



# Using codispersion analysis to quantify and understand spatial patterns in species-environment relationships

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## 19 **Summary**

- 20 1. Analysis of spatial patterns in species-environment relationships can provide new insights  
21 about the niche requirements and potential co-occurrence of species, but species abundance  
22 and environmental data are routinely collected at different spatial scales. Here, we investigate  
23 the use of codispersion analysis to measure and assess the scale, directionality, and  
24 significance of complex relationships between plants and their environment in large forest  
25 plots.
- 26 2. We applied codispersion analysis to both simulated and field data on spatially-located tree  
27 species basal area and environmental variables. The significance of observed bivariate spatial  
28 associations between the basal area of key species and underlying environmental variables  
29 was tested using three null models.
- 30 3. Codispersion analysis reliably detected directionality (anisotropy) in bivariate species-  
31 environment relationships and identified relevant scales of effects. Null model-based  
32 significance tests applied to codispersion analyses of forest plot data enabled us to infer the  
33 extent to which environmental conditions, tree sizes, and/or tree spatial positions  
34 underpinned observed basal area-environment relationships, or whether relationships were  
35 due to other unmeasured factors.
- 36 4. Codispersion analysis, combined with appropriate null models, can be used to infer  
37 hypothesized ecological processes from spatial patterns allowing us to start disentangling the  
38 possible drivers of plant species-environment relationships.

39 **KEYWORDS:** Anisotropy, bivariate, environmental gradient, forest dynamics plot, spatial  
40 analysis, species-environment, variogram

41

## 42 **Introduction**

43 Environmental variability is a key driver of variation in biological diversity (Chesson 2000).  
44 Analysis of the spatial patterns in species-environment relationships can reveal clues about niche  
45 requirements of individual species and their potential for co-occurrence with other species  
46 (Silvertown 2004). Quantification of spatial patterns of species' distribution and abundance can  
47 illuminate scales of variation. These patterns often suggest experimentally testable hypotheses

48 about multiple interacting processes that may drive species distribution and abundance patterns  
49 (Hubbell 1979; Weigand et al. 2012).

50 The usual approach to relating spatial patterns of environmental gradients and  
51 populations of sessile organisms (e.g., plants, ant nests, barnacles) starts with recording the  
52 positions of individuals, or in the case of composite, plot-based measures, such as species  
53 richness or cover values, the positions of plots. This enumeration yields a spatial point pattern  
54 (Dale 1999). Environmental variables are then sampled, but they often are not measured at the  
55 same spatial grain as the point pattern. Examples include soil samples collected on a regularly-  
56 spaced grid (John et al. 2007; Turner and Engelbrecht. 2011), elevation and slope measurements  
57 derived from a digital elevation model (Franklin 1995) or climate variables derived from a  
58 spatial database, such as ‘WorldClim’ (Hijmans 2005). Relationships between point patterns and  
59 environmental data can be analyzed using non-spatial methods that emphasize causal  
60 relationships (e.g., canonical correspondence analysis [Lepš and Šmilauer 2003], species  
61 distribution models [Elith and Leathwick 2009], or regression models [Shen et al. 2009]), or by  
62 spatial methods that deal with the visualization of pattern and quantification of scales of  
63 variability in correlations; our focus here is on the latter.

64 The majority of the standard spatial descriptors used by ecologists, such as semi-  
65 variograms, assume that the spatial processes underlying the distribution of organisms (spatial  
66 point pattern), the associated environmental gradient, and their covariation are stationary (spatial  
67 processes are invariant under translation) and isotropic (non-directional) within the sampling  
68 extent (Cressie and Wikle 2011; see Table 1 for spatial terminology used in this paper).  
69 However, whilst these assumptions are convenient mathematically, they are typically unrealistic  
70 for most real-world examples.

71 First, the strong form of spatial stationarity (invariance under translation) is unlikely to be  
72 met in any real-world case. As a result, most spatial processes are assumed to have only second-  
73 order stationarity: only the mean, variance, and covariance need be stationary (Vieira et al.  
74 2010). However, even second-order stationarity is unlikely in many ecological cases, and we  
75 assume only the “intrinsic hypothesis” – that the mean and the semi-variance of the distribution  
76 are dependent on inter-point distances, not specific locations (Vieira et al. 2010). Second, in  
77 many ecologically realistic cases, environmental gradients create anisotropic patterns in the

78 distributions or abundances of species, where changes in species' distributions or abundances  
79 reflect changes in the magnitude of the environmental variable(s).

80 A familiar example of anisotropic relationships between environmental gradients and  
81 species distribution arises from the 'stress gradient hypothesis' (Bertness and Callaway 1994).  
82 This hypothesis posits that as the environment becomes less stressful for species (e.g., salt spray  
83 decreases with distance from the high tide line), intra- or interspecific interactions switch from  
84 predominantly facilitative to predominantly competitive. As a result, the pattern of species  
85 distributions may shift from aggregated to regular (e.g., Malkinson et al. 2003; Lingua et al.  
86 2008) or even hyper-dispersed. Additional processes that may influence clumping of species  
87 across environmental gradients include dispersal limitation, habitat filtering, and density-  
88 dependent interactions with natural enemies (Condit 2000; Morlon et al. 2008; McGill 2010).  
89 Accurate identification of the underlying causes of such complex spatial patterns requires  
90 analytical methods that are sensitive not only to the spatial grain of the pattern, but also to non-  
91 stationarity and anisotropic changes over space.

92 Here, we illustrate how to use codispersion analysis (Cuevas et al. 2013; Buckley et al.  
93 2016) to detect and display both isotropic and anisotropic spatial relationships between a spatial  
94 point pattern of species' locations and attributes, and associated environmental variables  
95 measured at larger spatial grain. The analysis is based on the codispersion coefficient between  
96 the ecological characteristics of a plant species (e.g., the relative abundance, biomass, size or  
97 other functional trait) and an environmental variable in a given direction and within a given  
98 distance across a particular spatial extent, such as a plot. Codispersion analysis has been applied  
99 previously only to a few data types in ecology, including the relationship between tree size and  
100 an underlying environmental gradient (topography) at a landscape-level spatial extent (Cuevas et  
101 al. 2013), multivariate spectral data (Vallejos et al. 2015), and species co-occurrences (Buckley  
102 et al. 2016). In this study, we apply codispersion analysis first to simulated data, and then to tree  
103 location and size (diameter) data from two large forest plots, one tropical and one temperate. Our  
104 results illustrate how codispersion analysis can be used to detect spatial patterns in tree size  
105 across environmental gradients. In addition, we demonstrate a framework for using different null  
106 models to test the significance of these spatial patterns (i.e., the departure of observed patterns  
107 from random expectation), and how differences in significance among null model tests can be

108 used to generate hypotheses about, and guide the structuring of, models of underlying spatial  
109 processes. Specifically, we ask, at a  $20 \times 20$ -m grain size, what is the direction, magnitude, and  
110 spatial pattern in covariation between selected tree species and environmental variables across  
111 these two large forest plots? For the purposes of illustrating this method, we selected common  
112 species that covaried with the environmental variables in a variety of ways to reflect some of the  
113 different underlying processes that can drive species-environment relationships. For example, we  
114 can explore if covariation is higher between a tree species' basal area and an environmental  
115 variable within 50 m in a northerly direction than would be expected if the species was randomly  
116 distributed.

117

## 118 **Materials and Methods**

### 119 *An overview of codispersion analysis*

120 Codispersion analysis quantifies the spatial covariation of two or more spatially-explicit  
121 datasets. The result is a two-dimensional codispersion graph that allows us to assess how the two  
122 datasets co-vary across a range of spatial lags (distances between points) and directions (Table 1;  
123 Fig. 1; Vallejos et al. 2014). Codispersion analysis can be applied to datasets organized as spatial  
124 point patterns, irregular plots, or rasters. Spatial point patterns depict the locations of individuals  
125 (e.g., trees) and possible attributes (“marks”) of these individuals (e.g., diameters or other  
126 functional traits) measured at these same locations. Rasters often are used to depict  
127 measurements of continuously-varying soil or topographic properties as regular grids of cells of  
128 a particular size (resolution), from interpolations of variables that have been measured within the  
129 same vicinity as, but not precisely at the locations of the point patterns. Spatial point patterns  
130 also may be converted (up-scaled) into rasters prior to codispersion analysis, such as by  
131 quantifying tree abundances (stem density) or basal areas within raster cells of a given size.

132 In-depth statistical details of the mechanics of codispersion are given in Ruhkin and  
133 Vallejos (2008), Cuevas et al. (2013), and Buckley et al. (2016); in the latter we consider species  
134 co-occurrences. Annotated R code (R version 3.1.2, R Core Team 2014) for performing  
135 codispersion analysis, including its application to examples from this study, is provided in  
136 Supporting Information Notes S1.

137 In brief, codispersion analysis for two spatial datasets involves five steps.

138 First, determine the set of spatial lags  $\mathbf{h} = \{h_1, h_2\}$ :  $\mathbf{h} \leq 0.25 \times$  maximum distance of the  
139 shortest side of the sample plot. The two components of  $\mathbf{h}$  are vectors representing the range of  
140 spatial lags to be analyzed for each input dataset  $X$  (e.g., tree basal area) and  $Y$  (e.g., elevation  
141 above sea level).  $h_1$  is oriented parallel to the  $x$  axis, and ranges from  $-h_{\max}$  to  $+h_{\max}$  (Fig. 1A).  $h_2$   
142 is oriented parallel to the  $y$  axis and ranges from 0 to  $h_{\max}$  (Fig. 1A). We note that two opposite  
143 directions are incorporated into the analysis along the  $x$  axis (positive and negative), so any  
144 anisotropy in the data will be more apparent along this axis. We therefore recommend that the  
145 dataset be oriented in such a way that the directionality of patterns of particular interest is along  
146 the  $x$  axis direction, or, that the data be rotated and analyzed in both directions.

147 Second, an Epanechnikov kernel function (Cuevas et al. 2013) is applied across all  
148 possible raster cell-to-cell distances for each  $\mathbf{h}$ , resulting in a smooth spatial variation surface for  
149 each individual dataset and their intersection. The “smoothness” of the kernel surfaces is  
150 controlled by a set of kernel bandwidth parameters  $\mathbf{k} = \{k_X, k_Y, k_{XY}\}$  (Cuevas et al. 2013). As  
151 rasterization of a spatial point process implies a uniform smoothing at the scale of the raster cell  
152 (Buckley et al. 2016), when analyzing rasterized data, we recommend setting each element of  $\mathbf{k}$   
153 equal to the dimension of the raster cell to avoid unintentional repeated smoothing of the data.

154 Third, semi-variograms for  $X$  and  $Y$  and the semi-cross-variogram of the intersection of  $X$   
155 and  $Y$  are computed for the kernel-smoothed surfaces (Cuevas et al. 2013).

156 Fourth, the empirical codispersion coefficient (Matheron 1965) is computed for each lag  
157  $\mathbf{h}$  as the semi-cross-variogram divided by the square root of the product of the semi-variograms  
158 for each of the two variables. The value of the codispersion coefficient ranges from -1.0 (strong  
159 negative codispersion) to + 1.0 (strong positive codispersion).

160 Finally, the codispersion values are plotted for each lag  $\mathbf{h}$  (Fig. 1B). The magnitude of the  
161 codispersion values on the graph, and the way in which codispersion values change across the  
162 graph, provide information regarding the strength and direction of covariation between the two  
163 datasets at different spatial grains (Fig. 1B).

164 Here, we first apply codispersion analysis to simulated data and use three null models to  
165 assess the significance of the observed patterns in both simulated and field data. We then apply  
166 codispersion analysis to explore spatial relationships between tree basal areas and underlying

167 environmental variables measured within multi-hectare forest plots. The results provide new  
168 insights into potential processes underlying observed patterns, and can provide guidance for the  
169 development of flexible, mechanistic process-based models for the data.

## 170 *Simulations*

171 To illustrate how to apply and interpret codispersion analysis for species-environment  
172 relationships, we first generated and analyzed a range of species patterns on environmental  
173 gradients (examples in Fig. 2; the complete set of simulated patterns is in Supporting Information  
174 Notes S2; R code to generate them is in Supporting Information Notes S4). We simulated  
175 marked point patterns in a  $300 \times 300$ -m “plot” by generating 1500 point locations (representing  
176 individual trees) that either were completely spatially random (CSR) or were generated by a  
177 Thomas process (using the `rThomas` function in the `spatstat` package of R [Baddeley and  
178 Turner 2005]). A Thomas process generates a clumped spatial distribution of points using  
179 parameters that describe the spatial intensity of the pattern (in this case,  $kappa = 20$  was used),  
180 the degree of variation within clumps ( $scale = 0.05$ ), and the average number of points per  
181 cluster ( $mu = 10$ ). A simulated diameter (i.e., a “mark”) was assigned to each simulated “tree”.  
182 Diameters were generated using a truncated lognormal distribution with minimum = 1,  
183 maximum = 80, mean = 40, and standard deviation =  $\ln(80/15)$  cm. These marks were distributed  
184 across the 1500 trees either randomly, increasing or decreasing to the left side, right side, left or  
185 right top corners, or increasing as a large clump in the center of the plot (Fig. 2). We calculated  
186 the basal area of the simulated trees within each of 225 contiguous  $20 \times 20$ -m cells within the  
187 simulated  $300 \times 300$ -m plot;  $20 \times 20$ -m cells were used because this is the size of typical forest  
188 inventory plots used to characterize stand structure. We then generated values for environmental  
189 variables within each raster cell. The values of the environmental variable were generated at  
190 3600 points within the plot ( $5 \times 5$  m cells) and were distributed randomly among the cells or  
191 increasing or decreasing to the left side, right side, left or right top corners, or increasing towards  
192 a maximum in the center of the plot; these examples include gradient patterns at a range of  
193 angles and rotations. The environmental raster gridded into  $5 \times 5$ -m cells was upscaled by taking  
194 the average value in  $20 \times 20$ -m cells so that the values were at the same locations and scale as the  
195 basal area data. For the codispersion analyses of these simulated data, we set the bandwidth  $k =$   
196  $\{20 \text{ m}, 20 \text{ m}, 20 \text{ m}\}$ .



197 ***Forest plot data***

198 We analyzed species-environment relationships between tree size (basal area) and environmental  
199 characteristics at two sites. The two datasets include environmental data that were collected in  
200 different ways: (1) direct measurements in each raster cell and (2) spatial interpolation  
201 (downscaling) of sparser data to individual raster cells using kriging (John et al. 2007).

202 The first data set is from the third (2000-2002) complete census of the 16-ha Luquillo  
203 Forest Dynamics Plot (LFDP) at the Luquillo Long-Term Ecological Research Site, Puerto Rico  
204 (Thompson et al. 2002). The four species selected were *Casearia arborea* (L. C. Rich.) Urban  
205 (Salicaceae), *Cecropia schreberiana* Miq. (Urticaceae), *Dacryodes excelsa* Vahl. (Burseraceae),  
206 and *Prestoea acuminata* var *montana* (Willd.) H.E. Moore (Arecaceae). These are four of the  
207 most common species (out of 152 total) in the third census of the LFDP; together they account  
208 for 44% of the total basal area of the plot (Table 2A). For each species, the basal area (m<sup>2</sup>) of the  
209 main stem of each tree was calculated from its measured diameter; basal areas of all trees of a  
210 given species in each raster cell were summed to give the species' total basal area for that cell.  
211 Elevation (range 333 – 428 m a. s. l.) was measured (1990 – 1992) and mean elevation was  
212 calculated for each cell as the mean of the elevations at the four corners of each 20 × 20-m cell  
213 (Thompson et al. 2002). Slope (range -0.7 – 65%) was calculated from the corner elevations of  
214 each 20 × 20-m cell (Thompson et al. 2002).

215 Basal area of *Casearia* and *Prestoea* decreases but basal area of *D. excelsa* increases with  
216 elevation in the LFDP due to the pattern of land-use history in the plot (Thompson et al. 2002).  
217 The northern (lower elevation) two-thirds of the plot were logged prior to 1934 and used for  
218 subsistence agriculture. Logging and agriculture ceased when the area was purchased in 1934,  
219 and the regenerating forest is dominated by *Casearia*, but *Prestoea* also has its highest basal area  
220 there. *Prestoea* is often associated with slopes and ravines and disturbed areas (Weaver 2010,  
221 Harris et al 2012). At the highest elevations and the southern third of the plot, human disturbance  
222 to the forest was limited to selective logging; *Dacryodes* dominates these areas of the plot  
223 (Thompson et al. 2002). The dominance of *Cecropia* in the northern portion of the plot recorded  
224 in the third census is thought to have resulted from interactions between land-use history and  
225 hurricane disturbance. *Cecropia* recruited in huge numbers following Hurricane Hugo in  
226 September 1989 (Zimmerman et al. 2010), such that more than 95% of *Cecropia* individuals of

227 this species recruited following this one disturbance event. Zimmerman et al. (1994) noted that  
228 *Casearia* was especially susceptible to uprooting during Hurricane Hugo, which opened the  
229 forest canopy. Walker (2000) found that *Cecropia* frequently recruited in soil pits caused by  
230 uprooted trees and survived longer in this area of the plot because of the persistence of canopy  
231 light gaps. Thus, the prevalence of *Cecropia* in the lowermost elevation and flatter northern  
232 portion of the plot may be the result of hurricane damage caused to *Caesaria* and other species  
233 in this portion of the plot.

234 The second dataset is from the Tyson Research Center Plot (TRCP), a 25-ha forest  
235 dynamics plot located at Washington University in St. Louis' Tyson Research Center, Missouri,  
236 USA (Spasojevic et al. 2014). We analyzed species-environment relationships for five woody  
237 species in the central 20-ha of the plot: *Frangula caroliniana* (Walter) A. Gray (Rhamnaceae),  
238 *Lindera benzoin* L. Blume (Lauraceae), *Quercus alba* L., *Q. rubra* L., and *Q. velutina* Lam.  
239 (Fagaceae). The three *Quercus* species were some of the most widespread species in the plot,  
240 whilst *Frangula* and *Lindera* were selected because they were the two most abundant species in  
241 the plot and had interesting, highly-clumped spatial patterns. Together these five species  
242 comprised 78% of the total basal area of the TRCP in the 2013 census (Table 2B). Principal  
243 components analysis (see Supporting Information Notes S3) was used to summarize, in two  
244 composite principal axes, the variation in 17 physico-chemical soil properties that were  
245 measured at points across the TRCP in 2013 and kriged to 20 × 20-m raster cells (Spasojevic et  
246 al. 2014). Maps of individual environmental variables are available on the TRCP website:  
247 <http://www.ctfs.si.edu/site/Tyson+Research+Center%2C+Missouri>.

#### 248 ***Null model analyses***

249 To assess the significance of the observed codispersion patterns, we used three different null  
250 models to randomize aspects of the spatial point processes and their marks (diameters) (Table 3).  
251 In each, only the species location data, rather than both species and environment data, were  
252 randomized because this was sufficient to break any spatial association of the species data with  
253 the environmental variable and allowed us to test the significance of their covariation. The three  
254 null models were a CSR model (CSRm), a random labelling model (RLM), and a toroidal shift  
255 model (TSM) (see Weigand and Moloney [2014] for detailed descriptions of these null models  
256 and other examples of their use).

257           The CSRSM generated new spatial locations for trees; observed tree diameters then were  
258 assigned randomly (without replacement) to each tree at its new location. Comparison of the  
259 observed codispersion patterns with those generated by this null model tested whether there was  
260 any non-random spatial pattern in the covariation of the observed tree population (basal area  
261 within  $20 \times 20$ -m grid cells) and the environmental variable (Table 3). One difficulty with the  
262 CSR is that where species distributions are clumped, this may result in a Type I error rate that is  
263 higher than 0.05. Thus, a significant departure from the expectation of this null model may  
264 reflect the presence of clumping in the species' distribution (Table 3) and the interpretation of a  
265 significant result must be made cautiously. For example, we can use a CSRSM to ask if a species  
266 increases in basal area at lower elevations in the plot but if the spatial distribution of the species  
267 is clumped, we could obtain a "significant" result even if there were no relationship between  
268 basal area and elevation. Overall, however, this significance test can be used as an initial test for  
269 spatial non-randomness in the dataset.

270           The RLM permuted the observed diameters of the trees while retaining the observed  
271 spatial position of each tree. This null model tested whether, given the underlying spatial  
272 distribution of trees (a particular autocorrelation structure), their sizes were important in  
273 determining any covariation with the environmental variable (Table 3). For example, under this  
274 null model, we can test whether covariation between basal area and soil fertility is due to  
275 differences in species' growth rates along a soil fertility gradient, rather than changes in stem  
276 density. Mechanistically, in this example, the tree distributions may be driven by clumped  
277 dispersal processes that are uniform across the plot area but species' growth rates may vary with  
278 soil fertility.

279           The TSM retained the autocorrelation structure of the tree populations by retaining their  
280 relative spatial positions and diameters but breaking their spatial association with the  
281 environmental variable by moving the entire species pattern in a random distance and direction  
282 as though the plot was a torus. This model tested whether the observed pattern in covariation  
283 between the species and environmental variable was the same in all parts of the plot, i.e., whether  
284 the pattern in covariation is stationary (Table 3). The TSM is similar to the CSRSM in that it  
285 completely breaks any association between the two variables, but it fixes the distribution pattern  
286 of the species. Thus, it distinguishes the case in which a non-random codispersion pattern may

287 simply be driven by relative tree positions from a process-based link between the environment  
288 and the species. For example, under this null model, we ask if tree basal area varies with soil  
289 fertility and if the nature of that covariation is the same throughout the plot. When combined  
290 with the results of the CSR, we can determine if non-randomness identified by using the  
291 CSR is due to a species-environment relationship (significant TSM) or due to clumping in the  
292 species distribution (non-significant TSM) (Table 3).

293 For each species, each of three null models was used to generate 199 new datasets. For  
294 each species-environment combination, empirical tail probabilities were obtained by comparing  
295 the observed codispersion values at each spatial lag with the vector of codispersion values at the  
296 same spatial lags and directions determined from each null model. If the observed value was  
297 greater than or equal to the 195<sup>th</sup> null value or less than or equal to the 5<sup>th</sup> null value, we deemed  
298 it to be significantly different from expected (i.e., a two-tailed test;  $P < 0.05$ ). Thus, the  
299 significance tests were made for each lag and direction for which we obtained a codispersion  
300 value.

301 Finally, we determined the Type I error rate for each of the three null models by  
302 comparing the observed codispersion between two CSR simulated patterns (see Supporting  
303 Information Notes S4) to values generated by the CSR, RLM, and TSM. Note that the Type I  
304 error rate, our ability to identify non-significant codispersion values, is invariant to rotation and  
305 the error rate tests of the null models do not address the Type II error rate (statistical power),  
306 which remains an issue of ongoing research. R code for the null model analysis is provided in  
307 Supporting Information Notes S1.

308

## 309 **Results**

### 310 *Species-environment associations of simulated forest plot data*

311 Codispersion plots clearly illustrated the relationships between simulated species and their  
312 environment, and detected anisotropic, positive, and negative covariation between the two  
313 variables (Fig. 2). When the simulated environmental pattern was generated using a CSR  
314 process, the cross-variogram and the codispersion both  $\approx 0$  (little or no spatial covariation),

315 whether or not the spatial pattern in basal area was also CSR (Fig. 2A; extended results in the  
316 Supporting Information Notes S2). When the environmental variable was generated using a  
317 uniform process across the plot, but the basal area of the species decreased from the bottom left  
318 to the top right of the plot (i.e., southwest to northeast), the codispersion was weakly negative  
319 and weakly anisotropic. This result reflected the changing pattern of covariation in the two  
320 variables in the  $x$ - and  $y$ -directions. In contrast, the cross-variogram  $\approx 0$  (Fig. 2B). Sequential  
321 pattern rotations of 15 degrees showed that codispersion analysis can also distinguish smaller  
322 changes in pattern orientation (Supporting Information Notes S2).

323         When basal area tightly co-varied with the environmental variable, the cross-variogram  
324 steeply increased and the codispersion was very high, only weakening at smaller scales that  
325 approached the spatial grain of the pattern (Fig. 2C). This pattern, and in fact all pattern  
326 combinations, had lower codispersion values when the underlying point pattern of the species  
327 was clumped (Thomas process) rather than CSR (Fig. 2D; extended results in Supporting  
328 Information Notes S2). A difference in pattern between the left- (west) and right-hand (east)  
329 sides of the codispersion graph indicated anisotropy. For example, where the environmental  
330 variable decreased from bottom left (SW) to top right (NE), and basal area increased from west  
331 to east, codispersion measured negative covariation in the west-to-east direction, but showed  
332 some positive covariation at larger scales when looking to the northeast and negative covariation  
333 at larger scales when looking to the east (Fig. 2E). This pattern was also reflected somewhat in  
334 the cross-variogram, which was flat at small lags but negative at larger lags (Fig. 2E). Similarly,  
335 where there was some covariation in a given direction (Fig. 2F), in this case from bottom left  
336 (SW) to top right (NE), the codispersion map illustrated the anisotropy (the right hand side of the  
337 plot was more negative than the left hand side), showing a relationship that was more negative at  
338 larger scales. In this case, the cross-variogram was most negative at similar scales (100-150 m),  
339 but did not reflect the anisotropy (Fig. 2F).

340         For all analysis combinations of the three null models and the two underlying tree  
341 distributions (CSR- and Thomas-process), none of the observed codispersion values from the  
342 two CSR patterns were significantly different from those expected under either model at the 5%  
343 level. In our simulations, the CSR model resulted in only one significant cell (out of 200 cells) in

344 the codispersion graph (see Supporting Information Notes S4). These results are indicative of a  
345 Type I error rate of less than or equal to 5%.

#### 346 *Species-environment associations of observed forest plot data*

347 In the LFDP, basal area of *Casearia*, *Cecropia* and *Prestoea* generally decreased with increasing  
348 elevation, whilst basal area of *Dacryodes* increased with increasing elevation (Fig. 3, Table 2A),  
349 reflecting the interaction of elevation and land-use history in the plot (Thompson et al. 2002).

