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Manuscript

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3

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26	NOTE I need to integrate reference manager with R markdown. Any favorites or recommendations?? I generally use Zotero (free), but think I have access to Mendeley through CMU...	
27		
28	NOTE I re-ran all of these after setting the seed for reproducibility. Figures should be up to date, but the numbers may change slightly i.e., 94.8% might become 95.1%, mean \pm SD values will be different.	
29		

30 **Abstract**

- 31 1. Size spectra represent a fundamental attribute of community organization and are increasingly being
32 used in assessments of fresh waters.
- 33 2. Many methods have been proposed for constructing size spectra relationships, but recent work has
34 shown that varied methods return biased estimates of relationship parameters, and different methods
35 in fact are not estimating the same parameter. Despite this variability in estimates, it is unclear if
36 the relative change across environmental gradients is consistent across methodologies. Here, we simu-
37 late data sets across an hypothetical environmental gradient and estimate the size spectra parameter
38 (slope or exponent, depending on method) at each site, and, importantly, estimate the relationship of
39 parameters across the hypothetical gradient. We also use two previously published body size datasets
40 across an anthropogenic stress gradient and an environmental temperature gradient and assess how
41 the conclusions of these studies would vary based on methods used.
- 42 3. We find that maximum likelihood methods always perform as well or better than common binning
43 methods. Additionally, the variance in estimates using MLE methods is markedly reduced when
44 compared to binning methods.
- 45 4. The uncertainty and variation in estimates when using binning methods is often greater than or equal
46 to the variation previously published in experimental and observational studies, bringing into question
47 the effect size of previously published results. However, re-analysis of two previously published datasets
48 does not markedly alter the conclusions reached. Further study is needed to identify how and when
49 these estimates may be biased, and when the general pattern of results can be considered to be “true”.

50 **Introduction**

51 Body size distributions are a fundamental characteristic of communities. The remarkable consistency of
52 these relationships across spatiotemporal scales and habitat types has led them to be recommended as a
53 “universal” indicator of ecological status (Petchey and Belgrano 2010). Size metrics have commonly been
54 used in marine systems, and are increasingly being applied to assess the condition of freshwater ecosystems
55 (Martinez et al. 2016, Pomeranz 2018).

56 Individual size distributions (ISD, also referred to as abundance size spectra) are commonly used. Generally,
57 there is a negative relationship between body size (M) and abundance (N). Theoretical and empirical data
58 support this relationship being described as a simple power law with exponent λ in the form of $N \sim M^\lambda$.
59 Commonly, N is the count of body sizes grouped into bins, and λ is estimated from OLS regressions of log
60 transformed data of N and the mid point of the body size bin M_{bin} : $\log(N_{count}) = \lambda \log(M_{bin})$. Myriad
61 binning methods have been proposed, including linear and logarithmic bin widths. Likewise, methods can
62 rely on the absolute count in the bins as well as normalization techniques where the count is divided by the
63 bin width (especially common with logarithmic binning). Alternatively, λ can be estimated directly using
64 maximum likelihood techniques.

65 Previous work has shown that the estimates of λ differ between MLE and OLS techniques. OLS methods
66 are particularly sensitive to decisions made in the binning process. Simulation studies have shown that MLE
67 offers consistently more accurate estimates of λ (White et al. 2007, Edwards et al. 2017), and reanalysis
68 of empirical datasets also indicates that the conclusions are dependent on the methodology used (White et
69 al. 2007, Edwards et al. 2020). However, recent empirical analysis of stream macroinvertebrate communities
70 across the NAtional Ecological Observatory Network (NEON, USA) showed that while the estimates of
71 λ varied, the relative change across the environmental gradient was consistent regardless of method used
72 (Pomeranz et al. 2022). While there is a growing consensus that MLE methods offer more reliable estimates
73 of λ , and binning methods result in biased estimates, it remains unclear if these biases are consistent and
74 systematic or stochastic, and whether or not the relative change in ISD parameters is consistent across
75 space and time. In other words, if the data within a study are all treated the same, does a relative change
76 of OLS slope parameters of 0.1 coincide with a relative change of MLE estimates of 0.1? In order to
77 answer this question, we simulate body size observations from bounded power law distributions with varied

78 λ exponents across a hypothetical environmental gradient and compare the results obtained using three
79 different methodologies common in the literature. In addition, we re-analyze two previously published
80 datasets of stream community body sizes across a stress and environmental gradient. We find that the MLE
81 method more accurately estimates the site-specific λ exponents as well as the relative change in exponents
82 across the hypothetical gradient, as well as having smaller variation. The logarithmic binning methods
83 generally perform well, but have larger confidence intervals around the estimates. However, the overall
84 conclusions of previously published empirical data sets are not dependent on the method used.

85 Methods

86 Data Simulation

87 In order to investigate the performance of commonly used methods, we simulate body size observations from
88 a bounded power law distribution using the inverse method, as described in Edwards et al. (2017). Let M
89 be a random variable of body sizes described by the probability density function:

$$f(M) = CM^\lambda, M_{min} \leq M \leq M_{max}$$

90 $M_{min} = 0.0026$ and $M_{max} = 1.2 * 10^3$. These values are based on empirical body sizes of stream benthic
91 communities reported in Pomeranz et al. (2020). Our results are not dependent on the range of body sizes,
92 and we show the results of other ranges in the supplemental information.

93 For the main analysis, presented here, we sampled $n = 1000$ body sizes from distributions described by
94 five different λ 's: (-1.5, -1.75, -2.00, -2.25, -2.5). The supplemental information contains results when the
95 value of n is varied (or maybe include in main?). Each value of λ was assumed to come from a community
96 across a hypothetical environmental gradient X . Values of X for each community are uniformly distributed
97 from -1 to 1. We repeated the data simulation 1000 times (reps). The main results presented here were not
98 dependent on the range of x -values or the number of sites (supplemental information).

99 Sample size, n

100 The number of observations in our simulations may bias the results. Therefore, we repeated the simulations
101 described above, but varied the sample size n . We tested values of $n = 200, 500, 1000, 5000, 10000$. (originally
102 had $n=100$, but thre errors based on random seed. Bumped it to 200 to try and get consistent error-free
103 runs)

104 “No” relationship

105 It is possible that our sampling or simulation framework could impact the results obtained, possibly by
106 inflating the type I error rate. In order to assess whether or not our simulations are robust to this, we
107 performed independent random samples from a bounded power law for five communities across a hypothetical
108 gradient as described above, but we set $\lambda = -2$ for all five communities. Hence, we are simulating a scenario
109 where the size spectra relationship is invariant to our hypothetical environmental gradient, and we should
110 expect the estimated relationship coefficient $\beta_1 = 0$.

111 Finer resolution of λ values

112 For the main analysis, we were interested in determining whether or not the methods were able to detect
113 relatively coarse changes to size spectra parameters, specifically, a change of 0.5 units across each value of X ,
114 or an absolute change of 1.0 units. However, many seminal works on variation in size spectra relationships in

115 freshwater are on a much finer scale (on the order of 0.1 to 0.25 units). Therefore, we performed simulations
116 as described above, but varied λ from -1.9 to -2.1 across the hypothetical environmental gradient. This
117 equates to a known relationship coefficient of $\beta_1 = 0.1$ across the hypothetical gradient, and an absolute
118 change of 0.2 units.

119 Estimation of Size spectra parameter λ

120 For each sample of M and each of the 1000 replicates, we estimated the exponent λ using MLE methods
121 modified from the `sizeSpectra` package (Edwards et al. 2020). In addition, we use two common binning
122 methods to estimate the OLS slope parameter in log-log space. For the first binning method, we created 6
123 equal logarithmic bins covering the range of body sizes. The count in each bin was normalized by dividing
124 by the bin width. This method has been used by (refs here, I think a lot of Woodward's group uses this...)
125 Throughout the manuscript, the normalized equal logarithmic binning method will be referred to as ELBn.
126 The second method was similar to ELBn, but bins of \log_2 widths are used. The count in each bin is
127 normalized in the same way. This method has been used by (Pomeranz et al. 2018, I think McGarvey
128 ~2018, Blanchard (\log_2 , ?normalized?)) and is referred to as the Normalized Abundance Spectrum (NAS).

129 Estimation of relationship across gradient, β_1

130 For each simulation replicate, we estimated how the size spectra parameters varied across the hypothetical
131 gradient. Simple OLS regression were conducted in the form $\lambda_{estimate} \beta_0 + \beta_1 * X$. The distribution of
132 the relationship coefficient, β_1 , were plotted compared to the known relationship. Likewise, the confidence
133 interval of β_1 was assessed to determine the proportion of estimates which contained the true value of the
134 known relationship.

135 Empirical Data

136 We re-analyze two datasets of benthic macroinvertebrate communities from stream habitats across two
137 different gradients. In the first, quantitative macroinvertebrate samples were collected from streams across
138 an acid mine drainage stress gradient. Details of the sample collection and processing can be found in
139 Pomeranz et al. (2018). Briefly, all individuals from each sample were identified to the lowest practical
140 taxonomic unit and body lengths were measured using image processing software from photos taken with
141 a camera mounted to a dissecting microscope. Body mass was estimated using published length weight
142 regressions.

143 The second data set was from the wadeable stream sites of the National Ecological Observatory Network
144 (NEON; **data product XXX**). These sites are located across a wide temperature gradient in the United
145 States, from Puerto Rico to Alaska. Quantitative macroinvertebrate samples were collected using the most
146 appropriate method based on the local habitat. All individuals were identified and had their body lengths
147 measured, and body mass was estimated using published length weight regressions. This data has been
148 analyzed previously using size spectra methods as described in Pomeranz et al. (2022). Detailed methods
149 of the sampling collection and data processing methods can be found on the NEON website (URL, or
150 macroinvertebrate DPI pubs).

151 Results

152 Relationship across the hypothetical environmental gradient

153 All methods performed reasonably well in detecting the known relationship across the hypothetical environ-
154 mental gradient. The regressions using the MLE method found a significant relationship 100% of the time,
155 while the ELBn and NAS method found significant relationships 95.8% and 96.9% of the time, respectively.

PLB

$m_{\text{range}} = (0.0026, 1200)$

$b = (-2.5, -1.5)$

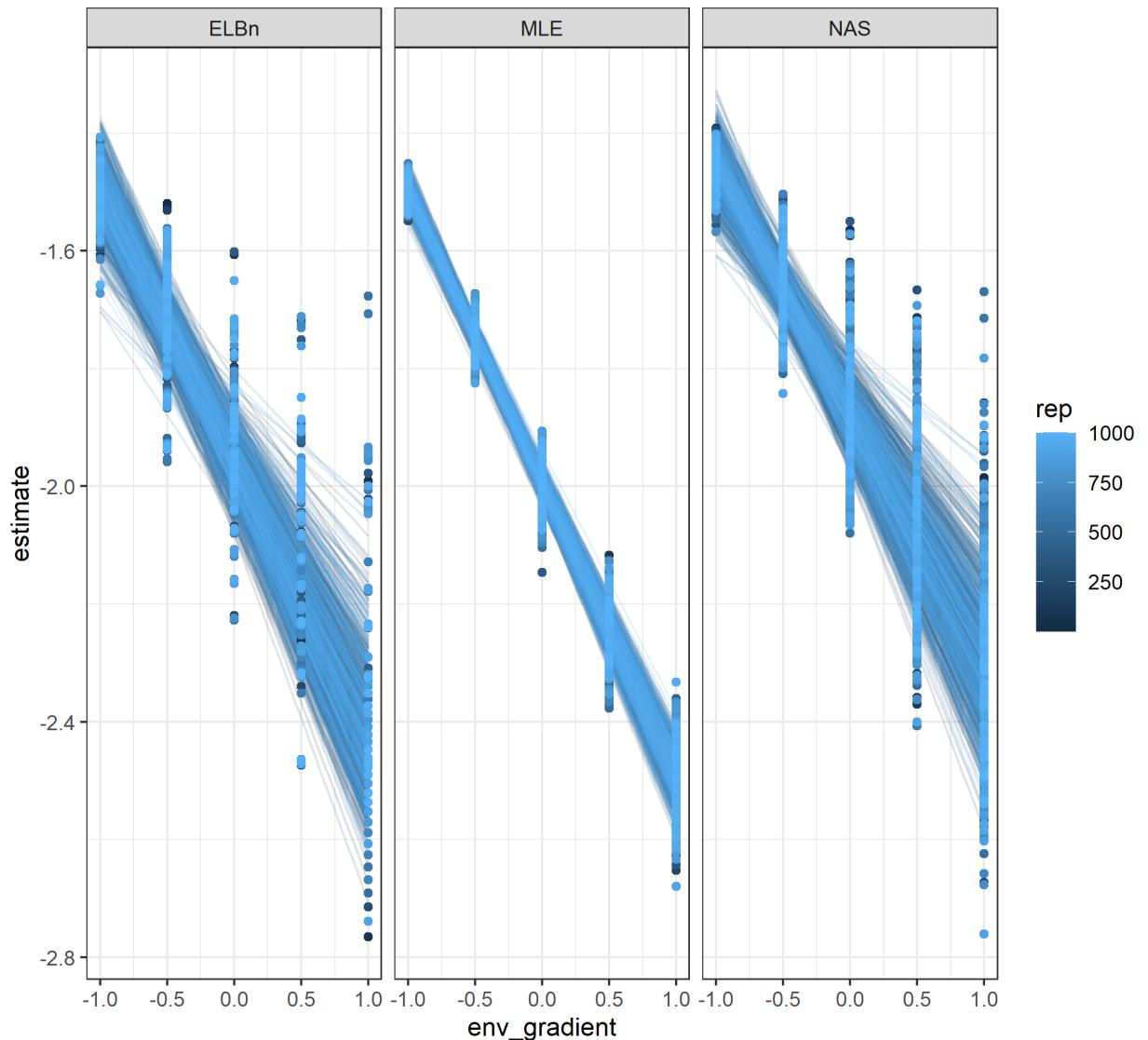


Figure 1: Relationship estimates across the hypothetical gradient for each replicate. Each panel is a different method for estimating the size spectra parameter.

