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Genomic responses to parallel temperature gradients in the eelgrass *Zostera marina* in adjacent bays

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1	Genomic responses to parallel temperature gradients in the eelgrass Zostera marina in
2	adjacent bays
3	Lauren M. Schiebelhut ¹ , Richard K. Grosberg ² , & John J. Stachowicz ² , Rachael A. Bay ²
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6	
7	Abstract
8	The extent of parallel genomic responses to similar selective pressures depends on a complex
9	array of environmental, demographic, and evolutionary forces. Laboratory experiments with
10	replicated selective pressures yield mixed outcomes under controlled conditions and our
11	understanding of genomic parallelism in the wild is limited to a few well-established systems.
12	Here, we examine genomic signals of selection in the eelgrass Zostera marina across
13	temperature gradients in adjacent embayments. Although we find many genomic regions with
14	signals of selection within each bay. However, there is very little overlap in signals of selection
15	at the SNP level, despite most polymorphisms being shared across bays. We do find overlap at
16	the gene level, potentially suggesting multiple mutational pathways to the same phenotype.
17	Using polygenic models we find that some sets of candidate SNPs are able to predict
18	temperature across both bays, suggesting that small but parallel shifts in allele frequencies may
19	be missed by independent genome scans. Together, these results highlight the continuous
20	rather than binary nature of parallel evolution in polygenic traits and the complexity of
21	evolutionary predictability.

22 **Keywords**: non-parallel evolution, population genomics, *Zostera marina*

23 Introduction

24 The question of whether patterns of trait and underlying genomic and developmental variation 25 show parallel (or convergent) responses across similar selection gradients is fundamental to our 26 understanding of how evolution operates and whether evolutionary outcomes are predictable 27 (reviewed in Bolnick, Barrett, Oke, Rennison, & Stuart, 2018). All else being equal (and 28 notwithstanding the stochastic effects of genetic drift), independent populations experiencing 29 comparable selective regimes should exhibit parallel responses, at least at the trait level. The 30 degree to which such populations share similar genetic histories should also govern the extent 31 to which they exhibit parallel responses at the genomic level (Härer, Bolnick, & Rennison, 2021; 32 Rennison, Delmore, Samuk, Owens, & Miller, 2020). Thus, populations most likely to evolve 33 along parallel evolutionary pathways should have recently diverged, sharing a similar pool of 34 ancestral genetic variation, and independently facing comparable forces of selection 35 (Bohutínská et al., 2021; Conte, Arnegard, Peichel, & Schluter, 2012). 36 The extent of parallelism in populations experiencing nominally comparable selective regimes may also depend on the level of organization under consideration, from the traits 37 38 themselves, to underlying variation at the level of nucleotides, genes, and developmental 39 pathways (Bolnick et al., 2018; Conte et al., 2012; Stuart, 2019). For example, many selectively 40 important traits are highly polygenic, reducing the likelihood of parallelism at the 41 genetic/genomic level, with different genetic combinations producing functionally equivalent 42 phenotypes (Arendt & Reznick, 2008). In addition, there are often multiple phenotypic 43 solutions, some based on historical contingency, to the same selective challenges, with 44 different combinations of traits leading to a suite of phenotypes with similar performance

(Bolnick et al., 2018). Finally, non-parallel mutations in particular genes, or mutations within the
same class of genes (but not the same genes), may produce parallel phenotypic or functional
effects (e.g., Cassin-Sackett, Callicrate, & Fleischer, 2019; Rosenblum, Römpler, Schöneberg, &
Hoekstra, 2010).

49 In principle, the strongest tests for parallel evolution would use highly replicated 50 populations with known evolutionary histories inhabiting comparable selective regimes in 51 which patterns can be assayed at both the trait and genomic levels. For these reasons, the 52 majority of studies exploring parallelism of both genomes and traits have involved long-term 53 laboratory studies of microbes, often initiated from a single clone, and allowed to evolve over 54 thousands of generations under varying selective regimes (reviewed in Blount, Lenski, & Losos, 55 2018; also see Pickersgill (2018) for analysis of crop plants). Consistent with predictions, parallel 56 outcomes are most likely in recently established populations experiencing equivalent selective 57 regimes (e.g., Blount et al., 2018). Nevertheless, responses are often strikingly inconsistent 58 among replicate lines, even those initiated from the same founder and subjected to presumably 59 identical selective regimes (Tenaillon et al., 2012). This suggests that stochastic processes such 60 as genetic drift, and the often complex relationships among genotypes, phenotypes and fitness 61 may also be shaping evolutionary responses at the genomic and trait levels (Conte et al., 2012). 62 Far less is known about evolutionary patterns in natural populations of multicellular organisms (Blount et al., 2018; Bolnick et al., 2018). The majority of the data that we do have 63 from a few well-characterized model systems suggests that parallelism is equally inconsistent in 64 these systems (Stuart et al., 2017). However, recent advances in the accessibility of genomic 65 66 tools make it possible to simultaneously assess population structure and evolutionary history

67	while identifying specific mutations associated with parallel selection pressures. This allows for
68	studies of parallel evolution in "replicate" populations with unknown/uncertain evolutionary
69	histories and longer generation times and thereby extends these experimental studies to
70	natural populations of more complex non-model organisms. Several recent studies comparing
71	natural populations identified substantial degrees of parallelism both in terms of traits and
72	underlying genetic patterns (e.g., Bohutínská et al., 2021; Roda et al., 2013; Stuart et al., 2017);
73	however, as with several laboratory studies on microbes, in many wild populations multiple
74	factors, including genetic drift (Szendro, Franke, de Visser, & Krug, 2013), environmental
75	heterogeneity (Magalhaes et al., 2021; Stuart et al., 2017), and different histories of fluctuating
76	selection (Liu, Ferchaud, Grønkjaer, Nygaard, & Hansen, 2018) often contribute to varying
77	degrees of decoupling of parallelism between genes and traits (e.g., Rivas et al., 2018).
78	As the most widely distributed marine angiosperm in the northern hemisphere, the
79	seagrass Zostera marina occurs from the Arctic to the subtropics and in the Pacific, Atlantic and
80	the Mediterranean. The broad distribution of <i>Z. marina</i> encompasses a wide range of
81	environmental conditions (with respect to light, salinity, and temperature) that vary both
82	seasonally and geographically. Z. marina undergoes both vegetative and sexual reproduction,
83	with varying proportions across sites (Reusch et al., 1999; Olsen et al., 2004). In most
84	populations, individual shoots (ramets) derived from a sexually produced individual are
85	intermingled to form the seagrass meadow (see map in Kollars et al. 2022), with only a few
86	extreme exceptions (Yu et al. 2022). Clonal genotypes, even those collected from the same bed,
87	differ in fitness-related traits, including shoot production, biomass, photosynthesis, and
88	nutrient uptake (Abbott, DuBois, Grosberg, Williams, & Stachowicz, 2018; Hughes, Stachowicz,

