**Temperature variability does not impact the capacity for phenotypic plasticity in ectotherms – a meta-analysis**

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**Abstract**

Phenotypic plasticity can allow individuals to compensate for potentially negative changes in their thermal environment and may increase resilience to environmental variability. Climate change affects both the mean temperature and the amplitudes of temperature fluctuations at different time scales. It is important, therefore, to understand the impacts of changes in both mean and fluctuation in temperature on plastic responses. Our aim was to establish the current state-of-knowledge regarding the influence of thermal variability on the capacity for phenotypic plasticity in ectothermic organisms. We derived a new effect size and conducted a quantitative synthesis of 44 studies (212 effect sizes across 40 species) to compare the effects of constant and fluctuating temperatures with the same mean on plastic responses (behavioural, biochemical assay, gene expression, life-history, morphological and physiological) across different ecosystems (terrestrial and aquatic) and types of phenotypic plasticity (acclimation and developmental plasticity). We found that most studies in the literature implemented diel temperature fluctuations (24 h cycles). Our analysis shows that phenotypic plasticity does not differ between constant and fluctuating thermal environments, but effects do depend on specific traits, but with effects generally being weak. We conclude that changes in diel fluctuations do not alter the resilience of ectotherms to temperature change in dramatic ways. Instead, plasticity and its attendant compensation for thermal variability is driven by changes in longer-term mean temperatures.

**Introduction**

both ; Angilletta, 2009). The thermal sensitivity of phenotypic traits follows a non-linear thermal performance curve (TPC) as a function of body temperature (Huey and Kingsolver, 1989). TPCs vary between species and traits (Bozinovic et al., 2020), but generally incorporate three common features: an initial increase in performance as temperature increases from a minimum critical temperature; a thermal optimum where maximum performance is reached; and a rapid decline in performance to a critical thermal maximum (Huey and Kingsolver, 1989). Thermal changes therefore can be both beneficial and detrimental to the performance of an organism depending on their location within the TPCs (Denny, 2019; Marshall et al., 2021). However, ectotherms can exhibit plastic responses that adjust TPCs to allow relatively constant function despite climate variability (Kingsolver et al., 2015; Noble et al. 2025).

Phenotypic plasticity can allow individuals to at least partially compensate for changes in their environment (Schulte, 2014). Developmental plasticity and acclimation are manifestations of within-individual phenotypic plasticity that can reduce variance in phenotypic trait values across environmental gradients (Beaman et al., 2016; Burggren, 2020). Developmental plasticity involves relatively persistent phenotypic changes in response to the thermal environment experienced during early development (Burggren, 2018; Loughland et al., 2021). Acclimation is a reversible phenotypic shift induced by environmental changes lasting from days to weeks (Guderley, 2004). The capacity for phenotypic plasticity has been tested mainly in response to changes in constant temperatures. However, in natural environments temperatures fluctuate calling into question whether constant temperature experiments are representative of natural conditions (Marshall et al., 2021).

Fluctuating environmental conditions may dampen the capacity for phenotypic plasticity because it reduces the variation in temperatures experienced by organisms limiting its potential to buffer populations for climate change. In addition, phenotypic plasticity can come at the cost of a mismatch between phenotype and environment, and plastic responses to short-term variation (e.g., daily variation) could exacerbate that cost especially if the environment changes rapidly (Beaman et al., 2016; Gabriel, 2006). Filtering out frequent short-term environmental signals may render plastic responses more efficient, and compensation for longer-term changes may be the principal benefit of plasticity (Leung et al., 2020). At present, empirical evidence is equivocal, leaving the relationship between temperature fluctuations and phenotypic plasticity unresolved. To predict the impacts of climate change, it is important therefore to understand whether short-term fluctuations around mean temperatures influence the capacity for phenotypic plasticity compared to constant mean temperatures (Dowd et al., 2015).

Here, we derive a new effect size that quantifies how plastic responses change between constant and fluctuation environments. We then conduct a quantitative synthesis that establishes the current state-of-knowledge regarding the influence of thermal variability on the capacity for phenotypic plasticity in ectotherms. Specifically, we conducted a meta-analysis that tested whether the capacity for phenotypic plasticity differed in constant and fluctuating thermal environments with the same mean temperature. The potential impacts of constant and fluctuating thermal environments were also investigated at different (i) ecological levels (individual and population), (ii) ecosystems (aquatic and terrestrial organisms), and (iii) forms of phenotypic plasticity (acclimation or developmental plasticity).

