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Supplementary Materials for

Precipitation drives global variation in natural selection

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Correction:
In conducting further analyses, we found an error in the supplemental analysis of climate-selection relationships in space and time separately (figs. S1 and S2). Data sets that were replicated in only one dimension were correctly handled, but others were erroneously included in both analyses. Using the correct subset of temporal replicates, we find, as before, very little association of temperature variables with selection. However, using the correct subset of the spatial replicates, we find evidence for associations of minimum, mean, and SD of temperature with the estimates of selection, but with large uncertainty (updated figs. S1 and S2). Precipitation variables (particularly the maximum and SD) explain appreciable proportions of the within-study variance of selection for both the temporal and spatial replicates. For most variables (minimum, maximum, mean, and SD) in both spatial and temporal comparisons, temperature explains lower or similar proportions of variation in selection than do precipitation variables. Thus, after correcting the subset analyses, the essential conclusions remain unchanged. However, there is some evidence for effects of temperature in explaining spatial, but not temporal, variation in selection. The revised supplement also contains additional text and two new figures (figs. S3 and S4) to assist with comparing the spatial and temporal subset analyses.

Materials and Methods

Selection database construction

We assembled a database of spatially (2 or more populations) and/or temporally (2 or more annual estimates from a given population) replicated studies of phenotypic selection on quantitative traits in the wild. By and large, the data sets were either spatially or temporally replicated; only 23 % of the selection estimates included both spatial and temporal replication in the same study. The database consists of standardized measures of selection coefficients: differentials and gradients. These standardized selection coefficients reflect selection on traits in terms of the relationship between relative fitness and variation in a quantitative trait measured in standard deviation units, and are desirable because they allow for cross-study comparisons, irrespective of study organism, fitness measure, or trait studied (*11, 12*).

   To begin, we combined earlier published databases that compiled studies on spatially (*25*) and temporally (*26*) replicated estimates of selection. Because the initial temporal database included studies published up until March 2008 and the spatial database studies up December 2011, we performed an additional literature search from March 2008 through December of 2012 to identify additional studies for inclusion. We reviewed the published literature for additional spatially and temporally replicated selection studies using the Web of Science indexing database system with the goal of identifying all studies estimating selection on multiple populations or multiple temporal replicates within populations. This search resulted in an additional 723 studies that we screened for inclusion in our final database. We also included two additional studies published shortly after December 2012 that we became aware of during our study.

   Our inclusion requirements included criteria used in previous database compilations (*12, 25, 26*). Specifically, we only included studies that (i) focused on wild, un-manipulated populations, (ii) estimated selection on quantitative traits that showed continuous variation, (iii) presented variance standardized selection differentials and/or gradients (*11, 12*) to facilitate comparisons across studies, and (iv) estimated selection in at least two populations or two annual temporal replicates within a population. When articles reported that selection had been measured on different populations, but data from multiple populations were combined for analyses, we contacted the authors to ask for population-specific selection coefficients. These later estimates were published in the appendix of (*26*). We relied on the author's designations of populations being unique if the populations were either noted by the authors as geographically distinct, or were reported in the article to be genetically distinct. We suspect some level of dispersal might occur between some populations, but most studies lacked information (e.g., analysis of neutral genetic markers) to evaluate this possibility. Three studies estimated selection over multiple years, but presented their data averaged over the duration of their study, and so we contacted these authors directly to obtain year-specific selection coefficients. These later estimates were published in the appendix of (*25*). When data were presented in figure format, we contacted authors directly to obtain values of the selection coefficients. Each article was entered into the database by one author and error checked

by a different author. The database is available from the Dryad Digital Repository and as Database S1.

In many studies, multiple datasets existed *within* studies. These within-study datasets represent selection estimated on different subsets of data defined by species, trait, fitness component, sex, age, etc. For clarity, we use the term "dataset" to refer to each unique combination of the above within studies.

Climate variables

We obtained local climate data at a resolution of 0.5 x 0.5 degree cells from the CRU-TS 3.1 Climate Database (*27*) spanning the years of data collected in the selection database. These climate data are one of the finest scale climate databases available at a global scale and are frequently used in large scale biological analyses such as ours (*28, 29*). Although the 0.5 degree cell size changes with latitude, our use of a 0.5 degree grid was simply the mechanism that rendered the opportunity to resolve the climate and selection databases. That is, with matched projections for coordinates and climate grids, the decrease in grid cell size with increasing latitude had little bearing on the fact that we simply extracted climate data from the 0.5 x 0.5 degree cell within which each population coordinate resides.

From these data, we generated grid files reflecting annual mean, annual standard deviation, and annual monthly minimum and maximum values for precipitation, temperature, and potential evapotranspiration (PET) across the study period. PET is an informative climatic index because it integrates the effects of temperature, humidity, and radiation to quantify the overall potential moisture deficit for a location (*30*). To obtain appropriate temporal and spatial climatic information for each study location, we performed a spatial overlay of study site coordinates over each climatic grid using the function *over* in the R package *sp* (*31*). This procedure was performed to estimate climate values experienced at each study location during the year in which the data were collected for a given population. This database is available from the Dryad Digital Repository and as Database S2.

We obtained annual global climate indices (ONI and NAO) from the National Weather Service at the National Oceanic and Atmospheric Administration. These indices relate variability in atmospheric forcing of climate change in northern and southern hemisphere mid-latitude regions. We used the Oceanic Niño Index (ONI) as a measure of the El Niño Southern Oscillation retrieved from http://www.esrl.noaa.gov/psd/data/correlation/oni.data [Accessed February, 2014]. The North Atlantic Oscillation (NAO) index was retrieved from http://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/nao.shtml [Accessed September, 2013]. For each year of study in our database we used the mean value of the monthly reported ONI and NAO indices.