89	& Williams, 2009; Reynolds, DuBois, Abbott, Williams, & Stachowicz, 2016; Salo, Reusch, &
90	Boström, 2015). However, the expression of these traits also depends on environmental
91	context, leading to differential fitness of genotypes at particular sites or seasons (DuBois,
92	Abbott, Williams, & Stachowicz, 2019; DuBois, Williams, & Stachowicz, 2021). This standing
93	genetic variation provides the foundation for local adaptation and reciprocal transplants have
94	demonstrated home-site advantage even at spatial scales on the order of a few km (DuBois,
95	Pollard, Kauffman, Williams, & Stachowicz, 2022; Hämmerli & Reusch, 2002). Moreover,
96	population structure in Z. marina tends to be high with significant divergence at all spatial
97	scales, including across tidal heights (Campanella, Bologna, Smith, Rosenzweig, & Smalley,
98	2010; DuBois et al., 2022; Kamel, Hughes, Grosberg, & Stachowicz, 2012; J. H. Kim et al., 2017),
99	so limited gene flow, even at the scale of meters, may facilitate local adaptation.
100	In this paper we simultaneously characterize patterns of genomic and functional
101	variation in multiple populations of Z. marina, across adjacent bays with overlapping thermal
102	gradients. We focus on populations of Z. marina inhabiting multiple locations along
103	temperature gradients in the adjacent Tomales Bay and Bodega Harbor in north-central
104	California, USA. These two bays are just 10 kilometers apart, making it likely that populations
105	within each bay arose from the same ancestral population. This, along with the overlapping
106	selective gradient (i.e., temperature) represents a set of conditions under which parallel
107	responses might be most likely. Previous work has demonstrated strong genetic structure in
108	this region, as well as local adaptation to temperature; reciprocal transplants in Tomales Bay
109	show home-site advantage and plants from cooler sites have decreased growth under
110	experimental warming (DuBois et al., 2022). Because of this strong population structure and

111	because warm sites in each embayment are farthest from the open sea and thus the most
112	distant from one another of all our sites, we can interpret parallel shifts in allele frequencies as
113	signatures of selection, relative to random processes such as genetic drift. We build on this
114	trait-based evidence of local adaptation to investigate the genomic basis of adaptation and the
115	potential for parallel evolution, focusing on three questions. We first ask whether genotype-
116	temperature associations exist across each temperature gradient independently and whether
117	there are parallel changes in allele frequencies across tidal heights. We then determine
118	whether parallelism at the genomic level exists across the two gradients, assessing overlap at
119	three levels of organization: the mutation, the gene, and the functional pathway. Finally, to
120	assess the predictability of detected genotype-temperature relationships, we test whether
121	genetic variation across many SNPs can be used to predict thermal environment from individual
122	genotypes, both within and between bays.
123	
124	Methods
125	
126	Sampling, DNA extraction, and sequencing
127	For population genomic analyses, we collected 2-3 shoots attached by a rhizome from fifteen
128	putative genets (separated by approximately 5-10 m) at 14 sites across Tomales Bay and
129	Bodega Harbor in California (Table 1) from a height below 0.0 mean lower low water (MLLW)
130	(i.e., not sampling the uppermost or lowermost vertical distribution of <i>Z. marina</i>). At our study
131	sites (and throughout much of the Pacific Ocean) genets cover a relatively small area such that

132 ramets sampled 1 - 2m apart rarely include the same multi-locus genotype (Kamel et al. 2012;

133	Reynolds et al. 2017; Duffy et al. 2022; Kollars et al. 2022). For two of the sites sampled in
134	Bodega Harbor (Mason's Marina and Westside Park) we also collected a deeper set of
135	specimens (at least –0.6m below MLLW) to test for genetic differences between shallower
136	versus deeper plants. We transported plants back to the University of California, Davis in a
137	cooler with ice packs, and stored them for no more than one day in a recirculating seawater
138	table before dissecting out the tissue from within the leaf sheath of all shoots within a genet
139	and then flash-froze them in liquid nitrogen and stored at -80°C. Using the inner leaf sheath
140	tissue allowed us to minimize the amount of non-eelgrass DNA by selecting tissue that was free
141	of epibionts and had lower chloroplast concentrations.
142	We extracted DNA from up to 200 mg of frozen tissue by grinding with a plastic pestle
143	and liquid nitrogen in a 1.5 ml tube until powdered and then by using a modified CTAB
144	chloroform extraction (Doyle & Doyle, 1987). Briefly, tissue was resuspended in 800 ul CTAB
145	(0.1 M Tris-HCl [pH 8.0], 0.02 M EDTA [pH 8.0], 3% CTAB, 1.4 M NaCl, 0.2% β-mercaptoethanol),
146	after the first chloroform-isoamyl alcohol step, the upper aqueous phase was transferred to a
147	new tube and treated with 2 μ l of RNAse A at 37°C for one hour, followed by an additional
148	chloroform-isoamyl alcohol step before completing the remaining steps. We quantified DNA on
149	a Qubit fluorometer and adjusted the concentration to ~13 ng/µl; in cases where the
150	concentration was lower than 17 ng/ μ l the concentration was not adjusted. DNA quality was
151	visually assessed on a 2% agarose gel. We submitted genomic DNA for 240 individuals to the
152	Genomics and Bioinformatics Services Texas A&M Agrilife Research centre (College Station, TX)
153	for library preparation using the high-throughput PerkinElmer NEXTFLEX® Rapid XP DNA-Seq Kit

and paired-end 150bp sequencing (targeting 10X coverage with ~5.8Gb/sample) on two lanes
of a NovaSeq 6000 S4 X.

156

157 Alignment and SNP calling

158 For the whole genome sequences we used bbduk from the BBTools suite v38.73 for adapter 159 trimming and quality and length filtering (Bushnell, 2021; see code for specific parameters). We 160 aligned whole genome sequences to the Zostera marina 3.1 genome (NCBI accession number 161 PRJNA701932; Ma et al., 2021; Olsen et al., 2016) with bwa-mem in bwa v0.7.13 (Li & Durbin, 162 2009) and called SNPs using GATK v. 4.1.0.0 (McKenna et al., 2010). Briefly, we converted sam 163 files to bam format and sorted using samtools v1.9 (Li et al., 2009). Using GATK, we marked 164 duplicates, called haplotypes, combined g.vcf files and then genotyped individuals across 165 batches of 50 (following GATK recommendations for working with large cohort sizes). After 166 retaining only SNPs, we applied additional hard filters for mapping quality, strand bias, variant 167 confidence, and variants with excessive depth following the best practices guidelines in (Van 168 der Auwera et al., 2013; see code for specific parameters). Genotypes for individuals were 169 recoded to missing if they did not have a minimum depth of 10 and a minimum genotype 170 quality score of 30. Although we sampled plants 5-10m apart to limit sampling multiple clonal 171 shoots from the same genet, we also used the SNP data to identify and remove clones, which 172 could confound downstream population genetic analyses. To filter clones from the data set, we 173 used Rclone v1.0.2 (Bailleul, Stoeckel, & Arnaud-Haond, 2016) in R v4.0.3 (R Core Team, 2020) 174 with a reduced set of SNPs without any missing data (as required by the program) for each 175 geographic location separately. After removing clones we used vcftools v0.1.16 (Danecek et al.,