156 The confidence intervals for the relationship coefficients (β_1) for both the MLE and ELBn method contained
157 the true value of the known relationship across the gradient $\geq 95\%$ of the time, whereas the confidence
158 interval for the NAS method only had the true value 83.1% of the time. Despite having similar accuracy,
159 the width of the CIs for the ELBn method were more than 3 times that of the MLE method (ELBn_CI_
160 = 0.386 ± 0.20 ; MLE_CI_ = 0.121 ± 0.056). The CI's for the NAS were slightly smaller than the ELBn
161 method, but still > 2.5 times as wide as the MLE method (NAS_CI = 0.339 ± 0.172).
162 On average, the relationship across the gradient was under estimated: MLE -0.002 (± 0.022); ELBn -0.039
163 (± 0.062); and NA -0.081 (± 0.061).
164 Interestingly, there was an interactive effect of the estimate accuracy between sample size and the value of
165 λ . All methods were more accurate with larger sample sizes, and smaller values of λ .

166 No relationship

167 All of the methods performed similarly when there was no relationship across the hypothetical gradient. The
168 Type I error rate for MLE, ELBn and NAS were 5%, 5.7% and 4.6%, respectively. However, the confidence
169 intervals for the binning methods were ~ 3 times as wide as the MLE method (mean CI widths: MLE =
170 0.116, ELBn = 0.372; NAS = 0.332).
171 Of the relationships which were estimated to be significant, the MLE, ELBn, and NAS method had a 58%,
172 49.1% and 54.3% probability of indicating a negative relationship, respectively.

173 Small variation in lambda

174 The performance of all methods declined when trying to detect variation in the λ parameter between -1.9
175 to -2.1 across the environmental gradient. The mean β_1 coefficient estimates for all methods were closely
176 associated with the known relationship. Once again the variation in the estimates using the MLE method
177 were much smaller than the estimates using both of the binning methods (Figure 4).
178 Of the 1000 simulation replicates, the MLE only detected a significant relationship 90% of the time, whereas
179 the ELBn and NAS methods detected significant relationships 19 and 23% of the time, respectively. Of the
180 replicates which were significant, the confidence interval contained the true value of the relationship 94.6,
181 88.4, and 89.1% of the time for the MLE, ELBn, and NAS methods, respectively.
182 Once again, the width of the confidence intervals for both of the binning methods were ≥ 2.8 times that
183 of the MLE method (mean \pm SD MLE CI width: 0.117 ± 0.051 ; ELBn CI width: 0.378 ± 0.169 ; NAS CI
184 width: 0.332 ± 0.150).
185 On average, the relationship estimates across the gradient were similar to the know value (mean deviation:
186 MLE = 0.00001, ELBn = -0.009, NAS = -0.012). However, when only looking at the relationships which
187 were significant, this variation increased considerably(MLE = -0.002, ELBN = -0.052, NAS = 0.034).

188 Empirical data

189 For both empirical datasets, the direction and magnitude of chnage (i.e. β_1 coefficients) are generally in
190 agreement. Size spectra parameters consistently increase (become flatter) in the AMD data (Fig. XX A).
191 Likewise, the size spectra parameters consistently increase (become steeper) with increasing temperature
192 across the NEON sites (Fig XX D)

193 **NOTE** combine all the figures below into one with 4 panels (AMD = A, B; NEON = C, D)

194 Because the β_1 coefficient estimates are similar, and the range of the gradient in the AMD data is relatively
195 small (9.5), the absolute change in the size spectra parameter across the AMD gradient are similar regardless
196 of method used (range: 0.59 to 0.72). Likewise, the absolute change in size spectra parameters across the
197 NEON temperature gradient ranges from 0.06 to 0.165, depending on the method used.

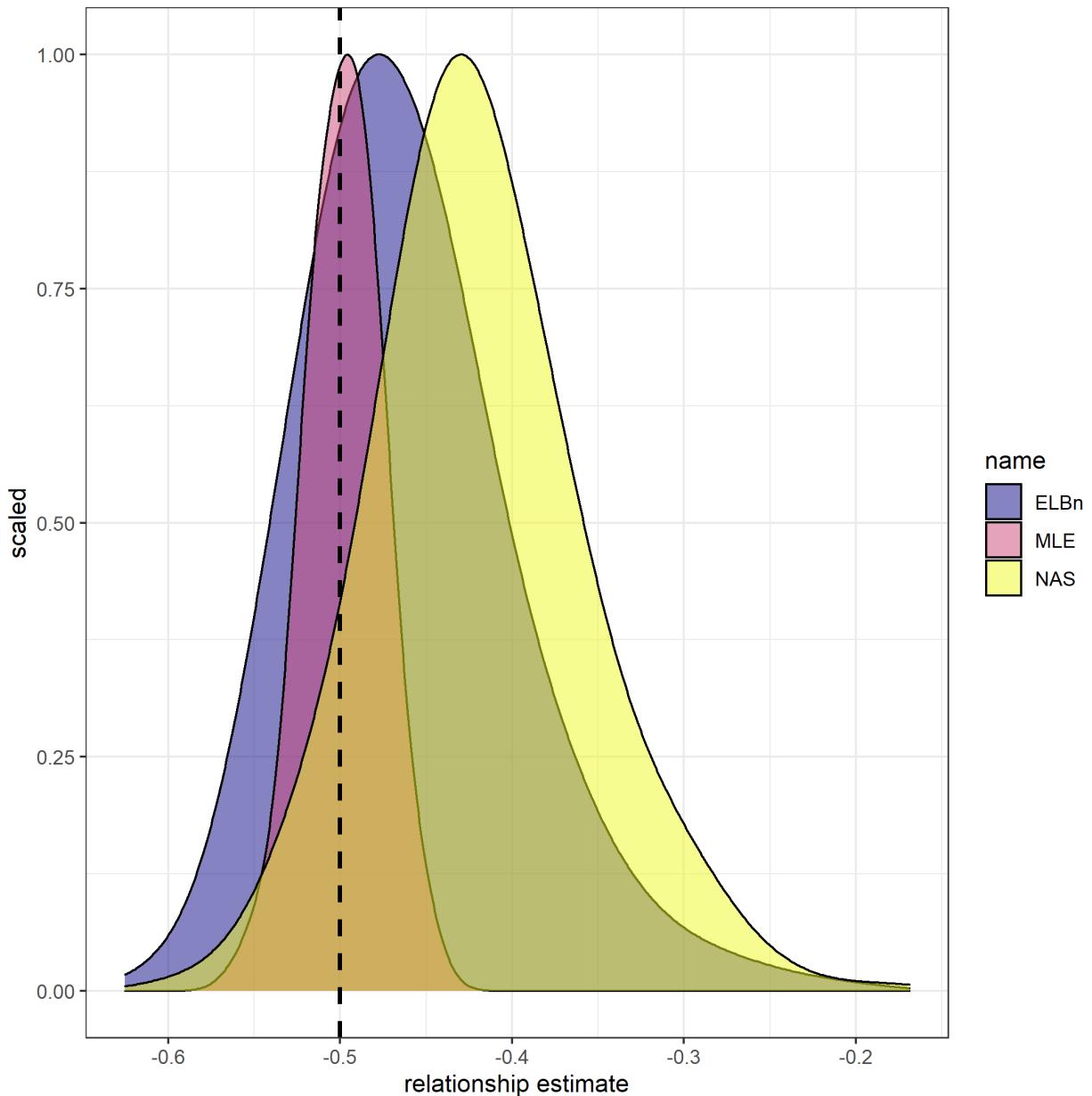


Figure 2: Distribution of relationship coefficient estimates. Vertical line is the known relationship. All methods under estimate the value, but the mean magnitude and distribution of values is greater for the ELBn and NAS methods.

Sample size and known b

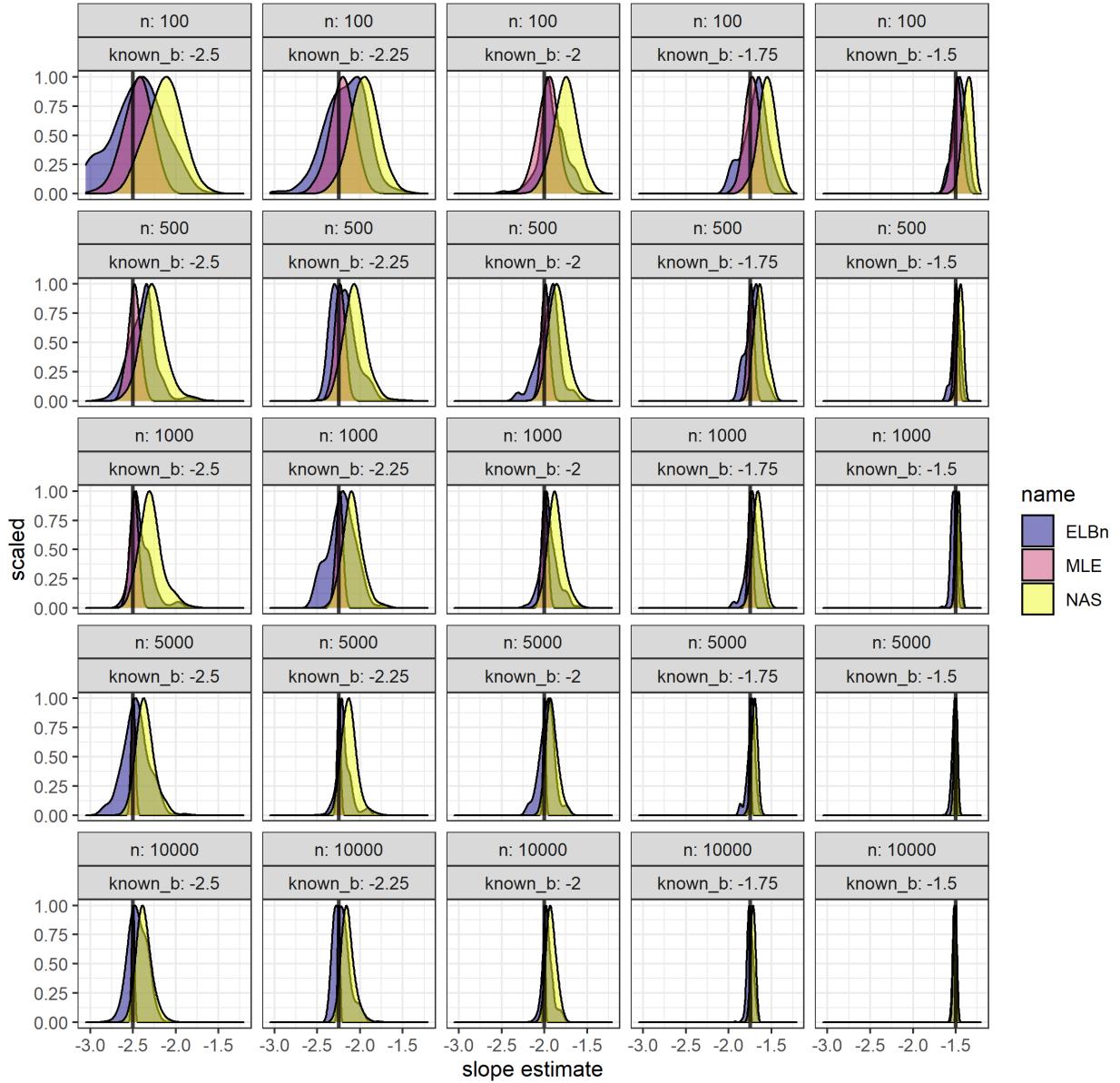


Figure 3: Distribution of size spectra parameter estimates. Vertical line is the known parameter which describes the bounded power law distribution from which the body size estimates were sampled. As n increases (top to bottom) and λ increases (left to right), the accuracy of the estimate improves across all methods.

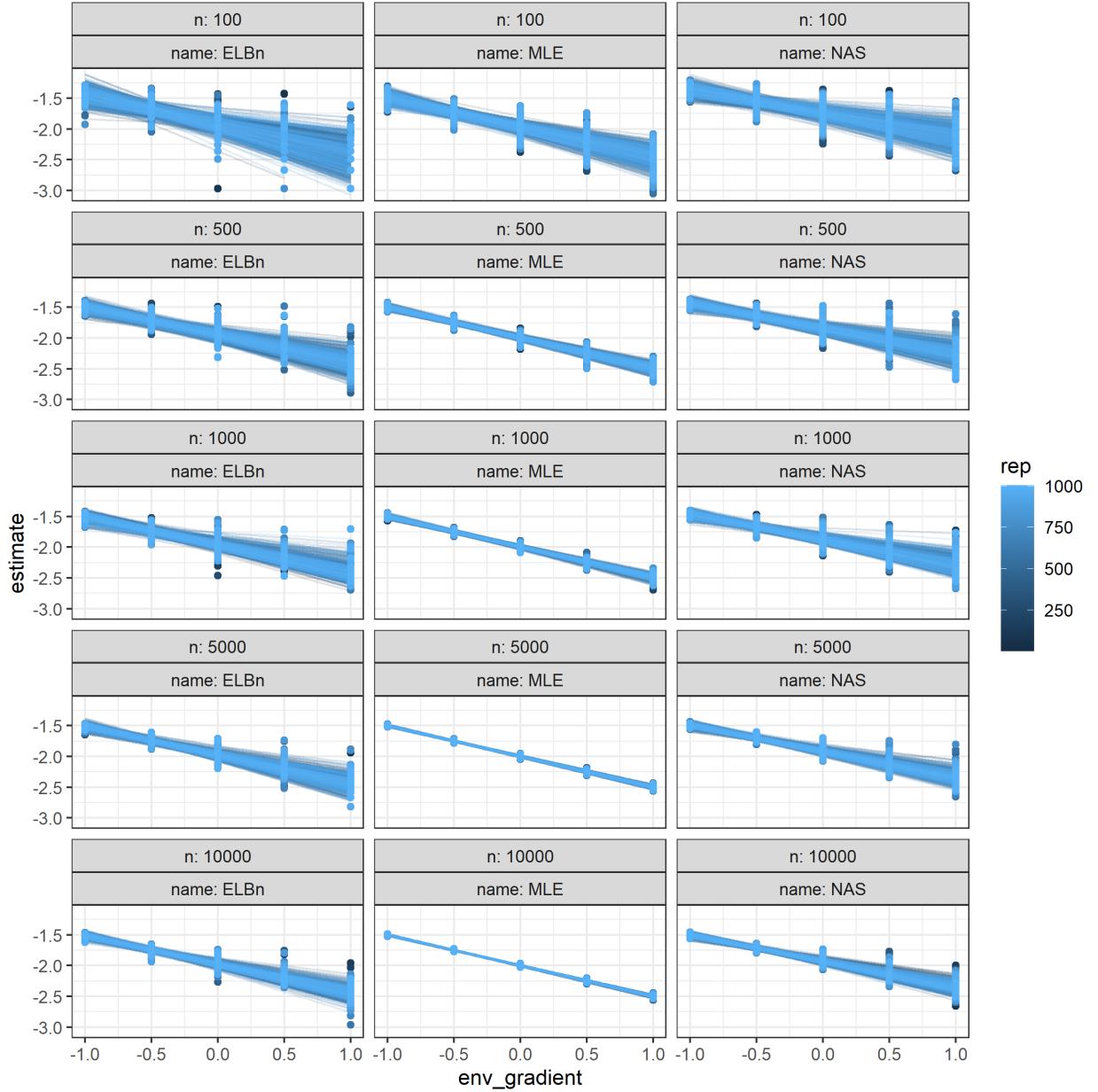


Figure 4: Individual regression estimates across the hypothetical gradient based on sample size (rows) and methodology used (columns).

