


Figure S10. Manhattan plot of the q-values from BayeScEnv for a test of genetic differentiation with PC1. Red points show those SNPs with q-values < 0.05. The horizontal dashed line gives the FDR threshold used. Alternating black and grey points along chromosomes denote different scaffolds. Note that scaffolds can be place on chromosomes in this genome assembly but are not yet ordered.

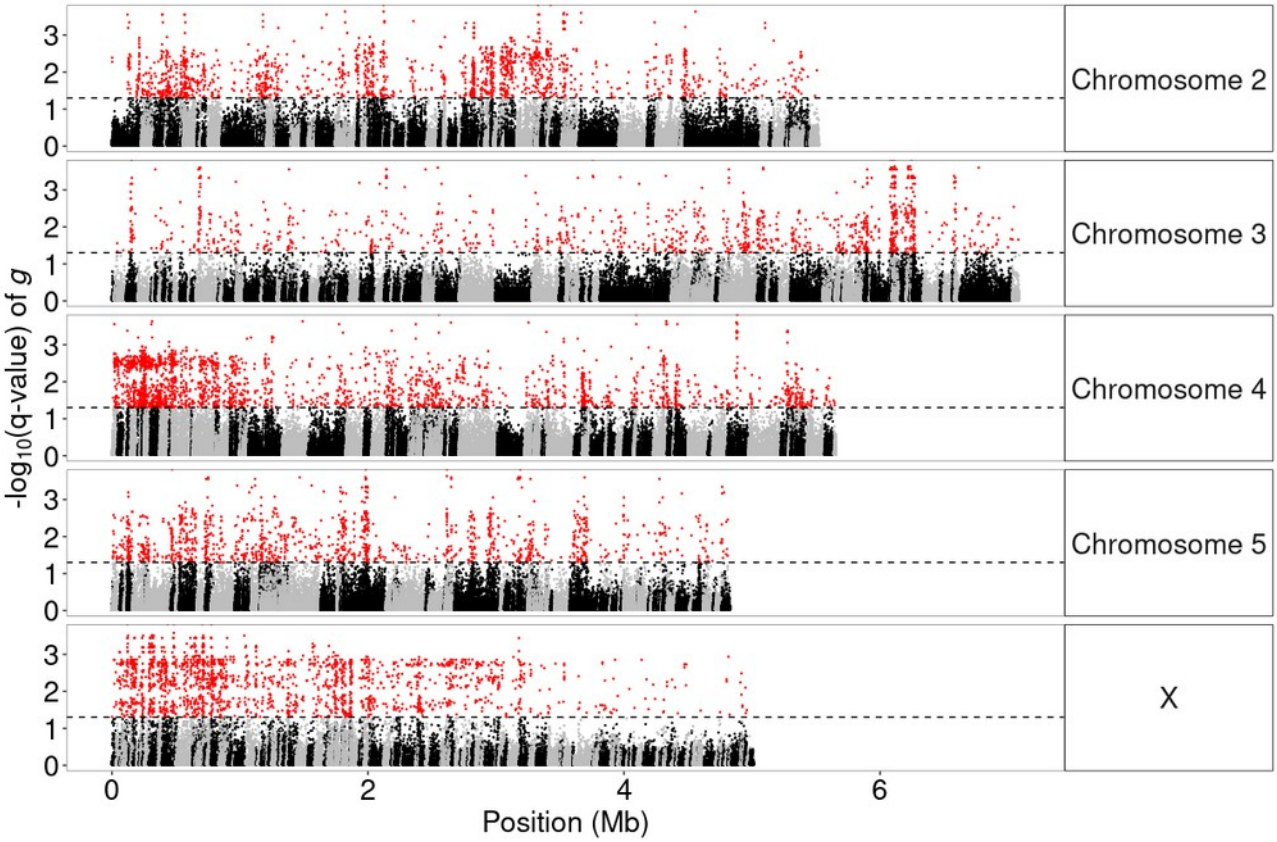


Figure S11. Manhattan plot of the q-values from BayeScEnv for a test of genetic differentiation with PC2. Red points show those SNPs with q-values < 0.05. The horizontal dashed line gives the FDR threshold used. Alternating black and grey points along chromosomes denote different scaffolds. Note that scaffolds can be place on chromosomes in this genome assembly but are not yet ordered.