We generated the Whittaker's biome plot (Fig. 1B of the main text) overlaid with selection estimates using the BIOMEplot package in R (*32*), where biomes are plotted

using annual mean cumulative precipitation and annual mean temperature that had been digitized from Ricklefs (*33*). To display the environments represented in our study samples through an overlay on Whittaker's biome plot, we used the annual mean temperature and annual cumulative precipitation generated from the CRU dataset for each location to calculate annual mean temperature and annual mean cumulative precipitation for each study across the duration of the study. Additionally, for the timeframe of each study we also calculated the lowest and highest annual mean temperature and annual mean cumulative precipitation to represent the climatic extremes experienced in each study.

<u>Meta-analytical model and analysis</u>

From earlier analyses, we know that there is non-trivial, detectable variation in selection in space and time (*25, 26, 34*), and progress has been made in developing meta-analytical methods to get at this variation accounting for the fact that variation in selection can be inflated by sampling error (*25, 34*). Thus, to control for sampling error we only used those records from the database that had associated standard errors with the selection coefficients (*n* = 2385 selection gradients and *n* = 946 selection differentials).

We used a random effects meta-analysis to determine the proportion of variation in selection across the entire database that could be accounted for by different climate variables after taking into account sampling error. This analysis can be most intuitively represented as a hierarchical model, separating the observation process (i.e., modelling statistical noise in inference of individual selection coefficients) and a process model (i.e., modelling variation in the underlying selection coefficients).

We model the observation process according to

(1) $\hat{\beta}_{i,j} \sim N\left(\beta_{i,j}, SE_{i,j}^2\right),$

where $\hat{\beta}_{i,j}$ is the *i*th selection coefficient (linear gradient or differential) estimate for the *j*th trait/study combination (that is, a given combination of phenotypic traits and/or fitness components, etc. for a given study; hereafter "trait"). Each selection gradient estimate $\hat{\beta}_{i,j}$ is assumed to be drawn from a normal distribution with a mean corresponding to the true, unobserved (i.e., latent), corresponding selection gradient $\beta_{i,j}$, and with a known variance defined by the square of the corresponding standard error $SE_{i,j}$.

We model the distribution of (latent) selection gradients according to

(2) $\beta_{i,j} = \alpha_j + b_j \times \varepsilon_{i,j} + e_{i,j},$

where α_j is the intercept for trait *j* and b_j is a trait-specific slope of the regression of the selection gradient on the climate variable $\varepsilon_{i,j}$ (e.g., precipitation, temperature, PET, NAO, etc.) for the *i*th selection coefficient of the *j*th trait, and $e_{i,j}$ is the residual (the deviation of the *i*th selection coefficient from its associated trait-specific regression). For all analyses, the climate variable is standardized within each dataset (as described above) to have a mean of zero and a variance of one. Under this standardization, trait-specific intercepts

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are interpretable as trait-specific mean selection gradients. Note that unlike most applications of mixed models, the $e_{i,j}$ are not simply random noise, but are the variation in selection among replicates (i.e., within traits), and as such is a parameter of biological interest. We assume

$$(3) \quad e_{i,j} \sim N(0, \sigma_e^2),$$

where σ_e^2 is the estimated residual variance. The random intercepts (α_j) and random slopes (b_j) were modelled with a bivariate normal distribution with means μ_α and μ_b, and standard deviations σ_α^2 and σ_b^2, respectively, and covariance $\sigma_{\alpha,b}$:

$$(4) \quad \begin{bmatrix} \alpha_j \\ b_j \end{bmatrix} \sim N\left(\begin{bmatrix} \mu_\alpha \\ \mu_b \end{bmatrix}, \begin{bmatrix} \sigma_\alpha^2 & \sigma_{\alpha,b} \\ \sigma_{\alpha,b} & \sigma_b^2 \end{bmatrix} \right),$$

where the mean intercept μ_α and slope μ_b, and their covariance matrix, are estimated parameters.

We implemented all analyses in a mixed model framework, using MCMCglmm (*35*). We used default diffuse normal priors on the fixed parameters (i.e., the overall intercept and average slope), parameter-expanded priors (*36, 37*) for the random (co)variance components (i.e., of the random slopes and intercepts), and a diffuse inverse gamma prior for the residual variance. The analysis is thus similar to the meta-analytic models of selection gradients in (*25*) and (*34*) for estimating within-study variance in selection, but with the extension to a random regression component to model the distribution of among-study variation in the dependence of selection on climate variables, via equation 4.

This model can be summarized in terms of the amount of variance in slopes (i.e., σ_b^2), but a more intuitive summary is obtained by considering how much (within-study) variance in selection coefficients is implied by the family of regressions between each climate factor ($\varepsilon_{i,j}$) and its corresponding selection estimate ($\beta_{i,j}$) that is estimated by the random regression mixed model. Given that within-study environmental covariates are standardized to mean zero and unit variance, the variance among studies is σ_α^2 (note that in a linear random regression model, the covariance of slopes and intercepts, $\sigma_{\alpha,b}$ does not enter into the among study variance). The variance within studies associated with environmental variables is σ_b^2, and the variance within studies that is not associated with the environment is the residual variance. The sum of these is the total variance in selection.