350 For *Casearia*, this pattern was reflected in a weak, anisotropic codispersion pattern where west-  
351 to-east codispersion was more positive than east-to-west codispersion, which became more  
352 negative in the north-east direction (Fig. 4A). The codispersion was weakly negative and  
353 anisotropic for the basal area of *Cecropia* (Fig. 4B) and similar, but positive, for that of  
354 *Dacryodes* (Fig. 4C). Basal area of *Prestoea* negatively co-varied with elevation at the larger  
355 scales, reflecting its lower basal area at the highest elevations (Fig. 4D). Basal area of *Casearia*  
356 negatively co-varied with slope, whilst basal area of *Cecropia* and *Dacryodes* positively co-  
357 varied with slope. In contrast, basal area of *Prestoea* was not strongly related to slope.

358 The comparison of the observed patterns with the codispersion values from the CSR  
359 randomizations revealed that the observed codispersion for all of the species with both elevation  
360 and slope was different from random expectation at some, but not all, scales and directions (Fig.  
361 4, columns 2 and 3). The only exception was for the relationship between *Prestoea* and slope,  
362 which was not significant (Fig. 4D). For all four species, the comparisons with the RLM showed  
363 that the number of significant observed codispersion values was lower than expected using the  
364 CSR for about half of the relationships tested, was higher for some, and stayed the same for a  
365 few (Figure 4, columns 4 and 5). The comparisons with the TSM showed that the observed  
366 codispersion values were significant at few scales and directions for most species-environment  
367 combinations (Figure 4, columns 6 and 7).

368 In the TRCP, the first two components from the principal component analysis of the soil  
369 chemistry data explained 65% of the variation in measured soil chemistry (plots and PC loadings  
370 are given in Supporting Information Notes S2). Variables loading strongly on PC1 were  
371 associated with soil fertility and cations (i.e., pH, base saturation, calcium, magnesium,  
372 potassium, aluminum, and iron), whilst variables loading strongly on PC2 were associated with

373 soil nitrogen availability (i.e., total nitrogen,  $\text{NH}_4$ , and nitrogen mineralization rate). These two  
374 principal components were used in the codispersion analysis of species-environment  
375 relationships for the five focal species.

376 The basal area of the five focal species in the  $20 \times 20$ -m raster cells at TRCP showed a  
377 range of strong, weak, positive, and negative relationships with both soil pH and cations (PC1)  
378 and soil nitrogen (PC2) (Table 2B, Fig. 5). Although abundant, *Frangula* and *Lindera* were less  
379 widespread and their populations were concentrated largely in one or a few patches that  
380 corresponded to high values on PC1, generating positive covariation (Fig. 5A–B). The three  
381 *Quercus* species (Fig. 5C–E) were more widespread within the plot; *Q. alba* was weakly and *Q.*  
382 *rubra* and *Q. velutina* were more strongly negatively related to more fertile soils (high values on  
383 PC1). *Quercus alba* positively co-varied with nitrogen (PC2), whilst *Q. rubra* and *Q. velutina*  
384 had little or negative co-variation with nitrogen (Fig 5C–E).

385 Codispersion plots revealed both spatial gradients in covariation between basal area and  
386 environment and the spatial scales at which covariation was the strongest (Fig. 6, column 1). For  
387 example, anisotropic species-environment associations for *Frangula* and *Lindera* were illustrated  
388 by positive codispersion with PC2 to the east within the plot, but negative codispersion when  
389 looking to the west (Fig. 6A, B). In addition, the spatial scales of covariation differed among  
390 species. For instance, the positive co-variation between *Quercus alba* and PC2 was highest at  
391 large lags (greater than 50 m) in the east-west direction, whilst *Q. velutina* negatively co-varied  
392 with PC1 at larger lags (greater than 60 m) in the north direction, but at smaller lags in the east-  
393 west direction (up to 50 m).

394 Observed patterns of species-environment associations at the TRCP often differed from  
395 null expectations, but the magnitude of the effect sizes varied among the different null models.  
396 The comparison of observed codispersion patterns with those from the null models revealed that  
397 the weaker observed codispersion patterns with both soil fertility and cations (PC1) and soil  
398 nitrogen variables (PC2) tended not to be significant when compared to expectation when trees  
399 were distributed CSR within the plot (Fig. 6, columns 2 and 3). In contrast, comparisons with the  
400 RLM (Fig. 6, columns 4 and 5) showed that observed codispersion values were mostly higher  
401 than expected. The exceptions to this were, for some scales and directions, for *Frangula* and *Q.*  
402 *velutina* with PC2, and for *Q. rubra* with PC1, each of which had significantly more negative

403 codispersion at some scales when looking to the west in the plot. The comparisons with the  
404 expected values from the TSM largely mirrored those of the CSR comparisons, but with fewer  
405 significant values in most cases, such as for *Frangula* and PC2, which was non-significant at all  
406 lags.

407

## 408 **Discussion**

409 Codispersion analysis is a useful method for exploring species-environment relationships in a  
410 spatially-explicit context. Simulations showed that the method correctly detected anisotropy and  
411 other spatial regularities in the co-variation of the two variables and correctly measured the scale  
412 of these effects (Fig. 2). Codispersion values in these simulations were influenced by the  
413 underlying spatial pattern of both the species and the environmental variable; more clumping in  
414 the tree distribution patterns reduced the magnitude of the codispersion values, even with the  
415 same basal area and environmental gradients (Fig. 2; Supporting Information Notes S2).  
416 Similarly, a uniform distribution of the environmental variable led to higher magnitude of  
417 codispersion values than resulted from a CSR environmental variable (Fig. 2; Supporting  
418 Information Notes S2). When observed patterns in field data were combined with null model  
419 analysis, codispersion analysis detected the scales and directions of statistically significant  
420 codispersion in basal area-environment relationships, and suggested the possible drivers of those  
421 relationships (Table 2).

422         The selection of appropriate null models for analyzing spatial point patterns is especially  
423 important when the results are used to generate testable hypotheses about processes underlying  
424 the observed point patterns (Weigand and Moloney 2014). We suggest that comparisons of the  
425 results of the three null models we used to explore significance of codispersion in species-  
426 environment relationship can help to tease apart possible influences on observed codispersion  
427 patterns (Table 4). In particular, whether observed patterns are found to be significantly different  
428 from expectations for one, two, or all three of the null models leads to different hypotheses about  
429 possible processes and ecological mechanisms determining the observed patterns (Table 4).

430         The first possibility is that the observed pattern is not significantly different from  
431 expectation of all three null models. We obtained this result when examining codispersion of



432 *Prestoea acuminata* and slope at the LFDP (Fig. 4D). We interpret this result as evidence that  
433 any observed spatial pattern of the basal area distribution of this species must be due to factors  
434 we did not measure. For example, *Prestoea* is dominant in the northern two thirds of the LFDP,  
435 which was disturbed by the land use history, greater damage from Hurricane Hugo and is flatter  
436 than the southern third of the plot. The high abundance in the northern part of the plot as a result  
437 of the land use history reduces the relative strength of the association with slope in this analysis.  
438 A second possibility is that the pattern is significantly different under the CSR, but non  
439 significantly different under the TSM. This likely reflects the situation where clumping in the  
440 species distribution has resulted in correlation with environment at some lags and directions, but  
441 this is not consistent across the plot and therefore, unlikely to reflect a causal dependence of  
442 species on environment. Such a result can be used to identify and understand spatial pattern in  
443 the species data.

444 Alternatively, the observed pattern could be significantly different from expectation for  
445 only two of the three null models. For example, at TRCP, *Q. rubra* was strongly and negatively  
446 associated with soil pH and cations at all spatial lags when assessed with the CSR and TSM  
447 (Fig. 6D). However, spatial co-variation was non-significant for a number of lags under the RLM  
448 and where it was significant, the observed codispersion was higher than expected. This suggests  
449 that although *Q. rubra* basal area was negatively related to the soil environment, the pattern of  
450 this relationship, at least at some spatial lags and directions, was not dependent on tree sizes, but  
451 rather on their relative spatial positions (autocorrelation structure). Thus, the observed  
452 codispersion patterns is likely to be due to processes that drive intraspecific clumping such as  
453 unmeasured variation in other environmental variables or land-use history (Thompson et al.  
454 2002), interspecific interactions, or dispersal limitation (e.g., Plotkin et al. 2002).

455 Further, significant difference from expectation under the toroidal shift model reveals  
456 non-stationarity in the data, which should be taken into account in subsequently developed  
457 inferential statistical models. For example, variograms for the TRCP show non-stationarity in  
458 PC2 (a large scale trend such that the variogram does not level off and therefore has no sill).  
459 Observed codispersion of PC2 (soil nitrogen variables) and *Quercus alba* was significantly  
460 different from expectation at large scales suggesting that there was non-stationarity in this  
461 pattern. If, in a subsequent model, we were interested in regressing this covariation against other

462 variables, such as slope or elevation, we would need to account for the non-stationarity by  
463 applying a method such as generalized least squares, where the correlation in the errors is  
464 modelled and then specified in the regression model (Beale et al 2010).

465 These results, and others summarized in Table 4, demonstrate how the application of  
466 different null models to codispersion analysis can reveal subtle differences in potential causes of  
467 observed bivariate spatial relationships. Other null models that could be explored fruitfully in  
468 further research include pattern reconstruction methods (Wiegand and Moloney, pp 368) and  
469 spectral methods using raster data (Deblauwe et al. 2015; Wagner and Dray 2015). However, we  
470 must first understand what biological processes are being manipulated in each case to interpret  
471 observed departures from null expectations. Further, simultaneous comparisons across multiple  
472 lag distances can suffer from higher than desired Type I error rates (Loosmore and Ford 2006;  
473 Baddeley et al 2014). Future research should address developing a global significance test for  
474 codispersion where understanding scales of variation is important.

475 Finally, we note that there are three important considerations to keep in mind when  
476 applying codispersion analysis to species-environment data: selecting values for the maximum  
477 spatial lag distance, the kernel bandwidth, and the orientation of the pattern in the analysis. We  
478 recommend a maximum lag distance of no more than one-quarter of the smallest plot dimension.  
479 If the maximum lag is too large, edge effects will influence the largest scales considered. Setting  
480 the maximum lag to 25% of the smaller plot dimension ensures an adequate sample size to detect  
481 the spatial pattern and minimizes edge effects.

482 The selection of an appropriate kernel bandwidth is comparatively straightforward if data  
483 on a regular grid (raster) are used, as we have illustrated here. Because we rasterized the data to  
484 20-m grid cells, the scale at which the environmental data were obtained, setting each of the  
485 three bandwidth values ( $\mathbf{k} = \{k_X, k_Y, k_{XY}\}$ ) equal to 20 m makes sense, as 20 m is the smallest  
486 scale at which any pattern could be detected. However, if codispersion is used to analyze  
487 bivariate marked point patterns (e.g., two measurements, such as diameter and height, which are  
488 recorded for a single point location), the values used for the bandwidth parameters will  
489 determine the scales at which the codispersion analysis can detect patterns of spatial co-variation.  
490 If the scales of the two variables differ markedly, then their bandwidth parameters, and that of  
491 their cross-variogram, should be different. One possibility is to set the values of  $k_X$ ,  $k_Y$ , and  $k_{XY}$  to

492 the values of the nuggets of their respective variograms (for  $k_X$ ,  $k_Y$ ) or cross-variogram (for  $k_{XY}$ ).  
493 Alternatively, Cuevas et al. (2013) suggest an optimization method for identifying appropriate  
494 values for  $k$ .

495 The x,y orientation of the observed biological spatial pattern matters for pattern of  
496 codispersion values displayed in the codispersion graph (but not the significance tests) because  
497 we have greater resolution of pattern in the x-axis than in the y-axis. Thus, users should think  
498 about directionality in the processes driving the spatial patterns being tested. If little is known,  
499 rotating the pattern around the midpoint and analyzing it in both directions may aid in identifying  
500 directionality in the spatial pattern. Note that this consideration does not affect the data collection  
501 unless the plot size or shape precludes the species-environment pattern under study from being  
502 adequately sampled within the study extent; therefore, we encourage researchers to consider their  
503 hypotheses of pattern during sampling design.

504 Codispersion analysis is useful because it results in a graph that clearly identifies the  
505 magnitude, scale and directionality of the observed patterns; it can identify the presence and  
506 scale of anisotropy in the spatial pattern; when combined with null models, it can be used to  
507 suggest testable hypotheses of ecological process; and it can identify non-stationarity in the  
508 spatial pattern of covariation, which influences subsequent inferential modelling choices. It can  
509 be used to address a wide range of ecological questions where we are interested in the scale and  
510 nature of spatial covariation in variables derived from point-based or grid-based sampling  
511 schemes. Such variables may be associated with any attribute of organisms or their locations.  
512 The fact that fundamentally different processes can generate similar observed pattern of  
513 clumping reinforces the need for spatial methods, combined with appropriate null models, that  
514 allow ecologists to discern the relative importance of different processes. Importantly,  
515 codispersion can be used for composite measures, such as plant community richness or biomass,  
516 and extended to more than two variables (Vallejos et al. 2015), which may be a fruitful path for  
517 further ecological applications. Although this method is computationally intensive, the code  
518 provided here (Supporting Information Notes S1) is readily adapted for use in a parallel  
519 computing framework. Future applications of this approach across a broad range of organisms  
520 and biogeographic regions will provide new insights into the ecological causes and consequences  
521 of species-environment associations.

522

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542 **Author contributions**

543 H.L.B., B.S.C. and A.M.E. planned and designed the research. J.T., J.K.Z. and J.A.M. collected  
544 the data. H.L.B. and B.S.C. analyzed the data. All authors contributed to writing the manuscript.

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644 **Supporting Information**

645 **Notes S1:** Annotated R code for all analyses and figures

646 **Notes S2:** Full output from codispersion analysis of simulated point patterns

647 **Notes S3:** Results of principal components analysis of Tyson soil chemistry data

648 **Notes S4:** Type I error rates associated with null model analyses

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652

653 **FIGURE CAPTIONS**

654 Figure 1. A. An illustration of the creation of directional spatial lags for ecological data  
 655 organized as rasterized surfaces (both variables are represented by the large grid). The dashed  
 656 lines represent different spatial lags  $h$  over which codispersion is calculated in different  
 657 directions. B. The codispersion graph. The color of each cell is the value of the codispersion  
 658 coefficient of two variables for each given spatial lag  $h$  and direction in  $x,y$  space. In this  
 659 example, the graph shows negative covariation between the two variables when looking in the  
 660 east direction, but positive covariation when looking in the northwest direction, indicating  
 661 anisotropy in the way the two variables covary. The colour pattern on the graph also indicates  
 662 that the two variables are most negatively correlated at spatial lags above 20m in the positive  $x$   
 663 direction, and most positively correlated at scales of about 20-30 m in the negative  $x$  direction  
 664 and at about 50-80 m in the  $y$  direction. Figures taken from Buckley et al. (2016).

665

666 Figure 2. Simulated species-environment patterns on  $20 \times 20$ -m grids in  $300 \times 300$ -m plots, their  
 667 variograms and cross-variograms, and codispersion graphs. In the variograms, the blue line is the  
 668 environment variogram, the green line is the species variogram and the pink line is the cross-  
 669 variogram. The colours of the codispersion graphs are scaled from  $-1$  (purple) to  $+1$  (orange).  
 670 The underlying pattern (environment, basal area) and mean (standard deviation) codispersion  
 671 values for each analysis were: (A) CSR, CSR: 0.03 (0.04), (B) uniform, decreasing  $x$  and  $y$ : 0.13  
 672 (0.04), (C) decreasing  $x$ , decreasing  $x$ : 0.46 (0.19), (D) decreasing  $x$ , decreasing  $x$  (underlying  
 673 Thomas distribution): 0.25 (0.15), (E) decreasing  $x$  and  $y$ , increasing  $x$ :  $-0.16$  (0.29), and (F)  
 674 bivariate normal, increasing  $x$  and  $y$ :  $-0.23$  (0.11).

675

676 Figure 3. Observed patterns on  $20 \times 20$ -m grids in the 16-ha Luquillo Forest Dynamics Plot of  
 677 elevation (top left), slope (top right), and basal area ( $\text{m}^2 \cdot \text{ha}^{-1}$ ) of *Casearia arborea* (CASARB),  
 678 *Cecropia schreberiana* (CECSCH), *Dacryodes excelsa* (DACEXC) and *Prestoea acuminata*  
 679 (PREMON). The variogram for the environmental variable (blue line), variogram for the species  
 680 (green line) and their cross-variogram (pink line) are shown for each species-environment  
 681 combination; variables were centered and standardized prior to analysis. In each bubble plot, the

682 dots are positioned at the center of each grid cell point and the sizes of the symbols are scaled to  
683 the variable displayed.

684

685 Figure 4. Observed codispersion values; observed minus expected values; and significance (red)  
686 or not (blue) at the  $P < 0.05$  level relative to null expectation from three null models for bivariate  
687 species-environment combinations for four species (abbreviations as in Fig. 3) in the 16-ha  
688 Luquillo Forest Dynamics Plot. The colours on the codispersion and observed–expected graphs  
689 are scaled from  $-1$  (purple) to  $+1$  (orange); contour lines are at intervals of 0.1. The means and  
690 ranges of observed codispersion values are given in Table 2A.

691

692 Figure 5. Observed patterns on  $20 \times 20$ -m grids in a 20-ha area of the Tyson Research Center  
693 Plot of soil variables represented by two principal components PC1 (top left), PC2 (top right),  
694 and basal area ( $\text{m}^2 \cdot \text{ha}^{-1}$ ) of five species: *Frangula caroliniana* (FRACAR), *Lindera benzoin*  
695 (LINBEN), *Quercus alba* (QUEALB), *Quercus rubra* (QUERUB), and *Quercus velutina*  
696 (QUEVEL). The variogram for the environmental variable (blue line), variogram for the species  
697 (green line) and their cross-variogram (pink line) are shown for each species-environment  
698 combination; variables were centered and standardized prior to analysis. In each bubble plot, the  
699 dots are positioned at the center of each grid cell point and the sizes of the symbols are scaled to  
700 the variable displayed.

701

702 Figure 6. Observed codispersion values; observed minus expected values; and significance (red)  
703 or not (blue) at the  $P < 0.05$  level relative to null expectation from three null models for bivariate  
704 species-environment combinations for five species (abbreviations as in Fig. 5) in the 22-ha area  
705 of the Tyson Research Center Plot. The colours of the codispersion and observed–expected  
706 graphs are scaled from  $-1$  (purple) to  $+1$  (orange); contour lines are at intervals of 0.1. The means  
707 and ranges of observed codispersion values are given in Table 2B.

708

## 709 TABLES

710 Table 1: Definitions of spatial terminology used in this paper

Term	Description	References
Anisotropy	When the spatial correlation is dependent on direction (opposite to isotropy, where the correlation is the same in all directions). For example, species across a stress gradient are anisotropic when associations vary between aggregated and segregated with decreasing stress (Bertness and Callaway 1994).	Dale 1999
Kernel bandwidth	The bandwidth is the set of parameters used in the kernel function of the codispersion analysis that is applied across all possible raster cell-to-cell distances for each spatial lag, resulting in a spatial variation surface. In the case of $20 \times 20$ -m grids, we apply a 20-m bandwidth because that is the smallest scale (spatial grain) of the data.	Cuevas et al. 2013; Buckley et al. (2016); this paper
Codispersion	A measure of the covariation of two variables in space. For example, covariation in the basal area of two tree species measured in $20 \times 20$ -m grid cells in a large forest plot.	Cuevas et al. 2013; Buckley et al. (2016); this paper
Marks	Attributes associated with each point in a spatial point pattern. For example, diameters or diseased/ healthy status of trees in a forest plot.	Wiegand and Moloney 2014
Semi-variogram	A function, usually plotted as a two dimensional	Dale 1999

graph, revealing spatial correlation among measurements from a set of samples. It has three key parameters: nugget, sill and range. The semi-variogram shows at what spatial lags spatial variability occurs in a spatial dataset, i.e., the scale of variation in the data.

Spatial autocorrelation	Dependence of observations on spatial proximity. For example, tree sizes may be spatially autocorrelated if growth is positively influenced by a patchily-distributed environmental resource; high-resource patches will contain large trees and low-resource patches will contain small trees.	Wiens 1989
Spatial lag	The distance over which a process is measured. For example, when visualizing codispersion of a species and an environmental variable, we plot the codispersion for a range of spatial lags (and directions), i.e., we ask, what is their covariation at distances (lags) of 20 m, 40 m, 60 m, ...?	Cuevas et al. 2013; Buckley et al. (2016); this paper
Spatial point pattern	A set of locations in $x,y$ space. Spatial point patterns may be simply locations (unmarked pattern), or locations with attributes (marked pattern). For example, the $x,y$ coordinate locations of trees in a forest plot.	Dale 1999; Weigand and Moloney 2014
Spatial processes	A process whose action causes changes in a spatial pattern.	Wiens 1989

Stationarity	<p>The “strong” form of spatial stationarity is the situation in which the joint distribution of the data is invariant when the pattern of either one is moved (translated) through space. A weaker form of spatial stationarity, “second-order stationarity,” assumes that only the mean, variance, and covariance must be stationary. A still weaker form of stationarity – the “intrinsic hypothesis” – is a lack of spatial trend, such that the mean and semi-variance of the distribution are dependent only on the distance between points, not their locations. Either second-order stationarity or the intrinsic hypothesis is an assumption of most spatial statistical inference methods.</p>	Dale 1999; Vieira et al. 2010
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711

712

713 Table 2: Abundances, mean diameters (DBH) in centimeters (standard deviation), and the means and ranges in codispersion for basal  
 714 area-environment relationships for the analyzed species in the (A) Luquillo Forest Dynamics Plot and (B) Tyson Research Center  
 715 Forest Plot

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**A. Luquillo Forest Dynamics Plot (2000-2002 census data)**

Species	Number of stems	Mean DBH (s.d.)	Total basal area (m <sup>2</sup> h <sup>-1</sup> )	Mean (s.d.) codispersion with elevation	Range in codispersion with elevation (min, max)	Mean (s.d.) codispersion with slope	Range in codispersion with slope (min, max)
<i>Dacryodes excelsa</i>	1544	21.18 (15.71)	84.28	0.00 (0.08)	-0.17, 0.14	0.03 (0.02)	-0.03, 0.10
<i>Cecropia schreberiana</i>	2902	10.02 (6.65)	32.95	0.14 (0.04)	0.06, 0.22	0.11 (0.06)	-0.05, 0.25
<i>Casearia arborea</i>	3861	5.63 (5.38)	18.39	0.05 (0.09)	-0.12, 0.21	-0.13 (0.06)	-0.24, 0.02
<i>Prestoea acuminata</i>	7707	14.29 (2.96)	128.82	-0.10 (0.07)	-0.24, 0.02	0.10 (0.03)	0.02, 0.17

---

**B. Tyson Research Center Plot (2013 census data)**

Species	Number of stems	Mean DBH (s.d.)	Total basal area (m <sup>2</sup> h <sup>-1</sup> )	Mean (s.d.) codispersion with soil PC1	Range in codispersion with soil PC1 (min, max)	Mean (s.d.) codispersion with soil PC2	Range in codispersion with soil PC2 (min, max)
<i>Frangula caroliniana</i>	8715	2.04 (0.85)	3.34	0.41 (0.12)	0.17, 0.62	0.03 (0.10)	-0.16, 0.21
<i>Lindera benzoin</i>	4922	1.84 (0.66)	1.48	0.28 (0.14)	0.06, 0.56	0.06 (0.13)	-0.11, 0.36
<i>Quercus alba</i>	2066	29.57 (16.24)	184.66	-0.04 (0.04)	-0.14, 0.07	0.13 (0.05)	0.03, 0.24

<i>Quercus rubra</i>	1551	30.03 (17.63)	147.73	-0.39 (0.12)	-0.56, -0.15	0.03 (0.05)	-0.06, 0.13
<i>Quercus velutina</i>	691	33.46 (13.92)	71.27	-0.09 (0.09)	-0.28, 0.08	-0.09 (0.05)	-0.19, 0.03

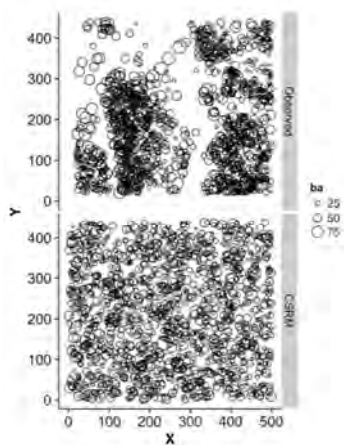
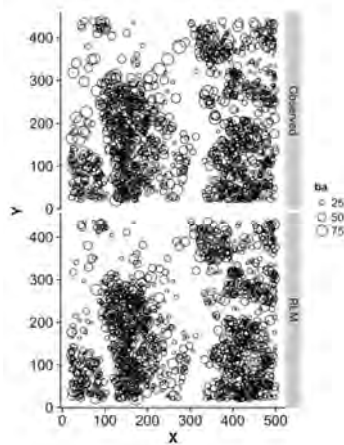
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716 Codispersion was estimated in the 20 × 20-m raster cells in which environmental variables were measured.

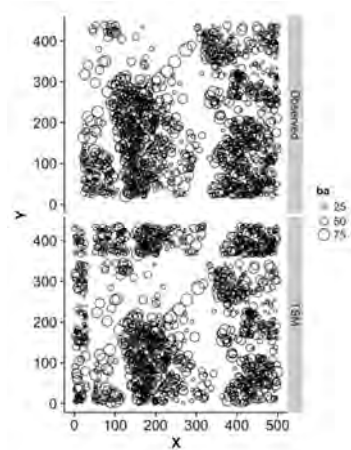
717



718 Table 3: The three null models, an example realization of each, how they were applied in this  
 719 paper, and their associated null process models. For each example, (which were randomized by  
 720 each null model), the hypothesized ecological process is that basal area (BA) is conditional on  
 721 one or more of the spatial point pattern of trees (ppp), their diameters (marks) and the spatial  
 722 distribution of the environmental variable (env):  $BA \mid (\text{ppp}, \text{marks}, \text{env})$ . Each null model breaks  
 723 apart this conditional process in a different way, as is indicated by the conditional statement (in  
 724 **bold** type) and its associated explanation in the “Null process” column.