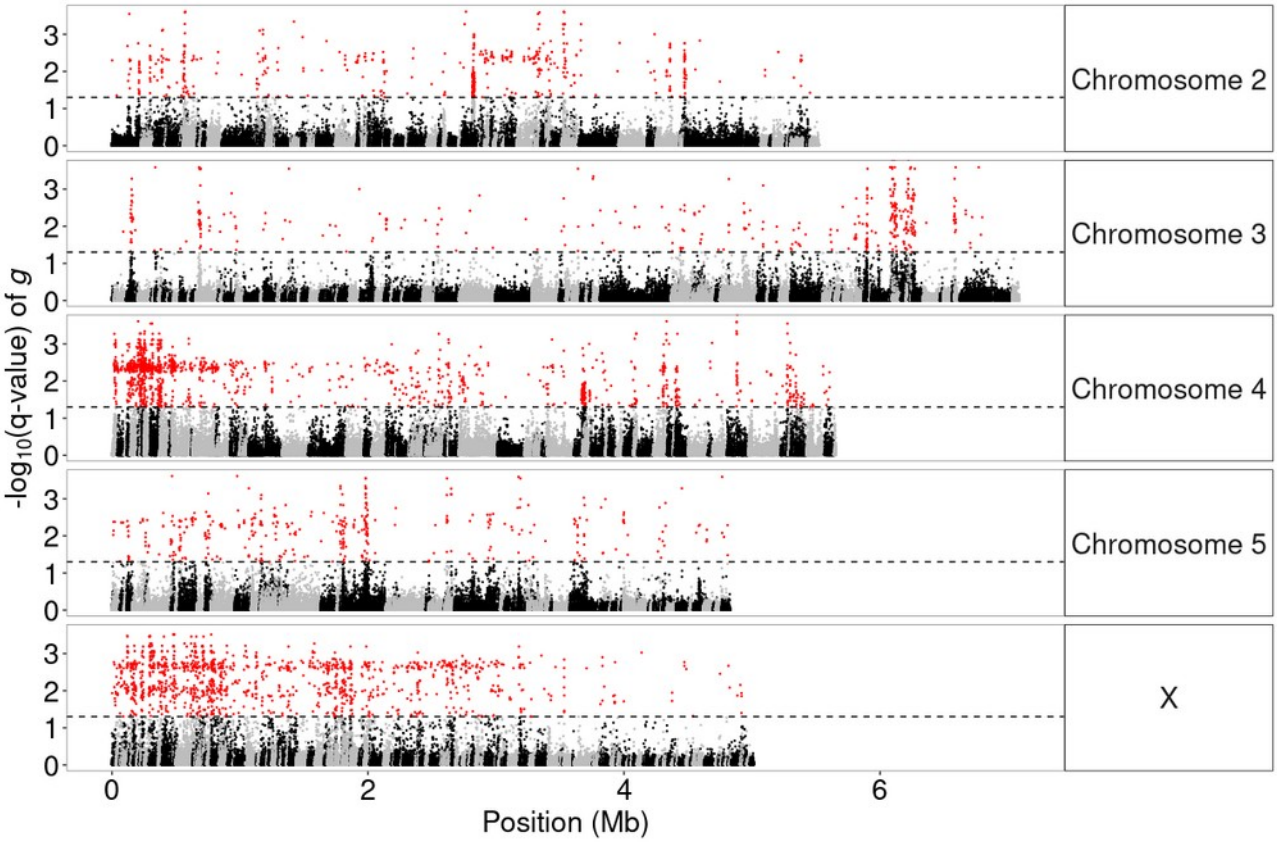


Figure S12. Manhattan plot of the q-values from BayeScEnv for a test of genetic differentiation with CTmin. Red points show those SNPs with q-values < 0.05. The horizontal dashed line gives the FDR threshold used. Alternating black and grey points along chromosomes denote different scaffolds. Note that scaffolds can be place on chromosomes in this genome assembly but are not yet ordered.