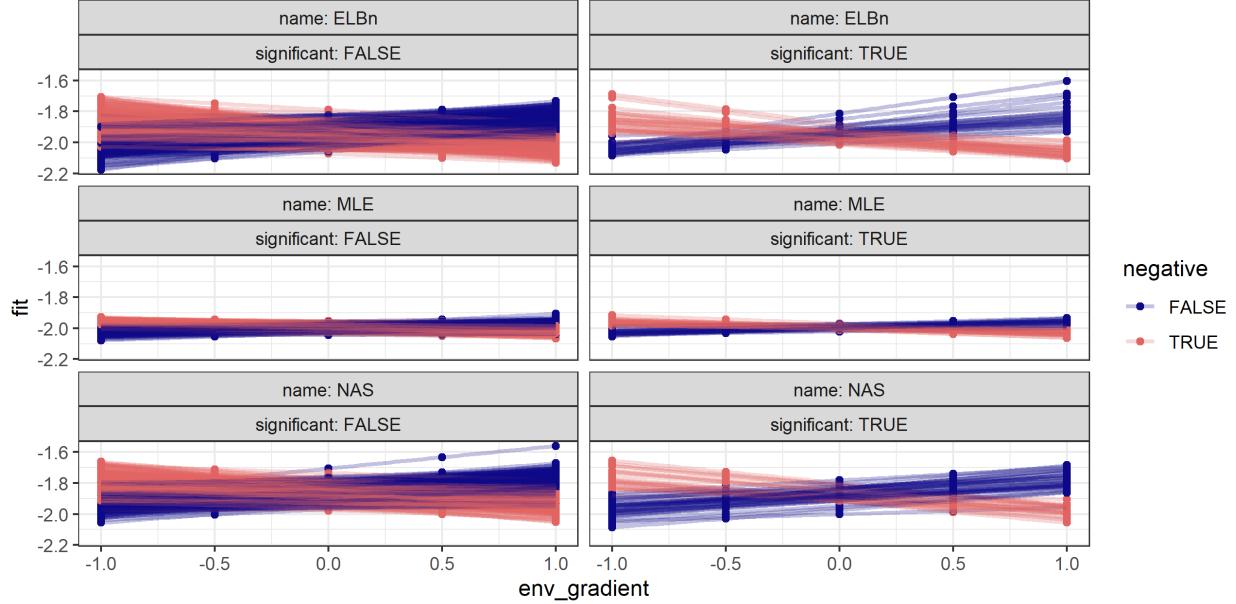


Figure 5: Individual regression estimates when no relationship exists across the hypothetical environmental gradient. The methods are separated by rows, and the left and right column show relationships which were non-significant and significant, respectively. The individual regressions coefficients are colored-coded to indicate positive and negative relationship estimates.

198 alternative absolute difference of ~0.1 units in λ across gradients is similar to differences reported in other
 199 studies (seasonally: 0.16, Mcgarvey and Kirk; landuse: 0.15 Martinez; O’Gorman 2017 ~0.25, Yvon and
 200 Dossena papers ~0.1? [need to redownload some of these and compare])

201 Simulating shallower lambdas

202 Estimates of the relationship between lambda and a hypothetical gradient varied depending on the method
 203 used. However, interpretations of empirical data were broadly consistent across methodologies. Upon closer
 204 inspection, the values of size spectra parameters in the empirical data were considerably shallower than -2.
 205 Given that we found the performance of all methods increased with shallower λ ’s we wanted to investigate
 206 how the methods performed with simulated values more similar to the empirical estimates of parameters
 207 describing size spectra relationships. Therefore, we repeated the simulation process as in the main analysis,
 208 but used λ values ranging from -1.1 to -1.5.

209 We found generally less variability in the relationship estimates across a gradient of distributions described
 210 with shallower λ parameters. All of the relationship coefficient estimates (β_1)’s across all replicates were
 211 significant regardless of method used. The confidence interval for β_1 estimate for the MLE method contained
 212 the true value 94.7% of the time. However, the true value was in the confidence interval for the ELBN and
 213 NAS method only 90.9% and 76.9% of the time, respectively. Once again, the mean width of the CI for the
 214 binning methods were ~2 times as large as for the MLE method. Mean \pm SD CI width: MLE = $0.0442 \pm$
 215 0.0196 ; ELBn = 0.0920 ± 0.0482 , NAS = 0.0798 ± 0.0324 .

216 On average, the relationship across the gradient was under estimated, but by nearly an order of magnitude
 217 less than when simulating across steeper values of λ . Differences between known and estimated relationship
 218 coefficients: MLE -0.0007 (± 0.0079); ELBn -0.0058 (± 0.0177); NAS -0.0251 (± 0.0124).

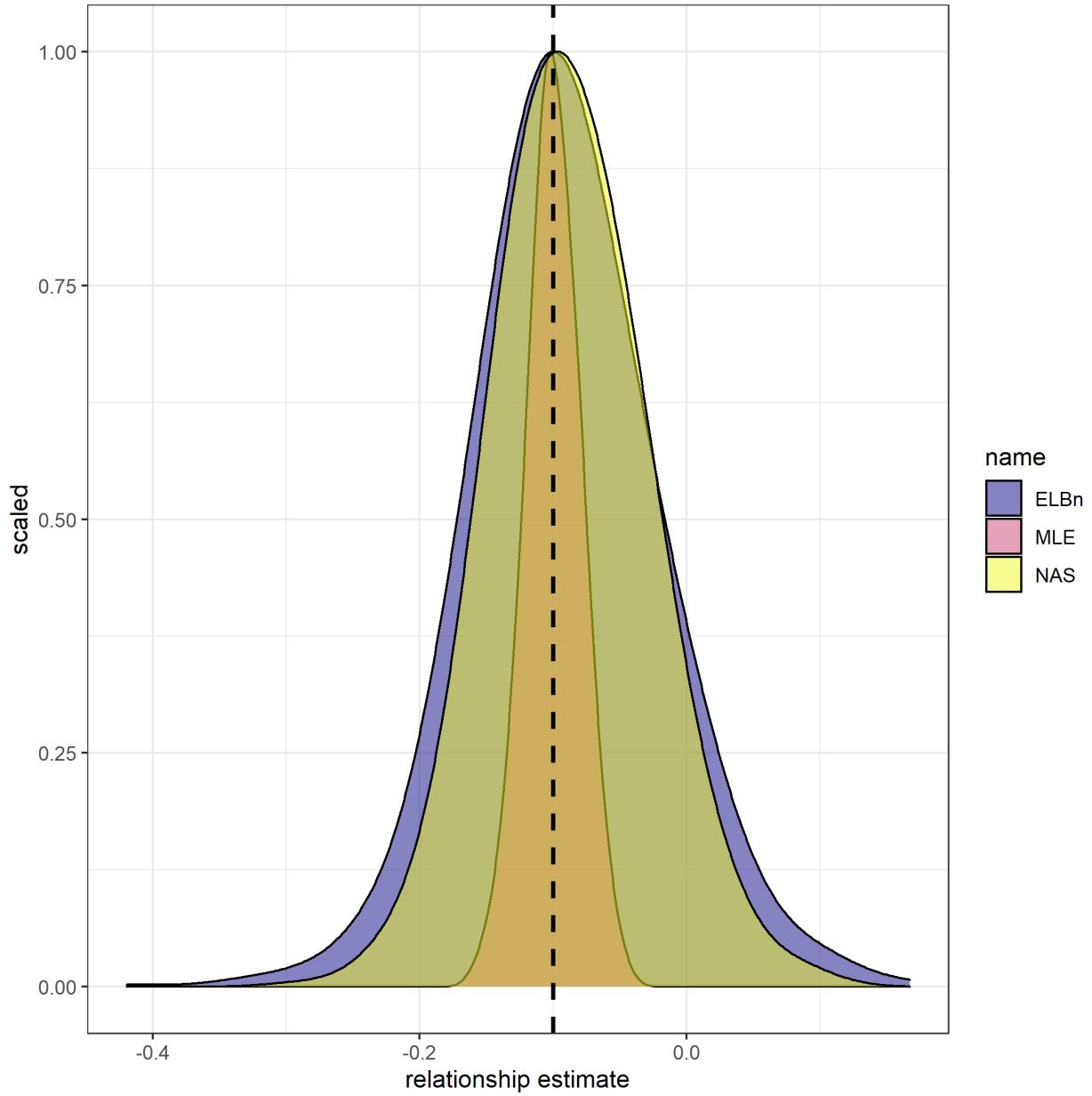


Figure 6: Mean difference between relationship estimate and known relationship coefficient for each method. Here, λ varied from -1.9 to -2.1, with a known relationship of -0.1 across the gradient.

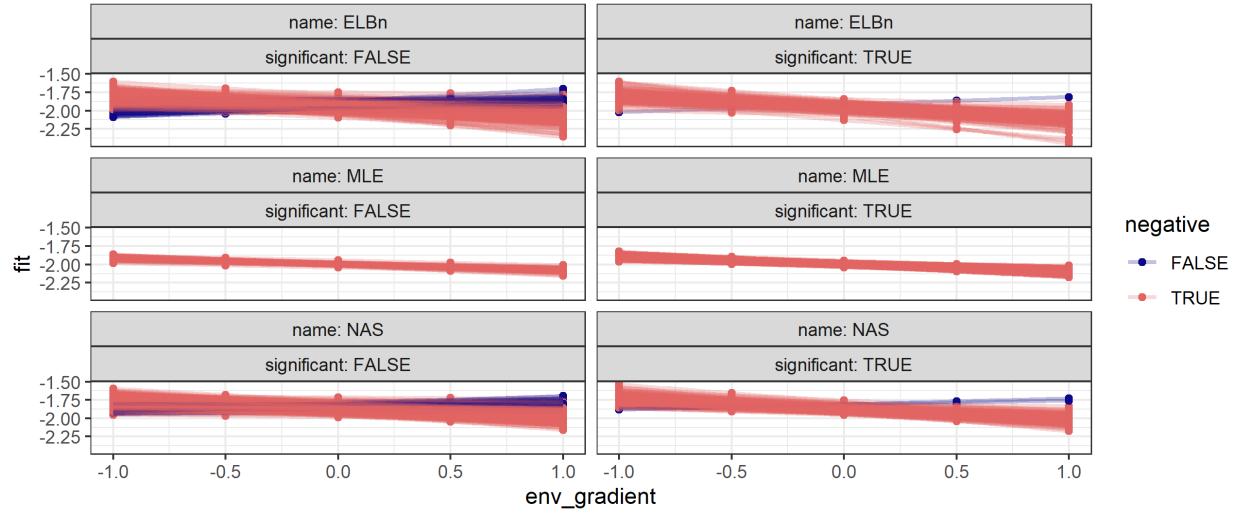


Figure 7: Linear regressions across the hypothetical gradient when lambda varies from -1.9 to -2.1. Each method is displayed in the rows, and the left column shows the non-significant estimates, while the right column shows the relationships which were significant (β_1 coefficient p-value < 0.05). The colors indicate when the beta coefficient estimate was negative (pink) and when it was positive (purple).