Null model	Example	Null process	Test
Completely spatially random (CSR)		<p><b>BA; (ppp, marks)   env</b></p> <p>The spatial distribution and diameters of individual trees, from which basal area is computed, are random and therefore independent of the environment.</p>	<p>This model tests for non-random spatial covariation between BA and the environmental variable.</p>
Random labelling model (RLM)		<p><b>BA; marks   (ppp, env)</b></p> <p>Where individual trees grow is fixed (due to another process, such as competition), but how they grow (size) is independent of the environment.</p>	<p>This model tests if the environmental variable is associated with growth differences among individual trees, whose diameters are aggregated to compute BA in each raster cell.</p>

Toroidal  
shift model  
(TSM)



**BA; env | (ppp, marks)**  
Where trees grow relative to one another and the spatial distribution of their relative sizes is driven by an unknown (unmeasured) process, but where and how they grow (e.g., size) is independent of the environment.

This model tests for non-random spatial co-variation between BA and the environmental variable, given the underlying marked spatial point pattern of the species.

726 Table 4: Interpretation of the null model results with examples from the two forest plot datasets

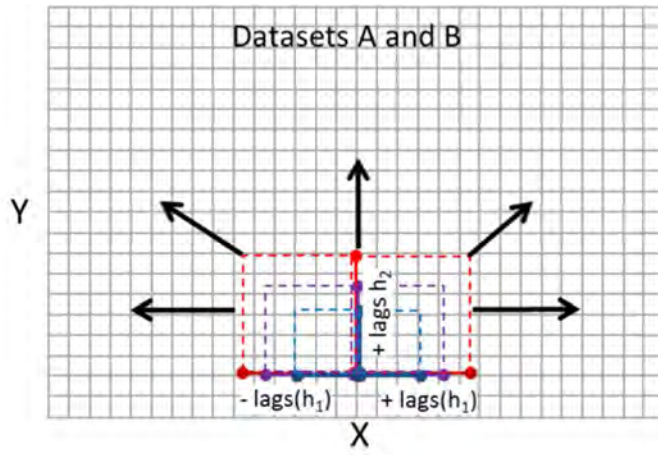
Null model results			Interpretation	Species-environment examples
CSR	RLM	TSM		
N.S.	N.S.	N.S.	Basal area is independent of the environment.	<i>Prestoea acuminata</i> vs. slope (Fig. 4D)
<b>Sig.</b>	N.S.	N.S.	Basal area is independent of the environment but aggregated in space; this pattern depends on tree spatial distributions, not tree sizes, i.e., the spatial pattern of basal area is not different than expected if diameters were randomly assigned to trees.	<i>Casearia arborea</i> vs. elevation (Fig. 4A)
N.S.	<b>Sig.</b>	N.S.	Basal area is not strongly related to the environment because tree positions are independent of the environmental variable; however, the environment causes non-random differences in tree growth.	<i>Quercus alba</i> vs. PC1 (Fig. 6C)
<b>Sig.</b>	N.S.	<b>Sig.</b>	Basal area is non-randomly related to the environment; this pattern depends on the relative spatial positions of trees, not their sizes.	<i>Quercus rubra</i> vs. PC1 (Fig. 6D)
<b>Sig.</b>	<b>Sig.</b>	N.S.	Tree sizes, but not necessarily their positions, depend on the environment (the environment causes differences in tree growth; tree distributions are aggregated within the plot).	<i>Cecropia schreberiana</i> vs. elevation (Fig. 4B)
<b>Sig.</b>	<b>Sig.</b>	<b>Sig.</b>	Basal area is non-randomly related to the	<i>Frangula caroliniana</i>

environment and this depends on both tree vs. PC1 (Fig. 6A)  
spatial distributions and their sizes. The  
environment influences both where trees  
grow and their sizes.

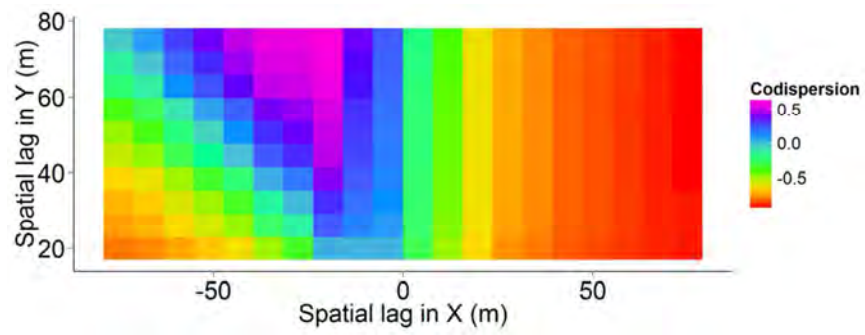
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727 The CSR model (CSRM) resulted in completely spatially random (CSR) tree spatial positions  
728 within the plot. The random labelling model (RLM) shuffled the marks (here, diameters)  
729 associated with each tree. The toroidal shift model (TSM) fixed the relative tree positions and  
730 their observed diameters, but moved the entire set of tree point locations in a random distance  
731 and direction as though the plot is a torus.

A.



B.



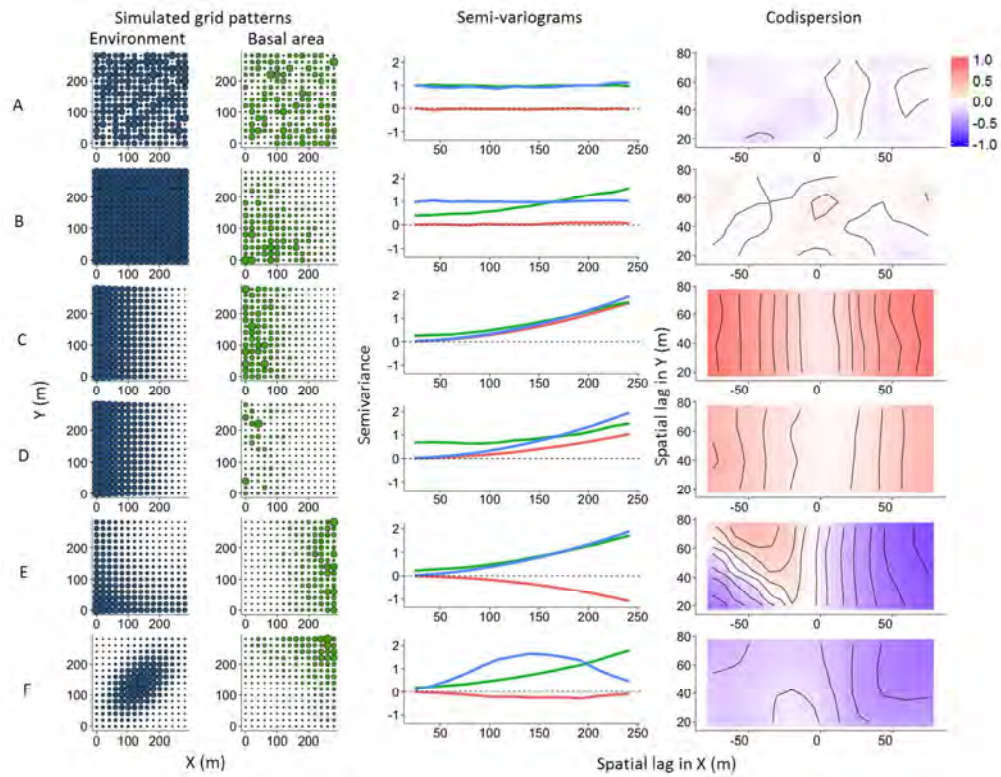


Figure 2. Simulated species-environment patterns on  $20 \times 20$ -m grids in  $300 \times 300$ -m plots, their variograms and cross-variograms, and codispersion graphs. In the variograms, the blue line is the environment variogram, the green line is the species variogram and the pink line is the cross-variogram. The colours of the codispersion graphs are scaled from  $-1$  (purple) to  $+1$  (orange). The underlying pattern (environment, basal area) and mean (standard deviation) codispersion values for each analysis were: (A) CSR, CSR: 0.03 (0.04), (B) uniform, decreasing x and y: 0.13 (0.04), (C) decreasing x, decreasing x: 0.46 (0.19), (D) decreasing x, decreasing x (underlying Thomas distribution): 0.25 (0.15), (E) decreasing x and y, increasing x: -0.16 (0.29), and (F) bivariate normal, increasing x and y: -0.23 (0.11).  
348x274mm (300 x 300 DPI)

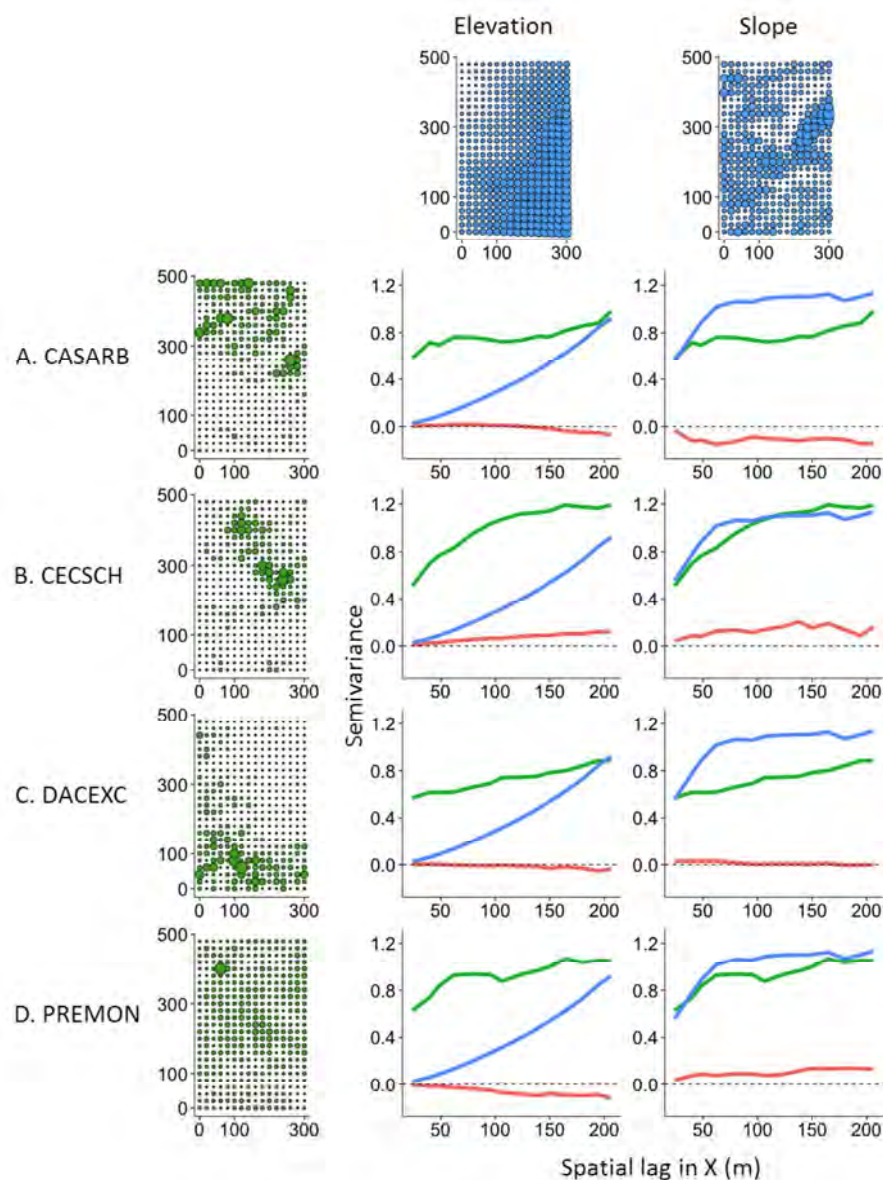


Figure 3. Observed patterns on 20 × 20-m grids in the 16-ha Luquillo Forest Dynamics Plot of elevation (top left), slope (top right), and basal area (m<sup>2</sup>.ha<sup>-1</sup>) of *Casearia arborea* (CASARB), *Cecropia schreberiana* (CECSCH), *Dacryodes excelsa* (DACEXC) and *Prestoea acuminata* (PREMON). The variogram for the environmental variable (blue line), variogram for the species (green line) and their cross-variogram (pink line) are shown for each species-environment combination; variables were centered and standardized prior to analysis. In each bubble plot, the dots are positioned at the center of each grid cell point and the sizes of the symbols are scaled to the variable displayed.

370x500mm (300 × 300 DPI)

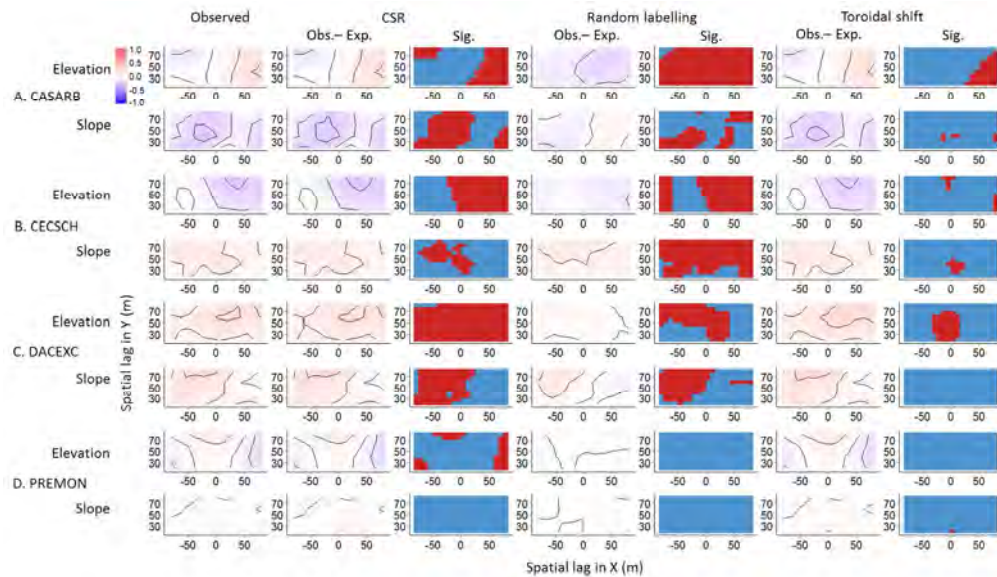


Figure 4. Observed codispersion values; observed minus expected values; and significance (red) or not (blue) at the  $P < 0.05$  level relative to null expectation from three null models for bivariate species-environment combinations for four species (abbreviations as in Fig. 3) in the 16-ha Luquillo Forest Dynamics Plot. The colours on the codispersion and observed-expected graphs are scaled from -1 (purple) to +1 (orange); contour lines are at intervals of 0.1. The means and ranges of observed codispersion values are given in Table 2A.

308x180mm (300 x 300 DPI)



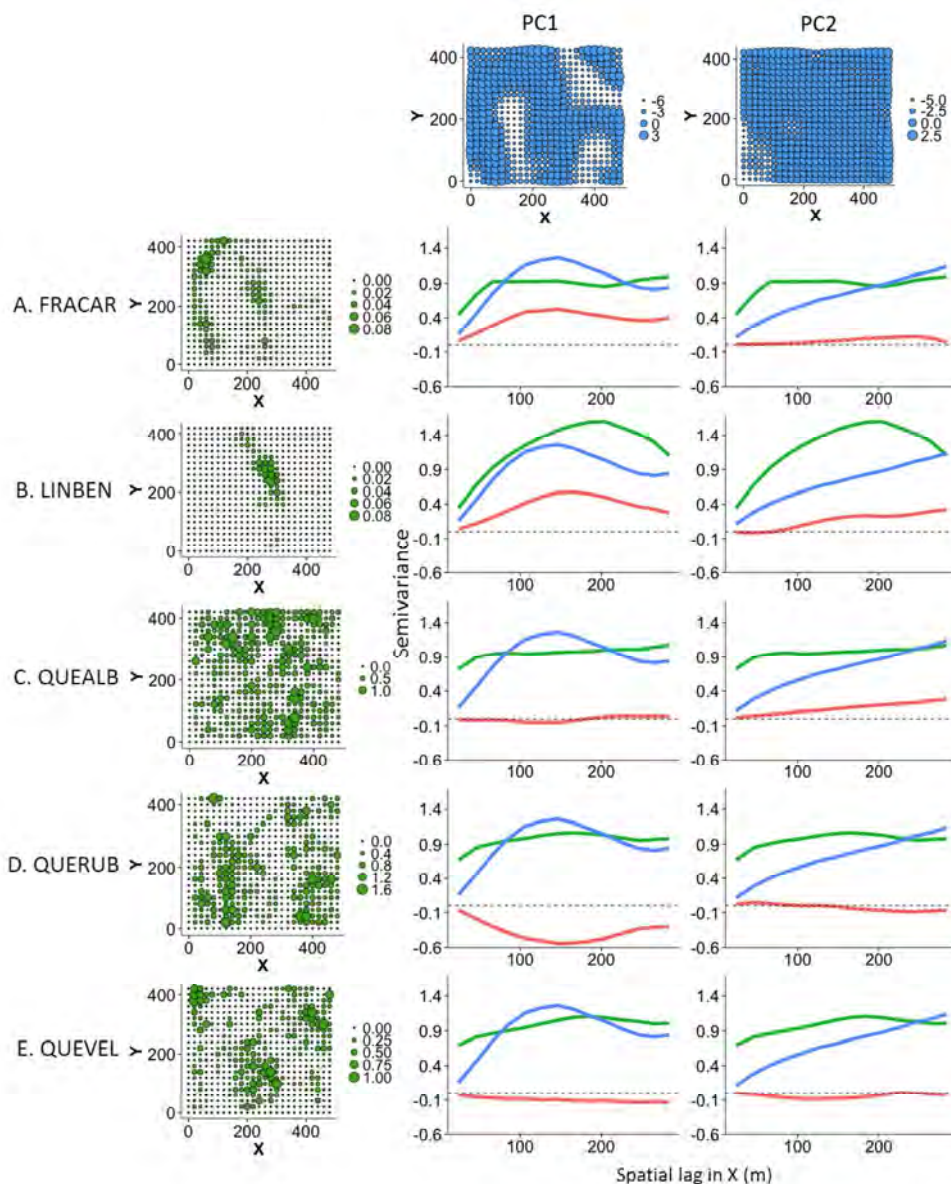


Figure 5. Observed patterns on 20 × 20-m grids in a 20-ha area of the Tyson Research Center Plot of soil variables represented by two principal components PC1 (top left), PC2 (top right), and basal area ( $\text{m}^2\cdot\text{ha}^{-1}$ ) of five species: *Frangula caroliniana* (FRACAR), *Lindera benzoin* (LINBEN), *Quercus alba* (QUEALB), *Quercus rubra* (QUERUB), and *Quercus velutina* (QUEVEL). The variogram for the environmental variable (blue line), variogram for the species (green line) and their cross-variogram (pink line) are shown for each species-environment combination; variables were centered and standardized prior to analysis. In each bubble plot, the dots are positioned at the center of each grid cell point and the sizes of the symbols are scaled to the variable displayed.

407x505mm (300 × 300 DPI)

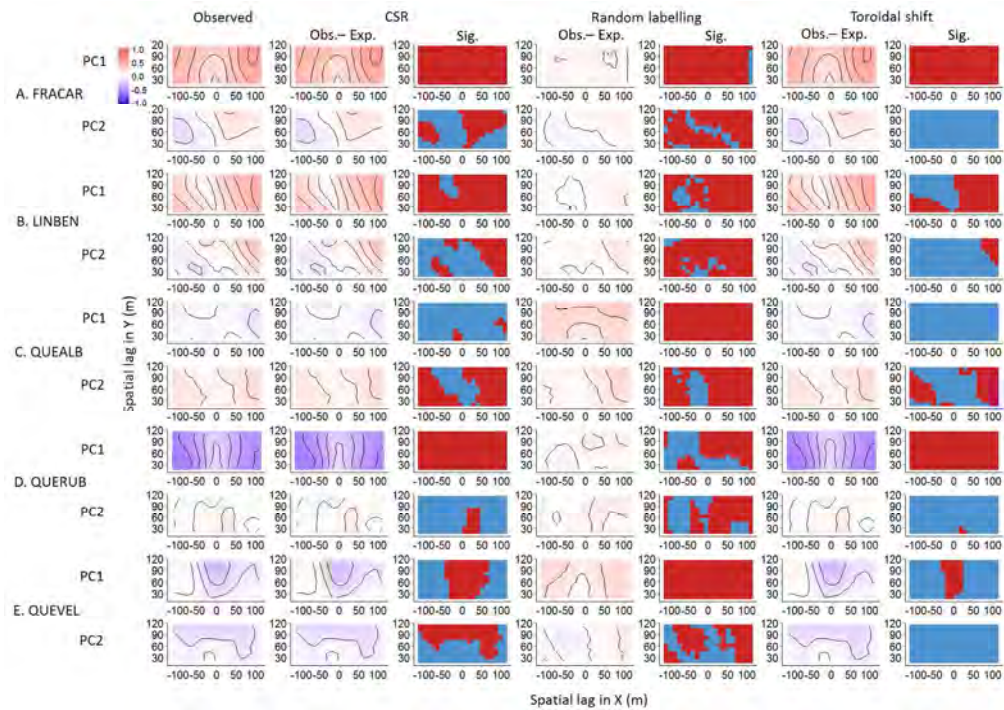


Figure 6. Observed codispersion values; observed minus expected values; and significance (red) or not (blue) at the  $P < 0.05$  level relative to null expectation from three null models for bivariate species–environment combinations for five species (abbreviations as in Fig. 5) in the 22-ha area of the Tyson Research Center Plot. The colours of the codispersion and observed–expected graphs are scaled from  $-1$  (purple) to  $+1$  (orange); contour lines are at intervals of  $0.1$ . The means and ranges of observed codispersion values are given in Table 2B.

377x270mm (300 x 300 DPI)

## ***New Phytologist* Supporting Information**

Article title: Using codispersion analysis to quantify and understand spatial patterns in species-environment relationships

Authors: Hannah L. Buckley, Bradley S. Case, Jess K. Zimmerman, Jill Thompson, Jonathan A. Myers, Aaron M. Ellison

Article acceptance date: [Click here to enter a date.](#)

The following Supporting Information is available for this article:

**Notes S1** Annotated R code for all analyses and figures.

**Notes S2** Full output from codispersion analysis of simulated marked point patterns across a variety of environmental gradients.

**Notes S3** Results of principal components analysis of Tyson soil chemistry data.

**Notes S4** Type I error rates of the null models.

## Notes S1 Annotated R code for all analyses and figures.

R code for the simulations and the analysis of the Luquillo and Tyson datasets. Note that to run the first three sections of code that analyze the (1) simulated datasets, (2) the LFDP data, (3) the TRCP data, you need to save the code in the section at the bottom of this file as "CoDisp\_functions.R" and run this file as a source code before you begin. Note that CoDisp\_functions.R loads the required R libraries – spatstat, geoR, fields, SpatialPack, ggplot2, grid, raster, and gstat – which, along with their dependencies, should be installed on your local machine. This code was developed and run in RStudio version 0.98.1103 using R version 3.1.2 “Pumpkin Helmet” on platform: x86\_64-w64-mingw32/x64 (64-bit).

```
#####  
### Spatial point pattern simulations for illustrating the use of  
### the codispersion function  
#####  
  
source("CoDisp_functions.R")  
  
#####  
## Simulated anisotropic spp-environment patterns for the MEE paper  
#####  
  
for(k in 1:10){ # Ten types of spp-environment patterns  
  
  ##### APP - 1500 trees with varying environmental gradients in 300 x 300m plots  
  
  gtitles <- vector("numeric")  
  app.ls <- vector("list")  
  
  #####-----Basal Area  
  
  if(k==1){  
    title="CSR_Thomas"  
    ##### Quantitative marks = env gradient vs. DBH  
    ##### Thomas = ppp of species  
  
    ## CSR = environmental gradient  
    app.ls[[1]] <-  
    app.sim.fn(grid.points=5,env.func="CSR",pattern.method="quant.marks",ppp.model="Thomas",marks.met  
hod="random",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,ntree  
s=1500,Print=FALSE); gtitles[1] = "CSR_mpp_Thomas_rand"  
  
    app.ls[[2]] <-  
    app.sim.fn(grid.points=5,env.func="CSR",pattern.method="quant.marks",ppp.model="Thomas",marks.met  
hod="decreasing.x",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10  
,ntrees=1500,Print=FALSE); gtitles[2] = "CSR_mpp_Thomas_decx"  
  
    app.ls[[3]] <-  
    app.sim.fn(grid.points=5,env.func="CSR",pattern.method="quant.marks",ppp.model="Thomas",marks.met  
hod="increasing.x",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10  
,ntrees=1500,Print=FALSE); gtitles[3] = "CSR_mpp_Thomas_incx"  
  
    app.ls[[4]] <-  
    app.sim.fn(grid.points=5,env.func="CSR",pattern.method="quant.marks",ppp.model="Thomas",marks.met  
hod="decreasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=1  
0,ntrees=1500,Print=FALSE); gtitles[4] = "CSR_mpp_Thomas_decxy"  
  
    app.ls[[5]] <-  
    app.sim.fn(grid.points=5,env.func="CSR",pattern.method="quant.marks",ppp.model="Thomas",marks.met  
hod="increasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=1  
0,ntrees=1500,Print=FALSE); gtitles[5] = "CSR_mpp_Thomas_incxxy"  
  
    app.ls[[6]] <-  
    app.sim.fn(grid.points=5,env.func="CSR",pattern.method="quant.marks",ppp.model="Thomas",marks.met  
hod="bivariate.normal",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,m  
u=10,ntrees=1500,Print=FALSE); gtitles[6] = "CSR_mpp_Thomas_bivnorm"
```

```

}

if(k==2){
  title="Uniform_Thomas"
  ## uniform = environmental gradient
  app.ls[[1]] <-
app.sim.fn(grid.points=5,env.func="uniform",pattern.method="quant.marks",ppp.model="Thomas",marks
.method="random",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,n
trees=1500,Print=FALSE); gtitles[1] = "uniform_mpp_Thomas_rand"

  app.ls[[2]] <-
app.sim.fn(grid.points=5,env.func="uniform",pattern.method="quant.marks",ppp.model="Thomas",marks
.method="decreasing.x",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,m
u=10,ntrees=1500,Print=FALSE); gtitles[2] = "uniform_mpp_Thomas_decx"

  app.ls[[3]] <-
app.sim.fn(grid.points=5,env.func="uniform",pattern.method="quant.marks",ppp.model="Thomas",marks
.method="increasing.x",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,m
u=10,ntrees=1500,Print=FALSE); gtitles[3] = "uniform_mpp_Thomas_incx"

  app.ls[[4]] <-
app.sim.fn(grid.points=5,env.func="uniform",pattern.method="quant.marks",ppp.model="Thomas",marks
.method="decreasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,
mu=10,ntrees=1500,Print=FALSE); gtitles[4] = "uniform_mpp_Thomas_decxy"

  app.ls[[5]] <-
app.sim.fn(grid.points=5,env.func="uniform",pattern.method="quant.marks",ppp.model="Thomas",marks
.method="increasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,
mu=10,ntrees=1500,Print=FALSE); gtitles[5] = "uniform_mpp_Thomas_incxxy"

  app.ls[[6]] <-
app.sim.fn(grid.points=5,env.func="uniform",pattern.method="quant.marks",ppp.model="Thomas",marks
.method="bivariate.normal",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.
05,mu=10,ntrees=1500,Print=FALSE); gtitles[6] = "uniform_mpp_Thomas_bivnorm"
}

if(k==3){
  title="decx_Thomas"
  ## decreasing.x = environmental gradient
  app.ls[[1]] <-
app.sim.fn(grid.points=5,env.func="decreasing.x",pattern.method="quant.marks",ppp.model="Thomas",
marks.method="random",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu
=10,ntrees=1500,Print=FALSE); gtitles[1] = "decx_mpp_Thomas_rand"

  app.ls[[2]] <-
app.sim.fn(grid.points=5,env.func="decreasing.x",pattern.method="quant.marks",ppp.model="Thomas",
marks.method="decreasing.x",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0
.05,mu=10,ntrees=1500,Print=FALSE); gtitles[2] = "decx_mpp_Thomas_decx"

  app.ls[[3]] <-
app.sim.fn(grid.points=5,env.func="decreasing.x",pattern.method="quant.marks",ppp.model="Thomas",
marks.method="increasing.x",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0
.05,mu=10,ntrees=1500,Print=FALSE); gtitles[3] = "decx_mpp_Thomas_incx"

  app.ls[[4]] <-
app.sim.fn(grid.points=5,env.func="decreasing.x",pattern.method="quant.marks",ppp.model="Thomas",
marks.method="decreasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=
0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[4] = "decx_mpp_Thomas_decxy"

  app.ls[[5]] <-
app.sim.fn(grid.points=5,env.func="decreasing.x",pattern.method="quant.marks",ppp.model="Thomas",
marks.method="increasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=
0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[5] = "decx_mpp_Thomas_incxxy"

  app.ls[[6]] <-
app.sim.fn(grid.points=5,env.func="decreasing.x",pattern.method="quant.marks",ppp.model="Thomas",
marks.method="bivariate.normal",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sig
ma=0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[6] = "decx_mpp_Thomas_bivnorm"
}
}