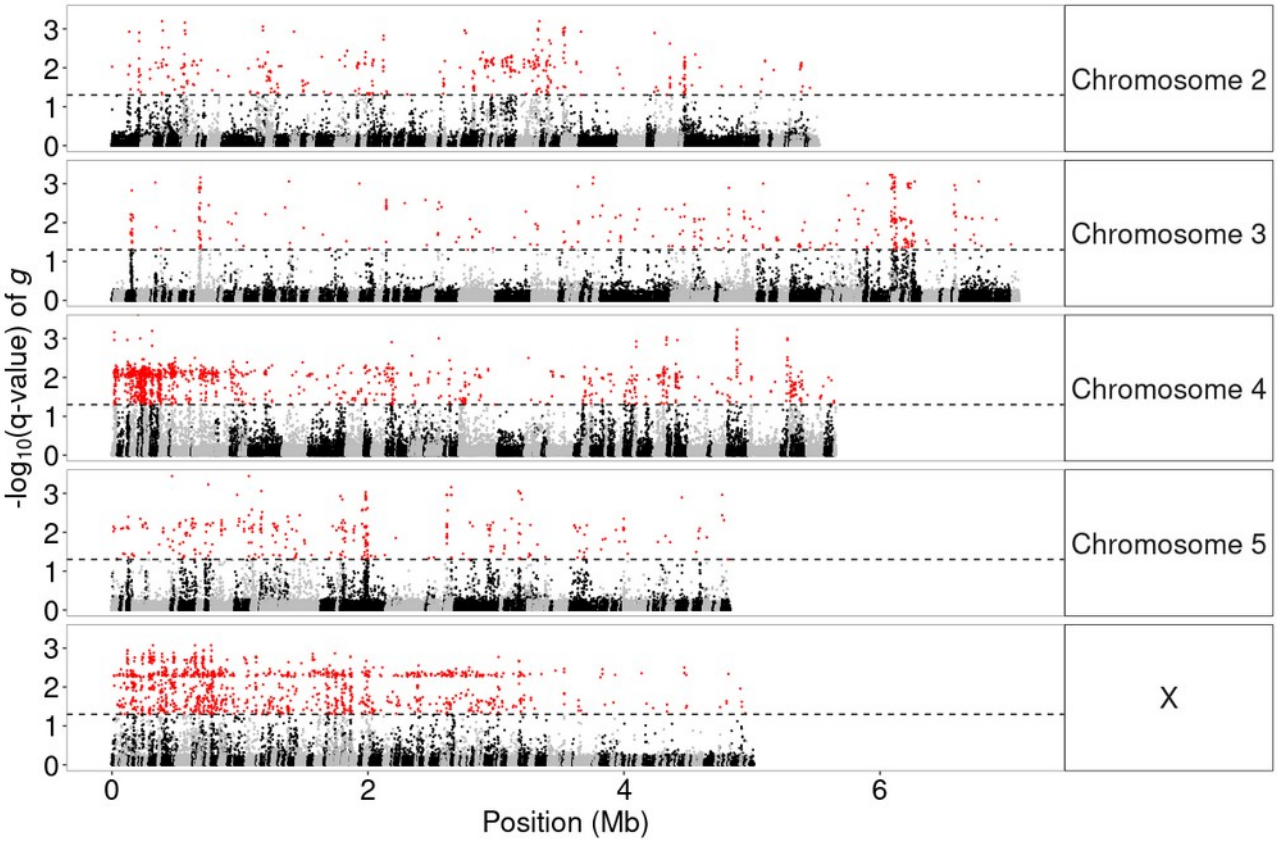


Figure S13. Manhattan plot of the q-values from BayeScEnv for a test of genetic differentiation with CCRT. Red points show those SNPs with q-values < 0.05. The horizontal dashed line gives the FDR threshold used. Alternating black and grey points along chromosomes denote different scaffolds. Note that scaffolds can be place on chromosomes in this genome assembly but are not yet ordered.