**Materials and Methods**

We followed, as closely as possible, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Moher et al., 2015) guidelines, modified for Ecology and Evolution (PRISMA-Eco Evo) (O’Dea et al., 2021) (Supplementary Materials 7.1 & 7.3). Question formulation, literature searching and screening were performed according to (Foo et al., 2021).

*Systematic Literature Search and Screening*

We adhered to the PECO (Population, Exposure, Comparator, Outcome) framework (Morgan et al., 2018) in the development of focus questions and the literature search and screening processes (Supplementary Materials 7.1). The systematic literature search was conducted on the 5th of April 2022 in Scopus, Web of Science and ScienceDirect databases. Search terms included synonyms for ‘plasticity’, ‘acclimation’ and ‘developmental effects’ to identify studies that conducted treatments during the lifespan of an individual (Noble et al., 2018) . To limit the search string to temperature treatments ‘thermal’ and ‘temperature’ were added as search terms (Barley et al., 2021; Noble et al., 2018). Synonyms for ‘fluctuating’ or ‘varying’ were added to explicitly look for studies with a fluctuating temperature treatment. The exact search strings used in each database can be found in the Supplementary Materials 7.2.

These searches returned a total of 13,549 unique studies (Supplementary Materials 7.3). A total of 57 studies were identified that were in English and experimentally compared the plastic responses in both constant and fluctuating temperature treatments for ectothermic organisms under controlled laboratory conditions. In addition, we used Scopus, Web of Science, ScienceDirect and Google Scholar to conduct a forward (papers citing the original study) and backward (papers that were cited in the original study) search on the 19th of October 2022, and identified an additional 87 studies. There was one species that was removed from the compiled data set due to an unresolved phylogeny in the Open Tree of Life database (Michonneau et al., 2016). We conducted an abstract and full-text screening (in Rayyan Software) (Ouzzani et al., 2016) of all identified papers following our exclusion and inclusion criteria (Supplementary Materials 7.4). For a study to be included in the analysis, experiments had to have: (a) identical housing and habituating periods across treatments; (b) acclimation or developmental plasticity treatments (within the lifespan of an individual); (c) fluctuating and constant temperature treatments pairs with the same mean temperature; (d) all other treatment conditions needed to be identical (e.g., photoperiod and salinity); (e) measurements of plastic phenotypic responses (excluding metrics of thermal performance, critical thermal minima and maxima). Phenotypic response measurements across temperature could be either at the population-level (measured for an entire population, e.g., survival) or individual-level (measured in an individual, e.g., development time or locomotor performance). All relevant statistical information needed to be available (including sample size, mean, and error metrics) and principal components and factor loadings were excluded (Tarka et al., 2018). Following this search, 44 studies were included in the final analysis (Supplementary Materials 7.5).

*Data Extraction*

All studies included in the analysis had at least four principal chronic (days to weeks) treatments: two constant temperature treatments at a "high" and "low" temperature, and two fluctuating temperature treatments with mean temperatures corresponding to those of the constant treatments (Figure 1). The acute test temperatures at which phenotypic traits were measured had to coincide with the mean temperatures of the corresponding thermal treatments (Seebacher et al., 2015). If there were more than two treatment temperatures, we selected the two experimental temperatures that coincided best with the natural temperature range of each study species (Seebacher et al., 2015). In experiments that had multiple fluctuating treatments with different amplitudes or types of fluctuations (e.g., sinusoidal, stepwise, alternating, or stochastic), we compared each to the corresponding constant treatment to calculate separate effect size. We extracted data (sample sizes, means, and errors) from these treatments from texts, tables, supplementary materials, and figures (using R package *metaDigitise* to extract data from figures)(Pick et al., 2019). We used only biological replicates as the sample size (Wu and Seebacher, 2020).