```

```

if(k==4){
  title="decxy_Thomas"
  ##### Quantitative marks = env gradient vs. DBH
  ##### Thomas = ppp of species
  ## decreasing.xy = environmental gradient
  app.ls[[1]] <-
app.sim.fn(grid.points=5,env.func="decreasing.xy",pattern.method="quant.marks",ppp.model="Thomas",marks.method="random",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[1] = "decxy_mpp_Thomas_rand"

  app.ls[[2]] <-
app.sim.fn(grid.points=5,env.func="decreasing.xy",pattern.method="quant.marks",ppp.model="Thomas",marks.method="decreasing.x",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[2] = "decxy_mpp_Thomas_decx"

  app.ls[[3]] <-
app.sim.fn(grid.points=5,env.func="decreasing.xy",pattern.method="quant.marks",ppp.model="Thomas",marks.method="increasing.x",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[3] = "decxy_mpp_Thomas_incx"

  app.ls[[4]] <-
app.sim.fn(grid.points=5,env.func="decreasing.xy",pattern.method="quant.marks",ppp.model="Thomas",marks.method="decreasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[4] = "decxy_mpp_Thomas_decxy"

  app.ls[[5]] <-
app.sim.fn(grid.points=5,env.func="decreasing.xy",pattern.method="quant.marks",ppp.model="Thomas",marks.method="increasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[5] = "decxy_mpp_Thomas_incx"

  app.ls[[6]] <-
app.sim.fn(grid.points=5,env.func="decreasing.xy",pattern.method="quant.marks",ppp.model="Thomas",marks.method="bivariate.normal",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[6] = "decxy_mpp_Thomas_bivnorm"
}

if(k==5){
  title="bivnorm_Thomas"
  ##### Quantitative marks = env gradient vs. DBH
  ##### Thomas = ppp of species
  ## bivariate.normal = environmental gradient
  app.ls[[1]] <-
app.sim.fn(grid.points=5,env.func="bivariate.normal",pattern.method="quant.marks",ppp.model="Thomas",marks.method="random",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[1] = "bivnorm_mpp_Thomas_rand"

  app.ls[[2]] <-
app.sim.fn(grid.points=5,env.func="bivariate.normal",pattern.method="quant.marks",ppp.model="Thomas",marks.method="decreasing.x",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[2] = "bivnorm_mpp_Thomas_decx"

  app.ls[[3]] <-
app.sim.fn(grid.points=5,env.func="bivariate.normal",pattern.method="quant.marks",ppp.model="Thomas",marks.method="increasing.x",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[3] = "bivnorm_mpp_Thomas_incx"

  app.ls[[4]] <-
app.sim.fn(grid.points=5,env.func="bivariate.normal",pattern.method="quant.marks",ppp.model="Thomas",marks.method="decreasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[4] = "bivnorm_mpp_Thomas_decxy"

  app.ls[[5]] <-
app.sim.fn(grid.points=5,env.func="bivariate.normal",pattern.method="quant.marks",ppp.model="Thomas",marks.method="increasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[5] = "bivnorm_mpp_Thomas_incx"

  app.ls[[6]] <-
app.sim.fn(grid.points=5,env.func="bivariate.normal",pattern.method="quant.marks",ppp.model="Thomas",marks.method="bivariate.normal",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,ntrees=1500,Print=FALSE); gtitles[6] = "env_bivnorm_mpp_Thomas_bivnorm"
}

```

```

if(k==6){
  title="CSR_CSR"
  ##### Quantitative marks = env gradient vs. DBH
  ##### CSR = ppp of species
  ## CSR = environmental gradient
  app.ls[[1]] <-
app.sim.fn(grid.points=5,env.func="CSR",pattern.method="quant.marks",ppp.model="CSR",marks.method
="random",xmin=0,xmax=300,ymin=0,ymax=300,lambda=200,minmark=1,maxmark=80,ntrees=1500,Print=FALSE
); gtitles[1] = "CSR_mpp_CSR_rand"

  app.ls[[2]] <-
app.sim.fn(grid.points=5,env.func="CSR",pattern.method="quant.marks",ppp.model="CSR",marks.method
="decreasing.x",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Print
=FALSE); gtitles[2] = "CSR_mpp_CSR_decx"

  app.ls[[3]] <-
app.sim.fn(grid.points=5,env.func="CSR",pattern.method="quant.marks",ppp.model="CSR",marks.method
="increasing.x",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Print
=FALSE); gtitles[3] = "CSR_mpp_CSR_incx"

  app.ls[[4]] <-
app.sim.fn(grid.points=5,env.func="CSR",pattern.method="quant.marks",ppp.model="CSR",marks.method
="decreasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Prin
t=FALSE); gtitles[4] = "CSR_mpp_CSR_decxy"

  app.ls[[5]] <-
app.sim.fn(grid.points=5,env.func="CSR",pattern.method="quant.marks",ppp.model="CSR",marks.method
="increasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Prin
t=FALSE); gtitles[5] = "CSR_mpp_CSR_incxxy"

  app.ls[[6]] <-
app.sim.fn(grid.points=5,env.func="CSR",pattern.method="quant.marks",ppp.model="CSR",marks.method
="bivariate.normal",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,P
rint=FALSE); gtitles[6] = "CSR_mpp_CSR_bivnorm"
}

if(k==7){
  title="Uniform_CSR"
  ##### CSR = ppp of species
  ## uniform = environmental gradient
  app.ls[[1]] <-
app.sim.fn(grid.points=5,env.func="uniform",pattern.method="quant.marks",ppp.model="CSR",marks.me
thod="random",xmin=0,xmax=300,ymin=0,ymax=300,lambda=200,minmark=1,maxmark=80,ntrees=1500,Print=F
ALSE); gtitles[1] = "uniform_mpp_CSR_rand"

  app.ls[[2]] <-
app.sim.fn(grid.points=5,env.func="uniform",pattern.method="quant.marks",ppp.model="CSR",marks.me
thod="decreasing.x",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,P
rint=FALSE); gtitles[2] = "uniform_mpp_CSR_decx"

  app.ls[[3]] <-
app.sim.fn(grid.points=5,env.func="uniform",pattern.method="quant.marks",ppp.model="CSR",marks.me
thod="increasing.x",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,P
rint=FALSE); gtitles[3] = "uniform_mpp_CSR_incx"

  app.ls[[4]] <-
app.sim.fn(grid.points=5,env.func="uniform",pattern.method="quant.marks",ppp.model="CSR",marks.me
thod="decreasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,
Print=FALSE); gtitles[4] = "uniform_mpp_CSR_decxy"

  app.ls[[5]] <-
app.sim.fn(grid.points=5,env.func="uniform",pattern.method="quant.marks",ppp.model="CSR",marks.me
thod="increasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,
Print=FALSE); gtitles[5] = "uniform_mpp_CSR_incxxy"

  app.ls[[6]] <-
app.sim.fn(grid.points=5,env.func="uniform",pattern.method="quant.marks",ppp.model="CSR",marks.me
thod="bivariate.normal",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=15
00,Print=FALSE); gtitles[6] = "uniform_mpp_CSR_bivnorm"
}

```

```

if(k==8){
  title="decx_CSR"
  ##### CSR = ppp of species
  ## decreasing.x = environmental gradient
  app.ls[[1]] <-
app.sim.fn(grid.points=5,env.func="decreasing.x",pattern.method="quant.marks",ppp.model="CSR",marks.method="random",xmin=0,xmax=300,ymin=0,ymax=300,lambda=200,minmark=1,maxmark=80,ntrees=1500,Print=FALSE); gtitles[1] = "decx_mpp_CSR_rand"

  app.ls[[2]] <-
app.sim.fn(grid.points=5,env.func="decreasing.x",pattern.method="quant.marks",ppp.model="CSR",marks.method="decreasing.x",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Print=FALSE); gtitles[2] = "decx_mpp_CSR_decx"

  app.ls[[3]] <-
app.sim.fn(grid.points=5,env.func="decreasing.x",pattern.method="quant.marks",ppp.model="CSR",marks.method="increasing.x",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Print=FALSE); gtitles[3] = "decx_mpp_CSR_incx"

  app.ls[[4]] <-
app.sim.fn(grid.points=5,env.func="decreasing.x",pattern.method="quant.marks",ppp.model="CSR",marks.method="decreasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Print=FALSE); gtitles[4] = "decx_mpp_CSR_decxy"

  app.ls[[5]] <-
app.sim.fn(grid.points=5,env.func="decreasing.x",pattern.method="quant.marks",ppp.model="CSR",marks.method="increasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Print=FALSE); gtitles[5] = "decx_mpp_CSR_incxxy"

  app.ls[[6]] <-
app.sim.fn(grid.points=5,env.func="decreasing.x",pattern.method="quant.marks",ppp.model="CSR",marks.method="bivariate.normal",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Print=FALSE); gtitles[6] = "decx_mpp_CSR_bivnorm"
}

if(k==9){
  title="decxy_CSR"
  ##### Quantitative marks = env gradient vs. DBH
  ##### CSR = ppp of species
  ## decreasing.xy = environmental gradient
  app.ls[[1]] <-
app.sim.fn(grid.points=5,env.func="decreasing.xy",pattern.method="quant.marks",ppp.model="CSR",marks.method="random",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Print=FALSE); gtitles[1] = "decxy_mpp_CSR_rand"

  app.ls[[2]] <-
app.sim.fn(grid.points=5,env.func="decreasing.xy",pattern.method="quant.marks",ppp.model="CSR",marks.method="decreasing.x",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Print=FALSE); gtitles[2] = "decxy_mpp_CSR_decx"

  app.ls[[3]] <-
app.sim.fn(grid.points=5,env.func="decreasing.xy",pattern.method="quant.marks",ppp.model="CSR",marks.method="increasing.x",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Print=FALSE); gtitles[3] = "decxy_mpp_CSR_incx"

  app.ls[[4]] <-
app.sim.fn(grid.points=5,env.func="decreasing.xy",pattern.method="quant.marks",ppp.model="CSR",marks.method="decreasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Print=FALSE); gtitles[4] = "decxy_mpp_CSR_decxy"

  app.ls[[5]] <-
app.sim.fn(grid.points=5,env.func="decreasing.xy",pattern.method="quant.marks",ppp.model="CSR",marks.method="increasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Print=FALSE); gtitles[5] = "decxy_mpp_CSR_incxxy"

  app.ls[[6]] <-
app.sim.fn(grid.points=5,env.func="decreasing.xy",pattern.method="quant.marks",ppp.model="CSR",marks.method="bivariate.normal",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=1500,Print=FALSE); gtitles[6] = "decxy_mpp_CSR_bivnorm"
}

```



```

if(k==10){
  title="bivnorm_CSR"
  ##### Quantitative marks = env gradient vs. DBH
  ##### CSR = ppp of species
  ## bivariate.normal = environmental gradient
  app.ls[[1]] <-
app.sim.fn(grid.points=5,env.func="bivariate.normal",pattern.method="quant.marks",ppp.model="CSR"
,marks.method="random",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntrees=150
0,Print=FALSE); gtitles[1] = "bivnorm_mpp_CSR_rand"

  app.ls[[2]] <-
app.sim.fn(grid.points=5,env.func="bivariate.normal",pattern.method="quant.marks",ppp.model="CSR"
,marks.method="decreasing.x",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntr
es=1500,Print=FALSE); gtitles[2] = "bivnorm_mpp_CSR_decx"

  app.ls[[3]] <-
app.sim.fn(grid.points=5,env.func="bivariate.normal",pattern.method="quant.marks",ppp.model="CSR"
,marks.method="increasing.x",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntr
es=1500,Print=FALSE); gtitles[3] = "bivnorm_mpp_CSR_incx"

  app.ls[[4]] <-
app.sim.fn(grid.points=5,env.func="bivariate.normal",pattern.method="quant.marks",ppp.model="CSR"
,marks.method="decreasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntr
ees=1500,Print=FALSE); gtitles[4] = "bivnorm_mpp_CSR_decxy"

  app.ls[[5]] <-
app.sim.fn(grid.points=5,env.func="bivariate.normal",pattern.method="quant.marks",ppp.model="CSR"
,marks.method="increasing.xy",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,ntr
ees=1500,Print=FALSE); gtitles[5] = "bivnorm_mpp_CSR_incx"

  app.ls[[6]] <-
app.sim.fn(grid.points=5,env.func="bivariate.normal",pattern.method="quant.marks",ppp.model="CSR"
,marks.method="bivariate.normal",xmin=0,xmax=300,ymin=0,ymax=300,lambda=300,minmark=1,maxmark=80,
ntrees=1500,Print=FALSE); gtitles[6] = "bivnorm_mpp_CSR_bivnorm"
}

# Specify parameters and options for CoDisp analysis
k=c(20,20,20)
max.window.size = 300/4
binwidth=0.1
xmin=0
xmax=300
ymin=0
ymax=300

Means.df <- data.frame(sim=1:6,mean_CoDisp=NA,sd_CoDisp=NA)

for(i in 1:length(app.ls)){

  print(date())
  print(paste("i =",i))

  Graphs_ls <- vector(mode="list",length=5) # empty list for output graphs

  ## Extract the data
  app.sims <- app.ls[[i]]

  ## Convert to point patterns to geodata objects
  geo.env <-
ppp.to.geoR.fn(app.sims[[1]],quad.size=20,xmin=xmin,xmax=xmax,ymin=ymin,ymax=ymax,method="mean.ma
rk")
  geo.sp <-
ppp.to.geoR.fn(app.sims[[2]],quad.size=20,xmin=xmin,xmax=xmax,ymin=ymin,ymax=ymax,method="total.b
a")

  ## Plot the observed patterns
  env.dat <- data.frame(X=geo.env$coords[,1],Y=geo.env$coords[,2],env=geo.env$data)
  sp.dat <- data.frame(X=geo.sp$coords[,1],Y=geo.sp$coords[,2],BA=geo.sp$data)

```

```

Graphs_ls[[1]] <- ggplot(env.dat, aes(x=X, y=Y, size=env))+geom_point(colour="black",
fill="steelblue4", shape=21)+t1.no.leg_lab
Graphs_ls[[2]] <- ggplot(sp.dat, aes(x=X, y=Y, size=BA))+geom_point(colour="black",
fill="#4dac26", shape=21)+t1.no.leg_lab

## Plot the variograms and cross variogram
dat <- data.frame(geo.env$coords,env=scale(geo.env$data),sp=scale(geo.sp$data))
g <- gstat(id="env", formula=env~1, locations=~qx+qy, data = dat)
g <- gstat(g, id="sp", formula=sp~1, locations=~qx+qy, data = dat)
v <- variogram(g, cutoff=250, cross=TRUE) # half the min. of the two plot dimensions
#plot(v)
Graphs_ls[[3]] <- ggplot(v,aes(x=dist,y=gamma,group=id,colour=id))+geom_line(lwd=2)+t1.no.leg
+ labs(x="Distance (m)",y = "Semivariance")

## Run Codispersion Analysis
CoDisp_sim <- codisp.fn(geo.env,geo.sp,k=k,max.window.size=max.window.size)

## Graph the output
Graphs_ls[[4]] <- print.CoDisp.plain(CoDisp_sim[[1]],scaled=FALSE)
Graphs_ls[[5]] <-
print.CoDisp.plain(CoDisp_sim[[1]],scaled=TRUE,contours=TRUE,binwidth=binwidth)

## Calculate the mean values
Means.df$mean_CoDisp[i] <- round(mean(CoDisp_sim[[1]]$Codispersion),2)
Means.df$sd_CoDisp[i] <- round(sd(CoDisp_sim[[1]]$Codispersion),2)

## Save the output objects
nam=(paste("CoDisp_app_ba",k,i,sep="_"))
assign(nam,CoDisp_sim)

## Save the output objects
nam=(paste("Graphs_ls",title,i,sep="_"))
assign(nam,Graphs_ls)

} # end i loop

nam=(paste("CoDisp_app_ba_means",k,sep="_"))
assign(nam,Means.df)

} # end k loop

save.image("mpp_env_ba.RData")

#####
### Graph output
#####

load("mpp_env_ba.RData")
source("CoDisp_functions.R")

# Graph species patterns for FIGURE

png("Graphs_SppEnvSims_Figure.png",width=1400,height=1100)

grid.newpage()
pushViewport(viewport(layout=grid.layout(6,6)))

for(i in 1:6){
  if(i==1){out <- Graphs_ls_CSR_CSR_1 }
  if(i==2){out <- Graphs_ls_Uniform_CSR_4 }
  if(i==3){out <- Graphs_ls_decx_CSR_2 }
  if(i==4){out <- Graphs_ls_decx_Thomas_2 }
  if(i==5){out <- Graphs_ls_decxy_CSR_3 }
  if(i==6){out <- Graphs_ls_bivnorm_CSR_5 }

  if(i==2){ out[[1]] <- out[[1]]+geom_point(aes(size=0.1)) } # plot uniform point sizes

g1 <- out[[1]]+coord_fixed(ratio=1)+xlab(NULL)+ylab(NULL)+t1.no.leg_lab # Env raster graph
g2 <- out[[2]]+coord_fixed(ratio=1)+xlab(NULL)+ylab(NULL)+t1.no.leg_lab # Spp raster graph
g3 <- out[[3]]+xlab(NULL)+ylab(NULL)+ylim(c(-1.2,2.1))+t1.fat.margins # Variogram graph
g4 <- out[[4]]+xlab(NULL)+ylab(NULL) # Unscaled CoDisp graph

```

```

g5 <- out[[5]]+t1.fat.margins_no.leg+xlabs(NULL)+ylabs(NULL)      # Scaled CoDisp graph

## Print the graphs to the layout
print(g1, vp=vplayout(i,1))
print(g2, vp=vplayout(i,2))
print(g3, vp=vplayout(i,3:4))
#print(g4, vp=vplayout(i,4:5))
print(g5, vp=vplayout(i,5:6))
}

dev.off()

# Graph all spp-env patterns for APPENDIX

png("Graphs_bivnorm_CSR.png",width=1800,height=1200)

grid.newpage()
pushViewport(viewport(layout=grid.layout(6,7))) # 6 rows by 7 columns
vplayout <- function(x,y)
  viewport(layout.pos.row=x,layout.pos.col=y)

for(i in 1:6){
  if(i==1){out <- Graphs.ls_bivnorm_CSR_1}
  if(i==2){out <- Graphs.ls_bivnorm_CSR_2}
  if(i==3){out <- Graphs.ls_bivnorm_CSR_3}
  if(i==4){out <- Graphs.ls_bivnorm_CSR_4}
  if(i==5){out <- Graphs.ls_bivnorm_CSR_5}
  if(i==6){out <- Graphs.ls_bivnorm_CSR_6}

  g1 <- out[[1]]
  g2 <- out[[2]]
  g3 <- out[[3]]
  g4 <- out[[4]]
  g5 <- out[[5]]

  ## Print the graphs to the layout
  print(g1, vp=vplayout(i,1))
  print(g2, vp=vplayout(i,2))
  print(g3, vp=vplayout(i,3))
  print(g4, vp=vplayout(i,4:5))
  print(g5, vp=vplayout(i,6:7))
}

dev.off()

#####
### Supplementary Online material: Null model analysis of CSR, CSR
### to obtain error rates
#####

load("mpp_env_ba.RData")
source("CoDisp_functions.R")

# Create data ppp objects and convert to geo.data objects for analysis
# Thomas
thomas.ppp <-
app.sim.fn(grid.points=20,env.func="CSR",pattern.method="quant.marks",ppp.model="Thomas",marks.metho
thod="random",xmin=0,xmax=300,ymin=0,ymax=300,minmark=1,maxmark=80,kappa=20,sigma=0.05,mu=10,ntr
es=1500,Print=FALSE)
thomas.ppp[[1]]$x <- thomas.ppp[[1]]$x+0.001 # shift the values off the lattice
thomas.ppp[[1]]$y <- thomas.ppp[[1]]$y+0.001
thomas.env.geo <-
ppp.to.geoR.fn(thomas.ppp[[1]],quad.size=20,xmin=xmin,xmax=xmax,ymin=ymin,ymax=ymax,method="mean.
mark")
thomas.spp.geo <-
ppp.to.geoR.fn(thomas.ppp[[2]],quad.size=20,xmin=xmin,xmax=xmax,ymin=ymin,ymax=ymax,method="total
.ba")

# CSR
csr.ppp <-
app.sim.fn(grid.points=20,env.func="CSR",pattern.method="quant.marks",ppp.model="CSR",marks.metho

```

```

d="random",xmin=0,xmax=300,ymin=0,ymax=300,lambda=200,minmark=1,maxmark=80,ntrees=1500,Print=FALSE)
csr.ppp[[1]]$x <- csr.ppp[[1]]$x+0.001 # shift the values off the lattice
csr.ppp[[1]]$y <- csr.ppp[[1]]$y+0.001
CSR.env.geo <-
ppp.to.geoR.fn(csr.ppp[[1]],quad.size=20,xmin=xmin,xmax=xmax,ymin=ymin,ymax=ymax,method="mean.mark")
CSR.spp.geo <-
ppp.to.geoR.fn(csr.ppp[[2]],quad.size=20,xmin=xmin,xmax=xmax,ymin=ymin,ymax=ymax,method="total.bas")

## Plot species grid plots
# Thomas
t1.dat <-
data.frame(xx=thomas.env.geo$coords[,1],yy=thomas.env.geo$coords[,2],AB=thomas.env.geo$data,Distribution="Thomas",Type="Environment")
t2.dat <-
data.frame(xx=thomas.spp.geo$coords[,1],yy=thomas.spp.geo$coords[,2],AB=thomas.spp.geo$data,Distribution="Thomas",Type="Species")
# CSR
c1.dat <-
data.frame(xx=CSR.env.geo$coords[,1],yy=CSR.env.geo$coords[,2],AB=CSR.env.geo$data,Distribution="CSR",Type="Environment")
c2.dat <-
data.frame(xx=CSR.spp.geo$coords[,1],yy=CSR.spp.geo$coords[,2],AB=CSR.spp.geo$data,Distribution="CSR",Type="Species")

(p1 <- ggplot(t1.dat, aes(x=xx, y=yy, size=AB))+geom_point(colour="black", fill="steelblue4",
shape=21)+ coord_fixed(ratio = 1)+t1.no.legend)
(p2 <- ggplot(t2.dat, aes(x=xx, y=yy, size=AB))+geom_point(colour="black", fill="#4dac26",
shape=21)+ coord_fixed(ratio = 1)+t1.no.legend)
(p3 <- ggplot(c1.dat, aes(x=xx, y=yy, size=AB))+geom_point(colour="black", fill="steelblue4",
shape=21)+ coord_fixed(ratio = 1)+t1.no.legend)
(p4 <- ggplot(c2.dat, aes(x=xx, y=yy, size=AB))+geom_point(colour="black", fill="#4dac26",
shape=21)+ coord_fixed(ratio = 1)+t1.no.legend)

png("CoDisp_Sims_TypeIerr_MEE.png",width=600,height=600)
grid.newpage()
pushViewport(viewport(layout=grid.layout(2,2))) # 6 rows by 7 columns
vplayout <- function(x,y)
  viewport(layout.pos.row=x,layout.pos.col=y)
## Print the graphs to the layout
print(p1, vp=vplayout(1,1))
print(p2, vp=vplayout(1,2))
print(p3, vp=vplayout(2,1))
print(p4, vp=vplayout(2,2))
dev.off()

# settings for codispersion analysis
k=c(20,20,20)
max.window.size = 300/4
binwidth=0.1
xmin=0
xmax=300
ymin=0
ymax=300
nsim = 49

# randomise species patterns using Homogeneous Poisson (CSR), RLM and Toroidal shift null models
# Thomas
HomP_Thomas.ls <- ppp.null.fn(thomas.ppp[[2]],nsim=nsim,model="HomP",marks=TRUE)
RLM_Thomas.ls <- ppp.null.fn(thomas.ppp[[2]],nsim=nsim,model="RLM",marks=TRUE)
Tor_Thomas.ls <- ppp.null.fn(thomas.ppp[[2]],nsim=nsim,model="Tor",marks=TRUE)

# CSR
HomP_CSR.ls <- ppp.null.fn(csr.ppp[[2]],nsim=nsim,model="HomP",marks=TRUE)
RLM_CSR.ls <- ppp.null.fn(csr.ppp[[2]],nsim=nsim,model="RLM",marks=TRUE)
Tor_CSR.ls <- ppp.null.fn(csr.ppp[[2]],nsim=nsim,model="Tor",marks=TRUE)

### make empty lists to hold null model results
CoDisp_Thomas_HomP <- vector("list",nsim)