In the analyses of all replicates (combined space and time) we did not decompose the residual variance into that associated with space, time, and their interaction. These possible separate components of the residual variance are not separable because very few studies report on both temporal and spatial replicates together (only 23 % of selection

estimates). Rather, the great majority report on variation in selection only in space or in time. It is for this reason that we can conduct analyses where we combine space and time, and then analyze space and time separately as we have done. Those few studies that report both spatial and temporal replication jointly typically have very low levels of replication in both, and will therefore not contribute sufficient information to separate these different, and potentially interesting, components of variation in selection. The residual variance, in the combined analysis, is thus simply interpretable as the total variance in selection, accounting for the climate variables, across both classes of replication.

In the main text, we assessed the proportion of variation explained by different climatic variables for the entire data set. However, when comparing the spatially versus temporally replicated data subsets, we found differences in the within-study variance in selection in either dataset (e.g., the denominator of the estimates shown in Fig. 2). Thus, the total variance in selection obtained from a mixed model meta-analysis following equations (1, 2, and 3), but without fitting a random slopes term in (eq. 2), yielded different within-study variances (the residual variance, σ_e^2 , in eq. 3) of selection gradients and differentials replicated in space versus in time. Since all analyses in Fig. 2, and comparisons within Figs. S1 and S2, address the same datasets, the total within-study variance (e.g., the denominator of the proportional measure of climate-selection associations) in selection will be constant across analyses of different climatic measures. However, for comparisons between space and time, differences in the total variance may hinder the interpretability of the proportional measure. Posterior modes and 95% CIs of the total within-study variance for gradients are: space $\sigma_e^2 = 2.6\times10^{-3}$, 95% CI: $1.6\times10^{-3} -$ 3.6×10^{-3}; time: $\sigma_e^2 = 5.0\times10^{-3}$, 95% CI: $4.2\times10^{-3} - 5.9\times10^{-3}$. Posterior modes and 95% CIs of the total within-study variance for differentials are: space $\sigma_e^2 = 1.5\times10^{-2}$, 95% CI: $1.1\times10^{-2} - 2.0\times10^{-2}$; time: $\sigma_e^2 = 2.1\times10^{-2}$, 95% CI: $1.7\times10^{-2} - 2.6\times10^{-2}$. Consequently, comparisons between space and time based on differences in the proportion of variation in selection alone (as in Figs. S1 and S2) will not give a complete picture, as the denominator varies. Thus, since there is more within-study variance in selection in time than space in the data subsets, we also present equivalent plots showing the absolute (rather than just proportion of) variance associated with climate variables (Figs. S3 and S4).

The results from the analyses using all available replication simultaneously (i.e., both space and time; as presented in the main text, Fig. 2) are, largely, intermediate to the results from the temporally replicated subsets (Figs. S1 and S3) relative to the spatially replicated datasets (Figs. S2 and S4). One exception is that the spatial replication analysis indicates more of an association of temperature variables with selection, whereas both the combined analyses and those for time alone estimate very little association of temperature variables with selection. The greater effect of the temporal component of the database on the overall analysis is likely a result of (i) more datasets available in time (time: $n = 362$ and 129 for gradients and differentials, respectively; space: $n = 278$ and 68 for gradients and differentials, respectively; somewhat fewer for minimum PET which often has little resolvable variation within datasets), (ii) greater replication (more estimates per dataset) in time, (iii) the greater within-study variation in selection in time, and (iv) for temperature variables, the fact that the credible intervals in time support only

values relatively close to zero, while the corresponding spatial estimates for temperature variables have higher uncertainty (when they are not very near zero themselves). In summary, in the smaller data set of spatially replicated estimates, there is evidence of associations of selection with temperature (but with large uncertainty), but there is no such evidence in the larger data set of temporally replicated estimates.

Multivariate extension

Whether individual climate-selection associations are attributable to the climate variable in question, or whether they arise largely via associations with other climate variables, is of interest. However, with the generally low level of replication in individual studies (e.g., typically 2-5 data points for any given trait within any given study) it is infeasible to include many climate variables simultaneously in a multivariate model. Thus, to target the most relevant comparisons in a multivariate analysis, we developed a model that included the means and standard deviations of both temperature and precipitation in a single model by expanding equations 2 and 4 to accommodate four, rather than one, estimates of variance in slopes.

To manage the complexity of the model, we did not estimate covariances among the random slope terms, and we applied the analysis only to selection gradients, which is the measure of selection for which we have the most data (Table 1). The variance explained by the random slopes in this model depends on the within-study correlations among variables, which varies among studies. Therefore, rather than presenting variance associated with each climate variable as a proportion of the within-study variance in selection, as done for the univariate models, we present the variances in direct effects for each climate covariate (Table S2).

Sub-set analysis of trait types, fitness components, and taxonomic groups

We also conducted analyses where we estimated how much variation in selection associated with local and global climatic factors varied among fitness components, trait types, and major taxonomic groups. These subsets are typical of meta-analyses such as ours (*12, 25, 26*). We conducted these analyses using selection gradients, and those fitness components, trait types, and taxonomic groups where we had the most substantial data (Table 1).

Results from this analysis reveal some very intriguing patterns of heterogeneity in the possible effects of climate on selection through fitness components (Table S3), trait types (Table S4) and taxonomic groups (Tables S5). However, interpretation of the results requires some caution. While the analysis benefits from drawing on a large database assembled from decades of accumulated inferences about natural selection (Table 1, Database S1) that are based on a solid theoretical framework (*11*), and the opportunity to resolve these selection inferences with detailed climate data, the somewhat low precision of the resulting estimates of the dependence of selection on climate variables (e.g., Figs. 2 and 3, S1 and S2) requires caution because such analyses result in many estimates, and their interpretation in isolation would likely be unreliable (*38, 39*).