176	2011) to filter the final data set to include only bi-allelic SNPs with a minor allele frequency of at
177	least 0.01 and a genotype call rate of at least 85% of individuals.
178	
179	Population genetic analyses
180	For population genetic analysis, we first thinned the SNPs based on linkage disequilibrium (LD)
181	using SNPRelate (Zheng et al., 2012) with an LD threshold of 0.5 based on SNPRelate's
182	"composite" measure of LD. This thinned set was used for clustering analysis, PCA, and F_{ST} . We
183	used SNPRelate to conduct principal components analysis and to calculate pairwise F_{ST} (Weir &
184	Cockerham, 1984) between all pairs of sites. We conducted clustering analysis and estimated
185	ancestry proportions using the R package tess3r (Caye, Deist, Martins, Michel, & François,
186	2016). For each K value (1-6) we ran five replicate runs with the lambda parameter set to 0 to
187	ignore priors based on the spatial distribution of samples.
188	
189	Sampling water temperature
190	To record water temperature we deployed HOBO Pendant® MX2201 loggers (fastened to PVC
191	pipe) in the area at each of the sites from which we collected genetic samples. The pipe was
192	driven into the sediment until the logger was approximately <15 cm above the sediment
193	surface, positioned to rarely be emersed except during low spring tides. We recorded water
194	temperature at 15-minute intervals during a two-week period at all sites from August 16th to
195	29th in 2019 and for 14 weeks (Aug 1st – Nov 11th, 2019) for a reduced set of sites that
196	excluded Mason's Marina and one logger at Westside Park in Bodega and Pelican Point and Pita
197	Beach in Tomales Bay. Because our main interest was to determine the relative differences in

198 temperatures between sites, we calculated the mean and first and third quartiles for each

199 location and used Spearman's correlation coefficient to evaluate whether the two-week

200 temperature interval correlated with the longer 14-week interval.

201

202 Environmental association analyses

203 We used two approaches to search for SNPs associated with environmental gradients in 204 Tomales Bay and Bodega Harbor separately: (1) latent factor mixed models (LFMM), correlating 205 individual genotypes at each SNP with mean temperature at the sampling location (Figure 1) 206 using lfmm2 in LEA v4.0.0 (Frichot & François, 2015) and (2) F_{ST} outliers using OutFLANK v0.2 207 (Whitlock & Lotterhos, 2015), grouping warmer vs. cooler sites. For LFMM analysis, genotypes 208 were first imputed in LEA using ancestry coefficients estimated by LEA (K=3). The temperature 209 gradient in Tomales Bay reaches much higher temperatures than that in Bodega Harbor, so to 210 capture a similar range of temperatures for comparisons between bays, we also repeated the 211 analyses with a subset of four sites in Tomales Bay (Lawson's Landing, Pita Beach, Nick's Cove, 212 and Sacramento Landing; Figure 1) that more closely matched the temperature range of 213 Bodega Harbor. We hereafter refer to this reduced Tomales sample as "Tomales (cool)" We also 214 used OutFLANK to identify SNPs associated with higher versus lower intertidal habitat in 215 Bodega. All selection scans were performed after first filtering for SNPs with a minor allele 216 frequency greater than 5% for samples within a given subset of sampling locations. This filter 217 reduces the number of tests performed and discards SNPs unlikely to result in true positives 218 (Caye et al., 2019). Additionally, we assessed outlier SNPs at two different significance cut-offs: 219 p < 0.001, a more liberal cutoff without multiple test correction and q < 0.05, adjusted for false

220	discovery rate. Because false negatives can be high especially for moderate sample sizes and
221	complex traits, the opportunity to compare across these two significant thresholds provides
222	information about the sensitivity of our conclusions to these decisions.
223	To characterize parallel associations with temperature at the SNP level between the two
224	bays, we directly compared the genomic positions of outlier SNPs from the LFMM and
225	OutFLANK analyses. At the gene level, we used LD-Annot v0.4 with $r^2 = 0.9$ (Prunier et al., 2019)
226	to first identify the genes in linkage disequilibrium with candidate SNPs and then compare lists
227	to detect overlapping genes. Finally, to determine whether there was overlap at the functional
228	level, we tested whether the outlier-associated gene sets were enriched for particular gene
229	ontology (GO) terms using TopGO v2.40.0 (Alexa & Rahnenführer, 2009) in R. We used a
230	possible gene universe of all genes within linkage disequilibrium (r ² = 0.9) of the full set of SNPs,
231	rather than the full set of annotated genes. We used a Fisher's exact test to identify significantly
232	enriched GO terms and required that more than two genes be significant for a particular GO
233	term. We used a significance threshold of p<0.05 and did not adjust for multiple testing, as
234	suggested in (Alexa & Rahnenführer, 2009), as our goal was to summarize the functional
235	categories based on our SNPs rather than to make strong conclusions about any particular GO
236	term.

To test predictability of genotype-environment associations within and across bays, we created polygenic scores using the R-package randomForest v4.6-14 (Liaw & Wiener, 2002). We used the mean temperature for each site as the response variable and candidate SNPs derived from LFMM or OutFLANK analyses as predictors. To reduce redundancy and computational time due to extensive linkage across our candidate SNPs, we first thinned the candidate SNP

242 sets based on linkage disequilibrium in SNPRelate (ld.threshold = 0.5). Because randomForest 243 cannot accept missing data, we used genotypes that were imputed with LEA. We ran separate 244 random forest models with the sets of candidate SNPs from LFMM and OutFLANK for each bay. 245 For each SNP set, we conducted runs using either all samples to train the model, or only 246 samples from the bay from which the candidate set was derived (e.g., when candidate SNPs 247 were identified using analysis of Bodega Harbor samples, we trained using either all samples or 248 Bodega Harbor samples only). For validation, we used either all samples, Bodega Harbor only, 249 or Tomales Bay only. To limit bias in the training set, we conducted cross-validation at the level 250 of the sampling site, training the random forest on the dataset with a single sampling site 251 removed, then predicting temperature for that site. For each random forest run, this procedure 252 gave us a random-forest predicted temperature for each individual sample based on candidate 253 SNPs. We then compared predicted and observed temperatures using Spearman's correlation 254 coefficient. For each run, we report the percent variance explained in the training model and 255 the correlation coefficient when comparing observed and predicted temperatures. 256 Because isolation-by-distance is strong in Z. marina at this scale in this region (Kamel et 257 al. 2012), we used two approaches to reduce the impacts of IBD driving our predictive power. 258 First, we included in our random forest predictors the sample loadings on the first two PC axes. 259 These first two PC axes represent the major geographical patterns in the system. Second, we 260 ran both training and prediction with 100 random sets of SNPs (in addition to the first two PC 261 axes). We used these randomizations to estimate a 90% confidence interval for a null 262 distribution, showing how well our predictions performed when based on neutral genetic