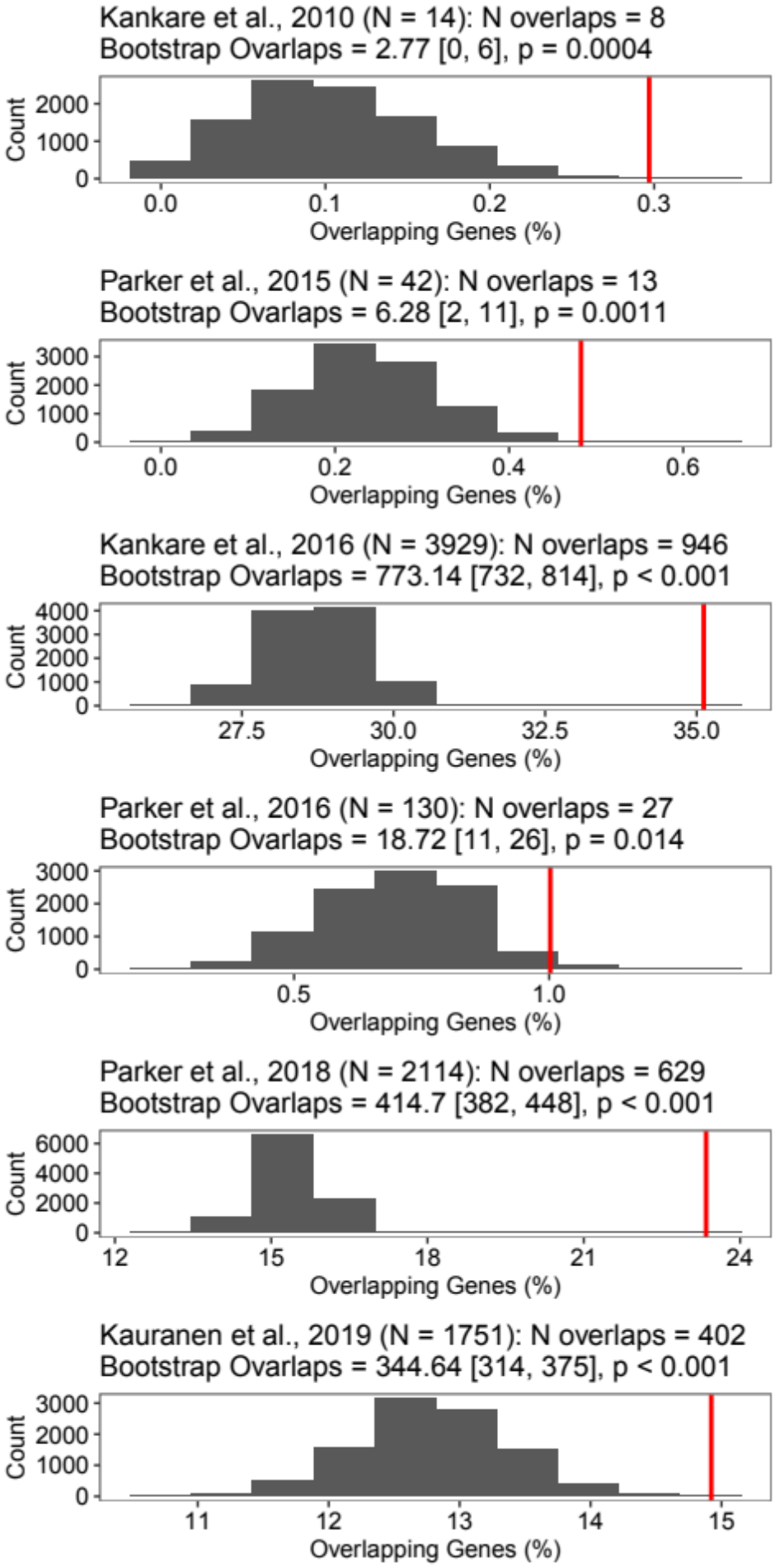

Kankare et al., 2010 (N = 14): N overlaps = 8
Bootstrap Ovarlaps = 2.77 [0, 6], p = 0.0004
Count
2000
1000
0
0.0
0.1
0.2
0.3
Overlapping Genes (%)
Parker et al., 2015 (N = 42): N overlaps = 13
Bootstrap Ovarlaps = 6.28 [2, 11], p = 0.0011
Count
3000
2000
1000
0
0.0
0.2
0.4
0.6
Overlapping Genes (%)
Kankare et al., 2016 (N = 3929): N overlaps = 946
Bootstrap Ovarlaps = 773.14 [732, 814], p < 0.001
Count
4000
3000
2000
1000
0
27.5
30.0
32.5
35.0
Overlapping Genes (%)
Parker et al., 2016 (N = 130): N overlaps = 27
Bootstrap Ovarlaps = 18.72 [11, 26], p = 0.014
Count
3000
2000
1000
0
0.5
1.0
Overlapping Genes (%)
Parker et al., 2018 (N = 2114): N overlaps = 629
Bootstrap Ovarlaps = 414.7 [382, 448], p < 0.001
Count
6000
4000
2000
0
12
15
18
21
24
Overlapping Genes (%)
Kauranen et al., 2019 (N = 1751): N overlaps = 402
Bootstrap Ovarlaps = 344.64 [314, 375], p < 0.001
Count
3000
2000
1000
0
11
12
13
14
15
Overlapping Genes (%)

Figure S14 (previous page). Bootstrap distributions, from 10,000 bootstrap samples, of overlaps between the union of genes within 10kb of SNPs associated with PC1, PC2, CTmin, ant CCRT and various previous candidate gene sets (see table S4). The red vertical lines give the empirical overlap value. Values above each figure give the citation to the study, the number of genes in the list considered from each study, the number of overlaps, the mean and 95% confidence intervals of the bootstrap distribution, and the empirical p-value (proportion of bootstrap samples with an overlap greater than the empirical overlap).