The causes of the low precision, despite large quantities of data (Table 1 and S1) is two-fold: the imprecision of individual selection estimates (*34*) and the somewhat limited extent of temporal and spatial replication of most studies (*25, 26, 34*). It is therefore important to note that apparently significant (i.e., non-overlapping 95% credible intervals), large estimated effect sizes would be inevitable given the low precision noted above (e.g., type M errors, *38, 39, 41*). These issues highlight the need for studies with larger sample sizes, and continued long-term and spatially replicated studies for tackling longstanding questions in ecology and evolution (*40*). Additionally, experimental approaches are needed to further investigate these patterns (*6*). Importantly, though, these cautionary statements do not in any way preclude the potential biological significance of these findings.
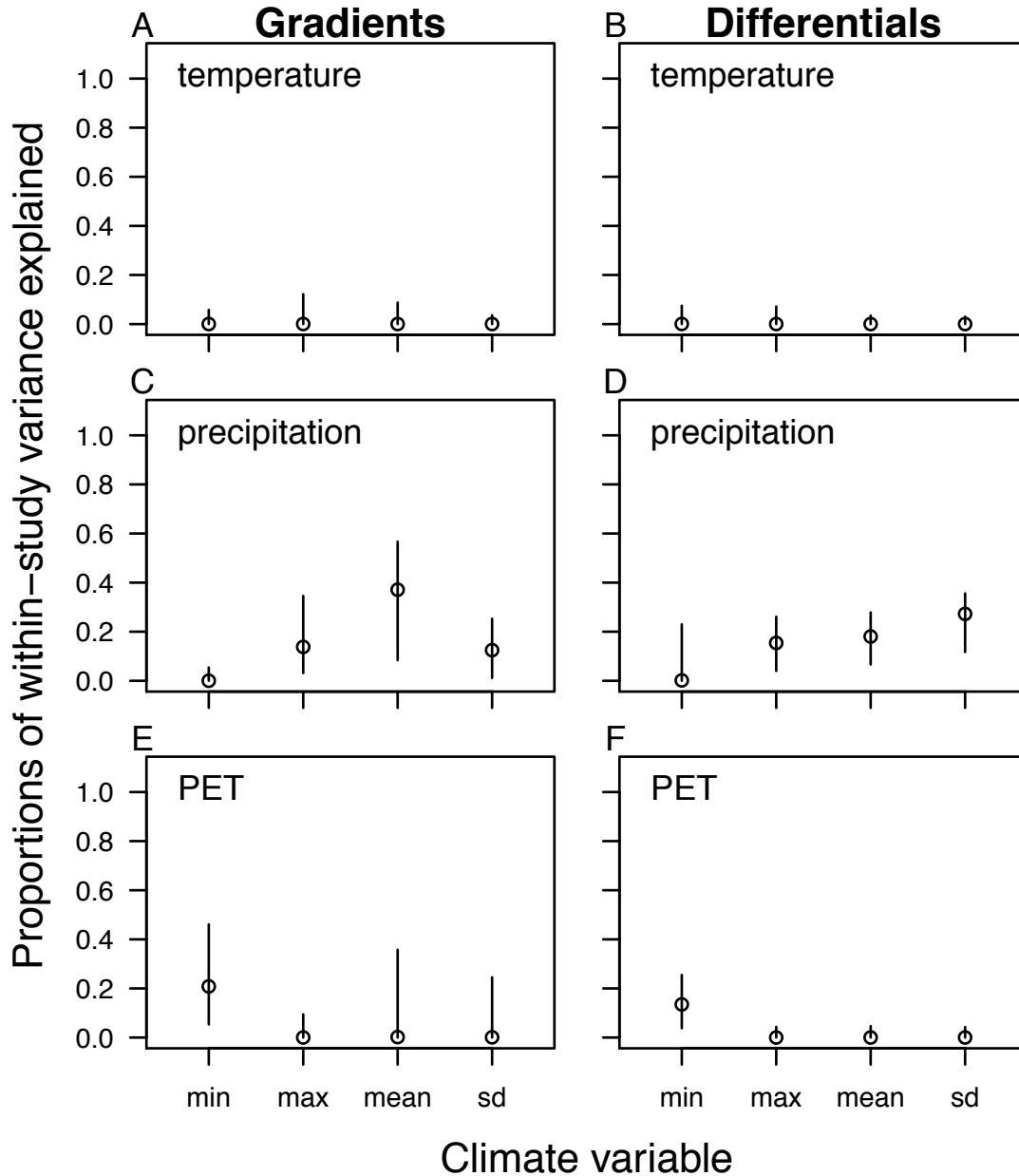
Fig. S1.

Temporal variation in selection explained by local climate factors. Shown are mean
and 95% credible intervals of the proportion of within-study temporal variation in
selection explained by a given climate variable ((A) and (B) temperature, (C) and (D)
precipitation, and (E) and (F) PET) from the Bayesian meta-analytical model. Across all
panels, the left column shows climate-selection associations with selection gradients and
the right column selection differentials.

Fig. S2.