```

```

CoDisp_Thomas_RLM <- vector("list",nsim)
CoDisp_Thomas_Tor <- vector("list",nsim)

CoDisp_CSR_HomP <- vector("list",nsim)
CoDisp_CSR_RLM <- vector("list",nsim)
CoDisp_CSR_Tor <- vector("list",nsim)

### Convert null ppp objects into geo.data objects
# Thomas
geo.HomP.Thomas <-
lapply(HomP_Thomas.ls,ppp.to.geoR.fn,quad.size=20,xmin,xmax,ymin,ymax,method="total.ba")
geo.RLM.Thomas <-
lapply(RLM_Thomas.ls,ppp.to.geoR.fn,quad.size=20,xmin,xmax,ymin,ymax,method="total.ba")
geo.Tor.Thomas <-
lapply(Tor_Thomas.ls,ppp.to.geoR.fn,quad.size=20,xmin,xmax,ymin,ymax,method="total.ba")

# CSR
geo.HomP.CSR <-
lapply(HomP_CSR.ls,ppp.to.geoR.fn,quad.size=20,xmin,xmax,ymin,ymax,method="total.ba")
geo.RLM.CSR <-
lapply(RLM_CSR.ls,ppp.to.geoR.fn,quad.size=20,xmin,xmax,ymin,ymax,method="total.ba")
geo.Tor.CSR <-
lapply(Tor_CSR.ls,ppp.to.geoR.fn,quad.size=20,xmin,xmax,ymin,ymax,method="total.ba")

# Run codispersion analysis on null model data
for(j in 1:nsim){
  # Thomas
  print(paste("CoDisp_Thomas_HomP, j",j)) # HomP
  CoDisp_Thomas_HomP[[j]] <-
codisp.fn(thomas.env.geo,geo.HomP.Thomas[[j]],k=k,max.window.size=max.window.size)

  print(paste("CoDisp_Thomas_RLM, j",j)) # Random labelling
  CoDisp_Thomas_RLM[[j]] <-
codisp.fn(thomas.env.geo,geo.RLM.Thomas[[j]],k=k,max.window.size=max.window.size)

  print(paste("CoDisp_Thomas_Tor, j",j)) # Toroidal shift
  CoDisp_Thomas_Tor[[j]] <-
codisp.fn(thomas.env.geo,geo.Tor.Thomas[[j]],k=k,max.window.size=max.window.size)

  # CSR
  print(paste("CoDisp_CSR_HomP, j",j)) # HomP
  CoDisp_CSR_HomP[[j]] <-
codisp.fn(CSR.env.geo,geo.HomP.CSR[[j]],k=k,max.window.size=max.window.size)

  print(paste("CoDisp_CSR_RLM, j",j)) # Random labelling
  CoDisp_CSR_RLM[[j]] <-
codisp.fn(CSR.env.geo,geo.RLM.CSR[[j]],k=k,max.window.size=max.window.size)

  print(paste("CoDisp_CSR_Tor, j",j)) # Toroidal shift
  CoDisp_CSR_Tor[[j]] <-
codisp.fn(CSR.env.geo,geo.Tor.CSR[[j]],k=k,max.window.size=max.window.size)
} # end simulations j loop

# Convert output lists to array objects
CoDisp_Thomas_HomP_ary <- list2ary(CoDisp_Thomas_HomP)
CoDisp_Thomas_RLM_ary <- list2ary(CoDisp_Thomas_RLM)
CoDisp_Thomas_Tor_ary <- list2ary(CoDisp_Thomas_Tor)

CoDisp_CSR_HomP_ary <- list2ary(CoDisp_CSR_HomP)
CoDisp_CSR_RLM_ary <- list2ary(CoDisp_CSR_RLM)
CoDisp_CSR_Tor_ary <- list2ary(CoDisp_CSR_Tor)

### Run the codispersion analysis on the observed patterns
CoDisp_Thomas <- codisp.fn(thomas.env.geo,thomas.spp.geo,k=k,max.window.size=max.window.size)
CoDisp_CSR <- codisp.fn(CSR.env.geo,CSR.spp.geo,k=k,max.window.size=max.window.size)

save.image("Simulated_MEE_CSR&CSR_null_49.RData")

load("mpp_env_ba.RData")
load("Simulated_MEE_CSR&CSR_null_199.RData")
source("CoDisp_functions.R")

```

```

### Make comparisons between observed and null expectation
# Thomas
Thomas_HomP_out.df <- codisp.compare(CoDisp_Thomas_HomP_ary,CoDisp_Thomas[[1]],round=TRUE)
Thomas_RLM_out.df <- codisp.compare(CoDisp_Thomas_RLM_ary,CoDisp_Thomas[[1]],round=TRUE)
Thomas_Tor_out.df <- codisp.compare(CoDisp_Thomas_Tor_ary,CoDisp_Thomas[[1]],round=TRUE)
write.table(Thomas_HomP_out.df,"Thomas_HomP_type I error rate.csv",sep=",")
write.table(Thomas_RLM_out.df,"Thomas_RLM_type I error rate.csv",sep=",")
write.table(Thomas_Tor_out.df,"Thomas_Tor_type I error rate.csv",sep=",")

# CSR
CSR_HomP_out.df <- codisp.compare(CoDisp_CSR_HomP_ary,CoDisp_CSR[[1]],round=TRUE)
CSR_RLM_out.df <- codisp.compare(CoDisp_CSR_RLM_ary,CoDisp_CSR[[1]],round=TRUE)
CSR_Tor_out.df <- codisp.compare(CoDisp_CSR_Tor_ary,CoDisp_CSR[[1]],round=TRUE)
write.table(CSR_HomP_out.df,"CSR_HomP_type I error rate.csv",sep=",")
write.table(CSR_RLM_out.df,"CSR_RLM_type I error rate.csv",sep=",")
write.table(CSR_Tor_out.df,"CSR_Tor_type I error rate.csv",sep=",")

### Draw graphs
# Thomas
### HomP
# Observed minus expected CoDispersion value graph
( g1 <-
ggplot(Thomas_HomP_out.df,aes(xx,yy))+geom_tile(aes(fill=diff))+scale_fill_gradientn(colours=c("#0000FF", "#FFFFFF", "#FF6666"),limits=c(-1,
1))+coord_fixed(ratio=1)+t1.no.leg+xlab(NULL)+ylab(NULL)+stat_contour(aes(x=xx,y=yy,z=diff),binwidth=binwidth) )

# P-value category graph
my.cols <- c("steelblue3","firebrick3")
if(levels(Thomas_HomP_out.df$P.value.cat)[1]=="Sig."){my.cols <- c("firebrick3")}
( g2 <-
ggplot(Thomas_HomP_out.df,aes(xx,yy))+geom_tile(aes(fill=P.value.cat))+scale_fill_manual(values=my.cols)+scale_colour_discrete(name="P.value.cat",limits=c(0,1))+coord_fixed(ratio=1)+t1.no.leg+xlab(NULL)+ylab(NULL) )

### RLM
# Observed minus expected CoDispersion value graph
( g3 <-
ggplot(Thomas_RLM_out.df,aes(xx,yy))+geom_tile(aes(fill=diff))+scale_fill_gradientn(colours=c("#0000FF", "#FFFFFF", "#FF6666"),limits=c(-1,
1))+coord_fixed(ratio=1)+t1.no.leg+xlab(NULL)+ylab(NULL)+stat_contour(aes(x=xx,y=yy,z=diff),binwidth=binwidth) )

# P-value category graph
my.cols <- c("steelblue3","firebrick3")
if(levels(Thomas_RLM_out.df$P.value.cat)[1]=="Sig."){my.cols <- c("firebrick3")}
( g4 <-
ggplot(Thomas_RLM_out.df,aes(xx,yy))+geom_tile(aes(fill=P.value.cat))+scale_fill_manual(values=my.cols)+scale_colour_discrete(name="P.value.cat",limits=c(0,1))+coord_fixed(ratio=1)+t1.no.leg+xlab(NULL)+ylab(NULL) )

### Toroidal shift
# Observed minus expected CoDispersion value graph
( g5 <-
ggplot(Thomas_Tor_out.df,aes(xx,yy))+geom_tile(aes(fill=diff))+scale_fill_gradientn(colours=c("#0000FF", "#FFFFFF", "#FF6666"),limits=c(-1,
1))+coord_fixed(ratio=1)+t1.no.leg+xlab(NULL)+ylab(NULL)+stat_contour(aes(x=xx,y=yy,z=diff),binwidth=binwidth) )

# P-value category graph
my.cols <- c("steelblue3","firebrick3")
if(levels(Thomas_Tor_out.df$P.value.cat)[1]=="Sig."){my.cols <- c("firebrick3")}
( g6 <-
ggplot(Thomas_Tor_out.df,aes(xx,yy))+geom_tile(aes(fill=P.value.cat))+scale_fill_manual(values=my.cols)+scale_colour_discrete(name="P.value.cat",limits=c(0,1))+coord_fixed(ratio=1)+t1.no.leg+xlab(NULL)+ylab(NULL) )

# CSR
### HomP
# Observed minus expected CoDispersion value graph

```

```

( g7 <-
ggplot(CSR_HomP_out.df,aes(xx,yy))+geom_tile(aes(fill=diff))+scale_fill_gradientn(colours=c("#000
0FF","#FFFFFF","#FF6666"),limits=c(-1,
1))+coord_fixed(ratio=1)+t1.no.legend+xlabs(NULL)+ylabs(NULL)+stat_contour(aes(x=xx,y=yy,z=diff),binwi
dth=binwidth) )

# P-value category graph
my.cols <- c("steelblue3","firebrick3")
if(levels(CSR_HomP_out.df$P.value.cat)[1]=="Sig."){my.cols <- c("firebrick3") }
( g8 <-
ggplot(CSR_HomP_out.df,aes(xx,yy))+geom_tile(aes(fill=P.value.cat))+scale_fill_manual(values=my.c
ols)+scale_colour_discrete(name="P.value.cat",limits=c(0,1))+coord_fixed(ratio=1)+t1.no.legend+xlabs(
NULL)+ylabs(NULL) )

### RLM
# Observed minus expected CoDispersion value graph
( g9 <-
ggplot(CSR_RLM_out.df,aes(xx,yy))+geom_tile(aes(fill=diff))+scale_fill_gradientn(colours=c("#0000
FF","#FFFFFF","#FF6666"),limits=c(-1,
1))+coord_fixed(ratio=1)+t1.no.legend+xlabs(NULL)+ylabs(NULL)+stat_contour(aes(x=xx,y=yy,z=diff),binwi
dth=binwidth) )

# P-value category graph
my.cols <- c("steelblue3","firebrick3")
if(levels(CSR_RLM_out.df$P.value.cat)[1]=="Sig."){my.cols <- c("firebrick3") }
( g10 <-
ggplot(CSR_RLM_out.df,aes(xx,yy))+geom_tile(aes(fill=P.value.cat))+scale_fill_manual(values=my.co
ls)+scale_colour_discrete(name="P.value.cat",limits=c(0,1))+coord_fixed(ratio=1)+t1.no.legend+xlabs(N
ULL)+ylabs(NULL) )

### Toroidal shift
# Observed minus expected CoDispersion value graph
( g11 <-
ggplot(CSR_Tor_out.df,aes(xx,yy))+geom_tile(aes(fill=diff))+scale_fill_gradientn(colours=c("#0000
FF","#FFFFFF","#FF6666"),limits=c(-1,
1))+coord_fixed(ratio=1)+t1.no.legend+xlabs(NULL)+ylabs(NULL)+stat_contour(aes(x=xx,y=yy,z=diff),binwi
dth=binwidth) )

# P-value category graph
my.cols <- c("steelblue3","firebrick3")
if(levels(CSR_Tor_out.df$P.value.cat)[1]=="Sig."){my.cols <- c("firebrick3") }
( g12 <-
ggplot(CSR_Tor_out.df,aes(xx,yy))+geom_tile(aes(fill=P.value.cat))+scale_fill_manual(values=my.co
ls)+scale_colour_discrete(name="P.value.cat",limits=c(0,1))+coord_fixed(ratio=1)+t1.no.legend+xlabs(N
ULL)+ylabs(NULL) )

png("CoDisp_Sims_TypeIerr_output_MEE_0.025_199.png",width=1400,height=250)
grid.newpage()
pushViewport(viewport(layout=grid.layout(2,12)))
vplayout <- function(x,y)
  viewport(layout.pos.row=x,layout.pos.col=y)
## Print the graphs to the layout
print(g1, vp=vplayout(1,1:2))
print(g2, vp=vplayout(1,3:4))
print(g3, vp=vplayout(1,5:6))
print(g4, vp=vplayout(1,7:8))
print(g5, vp=vplayout(1,9:10))
print(g6, vp=vplayout(1,11:12))
print(g7, vp=vplayout(2,1:2))
print(g8, vp=vplayout(2,3:4))
print(g9, vp=vplayout(2,5:6))
print(g10, vp=vplayout(2,7:8))
print(g11, vp=vplayout(2,9:10))
print(g12, vp=vplayout(2,11:12))
dev.off()

```

```

#####
#####
##### Analyse LFDP species on environmental gradients
##### using Codispersion analysis.
##### Run as a source file: source("CoDisp_functions.R")
#####
#####

source("CoDisp_functions.R")

#####
#### Read in the datasets
#####

# PuertoRico-LFDP data
LFDP_full <-
read.csv("http://luq.lternet.edu/sites/default/files/data/LFDP_Census3.csv",header=TRUE)
dim(LFDP_full[is.na(LFDP_full$GX)==F,])
LFDP.new <- LFDP_full[ order(LFDP_full[, "GX"]), ]
head(LFDP.new)
names(LFDP.new) <-
c("tag", "stentag", "sp", "quadrat", "subquadrat", "gx", "gy", "dbh", "status", "hom.m", "date", "census", "s
tatus.and.codes")
temp <- strsplit(as.character(LFDP.new$status.and.codes), split=";")
levels(factor(LFDP.new$status.and.codes))
LFDP.new$codes1 <- sapply(temp, function(x)x[1])
LFDP.new$codes2 <- sapply(temp, function(x)x[2])
LFDP.new$codes3 <- sapply(temp, function(x)x[3])
LFDP.new$codes4 <- sapply(temp, function(x)x[4])
LFDP.new$codes5 <- sapply(temp, function(x)x[5])
LFDP_sub2 <- LFDP.new[LFDP.new$codes1=="MAIN"&LFDP.new$codes2=="A", ]
LFDP_sub <- subset(LFDP_sub2, select=c(sp, gx, gy, dbh))
LFDP <- LFDP_sub[complete.cases(LFDP_sub), ]
LFDP$sp <- factor(LFDP$sp)
LFDP$dbh <- LFDP$dbh/10

dat <- LFDP[ order(LFDP[, "gx"]), ]
unique(dat$sp) # species list
nsp <- length(unique(dat$sp)) # number of species

rm(LFDP_full, LFDP.new, LFDP_sub2, LFDP_sub, LFDP)

# calculate basal area
dat$ba <- basal.area.fn(dat$dbh)

# set plot dimensions
plot(dat$gx, dat$gy)
max(dat$gx)
max(dat$gy)
xmin=0; xmax=320; ymin=0; ymax=500

# LFDP environmental data on 20 x 20m grid
env <- read.csv("http://luq.lternet.edu/sites/default/files/data/LFDPEnvironment20.csv",
header=TRUE)
env$qx <- (env$Col-1)*20
env$gy <- (env$Row-1)*20
env <- env[ order(env[, "qx"]), ]

plot(geo.elev <- as.geodata(env, coords.col=19:20, data.col=12))
plot(geo.slope <- as.geodata(env, coords.col=19:20, data.col=15))

#####
## Extract target species:
#####

nsp <- 4
spp.list <- c("CASARB", "PREMON", "CECSCH", "DACEXC")

ppp.ls <- vector("list", nsp)
for (i in 1:nsp){

```



```

ppp.ls[[i]] <-
ppp(dat$gx[dat$sp==spp.list[i]],dat$gy[dat$sp==spp.list[i]],xrange=c(xmin,xmax),yrange=c(ymin,ymax),marks=dat$dbh[dat$sp==spp.list[i]])
}
ppp.ls

#####
## Analysis using rasters
#####

for(i in 1:length(spp.list)){
  ppp.dat <- ppp.ls[[i]]

  Graphs_ls <- vector(mode="list",length=9) # empty list for output graphs
  Means.df <- data.frame(env=c("Elevation","Slope"),mean_CoDisp=NA,sd_CoDisp=NA)

  spe <- spp.list[i]

  geo.obs.ba <- ppp.to.geoR.fn(ppp.dat,quad.size=20,xmin,xmax,ymin,ymax,method="total.ba")

  # Graph the data
  elev.dat <- data.frame(X=geo.elev$coords[,1],Y=geo.elev$coords[,2],env=geo.elev$data)
  slope.dat <- data.frame(X=geo.slope$coords[,1],Y=geo.slope$coords[,2],env=geo.slope$data)
  sp.dat <- data.frame(X=geo.obs.ba$coords[,1],Y=geo.obs.ba$coords[,2],BA=geo.obs.ba$data)

  Graphs_ls[[1]] <- ggplot(elev.dat, aes(x=X, y=Y, size=env))+geom_point(colour="black",
fill="steelblue2", shape=21)+t1.no.legend
  Graphs_ls[[2]] <- ggplot(slope.dat, aes(x=X, y=Y, size=env))+geom_point(colour="black",
fill="steelblue2", shape=21)+t1.no.legend
  Graphs_ls[[3]] <- ggplot(sp.dat, aes(x=X, y=Y, size=BA))+geom_point(colour="black",
fill="#4dac26", shape=21)+t1.no.legend

  ## Plot the variograms and cross variograms
  # Elevation
  ddat <- data.frame(geo.elev$coords,env=scale(geo.elev$data),sp=scale(geo.obs.ba$data))
  g <- gstat(id="env", formula=env~1, locations=~qx+qy, data = ddat)
  g <- gstat(g, id="sp", formula=sp~1, locations=~qx+qy, data = ddat)
  v <- variogram(g, cutoff=(min(xmax,ymax)*0.67), cross=TRUE)
  Graphs_ls[[4]] <-
ggplot(v,aes(x=dist,y=gamma,group=id,colour=id))+geom_line(lwd=2)+t1.no.legend + labs(x="Distance
(m)",y = "Semivariance")
  # Slope
  ddat <- data.frame(geo.slope$coords,env=scale(geo.slope$data),sp=scale(geo.obs.ba$data))
  g <- gstat(id="env", formula=env~1, locations=~qx+qy, data = ddat)
  g <- gstat(g, id="sp", formula=sp~1, locations=~qx+qy, data = ddat)
  v <- variogram(g, cutoff=(min(xmax,ymax)*0.67), cross=TRUE)
  Graphs_ls[[5]] <-
ggplot(v,aes(x=dist,y=gamma,group=id,colour=id))+geom_line(lwd=2)+t1.no.legend + labs(x="Distance
(m)",y = "Semivariance")

#### run the codispersion analysis

binwidth=0.1
k=c(20,20,20)
max.window.size=320/4

# observed data BA
print(paste("Elevation",spe))
CoDisp_elev <- codisp.fn(geo.obs.ba,geo.elev,k=k,max.window.size=max.window.size)
print(paste("Slope",spe))
CoDisp_slope <- codisp.fn(geo.obs.ba,geo.slope,k=k,max.window.size=max.window.size)

## Graph the output
Graphs_ls[[6]] <- print.CoDisp.plain(CoDisp_elev[[1]],scaled=FALSE,labels=FALSE)
Graphs_ls[[7]] <-
print.CoDisp.plain(CoDisp_elev[[1]],scaled=TRUE,contours=TRUE,binwidth=binwidth,labels=FALSE)

Graphs_ls[[8]] <- print.CoDisp.plain(CoDisp_slope[[1]],scaled=FALSE,labels=FALSE)
Graphs_ls[[9]] <-
print.CoDisp.plain(CoDisp_slope[[1]],scaled=TRUE,contours=TRUE,binwidth=binwidth,labels=FALSE)

```

```

## Calculate the mean values
Means.df$mean_CoDisp[1] <- round(mean(CoDisp_elev[[1]]$Codispersion),2)
Means.df$sd_CoDisp[1] <- round(sd(CoDisp_elev[[1]]$Codispersion),2)

Means.df$mean_CoDisp[2] <- round(mean(CoDisp_slope[[1]]$Codispersion),2)
Means.df$sd_CoDisp[2] <- round(sd(CoDisp_slope[[1]]$Codispersion),2)

## Save the output objects
nam=paste("CoDisp_elev",spe,sep="_")
assign(nam,CoDisp_elev)

nam=paste("CoDisp_slope",spe,sep="_")
assign(nam,CoDisp_slope)

nam=(paste("Graphs_ls",spe,sep="_"))
assign(nam,Graphs_ls)

nam=(paste("Means.df",spe,sep="_"))
assign(nam,Means.df)

} # end i loop

save.image("LFDP_spp_env_obs_basalarea.RData")

#####
## Observed graphs for paper
#####

load("LFDP_spp_env_obs_basalarea.RData")
source("CoDisp_functions.R")

png("LFDP_Variograms_Figure.png",width=860,height=1200)

grid.newpage()
pushViewport(viewport(layout=grid.layout(5,3)))

# Print observed elevation and slope raster plots

print(Graphs_ls_CASARB[[1]]+coord_fixed(ratio=1)+scale_x_continuous(breaks=c(0,100,300))+scale_y_
continuous(breaks=c(0,100,300,500)), vp=vplayout(1,2))

print(Graphs_ls_CASARB[[2]]+coord_fixed(ratio=1)+scale_x_continuous(breaks=c(0,100,300))+scale_y_
continuous(breaks=c(0,100,300,500)), vp=vplayout(1,3))

# g1 <- out[[1]] # env var 1: elevation
# g2 <- out[[2]] # env var 2: slope
# g3 <- out[[3]] # BA of species
# g4 <- out[[4]] # first variogram plot: elevation
# g5 <- out[[5]] # second variogram plot: slope

for(i in 1:4){
  if(i==1){out <- Graphs_ls_CASARB

print(out[[3]]+coord_fixed(ratio=1)+scale_x_continuous(breaks=c(0,100,300))+scale_y_continuous(br
eaks=c(0,100,300,500)), vp=vplayout(2,1))
print(out[[4]]+t1.no.lab+yylim(c(-0.2,1.25)), vp=vplayout(2,2))
print(out[[5]]+t1.no.lab+yylim(c(-0.2,1.25)), vp=vplayout(2,3))
}
  if(i==2){out <- Graphs_ls_CECSCH

print(out[[3]]+coord_fixed(ratio=1)+scale_x_continuous(breaks=c(0,100,300))+scale_y_continuous(br
eaks=c(0,100,300,500)), vp=vplayout(3,1))
print(out[[4]]+t1.no.lab+yylim(c(-0.2,1.25)), vp=vplayout(3,2))
print(out[[5]]+t1.no.lab+yylim(c(-0.2,1.25)), vp=vplayout(3,3))
}
  if(i==3){out <- Graphs_ls_DACEXC

print(out[[3]]+coord_fixed(ratio=1)+scale_x_continuous(breaks=c(0,100,300))+scale_y_continuous(br
eaks=c(0,100,300,500)), vp=vplayout(4,1))
print(out[[4]]+t1.no.lab+yylim(c(-0.2,1.25)), vp=vplayout(4,2))
print(out[[5]]+t1.no.lab+yylim(c(-0.2,1.25)), vp=vplayout(4,3))
}
}