263	variation alone.	. When observe	d variance	explained b	by the rar	ndom for	rest model o	or Spearman's	S
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- 264 correlation coefficients fell outside this range, we considered them significant.
- 265
- 266 Results
- 267
- 268 Genetic variation

269 After filtering and removing 14 individuals due to low read count, we retained 446,718 SNPs. 270 Where putatively separate samples were identified as clonemates, we retained only one 271 individual from each genet, resulting in 42 additional samples excluded (Table 1, Figure S1). In 272 Tomales Bay, a greater fraction of our samples were identified as clonemates (Figure S1). In the 273 final set of 182 individuals and 446,718 SNPs, 91% of individuals had less than 20% missing 274 data; and all individuals had less than 29% missing genotypes. After thinning for linkage 275 disequilibrium, we were left with 46,166 SNPs for analysis of population structure. Both within 276 and among bays, we found strong isolation by distance (IBD), with pairwise F_{ST} correlated with 277 geographic distance between sites (Figure S3; Spearman's ρ =0.65). Differentiation between 278 bays was highest (mean pairwise F_{ST} = 0.058, SD = 0.020), and sites within Tomales Bay were 279 more differentiated (mean pairwise F_{ST} = 0.047, SD = 0.021) than sites within Bodega Harbor 280 (mean pairwise F_{ST} = 0.002, SD = 0.005). Both PCA and clustering analyses supported the IBD 281 pattern (Figure 1), with PC1 and PC2 explaining 4.06% and 1.98%, respectively. Bodega Harbor 282 and Tomales Bay represented distinct clusters on the PCA plot, separated along PC1. PC2 283 mirrored the geography of Tomales Bay, with higher values for sites closer to the mouth of the bay. In the clustering analysis, we observed decreasing cross-validation scores across all values 284

285	of K, suggesting no clear 'best' K value within the range we tested. We present K=3 (Figure 1),
286	as K=4 did not show further geographic differentiation but rather separated five Bodega Harbor
287	individuals. However, at higher K values (K=5,6) additional structure within Tomales Bay
288	became apparent, further highlighting the strong IBD signal (Figure S2).
289	
290	Environmental association analyses
291	We documented clear temperature gradients within both Bodega Harbor and Tomales Bay.
292	Summer mean temperatures recorded from 16-29 August in 2019 in Bodega Harbor and
293	Tomales Bay ranged from 16.1–18.5°C and 16.1–22.2°C, respectively, with the mouth of each
294	bay cooler than the back of the bay (Figure 1 <i>C</i> ; Figure S4). Mean temperatures over this two-
295	week period were highly correlated with an extended period (1 August to 11 November;
296	ρ =0.95, p <2.2e-16) for which we had logger coverage at all but three sites in Bodega Harbor
297	(two at Mason's Marina and one at Westside Park) due to logger failure, and all but two sites in
298	Tomales Bay, because the Pelican Point and Pita Beach loggers were not deployed until mid-
299	August (Figure S4). The ordinal ranking of sites by summer temperature reported here is
300	identical to that in other studies of subsets of these sites with longer temperature records (Aoki
301	et al., 2022; DuBois et al., 2022).
302	We identified SNP candidates for selection within each of the two embayments. After
303	filtering for minor allele frequency >5%, 357,010 SNPs remained for environmental association
304	analysis. The vast majority of genetic variation is shared across bays, with only 7,984 SNPs
305	(2.2%) being fixed in one of the bays. Table 2 summarizes the number of SNP outliers at each
306	significance threshold for all analyses. In this discussion and in downstream analyses, unless

307	stated otherwise, we use the false discovery rate-corrected (q<0.05). Bodega Harbor, 8560
308	candidate SNPs were associated with site mean temperature in the LFMM analysis and 314
309	SNPs were significant outliers when comparing the warmest vs. coolest sites in OutFLANK
310	(Figure 2; Table 2). Of the 8472 SNPs identified by LFMM, 8183 (96%) are largely located in a
311	single linked block on Chromosome 1 (Figure 2). Twenty-nine SNPs overlapped between these
312	two analyses. We found 711 genes in linkage disequilibrium with candidate SNPs from the
313	LFMM analysis and 62 from the OutFLANK analysis (see supplementary files), of which 17
314	overlapped between both analyses. Gene enrichment analyses of the candidate genes
315	identified 33 GO terms from LFMM (15 after removing the highly linked region) and 9 from
316	OutFLANK, though none overlapped between the two analyses (Table 2; supplementary files).
317	In the LFMM analysis, significant GO terms included categories broadly involved in cell wall
318	modification, nucleotide metabolism, and enzyme activity while the OutFLANK analysis
319	highlighted categories related to lipid metabolism and heme binding, among others.
320	For Tomales Bay, there were no SNPs significant (q<0.05) when including all Tomales
321	locations. At the unadjusted significance cutoff, 659 candidate SNPs ($p < 0.001$) were associated
322	with mean site temperature across all 10 sampling sites (Table 2; Figure 2). In the LFMM
323	analysis that was restricted to the four coolest sites that most closely matched the temperature
324	gradient of Bodega Harbor, LFMM identified 6710 SNPs (q<0.05) (Figure S5). As with the
325	Bodega Harbor LFMM analysis, the large number of significant SNPs in the reduced Tomales
326	LFMM analysis is largely due to a single highly linked block of SNPs on Chromosome 1; with
327	6256 of 6710 (93%) in that region. The OutFLANK analyses comparing warmer versus cooler
328	sites in Tomales did not yield any candidate SNPs, for either the full 10 sites or the reduced set

of four sites. We found 662 genes in linkage disequilibrium with candidate SNPs from the LFMM
analysis restricted to only the cooler sites. Twenty GO terms were enriched in the Tomales
(cool) LFMM analysis, including nucleic acid and amino acid metabolism functions and enzyme
activities. When the linked section of Chromosome 1 was excluded, 21 terms were enriched
including functions associated with oxidative stress, carbohydrate metabolism, and organic
compound binding.

335

336 Tidal height associations

337 The OutFLANK analysis comparing samples from upper and lower tidal heights in Bodega 338 Harbor identified 461 SNPs differentiating the two groups (Table 2, Figure S6, supplementary 339 file). Only one of these SNPs overlapped with other environmental association analysis at the 340 SNP, gene, or functional levels. The unique SNPs differentiating upper and lower intertidal 341 groups were in linkage disequilibrium with 108 genes (Table 2). Gene enrichment analysis found 342 49 enriched GO-terms (Table 2; supplementary files). Most enriched GO terms were generally 343 involved in transcriptional regulation. None of these GO terms overlapped with any of the 344 environment association analyses.