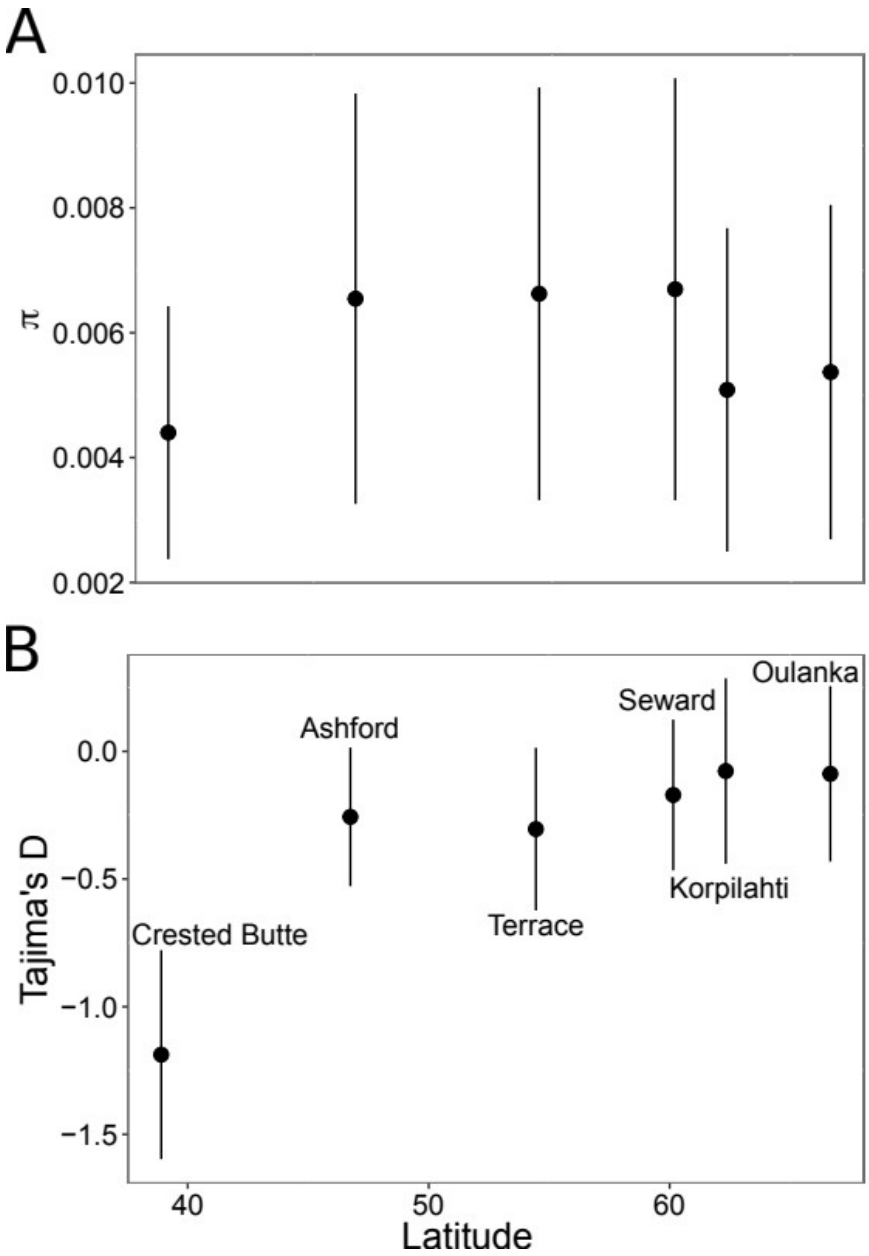


Figure S15. A nucleotide diversity (π) and **B** Tajima's D as a function of latitude. Inset labels give the names of the corresponding populations.