In addition, we recorded associated data which may influence phenotypic plasticity and used these in subset analyses and as moderators in meta-regression analyses. Hence, we recorded taxonomic information, preferred ecosystems, and life-history stages. We also recorded descriptors of the experimental fluctuations (mean temperature and the fluctuations amplitude, type, and period) that could influence phenotypic trait values (Raynal et al., 2022; Stocker et al., 2024). Phenotypic responses were sorted into trait category and specific phenotypic trait measurement, and we noted details of the experimental design including the type and duration of treatment exposure. Investigators involved in data extraction were not permitted to screen or extract data from studies they had a previous association with (Macartney et al., 2022).

*Data Processing and Transformations*

Standard errors (SE) and 95% confidence internals (CI) were converted to standard deviations (SD), which were used for effect size calculations (Quinn and Keough, 2002). Bounded data such as proportions (e.g., survival) were transformed before calculating effect sizes to obtain means and variances that were more likely to satisfy normality assumptions (Macartney et al., 2022):

|  |  |
| --- | --- |
|  | (1) |

|  |  |
| --- | --- |
|  | (2) |

where and are the transformed means and SD, respectively, and are the bounded (proportional) means and SD. We transformed means and variances that were reported as the natural logarithm using Equation 3 and 4 (Higgins et al., 2008):

|  |  |
| --- | --- |
|  | (3) |

|  |  |
| --- | --- |
|  | (4) |

where and are the transformed means and SD, respectively, and are the means and SD on the natural log scale. A constant of 0.5 was added to all means and SD to avoid taking the natural log of zero during effect size calculations.

We assigned developmental exposure periods, acclimation life-history stages, and traits into categories to facilitate comparisons between studies. Taxonomic information was retrieved from the Open Tree of Life (Michonneau et al., 2016). Amphibians were considered aquatic organisms for the analysis.

*Effect Size Calculations*

We developed and used a standardised interaction-based plasticity response ratio difference (PRRDS; Equation 7) and its corresponding sampling variance (Equation 8) as our effect. The PRRDS is derived by first calculating log response ratios (lnRR; Equation 9) within treatments (Noble et al., 2022) to estimate the change in phenotypic traits following either acclimation or developmental exposure to different temperatures. lnRR indicates the capacity for phenotypic plasticity, where a decreasing lnRR indicates that traits are affected by changes in temperature (i.e., have greater capacity for plasticity with lnRR = 0 indicating lack of plasticity). PRRDS capture the difference in phenotypic plasticity between (constant and fluctuating) treatments by subtracting the lnRR of the constant from the fluctuating thermal environment. To control for the fact that temperature gradients differed between studies, the PRRDS standardises the differences in lnRR to a 1oC change in treatment temperature (Noble et al., 2022; Pottier et al., 2021). PRRDS = 0 indicates that there is no difference in the capacity for phenotypic plasticity between constant and fluctuating thermal environments (PRRDS > 0, phenotypic plasticity increases in fluctuating temperatures; PRRDS < 0, phenotypic plasticity increases in constant temperatures).

|  |  |
| --- | --- |
|  | (7) |

|  |  |
| --- | --- |
|  | (8) |



where is the mean response, T is temperature, subscripted F and C denote the fluctuating and constant thermal treatments, respectively, and subscripted H and L denote the high and low temperatures, respectively.

***Statistical Analysis***

We used R 4.2.2 in RStudio version 2022.12.0 for all calculations, analyses, and figures (using R Package *ggplot2* for figures) (Wickham, 2011) . All data and code are available at <https://github.com/ClaytonStocker/Plasticity_Fluctuation_Meta> (Supplementary Materials 7.9). Data are presented as the mean PRRDS ± 95% CIs. For ease of interoperability, the mean PRRDs are transformed to give the percentage change of phenotypic plasticity from constant to fluctuating thermal environments (Pustejovsky, 2018). We visualised mean and raw effects using orchard and bubble plots (R package *orchard* version. 2.0, Nakagawa et al. 2023), which also provide 95% prediction intervals. Prediction intervals provide important information about effect heterogeneity (Noble et al. 2022; Nakagawa et al. 2021; Yang et al. 2025)

*Meta-analyses and non-independence*

Multi-level meta-analyses (MLMA) were fitted with frequentist models using restricted maximum likelihood (REML) and an adjusted convergence threshold (1e-8). Inferential tests were done using a *t*-distribution (Nakagawa et al., 2022b). The model was fitted with a modified sampling covariance matrix to account for multiple effect sizes using the same control treatment (Noble et al., 2022). We assumed that effect sizes sharing a common control were correlated by r = 0.5, and the shared sampling covariance was calculated using the sampling variances for each effect (Noble et al., 2017).