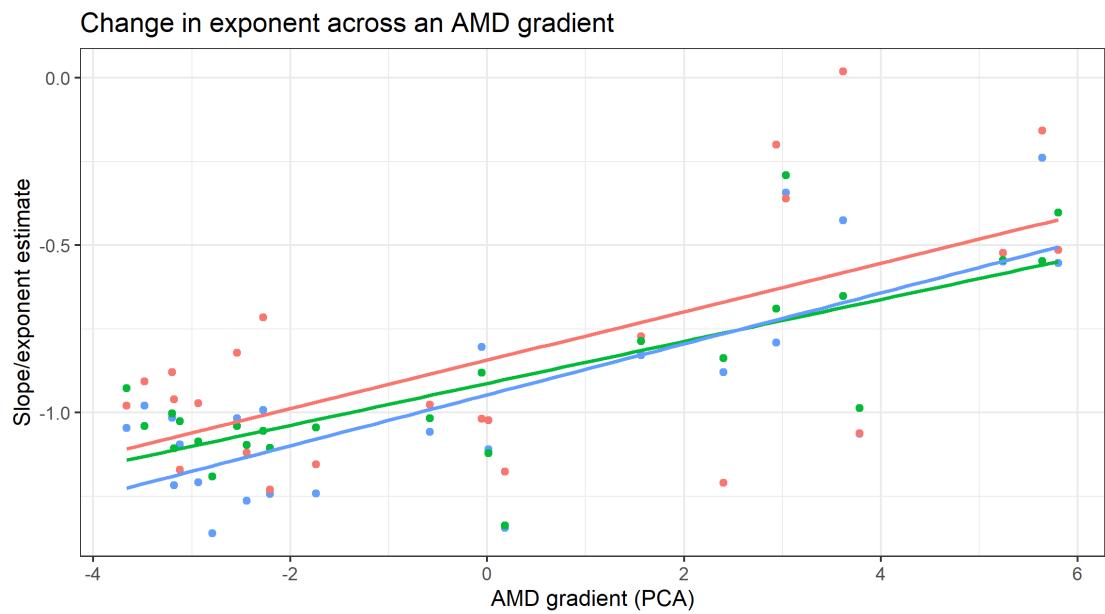


Figure 8: A

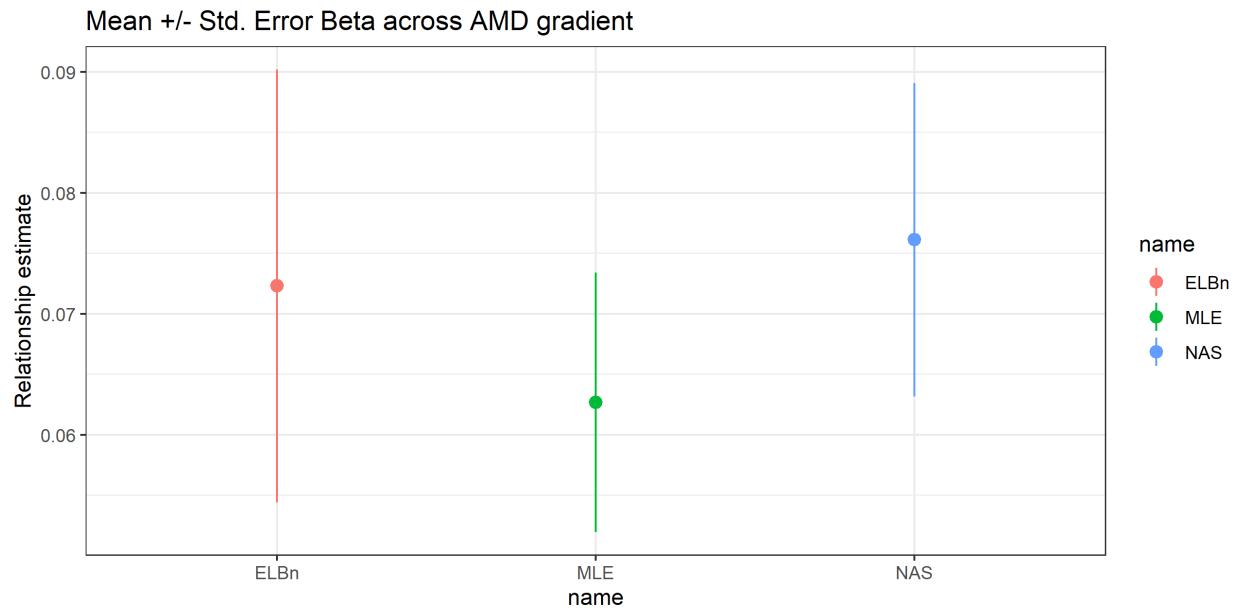


Figure 9: B.Relationship estimates across AMD gradient

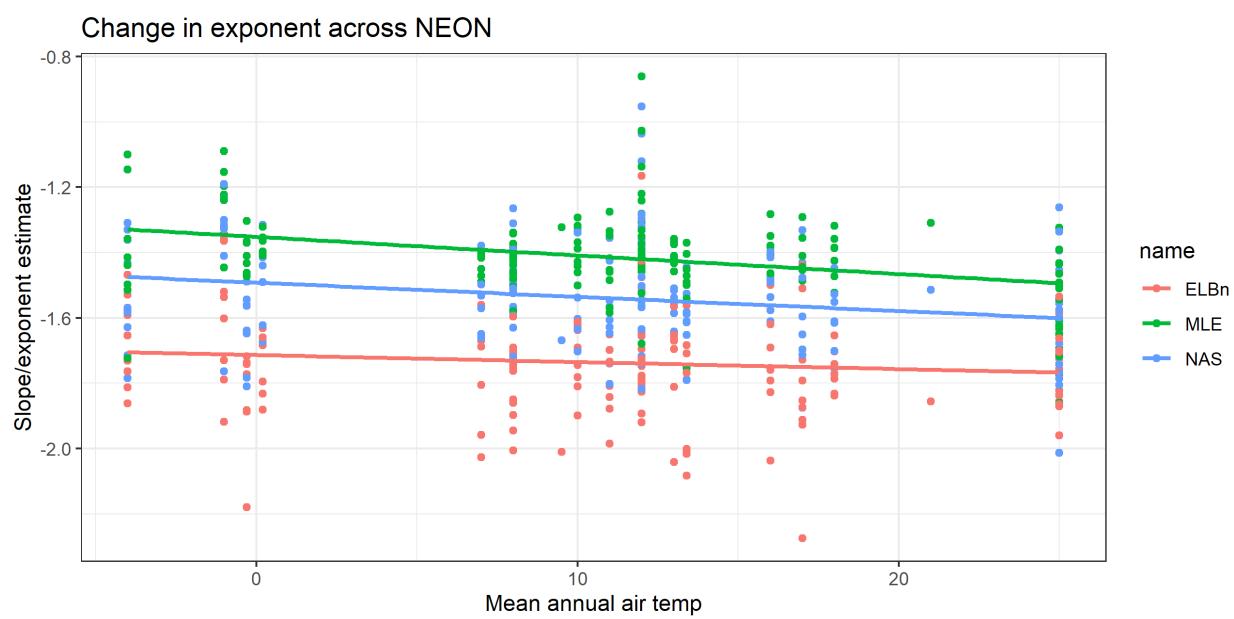


Figure 10: C.

Mean +/- Std. Error Beta across Neon

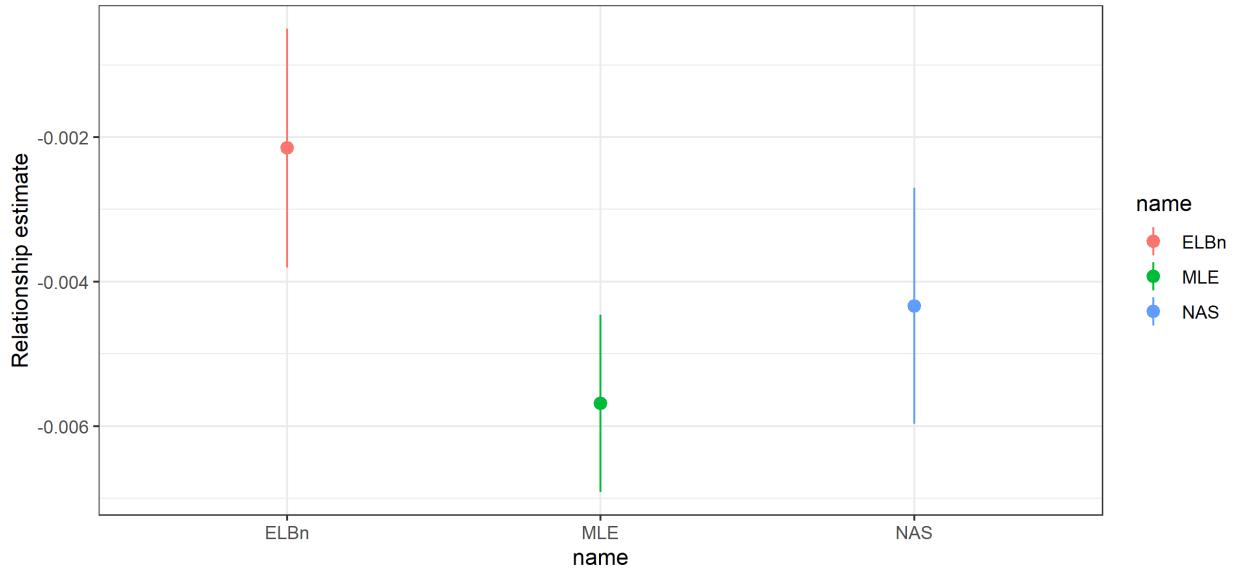


Figure 11: D.

PLB

$m_range = (0.0026, 1200)$
 $b = (-1.5, -1.1)$

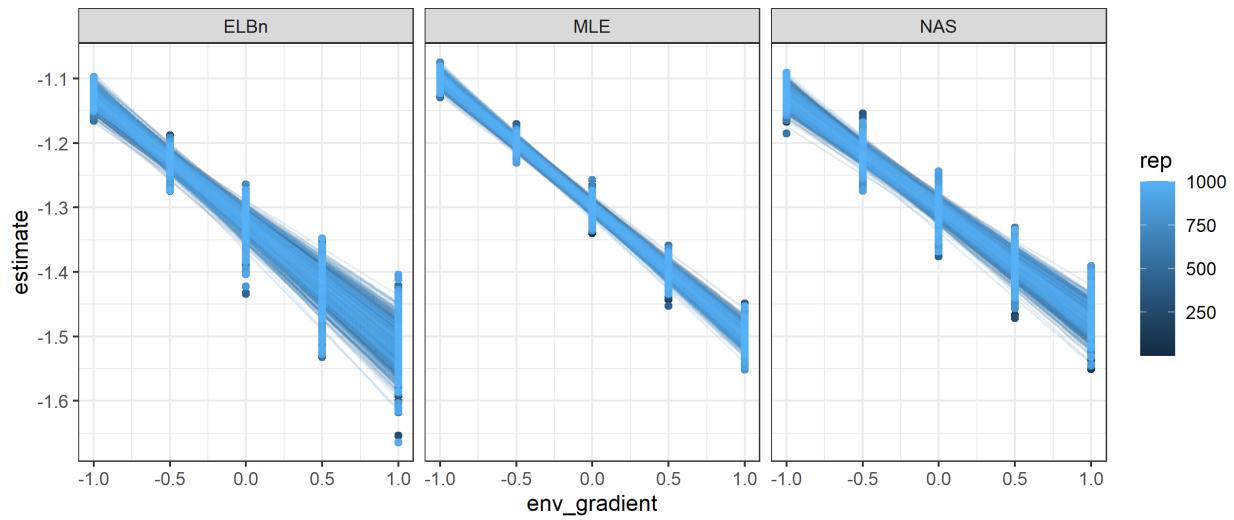


Figure 12: Relationship estimates across the hypothetical gradient for each replicate. Each panel is a different method for estimating the size spectra parameter.

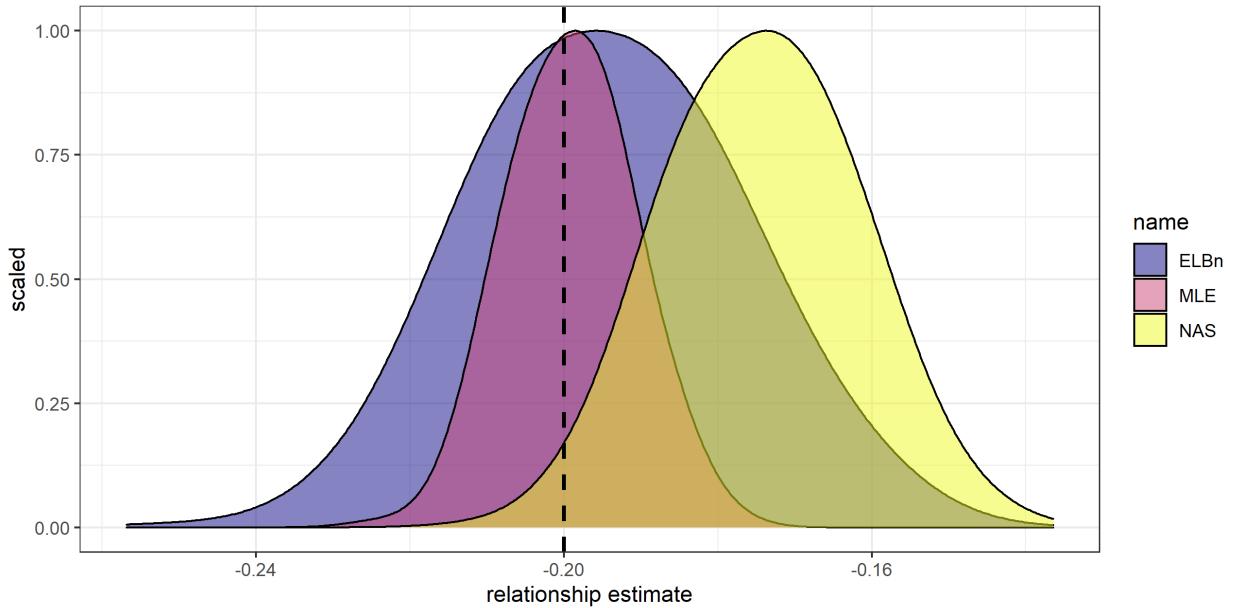


Figure 13: Distribution of relationship coefficient estimates. Vertical line is the known relationship. All methods under estimate the value, but the mean magnitude and distribution of values is greater for the ELBn and NAS methods.