```

```

    }
    if(i==4){out <- Graphs_ls_PREMON

print(out[[3]]+coord_fixed(ratio=1)+scale_x_continuous(breaks=c(0,100,300))+scale_y_continuous(breaks=c(0,100,300,500)), vp=vplayout(5,1))
print(out[[4]]+t1.no.lab+yylim(c(-0.2,1.25)), vp=vplayout(5,2))
print(out[[5]]+t1.no.lab+yylim(c(-0.2,1.25)), vp=vplayout(5,3))
    }
  }
  dev.off()

#####
## Null model comparison
#####

load("LFDP_spp_env_obs_basalarea.RData")
source("CoDisp_functions.R")

spp.list <- c("CASARB", "PREMON", "CECSCH", "DACEXC")
ppp.ls <- vector("list", nspp)
for (i in 1:nspp){
  ppp.ls[[i]] <-
ppp(dat$gx[dat$sp==spp.list[i]], dat$gy[dat$sp==spp.list[i]], xrange=c(xmin, xmax), yrange=c(ymin, ymax), marks=dat$dbh[dat$sp==spp.list[i]])
}

k=c(20,20,20)
max.window.size=320/4
nsim=199

HomP_sp1.ls <- ppp.null.fn(ppp.ls[[1]], nsim=nsim, model=c("HomP"))
HomP_sp2.ls <- ppp.null.fn(ppp.ls[[2]], nsim=nsim, model=c("HomP"))
HomP_sp3.ls <- ppp.null.fn(ppp.ls[[3]], nsim=nsim, model=c("HomP"))
HomP_sp4.ls <- ppp.null.fn(ppp.ls[[4]], nsim=nsim, model=c("HomP"))

RLM_sp1.ls <- ppp.null.fn(ppp.ls[[1]], nsim=nsim, model=c("RLM"))
RLM_sp2.ls <- ppp.null.fn(ppp.ls[[2]], nsim=nsim, model=c("RLM"))
RLM_sp3.ls <- ppp.null.fn(ppp.ls[[3]], nsim=nsim, model=c("RLM"))
RLM_sp4.ls <- ppp.null.fn(ppp.ls[[4]], nsim=nsim, model=c("RLM"))

Tor_sp1.ls <- ppp.null.fn(ppp.ls[[1]], nsim=nsim, model=c("Tor"))
Tor_sp2.ls <- ppp.null.fn(ppp.ls[[2]], nsim=nsim, model=c("Tor"))
Tor_sp3.ls <- ppp.null.fn(ppp.ls[[3]], nsim=nsim, model=c("Tor"))
Tor_sp4.ls <- ppp.null.fn(ppp.ls[[4]], nsim=nsim, model=c("Tor"))

# Generate null model geodata objects
geo.HomP.sp1 <-
lapply(HomP_sp1.ls, ppp.to.geoR.fn, quad.size=20, xmin, xmax, ymin, ymax, method="total.ba")
geo.HomP.sp2 <-
lapply(HomP_sp2.ls, ppp.to.geoR.fn, quad.size=20, xmin, xmax, ymin, ymax, method="total.ba")
geo.HomP.sp3 <-
lapply(HomP_sp3.ls, ppp.to.geoR.fn, quad.size=20, xmin, xmax, ymin, ymax, method="total.ba")
geo.HomP.sp4 <-
lapply(HomP_sp4.ls, ppp.to.geoR.fn, quad.size=20, xmin, xmax, ymin, ymax, method="total.ba")

geo.RLM.sp1 <-
lapply(RLM_sp1.ls, ppp.to.geoR.fn, quad.size=20, xmin, xmax, ymin, ymax, method="total.ba")
geo.RLM.sp2 <-
lapply(RLM_sp2.ls, ppp.to.geoR.fn, quad.size=20, xmin, xmax, ymin, ymax, method="total.ba")
geo.RLM.sp3 <-
lapply(RLM_sp3.ls, ppp.to.geoR.fn, quad.size=20, xmin, xmax, ymin, ymax, method="total.ba")
geo.RLM.sp4 <-
lapply(RLM_sp4.ls, ppp.to.geoR.fn, quad.size=20, xmin, xmax, ymin, ymax, method="total.ba")

geo.Tor.sp1 <-
lapply(Tor_sp1.ls, ppp.to.geoR.fn, quad.size=20, xmin, xmax, ymin, ymax, method="total.ba")
geo.Tor.sp2 <-
lapply(Tor_sp2.ls, ppp.to.geoR.fn, quad.size=20, xmin, xmax, ymin, ymax, method="total.ba")
geo.Tor.sp3 <-
lapply(Tor_sp3.ls, ppp.to.geoR.fn, quad.size=20, xmin, xmax, ymin, ymax, method="total.ba")

```

```

geo.Tor.sp4 <-
lapply(Tor_sp4.ls,ppp.to.geoR.fn,quad.size=20,xmin,xmax,ymin,ymax,method="total.ba")

CoDisp_HomP_splelev <- vector("list",nsim)
CoDisp_HomP_sp2elev <- vector("list",nsim)
CoDisp_HomP_sp3elev <- vector("list",nsim)
CoDisp_HomP_sp4elev <- vector("list",nsim)
CoDisp_HomP_splslope <- vector("list",nsim)
CoDisp_HomP_sp2slope <- vector("list",nsim)
CoDisp_HomP_sp3slope <- vector("list",nsim)
CoDisp_HomP_sp4slope <- vector("list",nsim)

CoDisp_RLM_splelev <- vector("list",nsim)
CoDisp_RLM_sp2elev <- vector("list",nsim)
CoDisp_RLM_sp3elev <- vector("list",nsim)
CoDisp_RLM_sp4elev <- vector("list",nsim)
CoDisp_RLM_splslope <- vector("list",nsim)
CoDisp_RLM_sp2slope <- vector("list",nsim)
CoDisp_RLM_sp3slope <- vector("list",nsim)
CoDisp_RLM_sp4slope <- vector("list",nsim)

CoDisp_Tor_splelev <- vector("list",nsim)
CoDisp_Tor_sp2elev <- vector("list",nsim)
CoDisp_Tor_sp3elev <- vector("list",nsim)
CoDisp_Tor_sp4elev <- vector("list",nsim)
CoDisp_Tor_splslope <- vector("list",nsim)
CoDisp_Tor_sp2slope <- vector("list",nsim)
CoDisp_Tor_sp3slope <- vector("list",nsim)
CoDisp_Tor_sp4slope <- vector("list",nsim)

for (i in 1:nsim) {
  # Run codispersion analysis on null model data

  # HomP elevation
  print(paste("CoDisp_HomP_splelev, i =",i))
  CoDisp_HomP_splelev[[i]] <-
codisp.fn(geo.elev,geo.HomP.sp1[[i]],k=k,max.window.size=max.window.size)
  print(paste("CoDisp_HomP_sp2elev, i =",i))
  CoDisp_HomP_sp2elev[[i]] <-
codisp.fn(geo.elev,geo.HomP.sp2[[i]],k=k,max.window.size=max.window.size)
  print(paste("CoDisp_HomP_sp3elev, i =",i))
  CoDisp_HomP_sp3elev[[i]] <-
codisp.fn(geo.elev,geo.HomP.sp3[[i]],k=k,max.window.size=max.window.size)
  print(paste("CoDisp_HomP_sp4elev, i =",i))
  CoDisp_HomP_sp4elev[[i]] <-
codisp.fn(geo.elev,geo.HomP.sp4[[i]],k=k,max.window.size=max.window.size)
  # HomP slope
  print(paste("CoDisp_HomP_splslope, i =",i))
  CoDisp_HomP_splslope[[i]] <-
codisp.fn(geo.slope,geo.HomP.sp1[[i]],k=k,max.window.size=max.window.size)
  print(paste("CoDisp_HomP_sp2slope, i =",i))
  CoDisp_HomP_sp2slope[[i]] <-
codisp.fn(geo.slope,geo.HomP.sp2[[i]],k=k,max.window.size=max.window.size)
  print(paste("CoDisp_HomP_sp3slope, i =",i))
  CoDisp_HomP_sp3slope[[i]] <-
codisp.fn(geo.slope,geo.HomP.sp3[[i]],k=k,max.window.size=max.window.size)
  print(paste("CoDisp_HomP_sp4slope, i =",i))
  CoDisp_HomP_sp4slope[[i]] <-
codisp.fn(geo.slope,geo.HomP.sp4[[i]],k=k,max.window.size=max.window.size)

  # RLM elevation
  print(paste("CoDisp_RLM_splelev, i =",i))
  CoDisp_RLM_splelev[[i]] <-
codisp.fn(geo.elev,geo.RLM.sp1[[i]],k=k,max.window.size=max.window.size)
  print(paste("CoDisp_RLM_sp2elev, i =",i))
  CoDisp_RLM_sp2elev[[i]] <-
codisp.fn(geo.elev,geo.RLM.sp2[[i]],k=k,max.window.size=max.window.size)
  print(paste("CoDisp_RLM_sp3elev, i =",i))
  CoDisp_RLM_sp3elev[[i]] <-
codisp.fn(geo.elev,geo.RLM.sp3[[i]],k=k,max.window.size=max.window.size)
  print(paste("CoDisp_RLM_sp4elev, i =",i))

```

```

    CoDisp_RLM_sp4elev[[i]] <-
codisp.fn(geo.elev,geo.RLM.sp4[[i]],k=k,max.window.size=max.window.size)
# RLM slope
print(paste("CoDisp_RLM_sp1slope, i =",i))
CoDisp_RLM_sp1slope[[i]] <-
codisp.fn(geo.slope,geo.RLM.sp1[[i]],k=k,max.window.size=max.window.size)
print(paste("CoDisp_RLM_sp2slope, i =",i))
CoDisp_RLM_sp2slope[[i]] <-
codisp.fn(geo.slope,geo.RLM.sp2[[i]],k=k,max.window.size=max.window.size)
print(paste("CoDisp_RLM_sp3slope, i =",i))
CoDisp_RLM_sp3slope[[i]] <-
codisp.fn(geo.slope,geo.RLM.sp3[[i]],k=k,max.window.size=max.window.size)
print(paste("CoDisp_RLM_sp4slope, i =",i))
CoDisp_RLM_sp4slope[[i]] <-
codisp.fn(geo.slope,geo.RLM.sp4[[i]],k=k,max.window.size=max.window.size)

# Tor elevation
print(paste("CoDisp_Tor_splelev, i =",i))
CoDisp_Tor_splelev[[i]] <-
codisp.fn(geo.elev,geo.Tor.sp1[[i]],k=k,max.window.size=max.window.size)
print(paste("CoDisp_Tor_sp2elev, i =",i))
CoDisp_Tor_sp2elev[[i]] <-
codisp.fn(geo.elev,geo.Tor.sp2[[i]],k=k,max.window.size=max.window.size)
print(paste("CoDisp_Tor_sp3elev, i =",i))
CoDisp_Tor_sp3elev[[i]] <-
codisp.fn(geo.elev,geo.Tor.sp3[[i]],k=k,max.window.size=max.window.size)
print(paste("CoDisp_Tor_sp4elev, i =",i))
CoDisp_Tor_sp4elev[[i]] <-
codisp.fn(geo.elev,geo.Tor.sp4[[i]],k=k,max.window.size=max.window.size)
# Tor slope
print(paste("CoDisp_Tor_sp1slope, i =",i))
CoDisp_Tor_sp1slope[[i]] <-
codisp.fn(geo.slope,geo.Tor.sp1[[i]],k=k,max.window.size=max.window.size)
print(paste("CoDisp_Tor_sp2slope, i =",i))
CoDisp_Tor_sp2slope[[i]] <-
codisp.fn(geo.slope,geo.Tor.sp2[[i]],k=k,max.window.size=max.window.size)
print(paste("CoDisp_Tor_sp3slope, i =",i))
CoDisp_Tor_sp3slope[[i]] <-
codisp.fn(geo.slope,geo.Tor.sp3[[i]],k=k,max.window.size=max.window.size)
print(paste("CoDisp_Tor_sp4slope, i =",i))
CoDisp_Tor_sp4slope[[i]] <-
codisp.fn(geo.slope,geo.Tor.sp4[[i]],k=k,max.window.size=max.window.size)

} # end i loop

# Convert output lists to array objects
CoDisp_HomP_splelev.ary <- list2ary(CoDisp_HomP_splelev)
CoDisp_HomP_sp2elev.ary <- list2ary(CoDisp_HomP_sp2elev)
CoDisp_HomP_sp3elev.ary <- list2ary(CoDisp_HomP_sp3elev)
CoDisp_HomP_sp4elev.ary <- list2ary(CoDisp_HomP_sp4elev)
CoDisp_HomP_sp1slope.ary <- list2ary(CoDisp_HomP_sp1slope)
CoDisp_HomP_sp2slope.ary <- list2ary(CoDisp_HomP_sp2slope)
CoDisp_HomP_sp3slope.ary <- list2ary(CoDisp_HomP_sp3slope)
CoDisp_HomP_sp4slope.ary <- list2ary(CoDisp_HomP_sp4slope)

CoDisp_RLM_splelev.ary <- list2ary(CoDisp_RLM_splelev)
CoDisp_RLM_sp2elev.ary <- list2ary(CoDisp_RLM_sp2elev)
CoDisp_RLM_sp3elev.ary <- list2ary(CoDisp_RLM_sp3elev)
CoDisp_RLM_sp4elev.ary <- list2ary(CoDisp_RLM_sp4elev)
CoDisp_RLM_sp1slope.ary <- list2ary(CoDisp_RLM_sp1slope)
CoDisp_RLM_sp2slope.ary <- list2ary(CoDisp_RLM_sp2slope)
CoDisp_RLM_sp3slope.ary <- list2ary(CoDisp_RLM_sp3slope)
CoDisp_RLM_sp4slope.ary <- list2ary(CoDisp_RLM_sp4slope)

CoDisp_Tor_splelev.ary <- list2ary(CoDisp_Tor_splelev)
CoDisp_Tor_sp2elev.ary <- list2ary(CoDisp_Tor_sp2elev)
CoDisp_Tor_sp3elev.ary <- list2ary(CoDisp_Tor_sp3elev)
CoDisp_Tor_sp4elev.ary <- list2ary(CoDisp_Tor_sp4elev)
CoDisp_Tor_sp1slope.ary <- list2ary(CoDisp_Tor_sp1slope)
CoDisp_Tor_sp2slope.ary <- list2ary(CoDisp_Tor_sp2slope)
CoDisp_Tor_sp3slope.ary <- list2ary(CoDisp_Tor_sp3slope)

```

```

CoDisp_Tor_sp4slope.ary <- list2ary(CoDisp_Tor_sp4slope)

save.image("LFDP_elev&slope_spp1_4_Null_199.RData")

load("LFDP_spp_env_obs_basalarea_20x20.RData")
load("LFDP_elev&slope_spp1_4_Null_199.RData")
source("CoDisp_functions.R")

#####
## Null model figure for paper
#####

# Generate comparison output objects for each species and null model analysis combination

binwidth = 0.1
n.spp = 4 # number of species
n.vars = 2 # number of variables
n.mods = 3 # number of null models

png("LFDP_CodispNull_Figure.png",width=1600,height=(n.spp*n.vars*120))

grid.newpage()
pushViewport(viewport(layout=grid.layout((n.spp*n.vars),14)))

# Loop through each species and plot the observed CoDisp graphs

obs.codisp.ls <-
list(CoDisp_elev_CASARB[[1]],CoDisp_slope_CASARB[[1]],CoDisp_elev_PREMON[[1]],CoDisp_slope_PREMON
[[1]],CoDisp_elev_CECSCH[[1]],CoDisp_slope_CECSCH[[1]],CoDisp_elev_DACEXC[[1]],CoDisp_slope_DACEX
C[[1]])

for (i in 1:length(obs.codisp.ls)) {
  # Observed graphs
  g1 <-
print.CoDisp.plain(obs.codisp.ls[[i]],labels="FALSE",legend="FALSE",scaled=TRUE,contours=TRUE,bin
width=binwidth)
  print(g1, vp=vplayout(i,1:2))
}

codisp.obj.ls <- list(
CoDisp_elev_CASARB[[1]],CoDisp_elev_CASARB[[1]],CoDisp_elev_CASARB[[1]],CoDisp_slope_CASARB[[1]],
CoDisp_slope_CASARB[[1]],CoDisp_slope_CASARB[[1]],CoDisp_elev_PREMON[[1]],CoDisp_elev_PREMON[[1]]
,CoDisp_elev_PREMON[[1]],CoDisp_slope_PREMON[[1]],CoDisp_slope_PREMON[[1]],CoDisp_slope_PREMON[[1
]],CoDisp_elev_CECSCH[[1]],CoDisp_elev_CECSCH[[1]],CoDisp_elev_CECSCH[[1]],CoDisp_slope_CECSCH[[1
]],CoDisp_slope_CECSCH[[1]],CoDisp_slope_CECSCH[[1]],CoDisp_elev_DACEXC[[1]],CoDisp_elev_DACEXC[[
1]],CoDisp_elev_DACEXC[[1]],CoDisp_slope_DACEXC[[1]],CoDisp_slope_DACEXC[[1]],CoDisp_slope_DACEXC
[[1]])

null.ary.ls <- list(
CoDisp_HomP_splelev.ary,CoDisp_RLM_splelev.ary,CoDisp_Tor_splelev.ary,CoDisp_HomP_splslope.ary,Co
Disp_RLM_splslope.ary,CoDisp_Tor_splslope.ary,CoDisp_HomP_sp2elev.ary,CoDisp_RLM_sp2elev.ary,CoDi
sp_Tor_sp2elev.ary,CoDisp_HomP_sp2slope.ary,CoDisp_RLM_sp2slope.ary,CoDisp_Tor_sp2slope.ary,CoDis
p_HomP_sp3elev.ary,CoDisp_RLM_sp3elev.ary,CoDisp_Tor_sp3elev.ary,CoDisp_HomP_sp3slope.ary,CoDisp_
RLM_sp3slope.ary,CoDisp_Tor_sp3slope.ary,CoDisp_HomP_sp4elev.ary,CoDisp_RLM_sp4elev.ary,CoDisp_To
r_sp4elev.ary,CoDisp_HomP_sp4slope.ary,CoDisp_RLM_sp4slope.ary,CoDisp_Tor_sp4slope.ary )

g2.ls <- vector("list",n.spp*n.vars*n.mods)
g3.ls <- vector("list",n.spp*n.vars*n.mods)

row.loop.no <- rep(1:(n.spp*n.vars),each=n.mods)
g2.col.loop.no <- rep(c(3,7,11),(n.spp*n.vars))
g3.col.loop.no <- rep(c(5,9,13),(n.spp*n.vars))

for(i in 1:length(null.ary.ls)){

  # Null model comparison graphs
  out.df <- codisp.compare(null.ary.ls[[i]],codisp.obj.ls[[i]])

  # Observed minus expected CoDispersion value graph
  g2 <-
ggplot(out.df,aes(xx,yy))+geom_tile(aes(fill=diff))+scale_fill_gradientn(colours=c("#0000FF","#FF

```

```

FFFF", "#FF6666"), limits=c(-1,
1))+coord_fixed(ratio=1)+t1.no.legend+labs(NULL)+ylab(NULL)+stat_contour(aes(x=xx,y=yy,z=diff), binwidth=binwidth)

# P-value category graph
my.cols <- c("steelblue3", "firebrick3")
if(levels(out.df$P.value.cat)[1]=="Sig.") {my.cols <- c("firebrick3")}
g3 <-
ggplot(out.df, aes(xx, yy))+geom_tile(aes(fill=P.value.cat))+scale_fill_manual(values=my.cols)+scale_colour_discrete(name="P.value.cat", limits=c(0,1))+coord_fixed(ratio=1)+t1.no.legend+labs(NULL)+ylab(NULL)

print(g2, vp=vplayout(row.loop.no[i], g2.col.loop.no[i]:(g2.col.loop.no[i]+1)))
print(g3, vp=vplayout(row.loop.no[i], g3.col.loop.no[i]:(g3.col.loop.no[i]+1)))

} # end create graph loop

dev.off()

```

```

#####
##### Analyse Tyson species on environmental gradients
##### using Codispersion analysis.
##### Run as a source file: source("CoDisp_functions.R")
#####
#####

##### Load required functions
#####

source("CoDisp_functions.R")
library(labdsv)
library(vegan)

##### Read in data
#####

dat <- read.csv("Tyson_spp.csv")
env <- read.csv("Tyson_env.csv")

##### Specify plot coordinates
#####

xmin=0; xmax=500; ymin=0; ymax=440

##### Generate ppp objects from species data
#####

spp.list <- c("fracar", "linben", "quealb", "querub", "quevel")

nspp <- length(spp.list)
ppp.ls <- vector("list", nspp)
for (i in 1:nspp){
  ppp.ls[[i]] <-
  ppp(dat$gx[dat$sp==spp.list[i]], dat$gy[dat$sp==spp.list[i]], xrange=c(xmin, xmax), yrange=c(ymin, ymax),
  marks=dat$dbh[dat$sp==spp.list[i]])
}

##### Create geodata objects from PC axes
#####

plot(geo.pcl <- as.geodata(env, coords.col=1:2, data.col=3))
plot(geo.pc2 <- as.geodata(env, coords.col=1:2, data.col=4))

#####
## Analysis using rasters
#####

# Select environmental dataset
geo.env <- geo.pcl; env.var = "PC1"
geo.env <- geo.pc2; env.var = "PC2"

for(i in 1:length(spp.list)){

  ppp.dat <- ppp.ls[[i]]

  Graphs_ls <- vector(mode="list", length=5) # empty list for output graphs
  Means.df <- data.frame(env=c(env.var), mean_CoDisp=NA, sd_CoDisp=NA)

  spe <- spp.list[i]
  #plot(ppp.dat, main=spe)

  geo.obs.ba <- ppp.to.geor.fn(ppp.dat, quad.size=20, xmin, xmax, ymin, ymax, method="total.ba")
}

```



```

# Graph the data
env.dat <- data.frame(X=geo.env$coords[,1],Y=geo.env$coords[,2],env=geo.env$data)
sp.dat <- data.frame(X=geo.obs.ba$coords[,1],Y=geo.obs.ba$coords[,2],BA=geo.obs.ba$data)

Graphs_ls[[1]] <- ggplot(env.dat, aes(x=X, y=Y, size=env))+geom_point(colour="black",
fill="steelblue2", shape=21)+coord_fixed(ratio=1)+t1.no.legend # ENV
Graphs_ls[[2]] <- ggplot(sp.dat, aes(x=X, y=Y, size=BA))+geom_point(colour="black",
fill="#4dac26", shape=21)+coord_fixed(ratio=1)+t1.no.legend # SP

## Plot the variograms and cross variograms
# ENV
ddat <- data.frame(geo.env$coords,env=scale(geo.env$data),sp=scale(geo.obs.ba$data))
g <- gstat(id="env", formula=env~1, locations=~qx+qy, data = ddat)
g <- gstat(g, id="sp", formula=sp~1, locations=~qx+qy, data = ddat)
v <- variogram(g, cutoff=(min(xmax,ymax)*0.67), cross=TRUE)
Graphs_ls[[3]] <-
ggplot(v,aes(x=dist,y=gamma,group=id,colour=id))+geom_line(lwd=2)+t1.no.legend + labs(x="Distance
(m)",y = "Semivariance")

#### run the codispersion analysis

binwidth=0.1
k=c(20,20,20)
max.window.size=min(xmax,ymax)/4

# observed data BA
print(paste("Env",spe))
CoDisp_env <- codisp.fn(geo.obs.ba,geo.env,k=k,max.window.size=max.window.size)

## Graph the output
Graphs_ls[[4]] <- print.CoDisp.plain(CoDisp_env[[1]],scaled=FALSE)
Graphs_ls[[5]] <- print.CoDisp.plain(CoDisp_env[[1]],scaled=TRUE,binwidth=binwidth)

## Calculate the mean values
Means.df$mean_CoDisp[1] <- round(mean(CoDisp_env[[1]]$Codispersion),2)
Means.df$sd_CoDisp[1] <- round(sd(CoDisp_env[[1]]$Codispersion),2)

## Save the output objects
nam=paste("CoDisp_env",env.var,spe,sep="_")
assign(nam,CoDisp_env)

nam=(paste("Graphs_ls",env.var,spe,sep="_"))
assign(nam,Graphs_ls)

nam=(paste("Means.df",env.var,spe,sep="_"))
assign(nam,Means.df)

} # end i loop

save.image("TY_spp_PC1&2_obs_basalarea_20x20.RData")

## Plot results graphs
load("TY_spp_PC1&2_obs_basalarea_20x20.RData")
source("CoDisp_functions.R")

#####
## Figure for paper - Variograms
#####

load("TY_spp_PC1&2_obs_basalarea_20x20.RData")
source("CoDisp_functions.R")

png("TY_Variograms_Figure.png",width=1000,height=1350)

grid.newpage()
pushViewport(viewport(layout=grid.layout(6,3)))

# Print observed elevation and slope raster plots
print(Graphs_ls_PC1_QUEALB[[1]]+scale_x_continuous(breaks=c(0,200,400))+scale_y_continuous(breaks
=c(0,200,400)), vp=vplayout(1,2))

```

```

print(Graphs_ls_PC2_quealb[[1]]+scale_x_continuous(breaks=c(0,200,400))+scale_y_continuous(breaks
=c(0,200,400)), vp=vplayout(1,3))

for(i in 1:5){
  if(i==1){out1 <- Graphs_ls_PC1_fracar
            out2 <- Graphs_ls_PC2_fracar

print(out1[[2]]+scale_x_continuous(breaks=c(0,200,400))+scale_y_continuous(breaks=c(0,200,400)),
vp=vplayout(2,1))
      print(out1[[3]]+coord_cartesian(ylim=c(-0.6,1.7))+scale_y_continuous(breaks=seq(-0.6,
1.7, 0.5))+t1.no.lab.20pt, vp=vplayout(2,2))
      print(out2[[3]]+coord_cartesian(ylim=c(-0.6,1.7))+scale_y_continuous(breaks=seq(-0.6,
1.7, 0.5))+t1.no.lab.20pt, vp=vplayout(2,3))
    }

  if(i==2){out1 <- Graphs_ls_PC1_linben
            out2 <- Graphs_ls_PC2_linben

print(out1[[2]]+scale_x_continuous(breaks=c(0,200,400))+scale_y_continuous(breaks=c(0,200,400)),
vp=vplayout(3,1))
      print(out1[[3]]+coord_cartesian(ylim=c(-0.6,1.7))+scale_y_continuous(breaks=seq(-0.6,
1.7, 0.5))+t1.no.lab.20pt, vp=vplayout(3,2))
      print(out2[[3]]+coord_cartesian(ylim=c(-0.6,1.7))+scale_y_continuous(breaks=seq(-0.6,
1.7, 0.5))+t1.no.lab.20pt, vp=vplayout(3,3))
    }

  if(i==3){out1 <- Graphs_ls_PC1_quealb
            out2 <- Graphs_ls_PC2_quealb

print(out1[[2]]+scale_x_continuous(breaks=c(0,200,400))+scale_y_continuous(breaks=c(0,200,400)),
vp=vplayout(4,1))
      print(out1[[3]]+coord_cartesian(ylim=c(-0.6,1.7))+scale_y_continuous(breaks=seq(-0.6,
1.7, 0.5))+t1.no.lab.20pt, vp=vplayout(4,2))
      print(out2[[3]]+coord_cartesian(ylim=c(-0.6,1.7))+scale_y_continuous(breaks=seq(-0.6,
1.7, 0.5))+t1.no.lab.20pt, vp=vplayout(4,3))
    }
  if(i==4){out1 <- Graphs_ls_PC1_querub
            out2 <- Graphs_ls_PC2_querub

print(out1[[2]]+scale_x_continuous(breaks=c(0,200,400))+scale_y_continuous(breaks=c(0,200,400)),
vp=vplayout(5,1))
      print(out1[[3]]+coord_cartesian(ylim=c(-0.6,1.7))+scale_y_continuous(breaks=seq(-0.6,
1.7, 0.5))+t1.no.lab.20pt, vp=vplayout(5,2))
      print(out2[[3]]+coord_cartesian(ylim=c(-0.6,1.7))+scale_y_continuous(breaks=seq(-0.6,
1.7, 0.5))+t1.no.lab.20pt, vp=vplayout(5,3))
    }
  if(i==5){out1 <- Graphs_ls_PC1_quevel
            out2 <- Graphs_ls_PC2_quevel

print(out1[[2]]+scale_x_continuous(breaks=c(0,200,400))+scale_y_continuous(breaks=c(0,200,400)),
vp=vplayout(6,1))
      print(out1[[3]]+coord_cartesian(ylim=c(-0.6,1.7))+scale_y_continuous(breaks=seq(-0.6,
1.7, 0.5))+t1.no.lab.20pt, vp=vplayout(6,2))
      print(out2[[3]]+coord_cartesian(ylim=c(-0.6,1.7))+scale_y_continuous(breaks=seq(-0.6,
1.7, 0.5))+t1.no.lab.20pt, vp=vplayout(6,3))
    }
  }
dev.off()

#####
## Null model comparison: analysis using rasters
#####

spp.list <- c("fracar","linben","quealb","querub","quevel")
nspp <- length(spp.list)

ppp.ls <- vector("list",nspp)
for (i in 1:nspp){