Dependencies in our data set were accounted for by including several random effects in the model (Nakagawa et al., 2017). A Study ID random effect was included to account for multiple effect sizes from the same study. A Shared Animal ID random effect was included to account for the same set of animals being used for several measured outcomes. To control for phylogenetic relatedness, a phylogenetic tree was created using the Open Tree of Life database and converted into a correlation matrix that was included in the model when estimating phylogenetic variance. Polytomies were randomly resolved (using R Package *Ape*) (Paradis and Schliep, 2018) and branch lengths were calculated with Grafen’s method (Power = 1) (Grafen, 1989). A species-level random effect was also included to account for the repeated use of the same species across effect sizes (Cinar et al. 2022). To reduce the likelihood of specific traits dominating the analysis, a trait-level random effect was added to the model (except in meta-regressions that analysed specific phenotypic traits as the moderator). Lastly, an observational-level random effect was added to estimate the ‘residual’ / ‘within-study’ variation (Nakagawa and Santos, 2012).

*Multi-level Meta-analytic Models*

MLMA models (using the function *rma.mv* in the R Package *metafor*) (Viechtbauer, 2010) were implemented to estimate the overall meta-analytic mean on data subsets (population- and individual-level traits) (Figure 2). The total heterogeneity statistic (*I2Total*) and partitions corresponding to each of the random effects (*I2Animal*, *I2Obs*, *I2Phylo*, *I2Species*, *I2Study*, and *I2Trait*,), were calculated for each of the MLMA models to quantify unexplained variation after removing the known sampling variance and proportional variance resulting from each level of stratification. It is common to achieve an *I2Total* greater than 90% in multispecies meta-analyses (Senior et al., 2016).

*Meta-regression Models*

For each data subset we conducted separate meta-regression models to compare moderators that had the potential to explain effect size variation. Categorical moderators included type of plasticity (acclimation and developmental plasticity), fluctuation type (sinusoidal, alternating, stepwise, and stochastic), phenotypic trait categories (behavioural, biochemical assay, gene expression, life-history, morphological, and physiological), the specific phenotypic trait (see Supplementary Materials 7.8 for full list of phenotypic traits), and broad taxonomic group (invertebrate vs vertebrate) (see Supplementary Materials 7.10 for phylogenetic tree). Categorical moderators and their levels were only included in analyses if the number of effect sizes were > 10 (O’Dea et al., 2021). We analysed the amplitude of fluctuations, and the number of fluctuations (treatment exposure duration/period of fluctuations; range = 4 – 546 fluctuations) as continuous moderators.

*Publication Bias and Sensitivity Analysis*

Publication bias was first investigated by visually examining funnel plots for asymmetry (Sterne et al., 2005). Second, our overall MLMA model was then altered to include z-transformed publication year and precision (inverse of sampling variance) as moderators to assess the presence of a time-lag effect (or decline effect) (Nakagawa et al., 2022a). There was no evidence of small-study effects (i.e., no relationship with precision) in our overall data set, however, mean PRRDs, unsurprisingly, did show evidence of time-lag bias where average effects have decreased towards zero through time (Supplementary Materials 7.11) coinciding with our overall meta-analytic means for most analyses.

A sample of effect sizes showed higher than expected precision. We carefully checked these extreme values to ensure that data was corrected extracted. However, we could not know for sure if these were reported incorrectlt. To understand how ‘robust’ our overall MLMA model was to influential data points, we therefore conducted Cook’s distance sensitivity analysis (using the function *cooks.distance* in the R Package *metafor*). Results suggest that our conclusions are robust and free from significant influential outliers (Supplementary materials 7.11). We also confirmed our results were consistent with robust variance estimators (Nakagawa et al. 2022) which better account for any sources of non-independence within studies that our models may not have accounted for well enough. All results were also largely consistent between our main analyses and those using robust variance estimators.