219 Discussion

- 220 Measuring parameters describing the decline in abundance with increasing body size in communities is
 221 being done with increasing frequency across ecology. Previous work has investigated the accuracy and
 222 inherent biases associated with different estimation methods. However, how these inaccuracies and biases
 223 compound across environmental gradients remains uncertain, making it difficult to detect variation in
 224 size spectra parameters across environmental gradients with confidence. Here, we sampled body sizes from
 225 known distributions and estimated their parameters across a hypothetical gradient in order to assess the
 226 relationship coefficients obtained.
- 227 Generally, there was large agreement in the direction and magnitude of average relationship coefficient
 228 estimates across methods. The estimate from the MLE method was always closer to the known relationship,
 229 and always had the smallest variation around the estimate.
- 230 All of the methods performed equally well when the λ value did not vary across the hypothetical gradient,
 231 with a Type I error rate of $\sim 5\%$, exactly as would be expected under the assumptions of frequentist statistics.
 232 This indicates that previous studies which have detected no difference in size spectra parameters across sites
 233 can be interpreted with confidence, regardless of the method used.
- 234 The performance of all methods improved as sample size increases, and as the exponent of the size spectra
 235 relationship gets larger (more shallow). As either or both of these variables change, the difference in estimated
 236 relationship coefficients declines across the methods. This is particularly interesting given the fact that both
 237 empirical data sets of stream communities examined here are shallower than the expected relationship of
 238 $\lambda = -2$, and the conclusions of the change in size spectra relationships across the gradients are not dependent
 239 on method used. If communities under study are in fact described by shallower exponents, the method used
 240 may not be critical in the conclusions reached. However, the MLE method performs as well or better than
 241 the two binning methods examined here under all contexts and should be the preferred method moving
 242 forward. At a minimum, future studies should report MLE estimates to ensure that the results are not
 243 dependent on the methodology used.
- 244 Alarmingly, the performance of all methods declined dramatically when trying to detect smaller variation in

245 λ values. We simulated observations from distributions varying by an absolute value of 0.2 units. This range
246 of variation is similar to that which has been reported in many seminal works on variation in size spectra
247 parameters. When using the MLE method, significant relationships were only detected ~88% of the time,
248 whereas both of the binning methods only detected significant trends ~20% of the time. Of the simulation
249 replicates which were significant, nearly all of them were negative across all methods except for one single
250 replicate using the NAS method which was positive (Figure. 5).

251 Despite the drop in performance with reduced variation in λ values, when a significant relationship was
252 observed, it was generally in the correct direction and of a similar magnitude. This suggests that previously
253 reported significant changes in size spectra parameters across environmental gradients and in experimental
254 manipulations are plausible, and the magnitude of the relative change is a reasonable estimate. Given that
255 all of the data within a study is treated identically, the the over all chnage in size spectra parameters is
256 likely reasonable. However, the biases and inconsistencies in relationship estimates presented here suggest
257 that it would be difficult if not impossible to compare the relative changes across different published studies
258 which use different methods. Publication of individual body size data with future studies of size spectra
259 relationships would greatly aid in our ability to generalize changes to this fundamental aspect of community
260 organization across spatiotemporal scales and in response to environmental stressors and perturbations.

261 **Concluding Remarks**

262 We reiterate the recommendations of White et al. (2007), Sprules and Barth (2016) and Edwards et al. (2017)
263 to estimate size spectra relationships using MLE methods due to their superior performance in nearly every
264 context. Furthermore, we strongly encourage authors to publish individual size data whenever possible. This
265 will allow for the consistent re-analysis of existing data sets as methodologies develop and improve. This
266 will aid in the ability for size spectra work to be synthesized between research groups and across scales.

267 **Supplementary material**

268 **Range of body sizes, M**

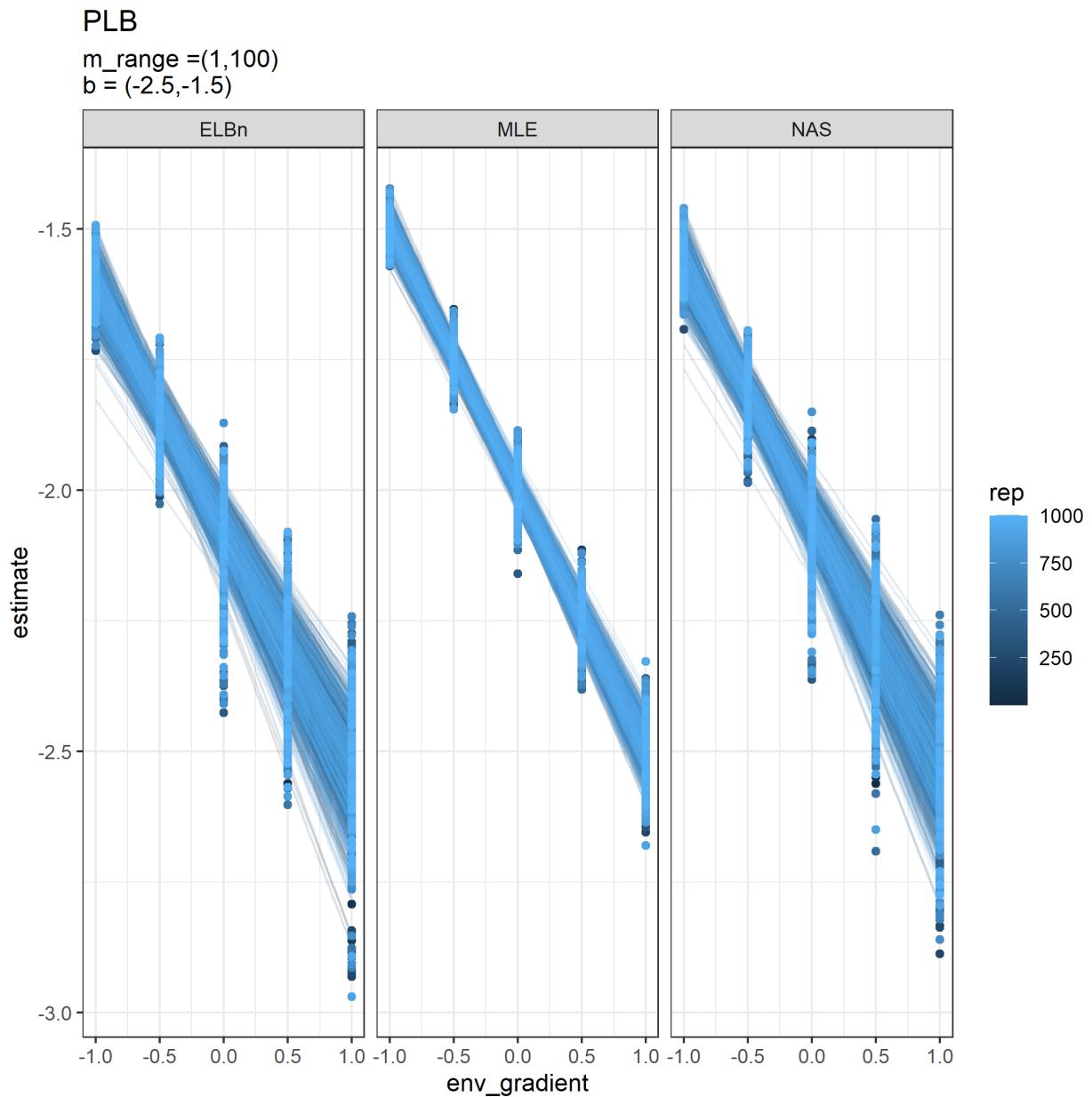


Figure S1: Individual regressions for five sites across a hypothetical gradient with a known relationship of 0.5. Range of body sizes is reduced and is from 1, to 100.

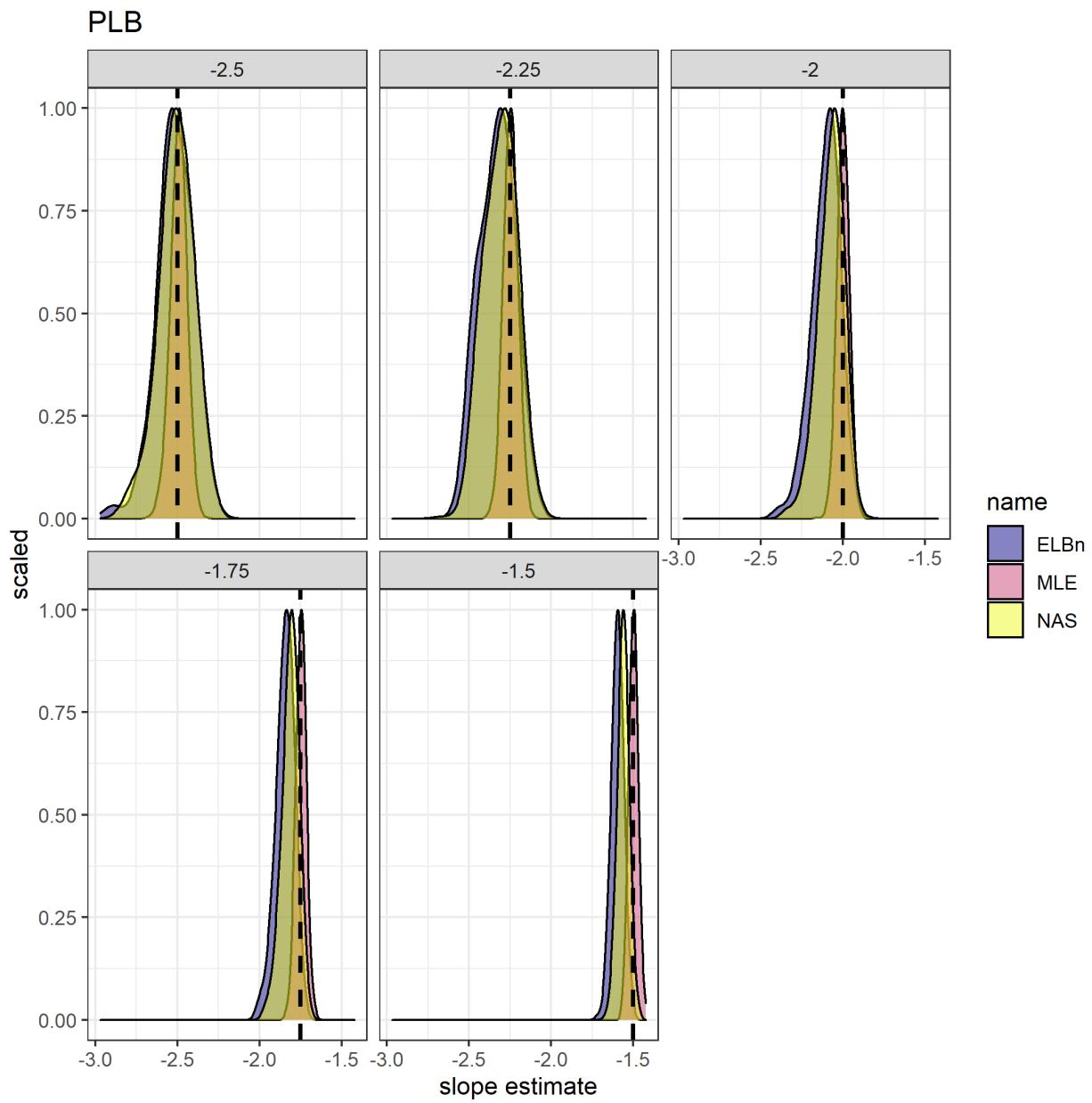


Figure S2: Distribution of estimated λ coefficient for five sites across a hypothetical gradient with known values. Range of body sizes is reduced and is from 1, to 100.

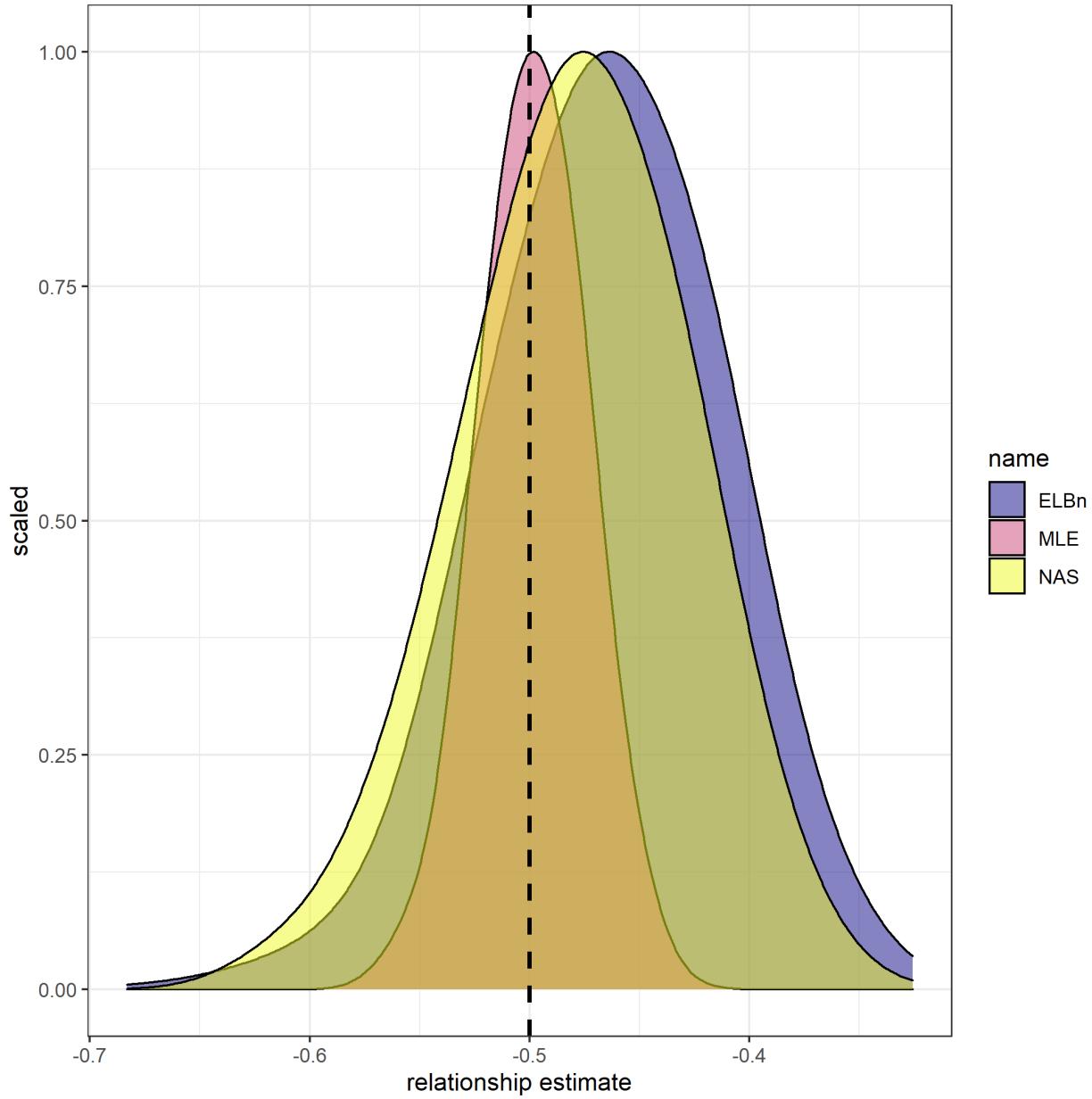


Figure S3: Distribution of estimated relationship (β_1) coefficient's for five sites across a hypothetical gradient with known value of 0.5. Range of body sizes is reduced and is from 1, to 100.