```

```

    ppp.ls[[i]] <-
ppp(dat$gx[dat$sp==spp.list[i]],dat$gy[dat$sp==spp.list[i]],xrange=c(xmin,xmax),yrange=c(ymin,ymax),marks=dat$dbh[dat$sp==spp.list[i]])
}

k=c(20,20,20)
max.window.size=320/4
nsim = 199

for(i in 1:length(spp.list)) {

spe <- spp.list[i]

# Generate null point patterns
HomP_sp.ls <- ppp.null.fn(ppp.ls[[i]],nsim=nsim,model="HomP")
RLM_sp.ls <- ppp.null.fn(ppp.ls[[i]],nsim=nsim,model="RLM")
Tor_sp.ls <- ppp.null.fn(ppp.ls[[i]],nsim=nsim,model="Tor")

# Generate null model geodata objects
geo.HomP.sp <-
lapply(HomP_sp.ls,ppp.to.geoR.fn,quad.size=20,xmin,xmax,ymin,ymax,method="total.ba")
geo.RLM.sp <- lapply(RLM_sp.ls,ppp.to.geoR.fn,quad.size=20,xmin,xmax,ymin,ymax,method="total.ba")
geo.Tor.sp <- lapply(Tor_sp.ls,ppp.to.geoR.fn,quad.size=20,xmin,xmax,ymin,ymax,method="total.ba")

CoDisp_PC1_HomP <- vector("list",nsim)
CoDisp_PC1_RLM <- vector("list",nsim)
CoDisp_PC1_Tor <- vector("list",nsim)

CoDisp_PC2_HomP <- vector("list",nsim)
CoDisp_PC2_RLM <- vector("list",nsim)
CoDisp_PC2_Tor <- vector("list",nsim)

for(j in 1:nsim){

# Run codispersion analysis on null model data
print(paste("CoDisp_HomP_sp, i j",i,j))
CoDisp_PC1_HomP[[j]] <- codisp.fn(geo.pcl,geo.HomP.sp[[j]],k=k,max.window.size=max.window.size)
CoDisp_PC2_HomP[[j]] <- codisp.fn(geo.pc2,geo.HomP.sp[[j]],k=k,max.window.size=max.window.size)
print(paste("CoDisp_RLM_sp, i j",i,j))
CoDisp_PC1_RLM[[j]] <- codisp.fn(geo.pcl,geo.RLM.sp[[j]],k=k,max.window.size=max.window.size)
CoDisp_PC2_RLM[[j]] <- codisp.fn(geo.pc2,geo.RLM.sp[[j]],k=k,max.window.size=max.window.size)
print(paste("CoDisp_Tor_sp, i j",i,j))
CoDisp_PC1_Tor[[j]] <- codisp.fn(geo.pcl,geo.Tor.sp[[j]],k=k,max.window.size=max.window.size)
CoDisp_PC2_Tor[[j]] <- codisp.fn(geo.pc2,geo.Tor.sp[[j]],k=k,max.window.size=max.window.size)

} # end simulations loop

# Convert output lists to array objects
CoDisp_PC1_HomP_ary <- list2ary(CoDisp_PC1_HomP)
CoDisp_PC1_RLM_ary <- list2ary(CoDisp_PC1_RLM)
CoDisp_PC1_Tor_ary <- list2ary(CoDisp_PC1_Tor)

CoDisp_PC2_HomP_ary <- list2ary(CoDisp_PC2_HomP)
CoDisp_PC2_RLM_ary <- list2ary(CoDisp_PC2_RLM)
CoDisp_PC2_Tor_ary <- list2ary(CoDisp_PC2_Tor)

## Save the output objects
nam=paste("CoDisp_PC1_HomP_ary",spe,sep="_")
assign(nam,CoDisp_PC1_HomP_ary)
nam=paste("CoDisp_PC1_RLM_ary",spe,sep="_")
assign(nam,CoDisp_PC1_RLM_ary)
nam=paste("CoDisp_PC1_Tor_ary",spe,sep="_")
assign(nam,CoDisp_PC1_Tor_ary)

nam=paste("CoDisp_PC2_HomP_ary",spe,sep="_")
assign(nam,CoDisp_PC2_HomP_ary)
nam=paste("CoDisp_PC2_RLM_ary",spe,sep="_")
assign(nam,CoDisp_PC2_RLM_ary)
nam=paste("CoDisp_PC2_Tor_ary",spe,sep="_")
assign(nam,CoDisp_PC2_Tor_ary)

```

```

} # end species loop

save.image("TY_PC1PC2_null_199.RData")

load("TY_PC1PC2_null_199.RData")
source("CoDisp_functions.R")

binwidth = 0.1
dataset="TY"
gtitle = "TY"

#####
## Figures for paper
#####

# Generate comparison output objects for each species and null model analysis combination

binwidth = 0.1
n.spp = 5 # number of species
n.vars = 2 # number of variables
n.mods = 3 # number of null models

png("TY_CodispNull_Tor_Figure.png",width=1600,height=(n.spp*n.vars*120))

grid.newpage()
pushViewport(viewport(layout=grid.layout((n.spp*n.vars),14)))

# Loop through each species and plot the observed CoDisp graphs

obs.codisp.ls <-
list(CoDisp_env_PC1_fracar[[1]],CoDisp_env_PC2_fracar[[1]],CoDisp_env_PC1_linben[[1]],CoDisp_env_PC2_linben[[1]],CoDisp_env_PC1_quealb[[1]],CoDisp_env_PC2_quealb[[1]],CoDisp_env_PC1_querub[[1]],CoDisp_env_PC2_querub[[1]],CoDisp_env_PC1_quevel[[1]],CoDisp_env_PC2_quevel[[1]])

for (i in 1:length(obs.codisp.ls)) {
  # Observed graphs
  g1 <-
print.CoDisp.plain(obs.codisp.ls[[i]],labels="FALSE",legend="FALSE",scaled=TRUE,contours=TRUE,binwidth=binwidth)
  print(g1, vp=vplayout(i,1:2))
}

codisp.obj.ls <-
list(CoDisp_env_PC1_fracar[[1]],CoDisp_env_PC1_fracar[[1]],CoDisp_env_PC1_fracar[[1]],CoDisp_env_PC2_fracar[[1]],CoDisp_env_PC2_fracar[[1]],CoDisp_env_PC2_fracar[[1]],CoDisp_env_PC1_linben[[1]],CoDisp_env_PC1_linben[[1]],CoDisp_env_PC1_linben[[1]],CoDisp_env_PC2_linben[[1]],CoDisp_env_PC2_linben[[1]],CoDisp_env_PC2_linben[[1]],CoDisp_env_PC1_quealb[[1]],CoDisp_env_PC1_quealb[[1]],CoDisp_env_PC1_quealb[[1]],CoDisp_env_PC2_quealb[[1]],CoDisp_env_PC2_quealb[[1]],CoDisp_env_PC2_quealb[[1]],CoDisp_env_PC1_querub[[1]],CoDisp_env_PC1_querub[[1]],CoDisp_env_PC1_querub[[1]],CoDisp_env_PC1_querub[[1]],CoDisp_env_PC2_querub[[1]],CoDisp_env_PC2_querub[[1]],CoDisp_env_PC2_querub[[1]],CoDisp_env_PC2_querub[[1]],CoDisp_env_PC1_quevel[[1]],CoDisp_env_PC1_quevel[[1]],CoDisp_env_PC1_quevel[[1]],CoDisp_env_PC2_quevel[[1]],CoDisp_env_PC2_quevel[[1]],CoDisp_env_PC2_quevel[[1]])

null.ary.ls <- list(
CoDisp_PC1_HomP_ary_fracar,CoDisp_PC1_RLM_ary_fracar,CoDisp_PC1_Tor_ary_fracar,CoDisp_PC2_HomP_ary_fracar,CoDisp_PC2_RLM_ary_fracar,CoDisp_PC2_Tor_ary_fracar,CoDisp_PC1_HomP_ary_linben,CoDisp_PC1_RLM_ary_linben,CoDisp_PC1_Tor_ary_linben,CoDisp_PC2_HomP_ary_linben,CoDisp_PC2_RLM_ary_linben,CoDisp_PC2_Tor_ary_linben,CoDisp_PC1_HomP_ary_quealb,CoDisp_PC1_RLM_ary_quealb,CoDisp_PC1_Tor_ary_quealb,CoDisp_PC2_HomP_ary_quealb,CoDisp_PC2_RLM_ary_quealb,CoDisp_PC2_Tor_ary_quealb,CoDisp_PC1_HomP_ary_querub,CoDisp_PC1_RLM_ary_querub,CoDisp_PC1_Tor_ary_querub,CoDisp_PC2_HomP_ary_querub,CoDisp_PC2_RLM_ary_querub,CoDisp_PC2_Tor_ary_querub,CoDisp_PC1_HomP_ary_quevel,CoDisp_PC1_RLM_ary_quevel,CoDisp_PC1_Tor_ary_quevel,CoDisp_PC2_HomP_ary_quevel,CoDisp_PC2_RLM_ary_quevel,CoDisp_PC2_Tor_ary_quevel)

g2.ls <- vector("list",n.spp*n.vars*n.mods)
g3.ls <- vector("list",n.spp*n.vars*n.mods)

row.loop.no <- rep(1:(n.spp*n.vars),each=n.mods)
g2.col.loop.no <- rep(c(3,7,11),(n.spp*n.vars))
g3.col.loop.no <- rep(c(5,9,13),(n.spp*n.vars))

```

```

for(i in 1:length(null.ary.ls)){

  # Null model comparison graphs
  out.df <- codisp.compare(null.ary.ls[[i]],codisp.obj.ls[[i]])

  # Observed minus expected CoDispersion value graph
  g2 <-
ggplot(out.df,aes(xx,yy))+geom_tile(aes(fill=diff))+scale_fill_gradientn(colours=c("#0000FF", "#FF
FFFF", "#FF6666"),limits=c(-1,
1))+coord_fixed(ratio=1)+t1.no.leg+xlab(NULL)+ylab(NULL)+stat_contour(aes(x=xx,y=yy,z=diff),binwi
dth=binwidth)

  # P-value category graph
  my.cols <- c("steelblue3","firebrick3")
  if(levels(out.df$P.value.cat)[1]=="Sig."){my.cols <- c("firebrick3")}
  g3 <-
ggplot(out.df,aes(xx,yy))+geom_tile(aes(fill=P.value.cat))+scale_fill_manual(values=my.cols)+scal
e_colour_discrete(name="P.value.cat",limits=c(0,1))+coord_fixed(ratio=1)+t1.no.leg+xlab(NULL)+yla
b(NULL)

  print(g2, vp=vplayout(row.loop.no[i],g2.col.loop.no[i):(g2.col.loop.no[i]+1)))
  print(g3, vp=vplayout(row.loop.no[i],g3.col.loop.no[i):(g3.col.loop.no[i]+1)))

} # end create graph loop

dev.off()

## stats for paper
round(tapply(dat$ba,dat$sp,sum),2)

round(range(CoDisp_env_PC1_fracar[[1]]$Codispersion),2)
round(range(CoDisp_env_PC2_fracar[[1]]$Codispersion),2)

round(range(CoDisp_env_PC1_linben[[1]]$Codispersion),2)
round(range(CoDisp_env_PC2_linben[[1]]$Codispersion),2)

```

```

#####
##### Required functions for codispersion analysis
#####
#####

#####
### LOAD REQUIRED PACKAGES (these must be installed first)
#####

library(spatstat)
library(geoR)
library(fields)
library(SpatialPack)
library(ggplot2)
library(grid)
library(raster)
library(gstat)

#####
### SIMPLE FUNCTIONS
#####

# basal area function: calculates basal area from DBH values (must be in cm)
basal.area.fn <- function(x){ (pi*(x)^2)/40000 } # calculate basal area in m^2

### Function to draw random values from a truncated log normal distribution
rtnorm <- function (n, meanlog = 0, sdlog = 1, lower = -Inf, upper = Inf)
{
  ret <- numeric()
  if (n > 1)
    n <- n
  while (length(ret) < n) {
    y <- rtnorm(n - length(ret), meanlog, sdlog)
    y <- y[y >= lower & y <= upper]
    ret <- c(ret, y)
  }
  stopifnot(length(ret) == n)
  ret
}

### Function for simulating a bivariate normal distribution
bivariate <- function(x,y){
  mu1 <- 0 # expected value of x
  mu2 <- 0 # expected value of y
  sig1 <- 1 # variance of x
  sig2 <- 1 # variance of y
  rho <- 0.5 # corr(x, y)
  term1 <- 1 / (2 * pi * sig1 * sig2 * sqrt(1 - rho^2))
  term2 <- (x - mu1)^2 / sig1^2
  term3 <- -(2 * rho * (x - mu1)*(y - mu2))/(sig1 * sig2)
  term4 <- (y - mu2)^2 / sig2^2
  z <- term2 + term3 + term4
  term5 <- term1 * exp((-z / (2 *(1 - rho^2))))
  return (term5)
}

#####
### DATA MANIPULATION
#####

# List to array function for Co_disp null model output objects
list2ary = function(input.list){ #input a list of lists
  temp.ls <- vector("list")
  for(i in 1:length(input.list)) { temp.ls[i] <- input.list[[i]][1] } # take the dataframes out
of the list and put them in a new list
  rows.cols <- dim(temp.ls[[1]])
  sheets <- length(temp.ls)
  output.ary <- array(unlist(temp.ls), dim = c(rows.cols, sheets))
  colnames(output.ary) <- colnames(temp.ls[[1]])
  row.names(output.ary) <- row.names(temp.ls[[1]])
}

```

```

    return(output.ary)    # output as a 3-D array
}

#### Function to generate a geodata object (used by packages geoR and the codispersion function)
from a ppp object.

# ppp.dat = input ppp object
# xmin, xmax, ymin, ymax = plot dimensions
# method = the measure that is used to generate the 'data' value for the geodata object

ppp.to.geoR.fn <-
function(ppp.dat,xmin,xmax,ymin,ymax,quad.size,method=c("abundance","mean.mark","mean.ba","total.
ba","sum")){ # function to generate geoR objects with abundance and basal area in 20x20m
quadrats. Note that DBH must be measured in cm. Input data= ppp object.
  x <- ppp.dat$x # extract x coordinate
  y <- ppp.dat$y # extract y coordinate
  z <- ppp.dat$marks # extract DBH values
  ba <- (pi*(z)^2)/40000 # calculate basal area in m^2
  xt <- cut(x,seq(xmin,xmax,quad.size)) # cut x coordinates using 20m spacing
  yt <- cut(y,seq(ymin,ymax,quad.size)) # cut y coordinates using 20m spacing
  coords <- dimnames(table(yt,xt)) # extract quadrat coordinate lists
  qx <- rep(seq(xmin,xmax-quad.size,length=length(coords$xt)),each=length(coords$yt)) # vector of
x coordinates for the bottom left corner of the quadrat
  qy <- rep(seq(ymin,ymax-quad.size,length=length(coords$yt)),length(coords$xt)) # vector of y
coordinates for the bottom left corner of the quadrat
  if(method=="abundance"){
    out.grid <- table(yt,xt) # count the trees in each quadrat
    out.grid[is.na(out.grid)==T] <- 0 # replace NAs in table with zeros for empty quadrats
  }
  if(method=="mean.mark"){
    out.grid <- tapply(z,list(yt,xt),mean) # calculate mean DBH in each quadrat
    out.grid[is.na(out.grid)==T] <- 0
  }
  if(method=="mean.ba"){
    out.grid <- tapply(ba,list(yt,xt),mean) # calculate mean ba in each quadrat
    out.grid[is.na(out.grid)==T] <- 0
  }
  if(method=="total.ba"){
    out.grid <- tapply(ba,list(yt,xt),sum) # calculate total ba in each quadrat
    out.grid[is.na(out.grid)==T] <- 0
  }
  if(method=="sum"){
    out.grid <- tapply(z,list(yt,xt),sum) # calculate sum of the marks in each quadrat
    out.grid[is.na(out.grid)==T] <- 0
  }

  out.df <- data.frame(qx,qy,as.vector(out.grid))
  out.geo <- as.geodata(out.df,coords.col=1:2,data.col=3)
  return(out.geo)
} # end function

#####
### CODISPERSION ANALYSIS
#####

#### Modified codispersion function (modified from Cuevas et al. 2013)
#### See 'Box 1' for a detailed explanation.
Codisp.Kern<-function(X,Y,h,k,gamma=1)
{
  Kernel<-function(u,gamma)
  {
    v=0
    v=ifelse(abs(u)<=1,(1/beta(0.5,gamma+1))*(1-u^2)^gamma,0)
  }
  ifelse(X$coords==Y$coords,1,
        {
          break
          print("The coordinates of X and Y are different")
        })
}

n=length(X$data)

```

```

mX <- matrix(X$data, nrow=n, ncol=n, byrow=FALSE)
mY <- matrix(Y$data, nrow=n, ncol=n, byrow=FALSE)
MatrixX <- (mX - t(mX))^2
MatrixY <- (mY - t(mY))^2
MatrixXY <- (mX - t(mX))*(mY - t(mY))
mX <- matrix(X$coords[,1], nrow=n, ncol=n, byrow=FALSE)
DesignX <- mX - t(mX)
mY <- matrix(X$coords[,2], nrow=n, ncol=n, byrow=FALSE)
DesignY <- mY - t(mY)

KERNMATRIXX=Kernel((h[1]-DesignX)/k[1],gamma)*Kernel((h[2]-DesignY)/k[1],gamma)

if(k[1]==k[2]&k[1]==k[3]){
  KERNMTRIYY=KERNMATRIXX
  KERNMTRIYX=KERNMATRIXX } else{
  KERNMTRIYY=Kernel((h[1]-DesignX)/k[2],gamma)*Kernel((h[2]-DesignY)/k[2],gamma)
  KERNMTRIYX=Kernel((h[1]-DesignX)/k[3],gamma)*Kernel((h[2]-DesignY)/k[3],gamma)
}

Numerador=sum(KERNMTRIYX*MatrixXY)/(2*sum(KERNMTRIYX))
Denominador1=sum(KERNMTRIYY*MatrixY)/(2*sum(KERNMTRIYY))
Denominador2=sum(KERNMATRIXX*MatrixX)/(2*sum(KERNMATRIXX))
v1=Denominador1
v2=Denominador2
v3=Numerador
v4=Numerador/sqrt(Denominador1*Denominador2)
print(c(v1,v2,v3,v4))
}

### Function to run codispersion window analysis (modified from Cuevas et al. 2013)

# geodata1 = first input data object (a geoR geodata object)
# geodata2 = second input object
# k = c(k1, k2, k3) = a vector of three bandwidth values for X, Y and XY
# max.window.size = the maximum lag distance
# lx = is the number of divisions in the lags in x (up to the max.window.size) that the kernel is
applied over. Half of these divisions are in the 'left', or positive direction, and half are in
the 'right', or negative x direction.
# ly = is the number of divisions in the lags in y (up to the max.window.size) that the kernel is
applied over in the 'up' direction of the plot

codisp.fn <- function(geodata1, geodata2, k=k, max.window.size=max.window.size, lx=20, ly=10){
  out <- vector("list",length=2)
  X=geodata1 # input data process 1
  Y=geodata2 # input data process 2
  k=c(k[1],k[2],k[3]) # Set the bandwidth for the kernel

  h_range <- max.window.size # set the spatial lags over which to calculate codisp
  h1=seq(-h_range,h_range,l=lx) # x-axis values for codispersion graph (lags)
  h2=seq(min(k),h_range,l=ly) # y-axis values for codispersion graph (lags)

  MCodisp=matrix(0,ncol=ly,nrow=lx) # loop through the lags
  for(i in 1:lx) # 'left-right' lags
  {
    for(j in 1:ly) # 'up' lags
    {
      MCodisp[i,j]=Codisp.Kern(X,Y,c(h1[i],h2[j]),k)[4]; # calculate codisp
    }
  }
  Codispersion <- as.numeric(MCodisp) # save codisp object as output
  xx <- rep(h1,length(h2)) # write out values for x-axis
  yy <- rep(h2,each=length(h1)) # write out values for y-axis
  graphing.data <- data.frame(xx,yy,Codispersion) # graphing object

  # put both the graphing object and the original object in an output list
  out[[1]] <- graphing.data
  out[[2]] <- MCodisp
  return(out)
}

```



```

#####
### NULL MODELS
#####

#### Function to generate a list of 'nsim' ppp objects (marked point patterns) under four
different null models
ppp.null.fn <- function(ppp.dat,nsim,model=c("RLM","HomP","HetP","Tor"),marks=TRUE) {
  #ppp.dat <- ppp.dat[[1]]
  ppp.out <- vector("list",nsim) # create output list object

  if(model=="RLM"){ # Random labelling model
    for(i in 1:nsim){ # start loop to generate simulations
      ppp.out[[i]] <- rlabel(ppp.dat, labels=marks(ppp.dat), permute=TRUE) # randomise marks
    } # end simulations loop
  } # end RLM loop

  if(model=="HomP"){ # Homogeneous Poisson model
    for(i in 1:nsim){ # start loop to generate simulations
      ppp.HomP <- rpoint(ppp.dat$n,win=ppp.dat$win) # randomise the observed ppp
      ppp.HomP$marks <- sample(ppp.dat$marks, replace=F) # assign shuffled marks to new ppp
      ppp.out[[i]] <- ppp.HomP # add new marked ppp to output list
    } # end simulations loop
  } # end HomP loop

  if(marks==TRUE){
    if(model=="HetP"){ # this null model generates random marks based on a lognormal fit to the
DBH distribution
      intensity_function <- density.ppp(ppp.dat, bw.diggle) # generate the intensity function
      LN_params <- fitdistr(ppp.dat$marks,"log-normal") # fit lognormal to DBH distribution
      for(i in 1:nsim){ # start loop to generate simulations
        ppp.HetP <- rpoispp(intensity_function) # generate randomised ppp using intensity
function
        ppp.HetP$marks <-
rtnlnorm(ppp.HetP$n,meanlog=LN_params$estimate[[1]],sdlog=LN_params$estimate[[2]],1,max(ppp.dat$ma
rks)) # generate marks using parameters of DBH distribution
        ppp.out[[i]] <- ppp.HetP # add new marked ppp to output list
      } # end simulations loop
    } # end HetP loop
  } # end marks==TRUE

  if(marks==FALSE){
    if(model=="HetP"){ # this null model ignores the marks
      intensity_function <- density.ppp(ppp.dat, bw.diggle) # generate the intensity function
      for(i in 1:nsim){ # start loop to generate simulations
        ppp.HetP <- rpoispp(intensity_function) # generate randomised ppp using intensity
function
        ppp.out[[i]] <- ppp.HetP # add new marked ppp to output list
      } # end simulations loop
    } # end HetP
  } # end marks==FALSE

  if(model=="Tor"){ # Toroidal shift null model
    for(i in 1:nsim){ # start loop to generate simulations
      ppp.out[[i]] <- rshift(ppp.dat, edge="torus") # toroidal shift randomisation
    } # end simulations loop
  } # end toroidal shift

  return(ppp.out)
} # end function

#####
### DEALING WITH CODISPERSION OUTPUTS
#####

# Function to return a data frame with the null model comparison results
# Inputs are the null model input array object and the observed CoDisp result list

codisp.compare <- function(null.input.ary,CoDisp_obs,round=FALSE){
  out.df <- CoDisp_obs # observed Codispersion result df

```

```

for(i in 1:length(null.input.ary[,1,1])) { # loop through each cell
  nsims <- length(null.input.ary[1,1,])
  obser <- out.df$Codispersion[i] # observed codispersion value
  expec <- null.input.ary[i,3,]
  prop.greater.than <- length(which(expec>obser))/nsims
  prop.less.than <- length(which(expec<obser))/nsims
  out.df$P.value[i]<-min(prop.greater.than,prop.less.than)
} # end cell loop

out.df$null_mean <- apply(null.input.ary[,3,],MARGIN=1,mean) # calculate mean codispersion
value for each cell from the array of null model results
out.df$difff <- out.df$Codispersion-out.df$null_mean # observed minus expected
out.df$P.value.cat <- factor(ifelse(out.df$P.value<0.025,"Sig.,"Non-sig.")) # significance at
alpha=0.05

if(round==TRUE){ # for printing table of results
  out.df$xx <- round(out.df$xx,1)
  out.df$yy <- round(out.df$yy,1)
  out.df$Codispersion <- round(out.df$Codispersion,3)
  out.df$P.value <- round(out.df$P.value,3)
  out.df$null_mean <- round(out.df$null_mean,3)
  out.df$difff <- round(out.df$difff,3)
}
return(out.df)
}

#####
### GRAPHING
#####

#### Graphing function for ViewPort Grid graphics
vplayout <- function(x,y) { viewport(layout.pos.row=x,layout.pos.col=y) }

#### gglot theme options

t1<-theme(
  plot.background = element_blank(),
  panel.grid.major = element_blank(),
  panel.grid.minor = element_blank(),
  panel.border = element_blank(),
  panel.background = element_blank(),
  axis.line = element_line(size=.4),
  axis.text = element_text(colour="black",size=20,angle=0),
  axis.title = element_text(colour="black",size=20),
  legend.key = element_blank(),
  legend.title = element_text(colour="black",size=14),
  legend.text = element_text(colour="black",size=14),
  plot.margin = unit(c(.2,.2,.2,.2),"lines"),
  panel.margin = unit(.2,"lines"),
  plot.background = element_rect(fill=NA)
)

t1.no.leg <-theme(
  plot.background = element_blank(),
  panel.grid.major = element_blank(),
  panel.grid.minor = element_blank(),
  panel.border = element_blank(),
  panel.background = element_blank(),
  axis.line = element_line(size=.4),
  axis.text = element_text(colour="black",size=20,angle=0),
  axis.title = element_text(colour="black",size=20),
  legend.text = element_text(colour="black",size=18),
  legend.position="none",
  plot.margin = unit(c(.5,.2,.2,.2),"lines"),
  panel.margin = unit(.2,"lines"),
  plot.background = element_rect(fill=NA)
  #axis.title.x = element_blank(),
  #axis.title.y = element_blank()
)