**Results**

The final data set included 212 effect sizes from 40 species (Supplementary Materials 7.10) derived from 44 studies (Supplementary Materials 7.5). The dataset was dominated by invertebrates (n = 32 species) but also included vertebrate ectotherms (n = 8 species). Overall, 98% of the studies used diurnal temperature fluctuations (24 h cycles).

In the overall MLMA analysis (effect size estimate = 0.0019; 95% CIs = [-0.009, 0.0128]; p = 0.7296; n = 212, Figure 2a) and the subsequent subset analyses (Figure 2b & Supplementary Materials 7.12), the mean plastic responses were not significantly different between constant and fluctuating thermal environments (Figure 2). Total heterogeneity however was high overall (*I2Total* rounded to 99.35%), with substantial between study (~38%) and within-study heterogeneity (~52%). Little between species heterogeneity was identified (phylogeny and species both 0% – see full heterogeneity statistics in Supplementary Materials 7.13).

We explored a priori factors we expected would explain the high heterogeneity. There were no significant differences in phenotypic plasticity between fluctuating and constant thermal environments across broad trait categories (Figure 3a), but small effects were observed for specific trait categories where enough data existed (Figure 3b). More specifically, fluctuating environments increased plastic changes with temperature for development time. In contrast, fluctuating temperatures resulted in plastic responses in body mass to be dampened relative to constant fluctuations (Figure 3b, Supplement Table S22). In each case, however, effect size magnitude was small despite being significant (0.97-1.57% change). Constant and fluctuating temperatures did not influence phenotypic plasticity differently between aquatic or terrestrial species or vertebrates and invertebrates (Figure 4). Neither the fluctuation type (Figure 5), plasticity type (Figure 6) or the amplitude of fluctuating temperature regimes (Figure 7) explained differences in phenotypic plasticity between fluctuating and constant temperature conditions. The results of the meta-regression analyses for individual trait data subsets (rather than population) paralleled those of the overall data set and are shown in the Supplementary Materials 7.12.

**Discussion**

Our meta-analysis shows that experiencing constant or fluctuating environmental conditions does not generally impact the capacity for phenotypic plasticity in ectothermic organisms. Our findings were remarkably consistent across species with low species-level heterogeneity in effects. Analyses of key moderators were also in strong agreement that the capacity for phenotypic plasticity remains unaltered by thermal variability. Only for two specific trait categories, development time and body mass, did we see differences in plasticity between constant and fluctuating temperatures, but these effects were small and largely in line with other effect sizes. The findings of our study suggest that the ability to maintain relatively constant phenotypes across environmental gradients is not influenced by regular, short-term fluctuations around the temperature mean.

Plasticity can be beneficial by allowing organisms to compensate for potentially negative environmental effects (Loughland et al., 2021; Schulte, 2014). However, the remodelling of phenotypes can be detrimental if inducing environments do not match current environmental conditions (Beaman et al., 2016). A mismatch cost can arise from a lag in the time to complete the compensatory response relative to the frequency of the variation in temperature (Pfab et al., 2016). Phenotype-environment mismatches occur for some time after the environment changes because environments induce phenotypes so that there necessarily is a lag between environmental and phenotypic change (Gabriel, 2005). The occurrence of such mismatches would increase if phenotypic plasticity was induced by frequent temperature fluctuations that would cause increasing frequencies of lag periods (Ghalambor et al., 2007). Findings from our analysis instead indicate that short periods of exposure to temperatures beyond the thermal mean are insufficient to impact plastic responses. Therefore, we conclude that plastic responses are driven by longer-term mean temperatures.

An interesting question that remains unresolved, is what the characteristics of the inducing environment are that lead to plastic responses (O’Connor et al., 2019; Zimmer et al., 2022) . Our analysis indicates that diel fluctuations do not induce plasticity. However, in the natural environment, animals experience thermal fluctuations around the mean at different spatial- and temporal scales (e.g., diurnal, seasonal, and annual) (Marshall et al., 2021). The ability to filter frequent, short-term thermal signals could be an advantageous mechanism that increases the efficacy of plastic responses. A ‘band-pass filter’ could explain this phenomenon, in which regular thermal noise around the mean is filtered out and does not contribute to the capacity for phenotypic plasticity (Lattin and Kelly, 2020). The efficient compensation for the effects of long-term changes in mean temperature could be the primary benefit of phenotypic plasticity that increases the resilience and persistence of ectotherms to future climate changes (Leung et al., 2020).