PLB

$m_range = (0.0026, 1200)$

$b = (-2.5, -1.5)$

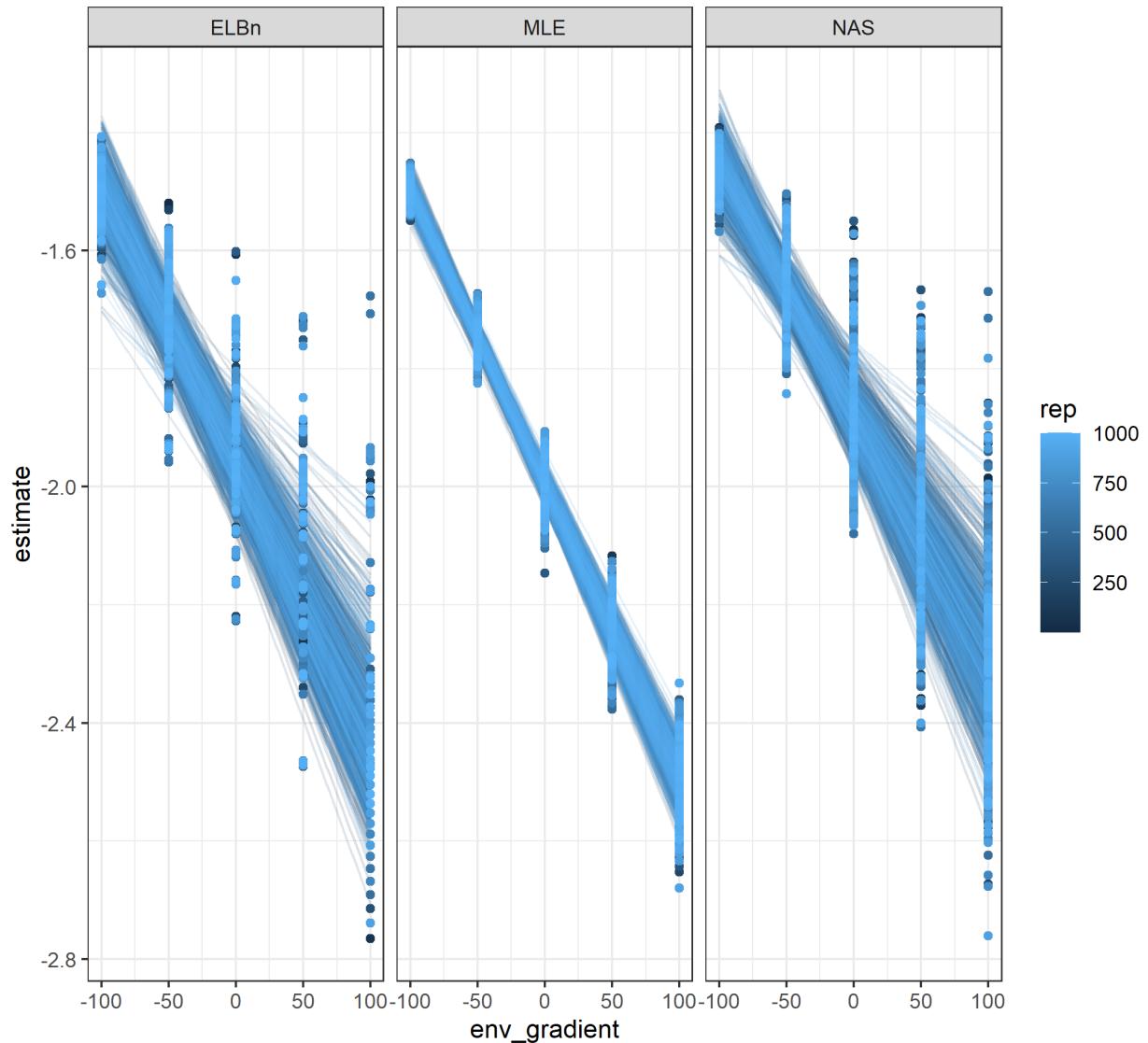


Figure S4: Individual regressions for five sites across a hypothetical gradient with a known relationship of 0.5. Range of environmental values (x -axis) increased to be -1000, to 1000.

PLB

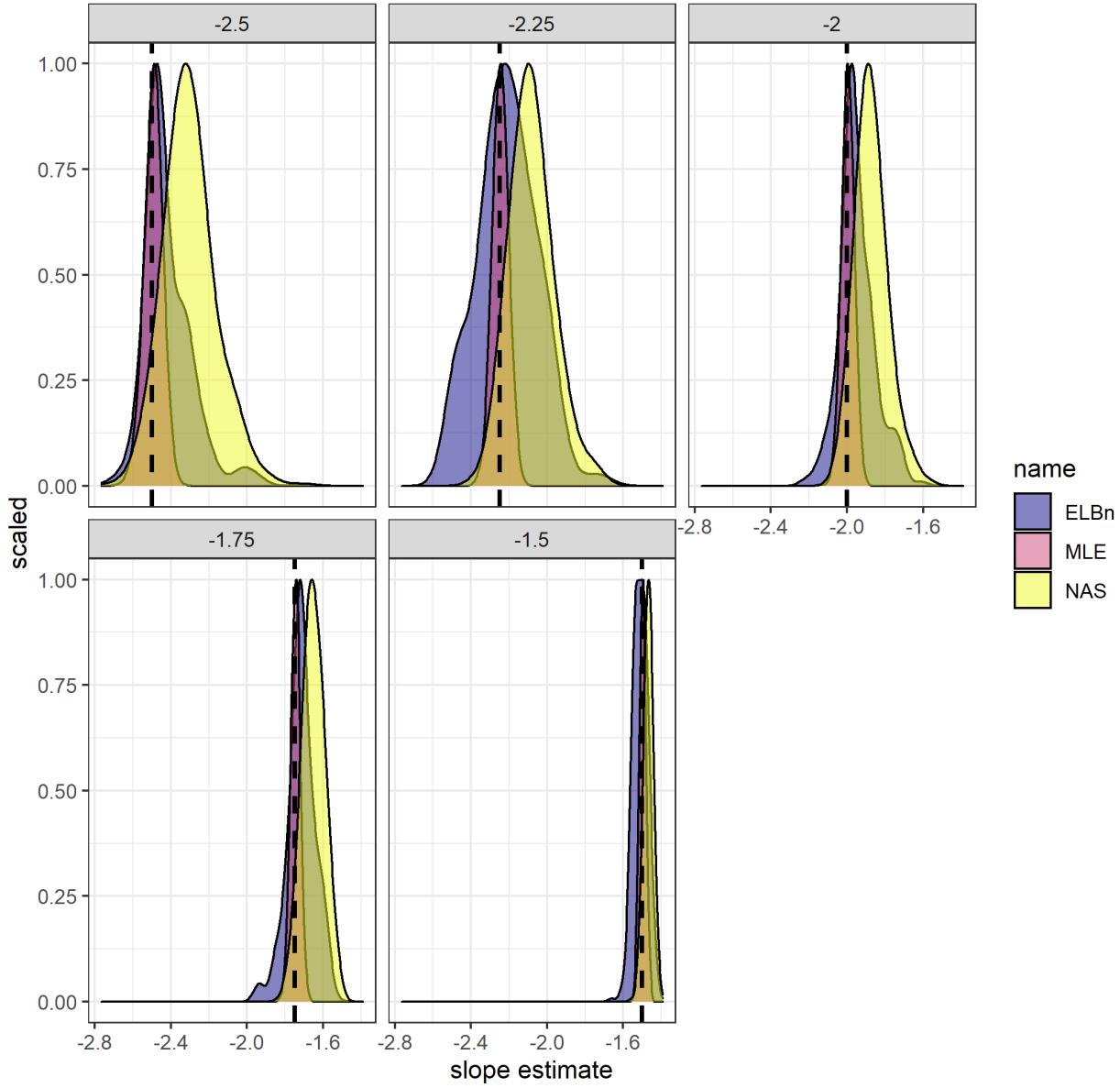


Figure S5: Distribution of estimated λ coefficient for five sites across a hypothetical gradient with known values. Range of environmental values (x -axis) increased to be -1000, to 1000.

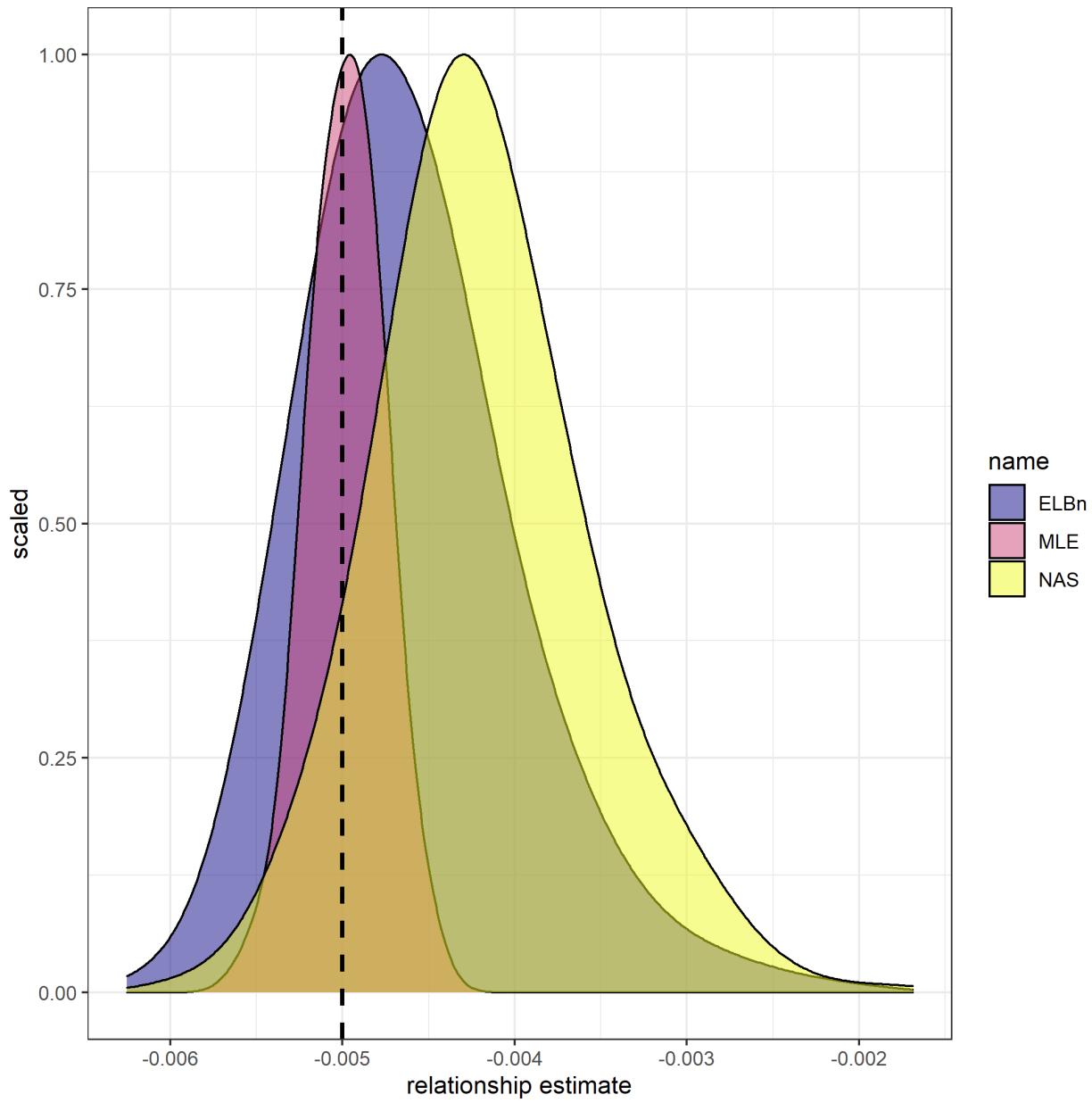


Figure S6: Distribution of estimated relationship (β_1) coefficient's for five sites across a hypothetical gradient with known value of 0.5. Range of environmental values (x-axis) increased to be -1000, to 1000.