Spatial variation in selection explained by local climate factors. Shown are mean and 95% credible intervals of the proportion of within-study spatial variation in selection explained by a given climate variable ((A) and (B) temperature, (C) and (D) precipitation, and (E) and (F) PET) from a Bayesian meta-analytical model. Across all panels, the left column shows climate-selection associations with selection gradients and the right column selection differentials.
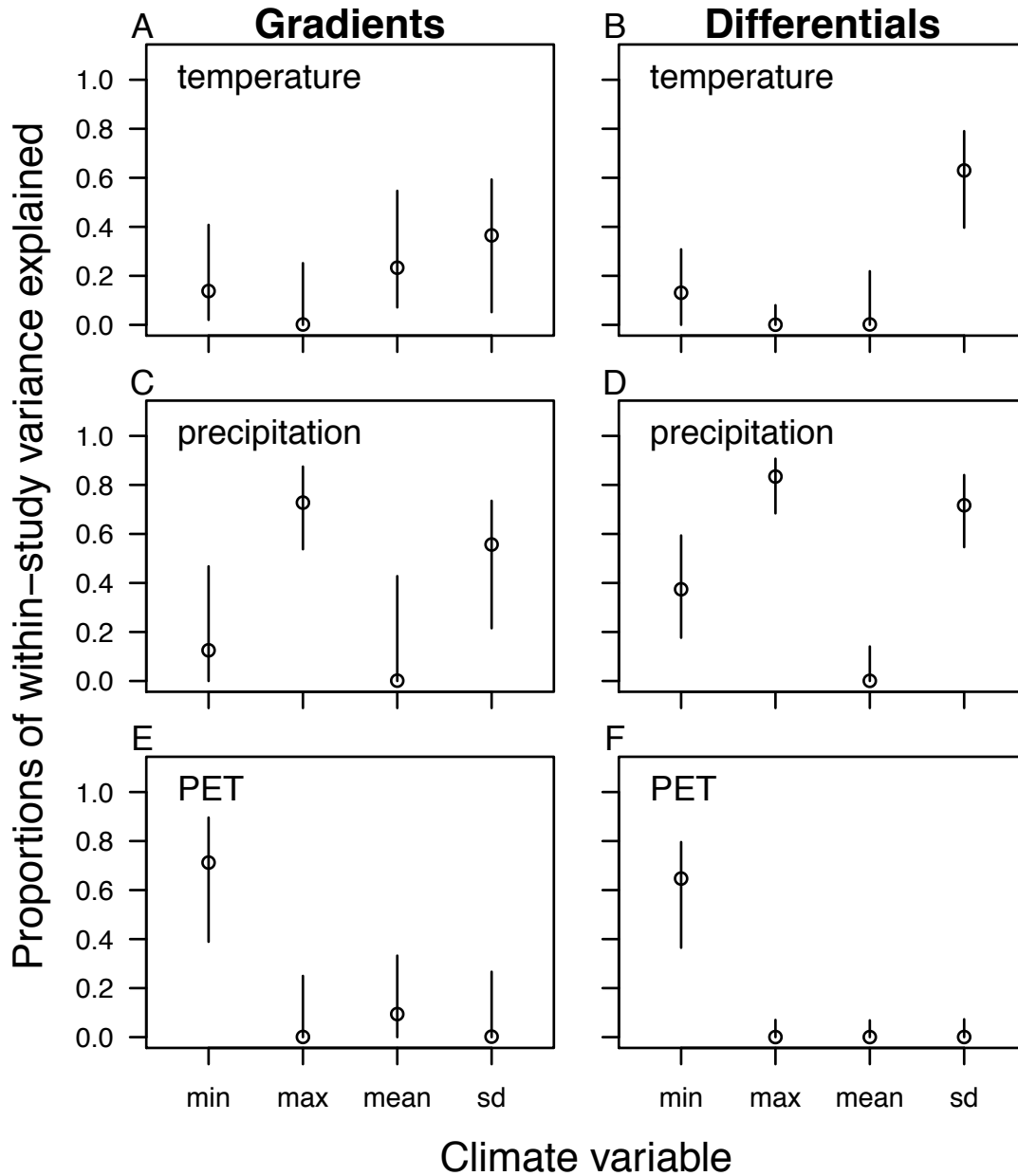
Fig. S3.