345

346 (Non)overlapping associations

347 There was no overlap in candidate SNPs between Tomales and Bodega Harbor association

- 348 analyses (Figure 3), with the exception of one highly linked region. Even at a more lenient
- 349 significance cutoff (unadjusted p<0.001) only 114 candidate SNPs overlapped between
- 350 embayments, a small fraction (0.8%) of the total 13,360 candidates across all analyses,

351	excluding the highly linked region (Figure S7). There were 5265 significant SNPs that overlapped
352	between the Tomales LFMM analysis restricted to cooler sites and the Bodega LFMM analysis.
353	These SNPs were all located on a single linked region of Chromosome 1 (Figure 2, Figure S5) and
354	so likely represent a single locus. We found 549 genes linked (at LD r^2 = 0.9) to candidate SNPs
355	in the Tomales LFMM analysis that was restricted to four cooler sites overlapped with the
356	Bodega OutFlank analysis. After excluding SNPs from the highly linked region, there was still
357	overlap in four genes, despite the absence of overlap at the SNP level. These included a
358	phytochrome interacting factor (PIF1) and endoglucanase, as well as two genes that also were
359	also significant in the more lenient (p<0.001) Tomales LFMM analyses that included all 10
360	locations: UDP-glucuronate:xylan and protein disulfide isomerase.
361	Gene ontology (GO) enrichment analysis for outlier-associated gene sets revealed 14 GO
362	categories that overlapped between the Bodega and Tomales analyses when all SNPs were
363	included. These categories include a range of functions associated with enzyme activity, RNA
364	metabolism, and binding of sugars and phosphates. However, when the large linked region is
365	removed, there are still five functional categories that overlap between Bodega and Tomales
366	(cool) analyses: carbohydrate biosynthetic process, heme binding, UDP-glycosyltransferase
367	activity, transferase activity, and tetrapyrrole binding. Although the large linked block of SNPs
368	represents a prime candidate for follow-up studies, it was not significant in the analysis of all
369	Tomales locations and was only slightly above the significance threshold in the reduced
370	Tomales set. Additionally, both the Bodega and reduced Tomales analyses contain few sites (6
371	in Bodega including high/low intertidal and 4 in Tomales), so further information is needed to
372	test a role for this region in parallel evolution.

373 Polygenic analyses using random forest successfully predicted temperature variation 374 from SNP variation within bays. We used four sets of candidate SNPs that yielded significant 375 candidates for SNPs associated with temperature: Candidates from the three analyses that 376 yielded significant SNPs at q<0.05 (Bodega LFMM, Bodega OutFLANK, and Tomales (cool) 377 LFMM) and an additional set from the full Tomales LFMM at p<0.001, which was included so 378 that we had representation from SNPs that might vary with temperature across the full length 379 of Tomales Bay. We trimmed each SNP set for LD, yielding 175, 61, 121, and 86 SNPs 380 respectively, and used these thinned sets as predictors in the random forest alongside the first 381 two PC axes (to reduce the impact of population structure). Figure 4A-C shows an example run, 382 in which we built the random forest model using SNPs significant in the Bodega LFMM analysis 383 and used all sites in both training and prediction (leaving out one site at a time). In this analysis, 384 the candidate SNPs result in a model with a higher fraction of variance explained (R²=0.84) than the same number of random SNPs (90% confidence interval 0.76-0.80). Additionally, the 385 386 correlation between observed temperature and that predicted by the random forest analysis 387 (Figure 4B) is higher than with a random set of SNPs (Figure 4C; ρ =0.80; 90% CI=0.62-0.69). In 388 all cases except the Tomales (cool) LFMM, the percent variation explained by the random forest 389 model was significantly higher than with a random set of SNPs. When Tomales Bay sites were 390 used to train the random forest, the null distribution also explained a large percentage of the 391 variance, likely because we included PC axes in the model, which represent the strong isolation 392 by distance in Tomales Bay rather than temperature per se. Still, candidate SNPs rather than 393 random SNPs explained a significantly higher proportion of the variance.

394	Although random forest models performed well when candidate SNP discovery and
395	prediction included only locations within a single embayment, the models did not necessarily
396	perform well when predicting across embayments (Figure 4D). Temperature-associated SNPs
397	discovered in Tomales Bay using LFMM did not predict the temperature at the sites from which
398	Bodega Harbor individuals were collected. Interestingly, random SNPs trained and predicted on
399	Bodega Harbor individuals had a high but negative correlation between observed and predicted
400	temperature (mean LFMM $ ho$ =-0.72; OutFLANK $ ho$ =-0.69). These negative correlations have been
401	seen in previous studies (Exposito-Alonso et al., 2019), and may reflect an unmeasured
402	environmental variable that is negatively correlated with temperature and with overall
403	population structure. Notably, however, models based on SNPs discovered in Bodega Harbor
404	(both LFMM and OutFLANK) show significantly higher predictive capability than random SNPs,
405	even when predicting the temperature of Tomales Bay sites and regardless of training
406	population.
407	Although the overall success of prediction within embayments and mixed performance
408	across bays is consistent with the lack of parallelism at the SNP level, the significant predictive
409	power of SNPs discovered within the Bodega Harbor candidate SNPs for plants in both
410	embayments suggests that our genome scans may have missed more subtle parallelism. We
411	used the variable importance rankings in the random forest to identify SNPs that contributed
412	most to models trained on Bodega Bay samples, which ultimately resulted in improved
413	predictions of temperature across both bays. Two measures of importance are available within
414	the random forest framework: increase in mean squared error and increase in node purity.

Both measures identified three SNPs (one from OutFLANK and two from LFMM) with

416 substantially higher importance than other SNPs or even PC axes (Figure S8), though none 417 overlapped directly with other candidate SNPs from Tomales Bay (Figure 3) or showed linkage 418 with the nearest candidate SNPs (with the range of LD r² from 0.001–0.089 at 0.11–6.7 Mb 419 away from the SNPs). Allele frequencies for these SNPs show that they are associated with 420 temperature across both bays and standard linear models indicate a significant correlation with 421 temperature (p<0.05), even when embayment is included as a covariate (Figure S9). Therefore, 422 while the overwhelming conclusion from the genome scans was a lack of parallelism, it appears 423 that the polygenic framework revealed subtle parallel signals. 424 425 Discussion 426 Many factors influence the degree of parallel change in parallel selective environments, such as 427 population size, population history (demographic and genetic), gene flow, environmental 428 heterogeneity, and the fact that there are multiple pathways to the same functional endpoint 429 (Bolnick et al., 2018; Conte et al., 2012; Ralph & Coop, 2015). That all of these vary widely in 430 natural populations at least in part explains the mixed results observed in analyses of

431 parallelism in the wild (Kern & Langerhans, 2018; Oke, Rolshausen, LeBlond, & Hendry, 2017;

432 Stuart et al., 2017). In our study we examine a system in which parallelism would be expected

433 to be likely due to overlapping selective gradients in geographically proximate populations.