Increases in the amplitude of thermal fluctuations can have detrimental impacts on phenotypic trait values by reaching extreme ranges that damage cellular function and structures (Raynal et al., 2022; Stocker et al., 2024; Stoks et al., 2017). Our meta-analysis indicates that increases in the magnitude of diel fluctuations do not impact plasticity and are therefore unlikely to affect the vulnerability of ectotherms. However, we do not know whether the fluctuation reported in the studies analysed here were actually damaging, but frequent damaging temperature spikes could alter the molecular mechanisms underlying plasticity (Murray et al., 2022). These dynamics are important in assessing the impact of climate change-induced increases in mean temperature and heat waves, but require more experimental studies. With that caveat in mind, our findings support the validity of experiments using different constant temperature treatments to assess thermal plasticity and suggest that findings from such experiments are transferable to environments with diel temperature variation. Our conclusions pertain to phenotypic plasticity within the lifetime of an organism (acclimation and developmental plasticity) and primarily in response to diel cycles. In the literature there are few data showing the impact of fluctuations with longer periods, and it will be important to determine the periodicity at which fluctuations become sufficient to induce or impact plastic responses. We suggest that future research should explore the impacts of transgenerational thermal variability and temporal scales on the capacity for phenotypic plasticity.

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**Figure Captions**

A screenshot of a computer

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**Figure 1 Quantifying changes in plasticity resulting from being acclimated in a constant or thermally fluctuating environment**. A) Measurement temperatures taken for two samples of organisms at low temperature (TL) and high temperature (TH) when each group is acclimated at a constant temperature. Calculating the plastic response ratio for the constant treatment (lnRRC) can be done by subtracting the natural logarithm of the sample means for the two measurement temperatures. B) Treatment groups where the temperatures fluctuated through the course of acclimation. The plastic response ratio for the fluctuating treatment (lnRRF)can also be computed by subtracting the natural logarithm of the sample means for the two measurement temperatures in the fluctuating treatment. From these effect sizes the PRRDS can be calculated according to equation 7 and 8.

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**Figure 2 Multi-level meta-analytic results for the overall data set (a) and only studies measuring at the individual level (b).** There were no significant differences in phenotypic plasticity between the constant and fluctuating temperature treatments (indicated by 95% CIs crossing zero). Orchard plots depict mean effect size (plasticity response ratio difference; PRRDS) estimates ± 95% CIs (solid circles and horizontal bars, respectively) as well as distributions of individual effect sizes. Effect sizes are weighted (sized) by their precision which is inverse of their sampling error (1/SE). Percentage labels are the mean PRRDS estimates transformed to show a proportional difference between the fluctuating and stable temperature treatments. k = number of effect sizes with the number of studies in brackets. x-axis limits are cropped for presentation.