Temporal variation in selection explained by local climate factors using an absolute measure. Shown are mean and 95% credible intervals of the within-study temporal variation in selection explained by a given climate variable ((A) and (B) temperature, (C) and (D) precipitation, and (E) and (F) PET) from a Bayesian meta-analytical model. Across all panels, the left column shows climate-selection associations with selection gradients and the right column selection differentials.
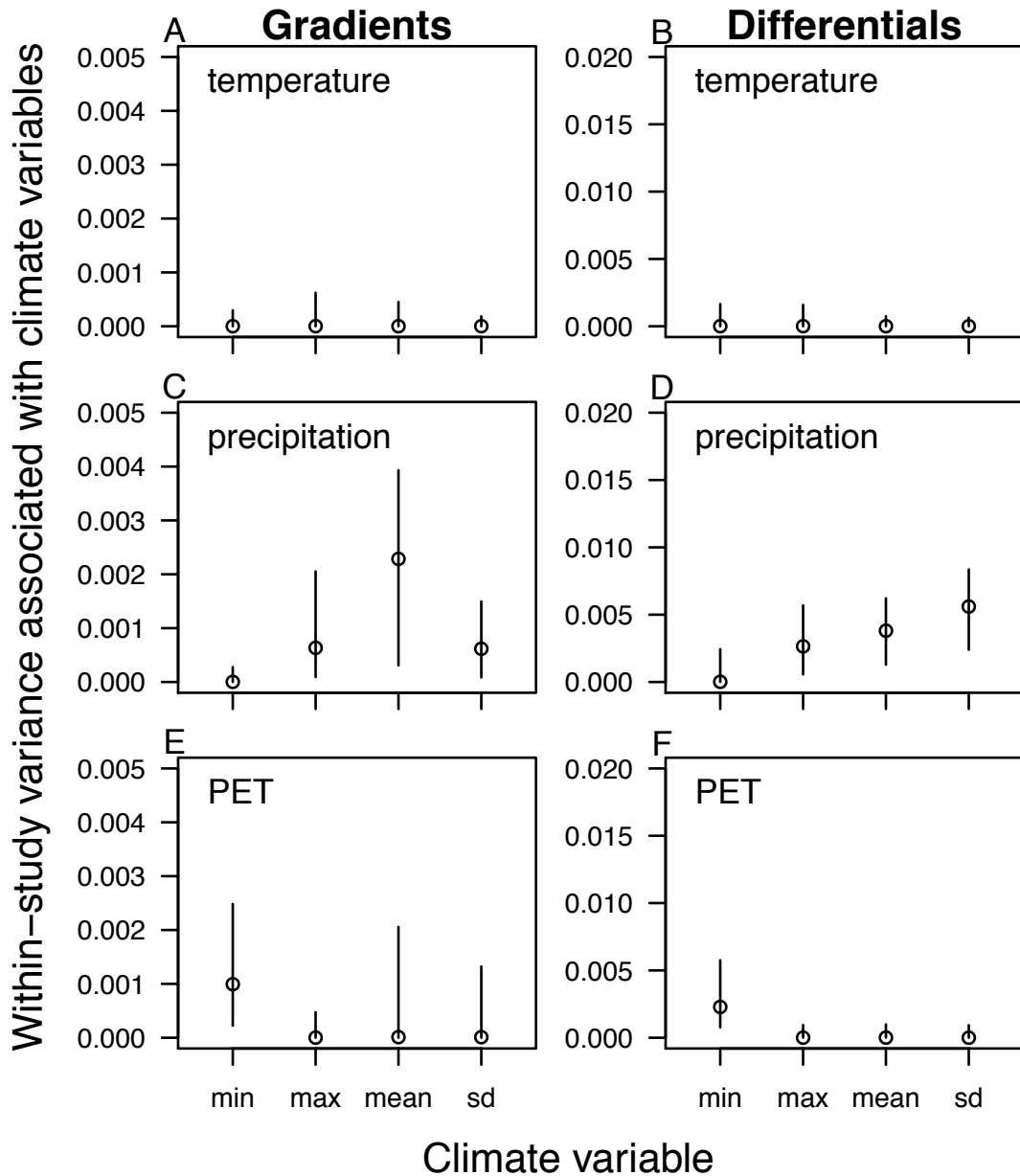
Fig. S4.

Spatial variation in selection explained by local climate factors using an absolute measure. Shown are mean and 95% credible intervals of the within-study spatial variation in selection explained by a given climate variable ((A) and (B) temperature, (C) and (D) precipitation, and (E) and (F) PET) from a Bayesian meta-analytical model. Across all panels, the left column shows climate-selection associations with selection gradients and the right column selection differentials.
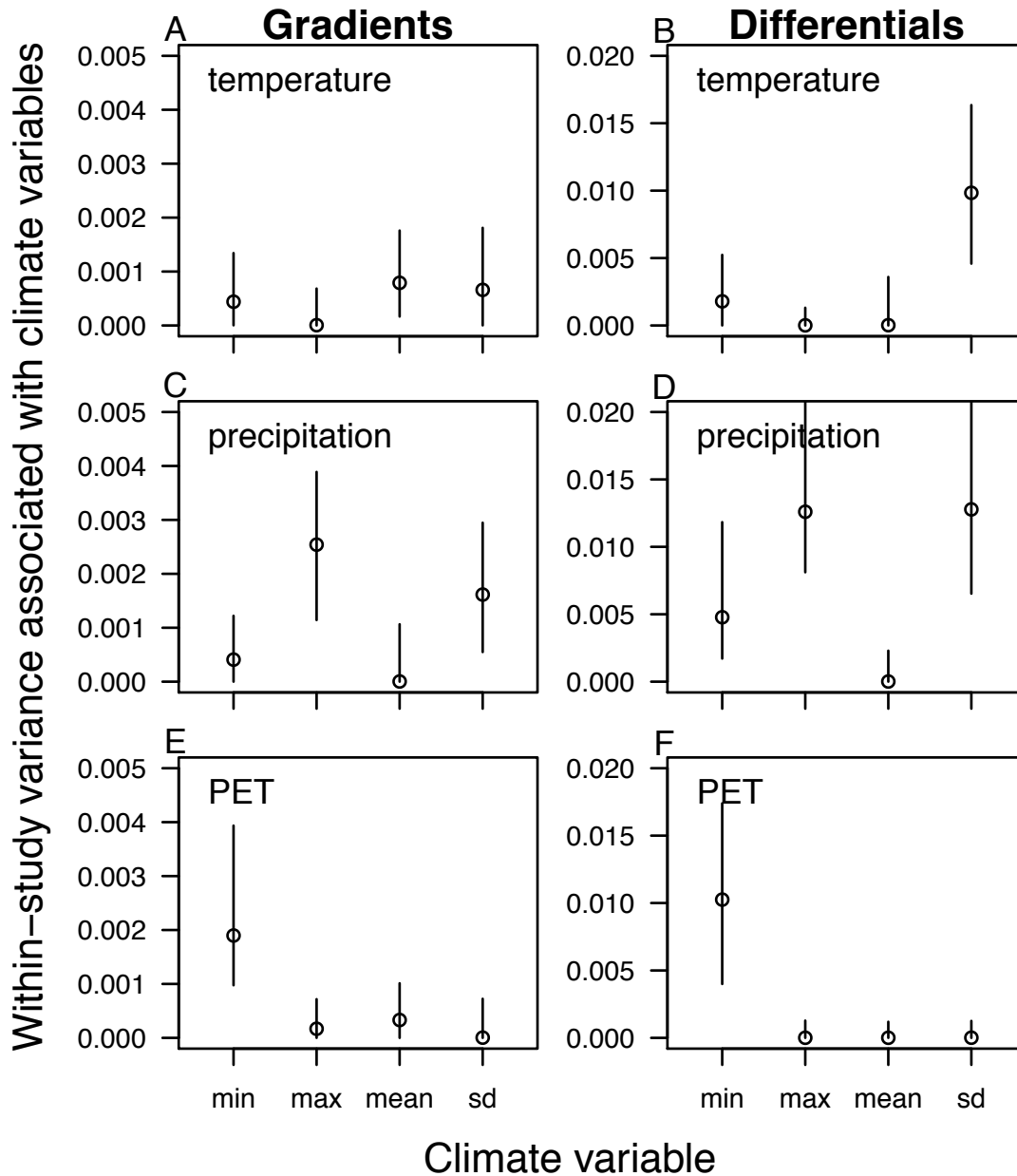
Table S1.