434 Counter to this expectation and despite a large degree of shared genetic variation overall, we

- 435 find that genomic signatures of selection in *Zostera marina* are largely non-overlapping at the
- 436 SNP level. However, there is detectable overlap in the genes and functional categories
- 437 associated with temperature variation, and some predictability of temperature across gradients

438 using polygenic scores. Together, these data suggest a complex pattern of subtle parallelism 439 within a mostly non-parallel signal. This supports the emerging view of parallelism as 440 continuous rather than binary (Bolnick et al., 2018). 441 The degree of local adaptation and parallelism can be influenced by the magnitude of 442 gene flow among populations, with migration from nearby populations providing sources of 443 both adaptive and maladaptive genetic variation. We find strong differentiation and isolation by 444 distance among our sample sites, both within and between bays. This is likely due to limited 445 pollen and seed dispersal in Z. marina (Ruckelshaus, 1996). Microsatellite studies from Bodega 446 Harbor and Tomales Bay, as well as several other regions, show consistently strong genetic 447 differentiation even at small spatial scales (Campanella et al., 2010; DuBois et al., 2022; Kamel 448 et al., 2012; J. H. Kim et al., 2017; Muñiz-Salazar, Talbot, Sage, Ward, & Cabello-Pasini, 2005; 449 Ort, Cohen, Boyer, & Wyllie-Echeverria, 2012). With limited gene flow to disrupt the effects of 450 selection, local adaptation might occur and be maintained very quickly even at microgeographic scales (Richardson, Urban, Bolnick, & Skelly, 2014). 451 452 Within each bay, genotype-environment associations were strong, consistent with

previous work establishing local adaptation among populations in Tomales Bay. Dubois et al.
(DuBois et al., 2022), in a reciprocal transplant that included three of the sites in the present
study, documented home-site advantage in survival and growth. Laboratory experiments
identified temperature (along with light and grazing pressure) as one of the drivers of local
adaptation, with plants from the cool end of the gradient showing decreased performance
under elevated temperatures. In Bodega Harbor, temperature-associated SNPs were linked to
genes enriched in metabolic processes (e.g., lipid metabolism, oxidation reduction) and cell wall

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460 synthesis (e.g., pectinesterase activity, cell wall modification). These perhaps reflect genotype
461 and environment-specific tradeoffs in the use of carbon for growth and metabolism. In Tomales
462 Bay, gene ontology enrichments involved both categories potentially related to growth (e.g.
463 carbohydrate biosynthetic process, cellular carbohydrate metabolic process), but also stress
464 response (e.g. response to oxidative stress, antioxidant activity).

465 Despite evidence for selection across each temperature gradient, there was little 466 overlap in signals of selection at the SNP level. The lack of a pervasive signal of parallelism at 467 the genomic level in the two populations inhabiting Tomales Bay and Bodega Harbor could 468 reflect the impacts of several historical and contemporary evolutionary processes. First, despite 469 their proximity, the two embayments may not be recently derived from the same ancestral 470 population and could instead originate from different sources that had already differentiated to 471 a greater or lesser extent. Second, contemporary gene flow is low between bays (based on our population structure analyses), and even within bays population structure is guite high, likely 472 473 because of overall limited pollen and seed dispersal (Ruckelshaus, 1996). Beneficial (and 474 deleterious) alleles will thus be slower to spread between bays. Using simulations, Ralph and 475 Coop (2015) demonstrated that in patchy habitats the threshold at which patches are more 476 likely to evolve independent beneficial mutations is a function of dispersal distance and 477 selective advantage of the mutations. In the patchy eelgrass system characteristic of both 478 Tomales Bay and Bodega Harbor, with limited dispersal of pollen and seeds, very strong and 479 persistent selection may be required to enhance the spread of shared adaptive alleles. This is 480 potentially exacerbated by the fact that warmer sites, which exert the strongest selection pressure, are farthest from the mouths of the bays so that when a beneficial allele arises it 481

482 must pass through less favorable habitat, impeding gene flow to other populations, even those
483 nearby (Ralph & Coop, 2010, 2015).

484 Finally, the range of temperatures within Tomales Bay is much greater than in Bodega 485 Harbor, although we did attempt to reduce the impact of these differences by conducting a 486 reduced analysis based only on overlapping temperature ranges. However, adaptation to other 487 factors besides temperature, whose relative importance may differ between the two 488 embayments, could disrupt parallel signals of selection. For example, seasonal upwelling and 489 phytoplankton and macroalgae blooms are associated with spatially and temporally fluctuating 490 temperature, salinity, chlorophyll, and dissolved oxygen (Hollarsmith et al., 2020; Kimbro, 491 Largier, & Grosholz, 2009). Two of our sites with very similar temperature conditions still 492 exhibited local adaptation to differences in light availability as a result of differences in 493 macroalgal abundance between the sites (DuBois et al., 2021). Although temperature may still 494 impose strong selection, these other sources of selection may constrain the degree of 495 parallelism through, for example through tradeoffs maintained by pleiotropy or epistasis. For 496 example, an analysis of lake-stream pairs of stickleback, although all had adapted across the 497 same primary axis (flow), parallelism was higher when environmental differences were 498 generally more similar (Stuart et al., 2017), highlighting the complexity of multivariate 499 adaptation in wild populations.

500 Even in highly controlled laboratory experiments, parallelism at the genomic level is far 501 from pervasive, suggesting that in natural populations, where ancestry, selective landscapes, 502 and historical and contemporary patterns of gene flow are far more complex, deep parallelism 503 is even less likely (Bailey, Blanguart, Bataillon, & Kassen, 2017; Lenski, 2017). Indeed, a growing

504	number of studies examining adaptation across parallel selection gradients reveal a mix of
505	parallel and non-parallel signals (e.g., Liu et al., 2018; Rivas et al., 2018; Stuart et al., 2017). In
506	our data, despite the overall lack of overlap of signals of selection between the two
507	embayments at the SNP level, there was a small amount of overlap at the gene level and some
508	power for predicting temperature with polygenic scores. Although candidate SNPs from each
509	bay analysed separately had little overlap, the random forest model could still predict Tomales
510	Bay temperatures based on Bodega Harbor candidate SNPs, an unlikely relationship in the
511	absence of any parallel signal.
512	Notably, the most informative SNPs in the random forest model showed correlations
513	between allele frequencies and temperature. These SNPs were perhaps undetected in the
514	genome scan because their effect in Tomales Bay was below the significance threshold; we did
515	not have the power in our study to detect their effects. This is likely a larger issue for detecting
516	parallelism in highly polygenic traits, where we expect small shifts in allele frequencies across
517	many SNPs. Despite the lack of overlap in candidate SNPs, four genes overlapped between
518	Bodega and Tomales analyses, even after we excluded the linked region on Chromosome 1.
519	Since some of the comparisons had no SNP overlap, this may be a case where different
520	mutations in the same gene can lead to comparable phenotypic effects. A similar case was seen
521	in a comparison of small and large morphs of Arctic Charr across multiple lakes in Labrador,
522	where outlier SNPs were largely non-overlapping, but there was overlap at the gene and
523	paralog levels, suggesting multiple mutational pathways to the same functional outcome
524	(Salisbury et al., 2020). In our study, the four genes overlapping between Bodega and Tomales
525	were UDP-glucurorate, protein disulfide isomerase (PDI), an endoglucanase, and PIF1. All of