²⁶⁹ Large environmental gradient

²⁷⁰ Varying number of sites

²⁷¹ 10 sites

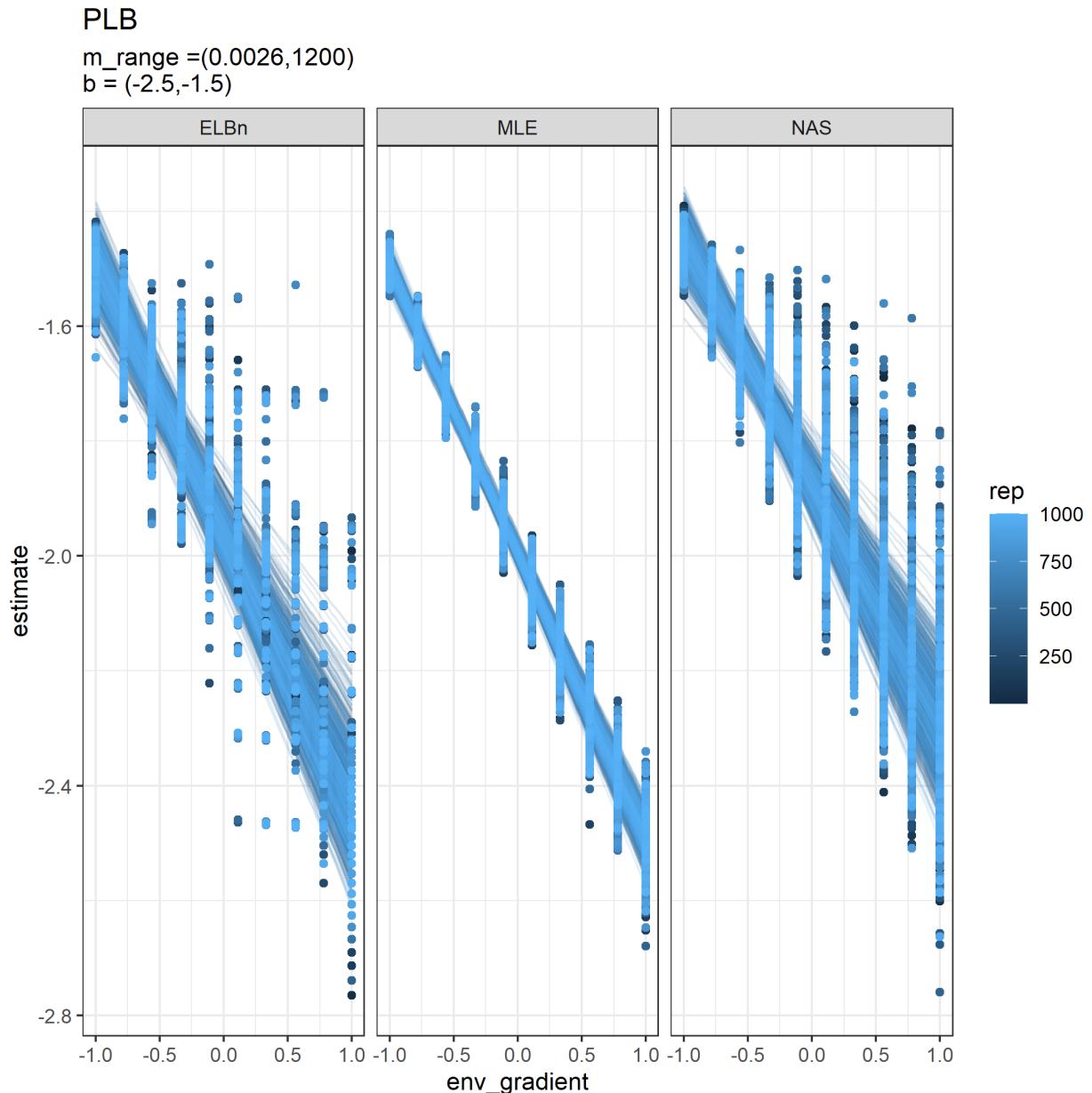


Figure S7: Individual regressions for ten sites across a hypothetical gradient with a known relationship of 0.5. All other parameters are the same as in the main analysis

²⁷² Sample size

²⁷³ note These plots still have n = 100. Need to re run and update if we end up going with n = 200

PLB

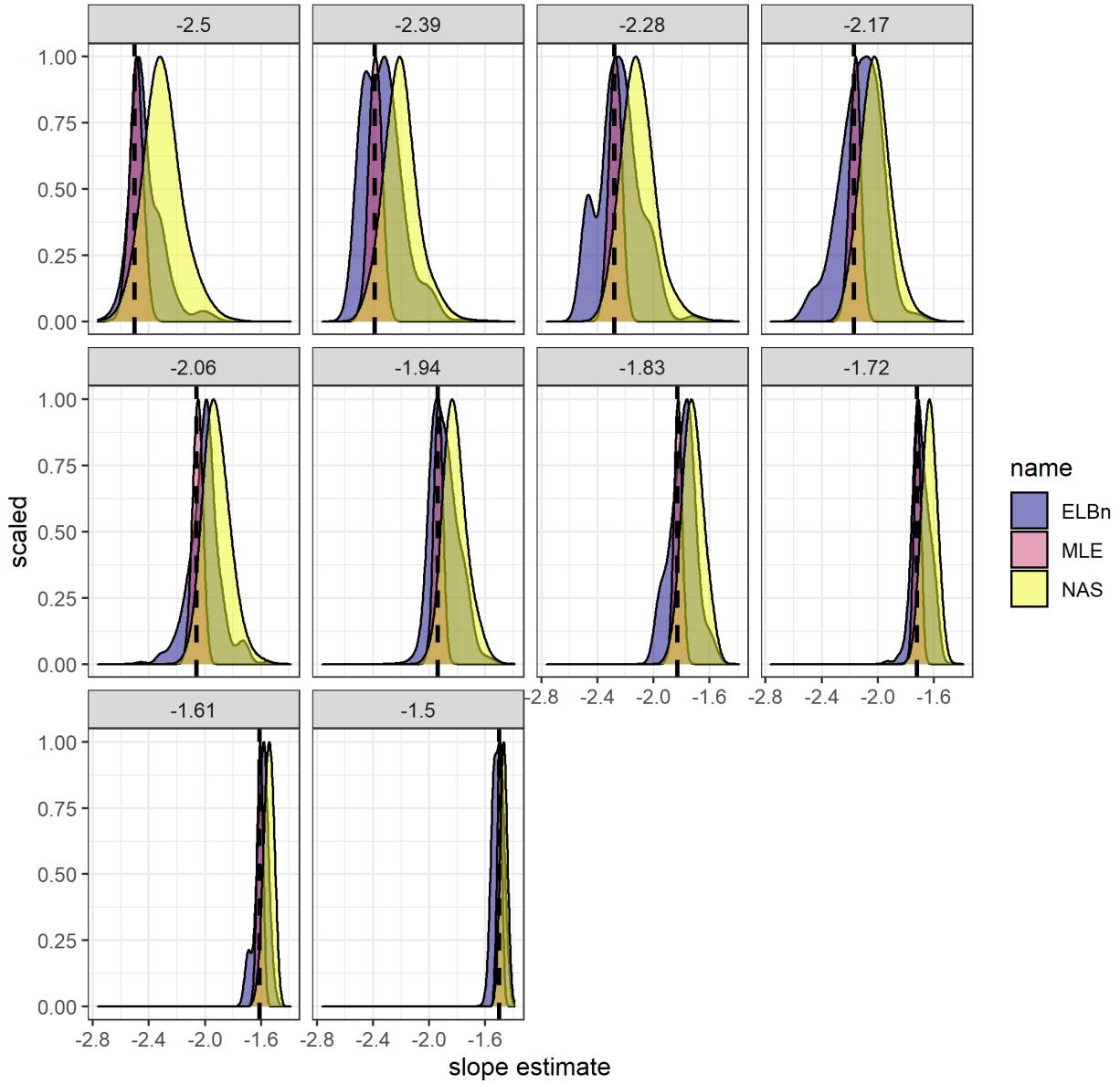


Figure S8: Distribution of estimated λ coefficient for ten sites across a hypothetical gradient with known values. All other parameters are the same as in the main analysis

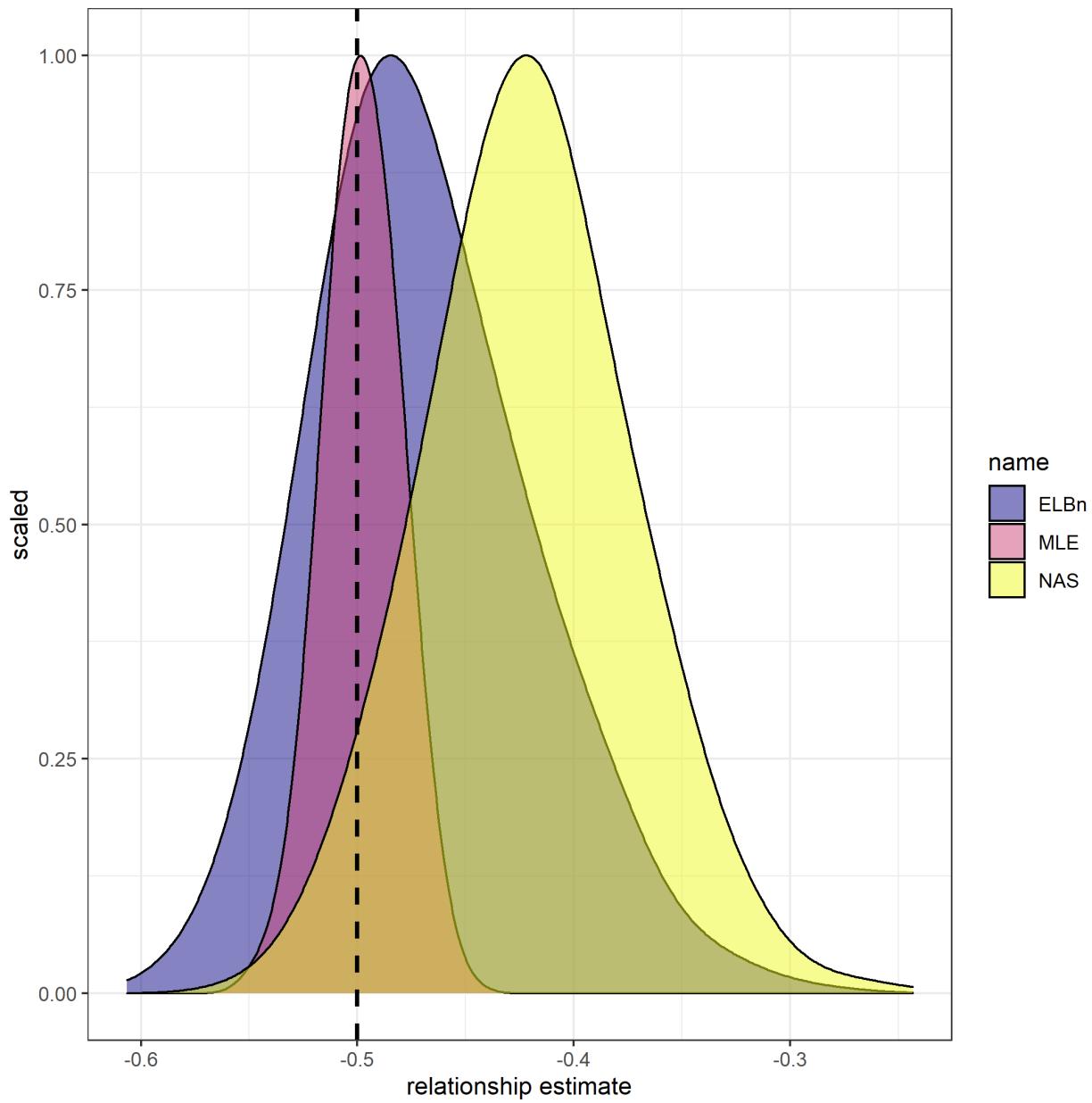


Figure S9: Distribution of estimated relationship (β_1) coefficient's for ten sites across a hypothetical gradient with known value of 0.5. All other parameters are the same as in the main analysis

PLB

$m_{range} = (0.0026, 1200)$

$b = (-2.5, -1.5)$

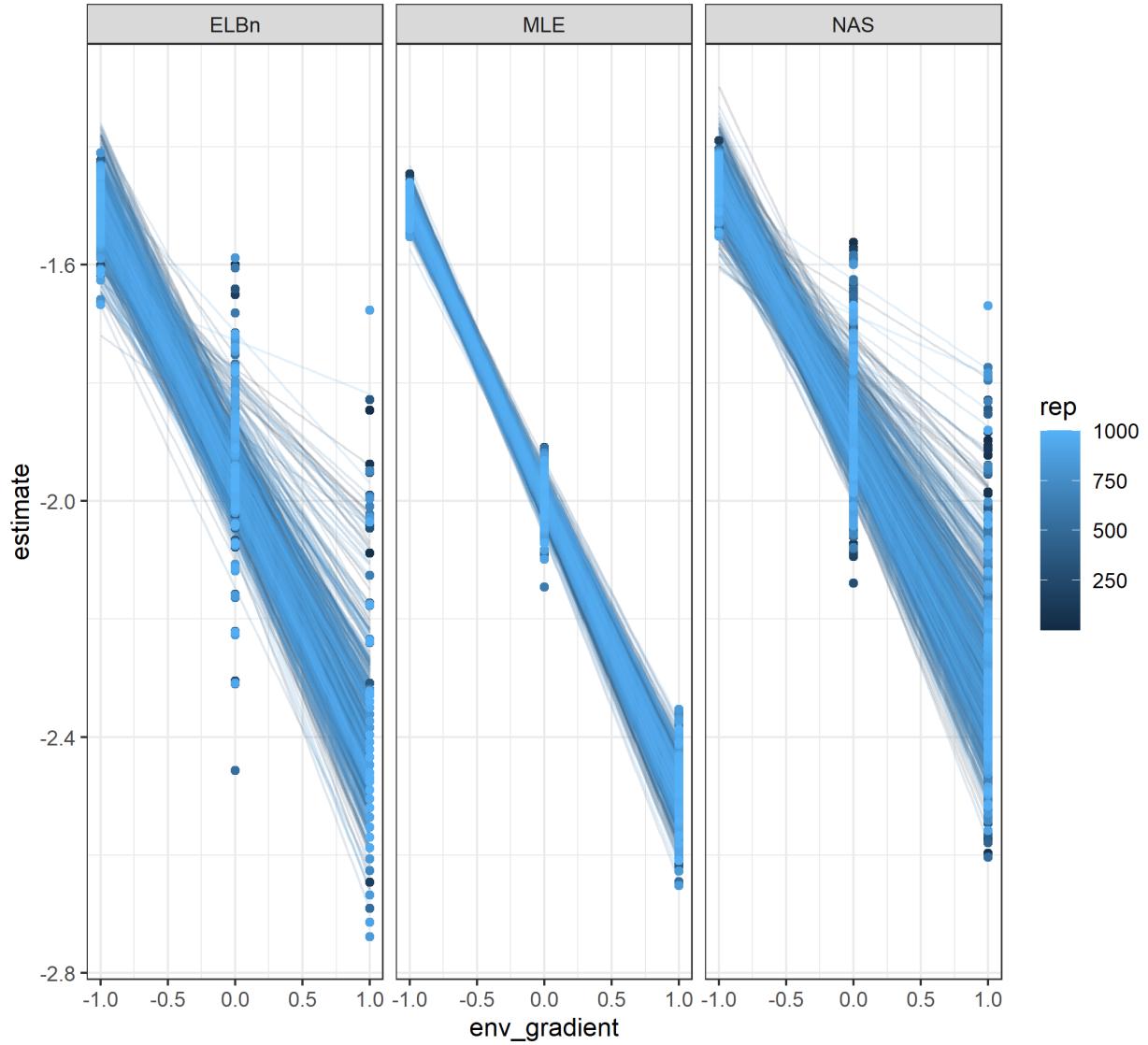


Figure S10: Individual regressions for three sites across a hypothetical gradient with a known relationship of 0.5. All other parameters are the same as in the main analysis.