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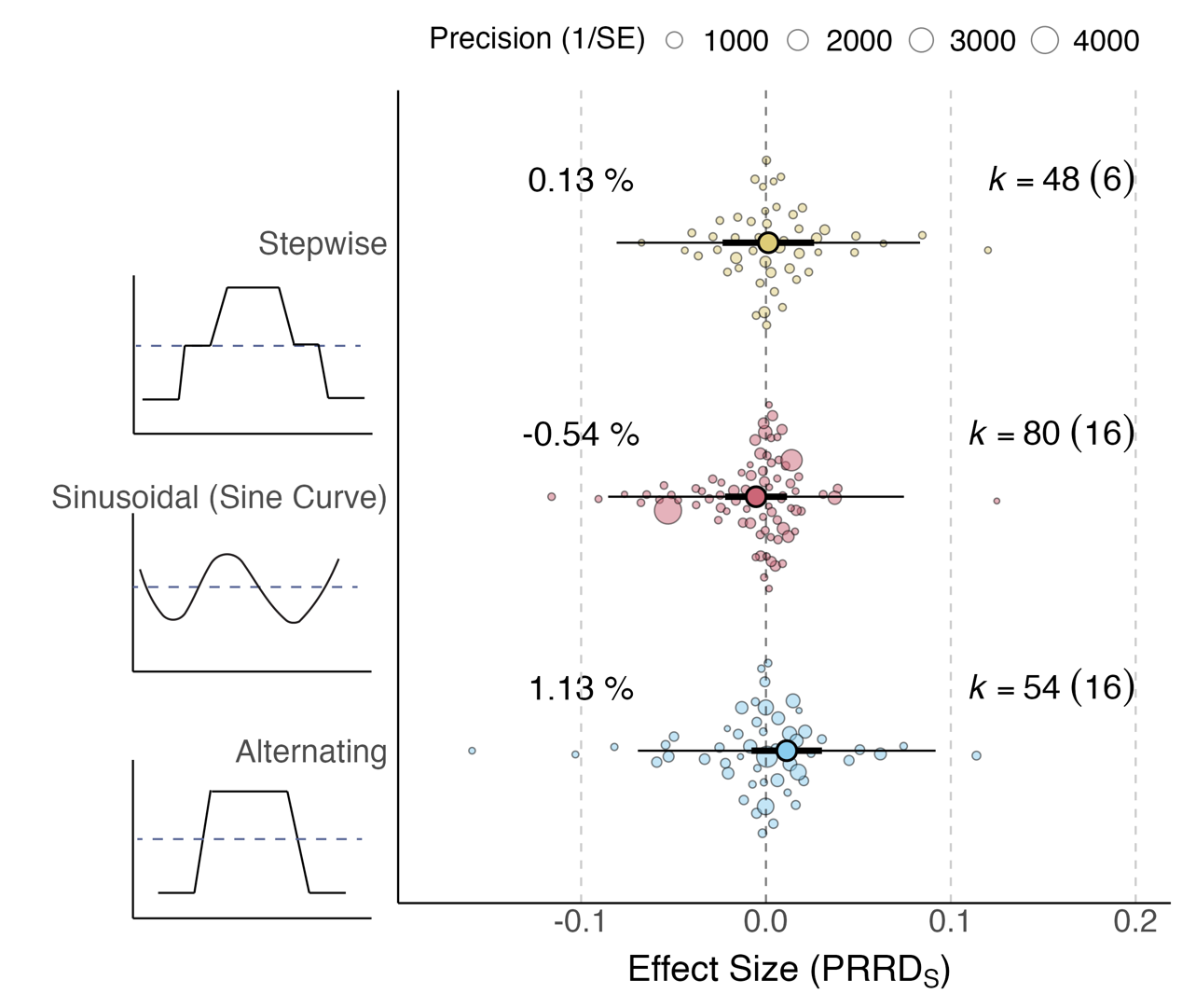
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**Figure 3 Meta-regression results for the overall data set with broad (a) and specific (b) phenotypic trait category as the moderator**. There were no significant differences in phenotypic plasticity between the constant and fluctuating temperature treatments (indicated by 95% CIs crossing zero). Presentation and abbreviations as in Figure 2. Asterisks (\*) indicate meta-analytic means that are significantly different from zero.

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**Figure 4 Meta-regression results for the overall data set across major habitat types (a) broad taxonomic group (b) as the moderator.** There were no significant differences in the phenotypic plasticity between the constant and fluctuating temperature treatments (indicated by 95% CIs crossing zero). Presentation and abbreviations as in Figure 2. Taxa silhouettes from *rphylopic* (Gearty & Jones, 2023)

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**Figure 5 Meta-regression results for the overall data set with fluctuation type as the moderator.** There were no significant differences in phenotypic plasticity between the constant and fluctuating temperature treatments (indicated by 95% CIs crossing zero). Presentation and abbreviations as in Figure 2.

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**Figure 6** **Meta-regression results for the subset data set with plasticity type as the moderator.** There were no significant differences in phenotypic plasticity between the constant and fluctuating temperature treatments (indicated by 95% CIs crossing zero). Presentation and abbreviations as in Figure 2.

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**7** in both our overall dataset (a) and the data set restricted to individual level traits (b)