Correlation matrix of climate variables across studies. Min. = minimum, max. = maximum, SD = standard deviation.

	Mean temp.	Min. temp.	Max temp.	SD temp.	Mean precip.	Min. precip.	Max precip.	SD precip.	Mean PET	Min. PET	Max. PET	SD PET
Mean temp.	1.000											
Min. temp.	0.868	1.000										
Max temp.	0.666	0.280	1.000									
SD temp.	-0.575	-0.864	0.147	1.000								
Mean precip.	0.020	0.236	-0.393	-0.403	1.000							
Min. precip.	-0.135	-0.006	-0.384	-0.125	0.738	1.000						
Max precip.	0.107	0.305	-0.278	-0.451	0.890	0.530	1.000					
SD precip.	0.177	0.365	-0.211	-0.498	0.826	0.368	0.968	1.000				
Mean PET	0.701	0.395	0.878	-0.086	-0.322	-0.406	-0.157	-0.061	1.000			
Min. PET	0.865	0.686	0.666	-0.464	-0.021	-0.164	0.085	0.163	0.834	1.000		
Max. PET	0.317	0.038	0.776	0.234	-0.536	-0.575	-0.351	-0.255	0.818	0.421	1.000	
SD PET	-0.231	-0.423	0.402	0.580	-0.591	-0.527	-0.461	-0.407	0.336	-0.206	0.787	1.000

Table S2.

Results from a multivariate model simultaneously estimating the variance of slopes of regressions of selection gradients on four key climate variables (mean and SD of temperature, and mean and SD of precipitation). Shown are intercepts and slopes with their 95% credible intervals (in parentheses) from a Bayesian meta-analytical model. The variances of slopes represent the variance in the partial effects (i.e., conditioning on the other climate variables) of each climate variable across study systems. Not surprisingly, given the typically low levels of replication within studies, we cannot unambiguously attribute a direct effect to any one of the four modelled key climate variables (the slope variances of each climate factor have similarly very low lower bounds to their CIs). However, the results are consistent with patterns revealed in the univariate analyses of climate variables that variation in selection within studies tends to be most strongly associated with variation in precipitation (Fig. 1, Figs. S1 and S2). All covariates were standardized within studies to a variance of one, so fixed and random slopes are in units of changes in standardized selection gradients per standard deviation of the environmental variable.

Coefficient	Fixed intercept or slope	Random variance of intercepts or slopes
Intercept	0.053 (0.026 - 0.080)	0.042 (0.035-0.051)
Mean temp.	-2.9×10^{-4} (-6.3×10^{-3} - 6.5×10^{-3})	4.1×10^{-5} ($1.6 \times 10^{-10} - 1.6 \times 10^{-4}$)
SD temp.	3.7×10^{-3} ($-3.8 \times 10^{-3} - 0.011$)	2.5×10^{-4} ($7.8 \times 10^{-10} - 9.2 \times 10^{-4}$)
Mean precip.	-1.9×10^{-3} (-0.012 - 7.7×10^{-3})	1.1×10^{-3} ($1.6 \times 10^{-10} - 2.4 \times 10^{-3}$)
SD precip.	-1.8×10^{-3} (-0.012 - 6.4×10^{-3})	4.0×10^{-4} ($6.5 \times 10^{-10} - 1.3 \times 10^{-3}$)
Residual	-	3.9×10^{-3} ($3.1 \times 10^{-3} - 4.8 \times 10^{-3}$)

Table S3.

Variation in selection explained by local and global climate factors among different fitness components. We only considered those fitness components that were well-represented in the database (Table 1). Shown are mean and 95% credible intervals (in parentheses) of the proportion of within-study variation (combining both spatial and temporal replication; temporal replication only for NAO and ONI) explained by a given climatic factor from a Bayesian meta-analytical model.