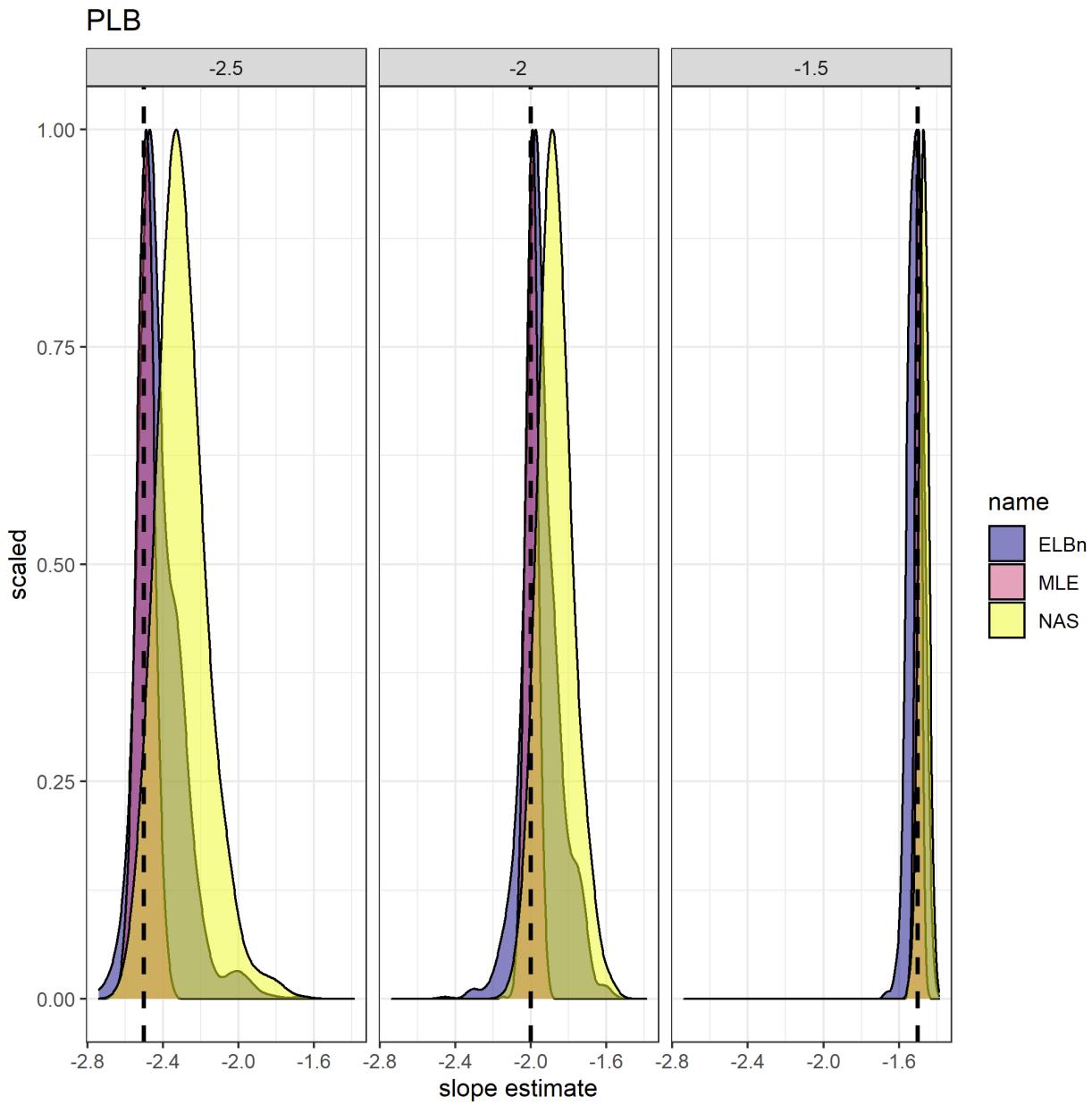


Figure S11: Distribution of estimated λ coefficient for three sites across a hypothetical gradient with known values. All other parameters are the same as in the main analysis.

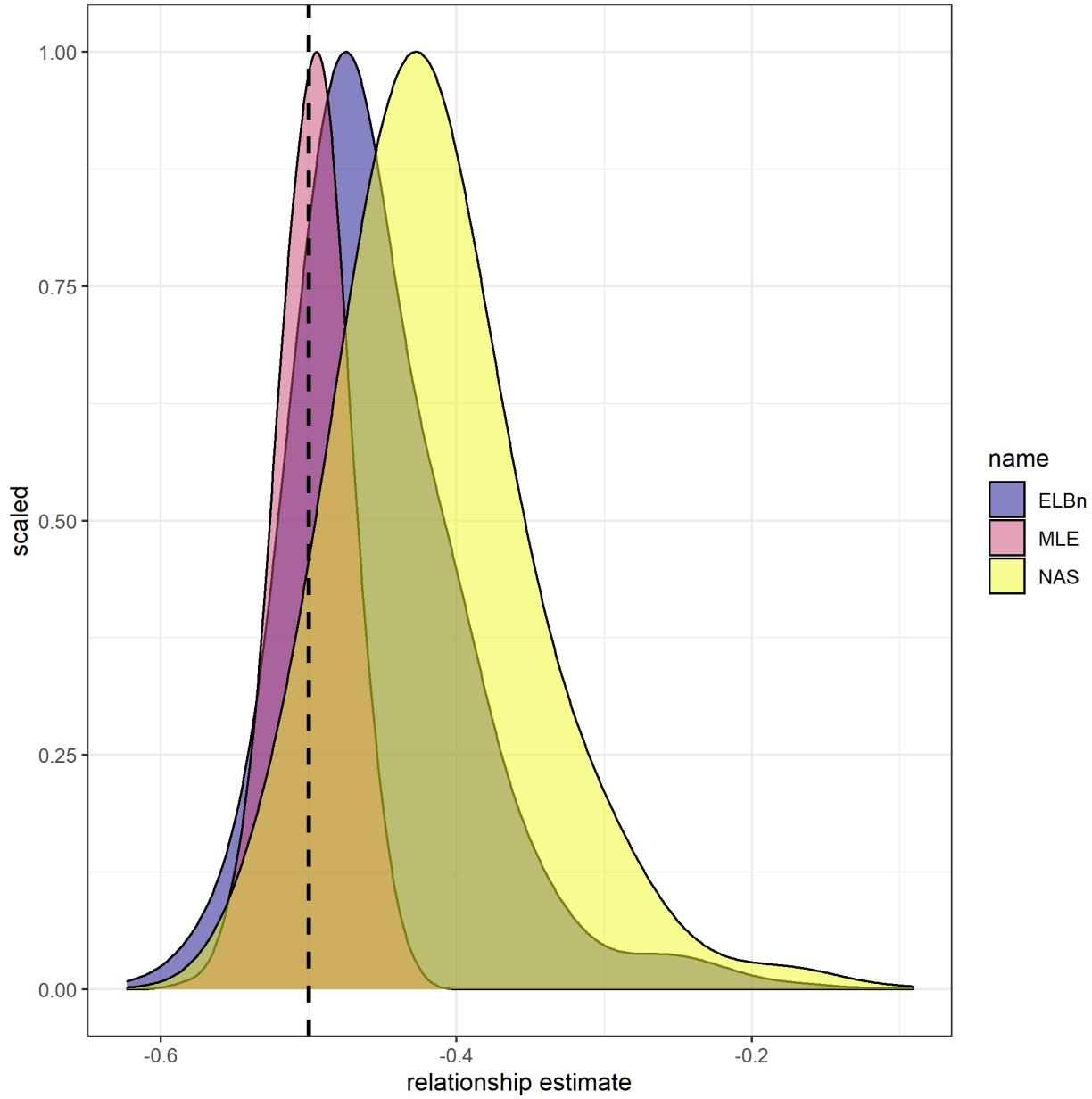


Figure S12: Distribution of estimated relationship (β_1) coefficient's for three sites across a hypothetical gradient with known value of 0.5. All other parameters are the same as in the main analysis

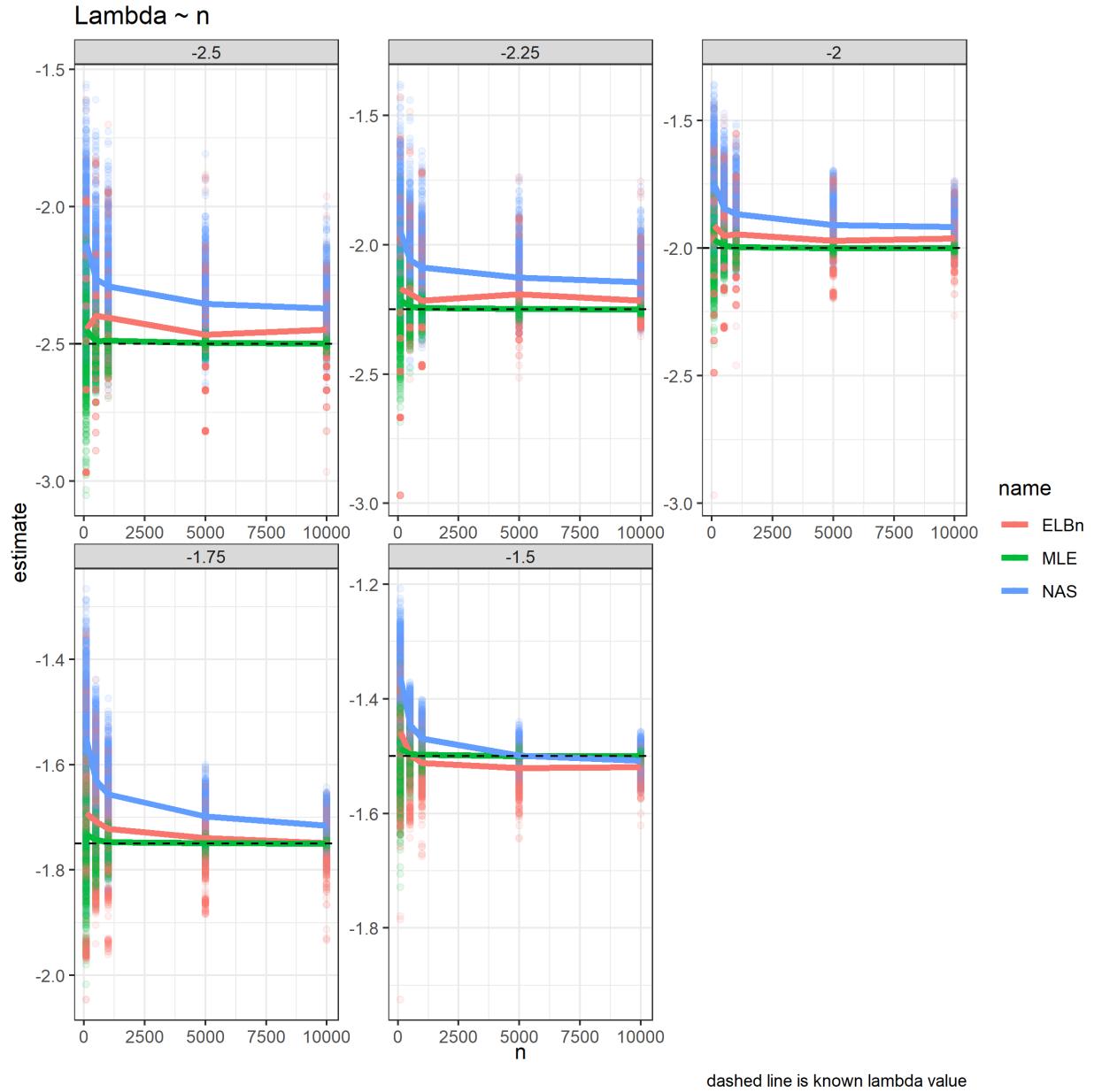


Figure S13: Plot showing the relationships between sample size and the estimated λ parameters. the dashed line indicates the known value of λ .