526	these genes have known functions in plants, many related to growth. Both the endoglucanase
527	and UDP-glucurorate function in cell wall synthesis (Kuang et al., 2016), and PDI and PIF1 are
528	involved in chloroplast regulation and chlorophyll biosynthesis (J. Kim & Mayfield, 1997; Moon,
529	Zhu, Shen, & Huq, 2008). This perhaps points to different genotypes having different light
530	harvesting abilities, which can result in differences in growth and thermal performance. This
531	hypothesis is in line with previous work in Z. marina showing genotypic differences in growth
532	under different temperature and seasonal (light) conditions (DuBois et al., 2021). At the
533	functional level, overlapping enriched GO terms between Bodega and Tomales may also be
534	interpreted as associated with growth, including "carbohydrate biosynthesis process" and UDP-
535	glycosyltransferase activity while others, such as "transferase activity" and "tetrapyrrole
536	binding" may be involved in signaling. Additionally, "heme binding" was enriched in both
537	Bodega and Tomales analyses. Hemes play a number of roles in eukaryotic cells, including
538	respiration, transcription, and protein degradation (Severance & Hamza, 2009).
539	The most striking exception to the lack of parallelism was a large region of completely
540	linked SNPs, covering approximately 5Mb on Chromosome 1. These SNPs were significant in
541	both LFMM analyses of Bodega Harbor sites and the four cooler sites in Tomales Bay. We
542	hypothesize that these linked sites represent a chromosomal rearrangement, such as an
543	inversion, that is polymorphic in the sampled populations. Because of the suppressed
544	recombination between alleles, inversions may preserve the integrity of co-adapted gene
545	complexes, which could be especially beneficial when there is gene flow across the selective
546	gradient (Thompson & Jiggins, 2014; Wellenreuther & Bernatchez, 2018). With the increasing
547	accessibility of whole genome sequencing, large inversions appear to be more common than

548	previously thought and may be maintained by selection for a long period (Wellenreuther &
549	Bernatchez, 2018). An interesting case study is that of the seaweed fly Coelopa frigida, where
550	inversions are associated with life-history trait variation and show strong and parallel
551	segregation across bioclimatic gradients on two continents (Mérot et al., 2018, 2021). However,
552	links between genotype and environment in our study must be cautiously interpreted because
553	of limited sampling replication across parallel thermal gradients. Further sequencing with long
554	reads will be required to characterize the putative rearrangement. Trait-mapping studies and
555	sampling with broader geographic scope are essential for understanding the fitness
556	consequences of the inversion across different environments.
557	The distribution of climate-associated standing genetic variation in contemporary
558	populations will determine their capacity to adapt to future environmental challenges.
559	However, predictions of future adaptive responses will be aided by an understanding of the
560	genetic architecture of local adaptation (Bay et al., 2017; Capblancq, Fitzpatrick, Bay, Exposito-
561	Alonso, & Keller, 2020). In Zostera marina there is mounting evidence that marine heatwaves
562	can reduce growth and reproduction (Ehlers, Worm, & Reusch, 2008; Qin et al., 2020; Saha et
563	al., 2020; Smale et al., 2019), but also that these impacts vary across individuals and
564	populations (Bergmann et al., 2010; DuBois et al., 2019; DuBois, Williams, & Stachowicz, 2020).
565	This study shows strong but largely non-parallel temperature-associated genetic variation
566	across adjacent bays. Whether this is due to a low overall dispersal distance, slowing the spread
567	of adaptive alleles, polygenic adaptation with little overlap in genetic architecture, or
568	populations are adapted to a different suite of complex environmental conditions remains
569	unclear. The distinction is important when considering the loss of genetic variation due to

570	disturbance or when choosing genotypes for restoration: do populations from comparable
571	thermal regimes offer comparably effective sources for restoration of impacted habitats? Our
572	results additionally set expectations for the degree of parallelism we might expect range-wide
573	in Z. marina. Our study, which represents conditions likely to generate parallelism (i.e.,
574	geographic proximity, overlapping gradients, contemporary gene flow) shows weakly parallel
575	signals at best, which suggests that parallelism at the genomic level across global Z. marina
576	populations is unlikely. Further understanding of the phenotypic effects of candidate SNPs
577	under a range of environmental conditions is essential for understanding how parallel selection
578	shapes the evolutionary trajectories of geographically distinct populations, and for developing a
579	more general framework for predicting individual and population response to warming
580	temperatures.

581

582 Authors' contributions

583 L.M.S.: conceptualization, data curation, formal analysis, investigation, methodology, project

administration, resources, validation, visualization, writing - original draft, writing - review &

585 editing. R.A.B.: conceptualization, data curation, formal analysis, funding acquisition,

586 investigation, methodology, project administration, resources, supervision, validation,

587 visualization, writing - original draft, writing - review & editing. R.K.G.: conceptualization,

588 funding acquisition, investigation, project administration, resources, supervision, writing -

review & editing. J.J.S.: conceptualization, funding acquisition, investigation, methodology,

590 project administration, resources, supervision, writing - review & editing

592 **Conflict of interest**

593 The authors have no conflict of interests.

594

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607 Data accessibility statement

- 608 All code, supplementary files, and temperature data are available from the Dryad Digital
- 609 Repository: https://doi.org/10.6071/M3DD4F (Schiebelhut, Grosberg, Stachowicz, & Bay,
- 610 2022b). Sequence data are available at the NCBI Sequence Read Archive (SRA) under BioProject
- 611 PRJNA887384 (Schiebelhut, Grosberg, Stachowicz, & Bay, 2022a).
- 612

613 Benefit-sharing statement

- 614 Benefits Generated: Benefits from this research accrue from the sharing of our data and results
- 615 on public databases as described above.
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618 Tables

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620 **Table 1.** List of sample sites, latitude, longitude, sample sizes for genetic analyses, and mean

621 temperature for *Z. marina* intertidal collections. Sample sizes indicate the final numbers of

622 individuals included in analyses after filtering out individuals with high missing data and those

Т

623 that came from the same genet. Parentheses indicate values for lower intertidal samples at