Climatic factor	Fitness component		
	Fecundity	Mating	Survival
Min. temp.	0.001 (0 - 0.277)	0.001 (0 - 0.239)	0.001 (0 - 0.113)
Max. temp.	0.001 (0 - 0.16)	0 (0 - 0.121)	0.001 (0 - 0.253)
Mean temp.	0.001 (0 - 0.143)	0.001 (0 - 0.174)	0.003 (0 - 0.417)
SD temp.	0.419 (0.062 - 0.612)	0.001 (0 - 0.181)	0 (0 - 0.077)
Min. precip.	0.001 (0 - 0.209)	0.001 (0 - 0.16)	0.608 (0.069 - 0.789)
Max. precip.	0.637 (0.395 - 0.78)	0.002 (0 - 0.284)	0.132 (0 - 0.44)
Mean precip.	0.002 (0 - 0.354)	0.001 (0 - 0.271)	0.351 (0.032 - 0.652)
SD precip.	0.579 (0.33 - 0.75)	0.001 (0 - 0.303)	0.059 (0 - 0.192)
Min. PET	0.389 (0 - 0.544)	0.003 (0 - 0.578)	0.422 (0.083 - 0.645)
Max. PET	0.001 (0 - 0.14)	0.001 (0 - 0.153)	0 (0 - 0.085)
Mean PET	0 (0 - 0.14)	0.001 (0 - 0.212)	0.474 (0 - 0.643)
SD PET	0 (0 - 0.112)	0.001 (0 - 0.145)	0.004 (0 - 0.585)
NAO	0.815 (0.44 - 0.912)	0.002 (0 - 0.301)	0.002 (0 - 0.235)
ONI	0.409 (0 - 0.76)	0.001 (0 - 0.187)	0 (0 - 0.032)

Table S4.

Variation in selection explained by local and global climate factors among different trait types. We only considered those trait types that were well-represented in the database (Table 1). Shown are mean and 95% credible intervals (in parentheses) of the proportion of within-study variation (combining both spatial and temporal replication; temporal replication only for NAO and ONI) explained by a given climatic factor from a Bayesian meta-analytical model.

Climatic factor	Trait type		
	Size	Morphology	Phenology
Min. temp.	0.325 (0 - 0.662)	0.004 (0 - 0.665)	0.001 (0 - 0.195)
Max. temp.	0.005 (0 - 0.604)	0.526 (0.039 - 0.706)	0.001 (0 - 0.207)
Mean temp.	0.579 (0.099 - 0.837)	0.471 (0.019 - 0.713)	0.001 (0 - 0.162)
SD temp.	0.005 (0 - 0.649)	0.003 (0 - 0.551)	0.001 (0 - 0.1)
Min. precip.	0.003 (0 - 0.475)	0.695 (0.377 - 0.842)	0.001 (0 - 0.154)
Max. precip.	0.001 (0 - 0.44)	0.522 (0.211 - 0.693)	0.001 (0 - 0.213)
Mean precip.	0.707 (0.288 - 0.85)	0.719 (0.484 - 0.841)	0.002 (0 - 0.323)
SD precip.	0.003 (0 - 0.447)	0.486 (0.189 - 0.727)	0.001 (0 - 0.217)
Min. PET	0.004 (0 - 0.633)	0.002 (0 - 0.293)	0.174 (0.022 - 0.556)
Max. PET	0.529 (0 - 0.707)	0.169 (0.008 - 0.604)	0.001 (0 - 0.149)
Mean PET	0.003 (0 - 0.66)	0.606 (0.002 - 0.725)	0.002 (0 - 0.307)
SD PET	0.407 (0.071 - 0.75)	0.003 (0 - 0.47)	0.001 (0 - 0.192)
NAO	0.467 (0 - 0.683)	0.663 (0.424 - 0.783)	0.003 (0 - 0.5)
ONI	0.001 (0 - 0.201)	0.397 (0.159 - 0.691)	0.001 (0 - 0.199)

Table S5.

Variation in selection explained by local and global climate factors among different taxonomic groups. Shown are mean and 95% credible intervals (in parentheses) of the proportion of within-study variation (combining both spatial and temporal replication; temporal replication only for NAO and ONI) explained by a given climatic factor from a Bayesian meta-analytical model.

Climatic factor	Taxonomic group		
	Invertebrates	Plants	Vertebrates
Min. temp.	0.869 (0.352 - 0.974)	0.003 (0 - 0.424)	0 (0 - 0.05)
Max. temp.	0.005 (0 - 0.814)	0.001 (0 - 0.188)	0 (0 - 0.061)
Mean temp.	0.958 (0.659 - 0.996)	0.002 (0 - 0.245)	0 (0 - 0.044)
SD temp.	0.765 (0 - 0.927)	0.561 (0.208 - 0.712)	0 (0 - 0.061)
Min. precip.	0.745 (0.243 - 0.966)	0.002 (0 - 0.402)	0 (0 - 0.061)
Max. precip.	0.004 (0 - 0.719)	0.666 (0.503 - 0.829)	0.001 (0 - 0.188)
Mean precip.	0.005 (0 - 0.715)	0.006 (0 - 0.466)	0.092 (0 - 0.384)
SD precip.	0.003 (0 - 0.627)	0.708 (0.47 - 0.811)	0 (0 - 0.094)
Min. PET	0.959 (0.184 - 0.996)	0.462 (0.114 - 0.725)	0.229 (0.051 - 0.456)
Max. PET	0.003 (0 - 0.618)	0.003 (0 - 0.396)	0 (0 - 0.048)
Mean PET	0.855 (0.219 - 0.981)	0.006 (0 - 0.426)	0 (0 - 0.084)
SD PET	0.003 (0 - 0.471)	0.001 (0 - 0.254)	0.001 (0 - 0.129)
NAO	0.629 (0.227 - 0.97)	0.896 (0.344 - 0.983)	0.001 (0 - 0.202)
ONI	0.002 (0 - 0.325)	0.789 (0.053 - 0.96)	0 (0 - 0.023)

Database S1 (separate file)

Database of selection coefficients for spatially and temporally replicated studies of selection.

Database S2 (separate file)

Database of local climate factors cross-referenced for each selection estimate in Database S1.

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