- 624 Mason's Marina and Westside Park.
- 625

Вау	Site name	Site code	Collection Date	Latitude	Longitude	n	Mean temperature (°C)
Bodega	Mason's Marina	ММ	16/Jul/2019; 29/Sep/2019	38.3334	-123.0595	11 (9)	17.4 (17.3)
	Doran Beach	DB	16/Jul/2019; 30/Sep/2019	38.3209	-123.0455	14	18.5
	Westside Park	WP	16/Jul/2019; 29/Sep/2019	38.3195	-123.0538	13 (10)	16.8 (16.4)
	Campbell Cove	сс	16/Jul/2019; 29/Sep/2019	38.3097	-123.0584	12	16.1
Tomales	Lawson's Landing	LL	18/Jul/2019; 27/Sep/2019	38.2303	-122.9588	14	17.3
	Pita Beach	РВ	16/Aug/2019	38.2049	-122.9495	7	16.1
	Nick's Cove	NC	01/Aug/2019; 27/Sep/2019	38.2048	-122.9272	14	20.3
	Pelican Point	РР	16/Aug/2019	38.1874	-122.9324	10	16.8
	Blake's Landing	BL	01/Aug/2019; 27/Sep/2019	38.1785	-122.9091	14	20.4
	Sacramento Landing	SL	30/Jul/2019; 26/Sep/2019	38.1496	-122.9056	10	19.8
	Marshall Store	MS	30/Jul/2019; 26/Sep/2019	38.1522	-122.8889	13	20.9
	Heart's Desire	HD	26/Sep/2019; 30/Jul/2019	38.1328	-122.8918	12	20.9
	Teacher's Beach	ТВ	30/Jul/2019; 26/Sep/2019	38.1141	-122.8694	8	22.0
	Millerton Point	MP	31/Jul/2019; 26/Sep/2019	38.1050	-122.8464	13	22.2

629 **Table 2.** Summary of candidate SNPs from environmental association analyses and linked

- 630 genes. Each analysis was conducted for each bay separately. For Tomales Bay, in addition to
- 631 using all sites in the LFMM and OutFLANK analyses we also performed the analyses on a
- reduced set of four locations that had a temperature profile more closely matching Bodega
- Harbor. The number of candidate SNPs are reported for p < 0.001 and false discovery rate
- adjusted q < 0.05. Numbers in parentheses exclude the large linked region on Chromosome 1
- 635 (positions 32,368,298–37,501,531). Numbers of candidate genes and functions were evaluated

636 for SNPs with q < 0.05.

637

Вау	Analysis	Candidate SNPs (p-value<0.001)	Candidate SNPs (qvalue<0.05)	Candidate Genes	Candidate Function
Bodega	LFMM	8472 (289)	8560 (377)	711 (138)	33 (15)
	OutFLANK	4704 (4682)	314	62	9
Tomales	LFMM - all sites	659	0	NA	NA
	OutFLANK - all sites	0	0	NA	NA
	LFMM - cooler sites	6704 (449)	6710 (454)	662 (97)	20 (21)
	OutFLANK - cooler sites	3439 (3411) 🦊	0	NA	NA
Bodega	OutFLANK - tidal	4285	461	108	49









Figure 1. Sampling locations and population genetic structure in Z. marina. (A) The map

indicates the geographic locations where Z. marina were collected and temperature loggers deployed (see Table 1 for site details and sample sizes). Colored points and letters correspond to points in the (B) PCA. (C) Estimated ancestry proportions from clustering analysis (K=3) for each individual, organized by sample site (D) Boxplots show the median temperature and first

and third quartiles for each site, as measured over a two-week period in August 2019.



Figure 2. Manhattan plots show putative regions of interest from environmental association analyses using LFMM with average site temperature and OutFLANK comparing warmer versus cooler sites for Bodega and Tomales separately. For LFMM plots, the red line indicates p=0.001 and for the OutFLANK points with q<0.05 are highlighted in red. Insets show the number of outlier SNPs by chromosome, excluding the outliers contained in the large linked region on Chromosome 1.

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Figure 3. Overlap among analyses for detecting SNP associations with temperature across two
 adjacent embayments. Three sets of candidate SNPs are represented, those detected in Bodega

adjacent embayments. Three sets of candidate SNPs are represented, those detected in Bodega
 by LFMM, in Bodega by OutFLANK, and detected in Tomales (cool) by LFMM. Other analyses did

681 not contain significant SNPs at a threshold of q<0.05. (**A,B**) Overlap at the SNP level for all SNPs

682 (A) and excluding the highly linked region on Chromosome 1 (B). (C,D) Overlap in genes linked

to all candidate SNPs (**C**) and excluding the highly linked region on Chromosome 1 (**D**).



684 685 Figure 4. Polygenic analysis with random forest suggests limited predictability of thermal 686 environment across bays. (A-C) An example run showing candidate SNPs from the LFMM 687 analysis in Bodega Bay. (A) Variance explained by random forest using candidate SNPs as 688 predictors (red line) vs. 100 runs with random SNPs (grey histogram). (B) Random forest 689 predicted temperatures plotted against observed temperatures for both Bodega and Tomales 690 samples. (C) Correlation coefficients between observed and random forest predicted 691 temperature using candidate SNPs as predictors (red line) vs. 100 runs with random SNPs (grey 692 histogram). (D) All combinations of SNP sets and training/prediction populations used in the 693 random forest models. The first panel summarizes which SNP set was used (from top to 694 bottom: LFMM Bodega, OutFLANK Bodega, LFMM Tomales (cool), LFMM Tomales; there is no 695 OutFLANK for Tomales because this analysis did not yield any significant outliers) and which 696 groups were used for training and prediction (i.e., trained using both embayments or only the 697 local embayment to predict Bodega, Tomales, or both). Grey lines are 90% confidence intervals 698 from the randomizations, filled dots are outside that (i.e., 'significant') and open dots are not 699 significant.

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Figure 2. Manhattan plots show putative regions of interest from environmental association analyses using LFMM with average site temperature and OutFLANK comparing warmer versus cooler sites for Bodega and Tomales separately. For LFMM plots, the red line indicates p=0.001 and for the OutFLANK points with q<0.05 are highlighted in red. Insets show the number of outlier SNPs by chromosome, excluding the outliers contained in the large linked region on Chromosome 1.

1763x1763mm (72 x 72 DPI)



Figure 3. Overlap among analyses for detecting SNP associations with temperature across two adjacent embayments. Three sets of candidate SNPs are represented, those detected in Bodega by LFMM, in Bodega by OutFLANK, and detected in Tomales (cool) by LFMM. Other analyses did not contain significant SNPs at a threshold of q<0.05. (A,B) Overlap at the SNP level for all SNPs (A) and excluding the highly linked region on Chromosome 1 (B). (C,D) Overlap in genes linked to all candidate SNPs (C) and excluding the highly linked region on Chromosome 1 (D).

304x304mm (72 x 72 DPI)







% Variance Explained

🔲 Bodega