```

```

t1.unscaled.leg <- theme(
  plot.background = element_blank(),
  panel.grid.major = element_blank(),
  panel.grid.minor = element_blank(),
  panel.border = element_blank(),
  panel.background = element_blank(),
  axis.line = element_line(size=.4),
  axis.text.y = element_text(colour="black",size=20,angle=0),
  axis.text.x = element_text(colour="black",size=20,angle=0,hjust=1),
  axis.title = element_text(colour="black",size=20),
  legend.key = element_blank(),
  legend.title = element_blank(),
  legend.text = element_text(colour="black",size=20),
  plot.margin = unit(c(.5,.2,.2,.2),"lines"),
  panel.margin = unit(.2,"lines"),
  plot.background = element_rect(fill=NA)
)

```

```

t1.no.leg_lab.20 <-theme(
  plot.background = element_blank(),
  panel.grid.major = element_blank(),
  panel.grid.minor = element_blank(),
  panel.border = element_blank(),
  panel.background = element_blank(),
  axis.line = element_line(size=.4),
  axis.text = element_text(colour="black",size=20,angle=0),
  axis.title = element_blank(),
  legend.position="none",
  plot.margin = unit(c(.5,.2,.2,.2),"lines"),
  panel.margin = unit(.2,"lines"),
  plot.background = element_rect(fill=NA)
)

```

```

t1.no.lab.20pt <-theme(
  plot.background = element_blank(),
  panel.grid.major = element_blank(),
  panel.grid.minor = element_blank(),
  panel.border = element_blank(),
  panel.background = element_blank(),
  axis.line = element_line(size=.4),
  axis.text = element_text(colour="black",size=20,angle=0),
  axis.title = element_text(colour="black",size=20),
  legend.key = element_blank(),
  #legend.title = element_text(colour="black",size=20),
  legend.title = element_blank(),
  legend.text = element_text(colour="black",size=20),
  plot.margin = unit(c(.2,.2,.2,.2),"lines"),
  panel.margin = unit(.2,"lines"),
  plot.background = element_rect(fill=NA),
  axis.title.x = element_blank(),
  axis.title.y = element_blank()
)

```

```

t1.no.leg_lab <-theme(
  plot.background = element_blank(),
  panel.grid.major = element_blank(),
  panel.grid.minor = element_blank(),
  panel.border = element_blank(),
  panel.background = element_blank(),
  axis.line = element_line(size=.4),
  axis.text = element_text(colour="black",size=20,angle=0),
  axis.title = element_blank(),
  legend.position="none",
  plot.margin = unit(c(.5,.2,.2,.2),"lines"),
  panel.margin = unit(.2,"lines"),
  plot.background = element_rect(fill=NA)
)

```

```

## Function to generate variograms and cross variograms for the two geo.data objects used in
codispersion analysis (observed patterns)

```

```

# labels is a two element vector used for labelling the graphs
# e.g. labels=c("species1", "species2")

cross.variog.fn <- function(geodata1, geodata2, lab=missing(lab)){
  Obs_graphs <- vector(mode="list", length=3) # create empty object to store graphs
  D1.dat <- data.frame(X=geodata1$coords[,1], Y=geodata1$coords[,2], D1=geodata1$data) # put
geodata object into a dataframe
  D2.dat <- data.frame(X=geodata2$coords[,1], Y=geodata2$coords[,2], D2=geodata2$data)
  # Plot the observed raster patterns
  g1 <- ggplot(D1.dat, aes(x=X, y=Y, size=D1))+geom_point(colour="black", fill="steelblue2",
shape=21)+coord_fixed(ratio=1)
  g2 <- ggplot(D2.dat, aes(x=X, y=Y, size=D2))+geom_point(colour="black", fill="#4dac26",
shape=21)+coord_fixed(ratio=1)

  ## Plot the variograms and cross variogram
  v.dat <-
data.frame(x=geodata1$coords[,1], y=geodata1$coords[,2], dat1=scale(geodata1$data), dat2=scale(geoda
ta2$data))
  g <- gstat(id="D1", formula=dat1~1, locations=~x+y, data = v.dat)
  g <- gstat(g, id="D2", formula=dat2~1, locations=~x+y, data = v.dat)
  v <- variogram(g, cutoff=(min((max(v.dat$x)-min(v.dat$x)), (max(v.dat$y)-min(v.dat$y)))*0.67),
cross=TRUE) # 2/3 the min. of the two plot dimensions
  g3 <- ggplot(v, aes(x=dist, y=gamma, group=id, colour=id))+geom_line(lwd=2) + labs(x="Distance
(m)", y = "Semivariance")

  if(missing(lab)==FALSE){ # put labels on the graphs
    Obs_graphs[[1]] <- g1 + scale_size_continuous(name=lab[1])
    Obs_graphs[[2]] <- g2 + scale_size_continuous(name=lab[2])
    Obs_graphs[[3]] <- g3 +
scale_colour_discrete(labels=c(paste(lab[1], "vs.", lab[2]), lab[2], lab[1])) +
theme(legend.title=element_blank())
  }

  if(missing(lab)==TRUE){ # don't put a label on the legend
    Obs_graphs[[1]] <- g1+t1.no.leg_lab
    Obs_graphs[[2]] <- g2+t1.no.leg_lab
    Obs_graphs[[3]] <- g3+t1.no.leg
  }

  return(Obs_graphs)
} # end of function

# Function to print a codispersion graph using the CoDisp output object
print.CoDisp <-
function(CoDisp.obj=CoDisp.obj, scaled=c("TRUE", "FALSE"), contours=c("TRUE", "FALSE"), binwidth=binwi
dth, input=input, gtitle=gtitle){

  if(scaled=="FALSE"){
    #
    print(ggplot(CoDisp.obj, aes(xx, yy))+geom_tile(aes(fill=Codispersion))+scale_fill_gradientn(colour
s=rainbow(7))+coord_fixed(ratio=1)+t1+xlab(expression(h[1]))+ylab(expression(h[2]))+ggtitle(paste
("Codispersion of", input, gtitle)))
    g1 <-
ggplot(CoDisp.obj, aes(xx, yy))+geom_tile(aes(fill=Codispersion))+scale_fill_gradientn(colours=rain
bow(7))+coord_fixed(ratio=1)+t1+xlab("Spatial lag in X (m)")+ylab("Spatial lag in Y
(m)")+ggtitle(paste("Codispersion of", input, gtitle)))
  }

  if(scaled=="TRUE"){
    if(contours=="TRUE"){
      #
      print(ggplot(CoDisp.obj, aes(xx, yy))+geom_tile(aes(fill=Codispersion))+scale_fill_gradientn(colour
s=c("#0000FF", "#FFFFFF", "#FF6666"), limits=c(-
1, 1))+coord_fixed(ratio=1)+t1+xlab(expression(h[1]))+ylab(expression(h[2])))
      g1 <-
ggplot(CoDisp.obj, aes(xx, yy))+geom_tile(aes(fill=Codispersion))+scale_fill_gradientn(colours=c("#
0000FF", "#FFFFFF", "#FF6666"), limits=c(-1, 1))+coord_fixed(ratio=1)+t1+xlab("Spatial lag in X
(m)")+ylab("Spatial lag in Y (m)") +

```

```

stat_contour(aes(x=xx,y=yy,z=Codispersion),binwidth=binwidth)+ggtitle(paste("Codispersion
of",input,gtitle))
}

if(contours=="FALSE"){
  g1 <-
ggplot(CoDisp.obj,aes(xx,yy))+geom_tile(aes(fill=Codispersion))+scale_fill_gradientn(colours=c("#
0000FF","#FFFFFF","#FF6666"),limits=c(-
1,1))+coord_fixed(ratio=1)+t1+xlab(expression(h[1]))+ylab(expression(h[2]))+ggtitle(paste("Codisp
ersion of",input,gtitle))
}
} # end of scaled

return(g1)

} # end of function

# Function to print a codispersion graph using the CoDisp output object
# With plain output (no labels)
print.CoDisp.plain <-
function(CoDisp.obj=CoDisp.obj,scaled=TRUE,contours=TRUE,labels=TRUE,legend=TRUE,binwidth=binwidt
h){

  if(labels=="TRUE"){
    if(scaled=="FALSE"){
      g1 <-
ggplot(CoDisp.obj,aes(xx,yy))+geom_tile(aes(fill=Codispersion))+scale_fill_gradientn(colours=rain
bow(7))+coord_fixed(ratio=1)+xlab("Spatial lag in X (m)")+ylab("Spatial lag in Y (m)")
}

    if(scaled=="TRUE"){
      if(contours=="TRUE"){
        g1 <-
ggplot(CoDisp.obj,aes(xx,yy))+geom_tile(aes(fill=Codispersion))+scale_fill_gradientn(colours=c("#
0000FF","#FFFFFF","#FF6666"),limits=c(-1,1))+coord_fixed(ratio=1)+xlab("Spatial lag in X
(m)")+ylab("Spatial lag in Y (m)") +
stat_contour(aes(x=xx,y=yy,z=Codispersion),binwidth=binwidth)
}

        if(contours=="FALSE"){
          g1 <-
ggplot(CoDisp.obj,aes(xx,yy))+geom_tile(aes(fill=Codispersion))+scale_fill_gradientn(colours=c("#
0000FF","#FFFFFF","#FF6666"),limits=c(-
1,1))+coord_fixed(ratio=1)+xlab(expression(h[1]))+ylab(expression(h[2]))
}
} # end of scaled
} # end of labels == TRUE

if(labels=="FALSE"){
  if(scaled=="FALSE"){
    g1 <-
ggplot(CoDisp.obj,aes(xx,yy))+geom_tile(aes(fill=Codispersion))+scale_fill_gradientn(colours=rain
bow(7))+coord_fixed(ratio=1) +xlab(NULL) +ylab(NULL)
}

    if(scaled=="TRUE"){
      if(contours=="TRUE"){
        g1 <-
ggplot(CoDisp.obj,aes(xx,yy))+geom_tile(aes(fill=Codispersion))+scale_fill_gradientn(colours=c("#
0000FF","#FFFFFF","#FF6666"),limits=c(-1,1))+coord_fixed(ratio=1)+
stat_contour(aes(x=xx,y=yy,z=Codispersion),binwidth=binwidth)+xlab(NULL) +ylab(NULL)
}

        if(contours=="FALSE"){
          g1 <-
ggplot(CoDisp.obj,aes(xx,yy))+geom_tile(aes(fill=Codispersion))+scale_fill_gradientn(colours=c("#
0000FF","#FFFFFF","#FF6666"),limits=c(-1,1))+coord_fixed(ratio=1)+xlab(NULL) +ylab(NULL)
}
} # end of scaled
} # end of labels == FALSE

```

```

    if(legend=="TRUE") { g1 <- g1 + t1.unscaled.leg }
    if(legend=="FALSE") { g1 <- g1 + t1.no.leg }

    return(g1)
} # end of function

#####
### SIMULATING PATTERNS
#####

#####
#### Function to simulate anisotropic point patterns

# # dimensions of the plot
xmin=0
xmax=300
ymin=0
ymax=300
grid.points=5 # the distance between points on the underlying grid (must divide evenly into the
plot dimensions)
env.func = "uniform"
ppp.model="Thomas" # or "CSR"
kappa=20
sigma=0.5
mu=10
lambda=200
pattern.method="abundance" # or "quant.marks"
marks.method="uniform"
minmark=1
maxmark=80
sp.pattern= "random" #
"decreasing.x","increasing.x","decreasing.xy","increasing.xy","bivariate.normal" # the
distribution pattern of the species
sp.maxab=15
ntrees = 1500 #the number of trees you want

app.sim.fn <- function(grid.points = grid.points,env.func =
c("uniform","CSR","decreasing.x","increasing.x","decreasing.xy","increasing.xy","bivariate.normal
"),pattern.method=c("quant.marks","abundance"),ppp.model=c("CSR","Thomas"),marks.method=c("random
","decreasing.x","increasing.x","decreasing.xy","increasing.xy","bivariate.normal"),sp.pattern=c(
"random","decreasing.x","increasing.x","decreasing.xy","increasing.xy","bivariate.normal"),ntrees
=ntrees,sp.maxab=sp.maxab,xmin=xmin,xmax=xmax,ymin=ymin,ymax=ymax,minmark=minmark,maxmark=maxmark
,kappa=kappa,sigma=sigma,mu=mu,lambda=lambda,Print=c("TRUE","FALSE")){ # begin function

# 1. Set up underlying grid coordinates
X <- seq(from=xmin,to=xmax-grid.points,by=grid.points)
Y <- seq(from=ymin,to=ymax-grid.points,by=grid.points)
gridxy <- expand.grid(x=X,y=Y)

# 2. Create a set of marks to use as values for the environmental variable based on the
'env.func' argument

if(env.func=="uniform"){Z <- jitter(rep(50,(length(X)*length(Y)))) }

if(env.func=="CSR"){Z <- rnorm(n=length(gridxy$x),mean=50,sd=15) }

if(env.func=="decreasing.x"){Z <- 1+(rev(2*gridxy$x+5))/10}

if(env.func=="increasing.x"){Z <- 1+(2*gridxy$x+5)/10}

if(env.func=="decreasing.xy"){
  Z <- 1+rev(((gridxy$x+1)^2+(gridxy$y+1)^2)/3000) # (x-u)^2+(y-v)^2
}

if(env.func=="increasing.xy"){
  Z <- 1+(((gridxy$x+2)^2+(gridxy$y+1)^2)/3000) # (x-u)^2+(y-v)^2
}

if(env.func=="bivariate.normal"){

```

```

Z <- bivariate(((gridxy$x-min(gridxy$x))/(max(gridxy$x)-min(gridxy$x))*4)-2,((gridxy$y-
min(gridxy$y))/(max(gridxy$y)-min(gridxy$y))*4)-2)
} # bivariate normal

epp.df <- data.frame(x=gridxy$x,y=gridxy$y,Z=Z)
epp.sim <- as.ppp(epp.df,marks=Z,W=owin(c(xmin,xmax),c(ymin,ymax)))
#plot(epp.sim)

# 3. Marked point pattern
# 3a. Create a ppp of trees using the selected model
if(pattern.method=="quant.marks"){
  if(ppp.model=="CSR"){ temp <-
rpoispp(lambda=lambda,win=owin(c(xmin/100,xmax/100),c(ymin/100,ymax/100)))
  mpp.sim <- temp[1:nrtrees] } # generate 2000 trees in the plot

  if(ppp.model=="Thomas"){ temp <-
rThomas(kappa=kappa,sigma=sigma,mu=mu,win=owin(c(xmin/100,xmax/100),c(ymin/100,ymax/100)))
  mpp.sim <- temp[1:nrtrees] }# generate 2000 trees in the plt

# 3b. Assign the marks to the point pattern using the selected method of codispersion
if(marks.method=="random"){ mrks <-
rtlnorm(mpp.sim$n,meanlog=log(maxmark/2),sdlog=log(maxmark/15),lower=minmark,upper=maxmark) } #
generate a random set of marks drawn from a lognormal distribution

if(marks.method=="decreasing.x"){ temp <- -18*mpp.sim$x+5
mrks <- temp+abs(min(temp)) }

if(marks.method=="increasing.x"){ mrks <- 18*mpp.sim$x+5 }

if(marks.method=="decreasing.xy"){
  temp <- -((mpp.sim$x+1)^2+(mpp.sim$y+1)^2)
  mrks <- temp+abs(min(temp)) } # (x-u)^2+(y-v)^2

if(marks.method=="increasing.xy"){
  mrks <- ((mpp.sim$x+1)^2+(mpp.sim$y+1)^2) } # (x-u)^2+(y-v)^2

if(marks.method=="bivariate.normal"){ mrks <- bivariate(((mpp.sim$x-
min(mpp.sim$x))/(max(mpp.sim$x)-min(mpp.sim$x))*3)-2,((mpp.sim$y-min(mpp.sim$y))/(max(mpp.sim$y)-
min(mpp.sim$y))*4)-2) } # bivariate.normal

mrks1 <- (mrks-min(mrks))/(max(mrks)-min(mrks)) # scale marks between 0 and 1
mpp.sim$marks <- minmark+mrks1/max(mrks1)*(maxmark-minmark) # spread marks between max and
min mark
mpp.sim$window <- owin(c(xmin,xmax),c(ymin,ymax)) # rescale window to metres
mpp.sim$x <- mpp.sim$x*100 # rescale x and y values to metres
mpp.sim$y <- mpp.sim$y*100
} # end quant.marks

# 4. Generate a species point pattern using the selected method
# 4a. First generate a grid of values in the selected pattern.

if(pattern.method=="abundance"){
  if(sp.pattern=="random"){ ab <- runif(n=length(c(gridxy$x)),min=0,max=sp.maxab) }

  if(sp.pattern=="decreasing.x"){ ab <- 1+(rev(2*gridxy$x+5))/10 }

  if(sp.pattern=="increasing.x"){ ab <- 1+(2*gridxy$x+5)/10 }

  if(sp.pattern=="decreasing.xy"){ ab <- 1+rev(((gridxy$x+1)^2+(gridxy$y+1)^2)/3000) } # (x-
u)^2+(y-v)^2

  if(sp.pattern=="increasing.xy"){ ab <- 1+((gridxy$x+2)^2+(gridxy$y+1)^2)/3000 } # (x-u)^2+(y-
v)^2

  if(sp.pattern=="bivariate.normal"){
    ab <- bivariate(((gridxy$x-min(gridxy$x))/(max(gridxy$x)-min(gridxy$x))*4)-2,((gridxy$y-
min(gridxy$y))/(max(gridxy$y)-min(gridxy$y))*4)-2) } # bivariate normal

  AB <- round(ab/max(ab)*sp.maxab,0) # scale abundance to maximum number of individuals per
grid cell
  mpp.df <- data.frame(x=gridxy$x,y=gridxy$y,ab=AB)

```

```

    mpp.sim <- as.ppp(mpp.df,marks=ab,W=owin(c(xmin,xmax),c(ymin,ymax)))

} # end abundance loop

# 5. Put both the environment ppp object and the species2 ppp object into an output list object
app.sim <- vector("list")
app.sim[[1]] <- epp.sim
app.sim[[2]] <- mpp.sim

# 6. Print map of points if desired
if(Print=="TRUE"){
  par(mfrow=c(1,2))
  (plot(epp.sim,main=paste("env.func =",env.func),cex.main=0.7))
  if(pattern.method=="quant.marks"){
    (plot(mpp.sim,main=paste("mrks =",marks.method,mpp.sim$n),cex.main=0.7)) }

  if(pattern.method=="abundance"){
    (plot(mpp.sim,main=paste("species =",sp.pattern,mpp.sim$n),cex.main=0.7)) }
} # end Print loop

return(app.sim)

} # end function

#app.sim <-
app.sim.fn(grid.points=5,env.func="increasing.x",pattern.method="abundance",sp.pattern="increasin
g.x",sp.maxab=20,xmin=0,xmax=200,ymin=0,ymax=200,Print="TRUE")

```

```

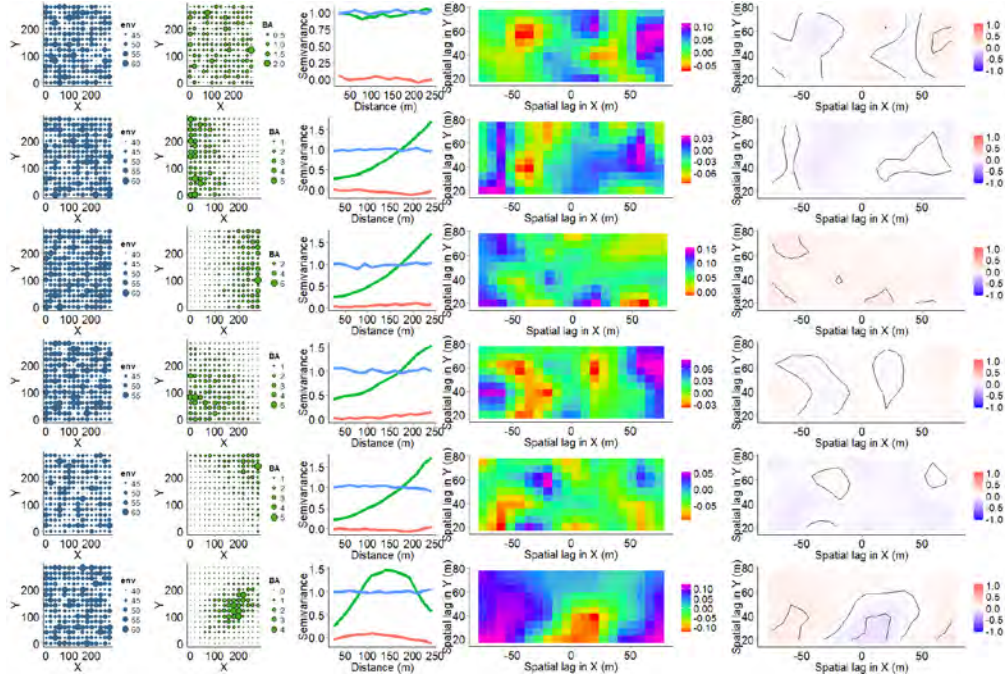
#####
#####
##### End of source file code
#####
#####

```

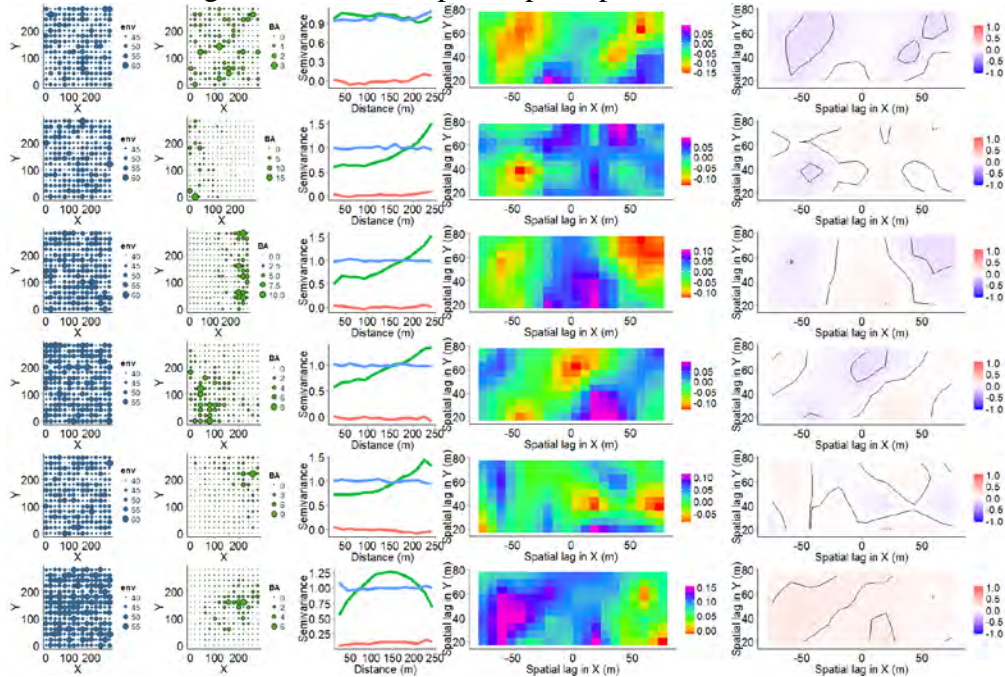


**Notes S2** Full output from codispersion analysis of simulated marked point patterns across a variety of environmental gradients.

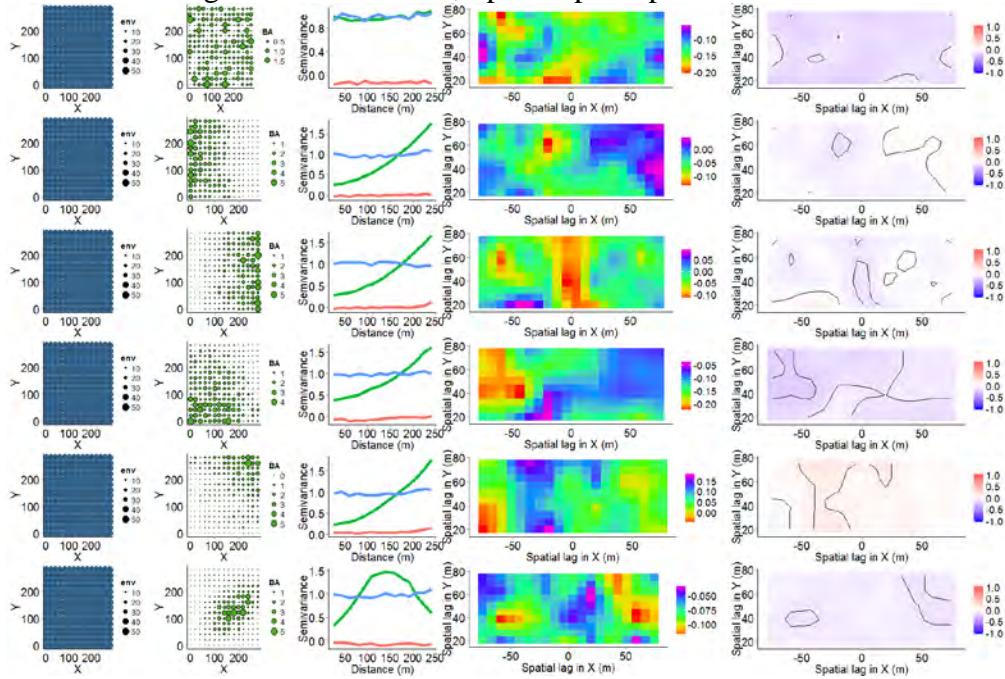
**Environmental gradient = CSR, Species point pattern = CSR**



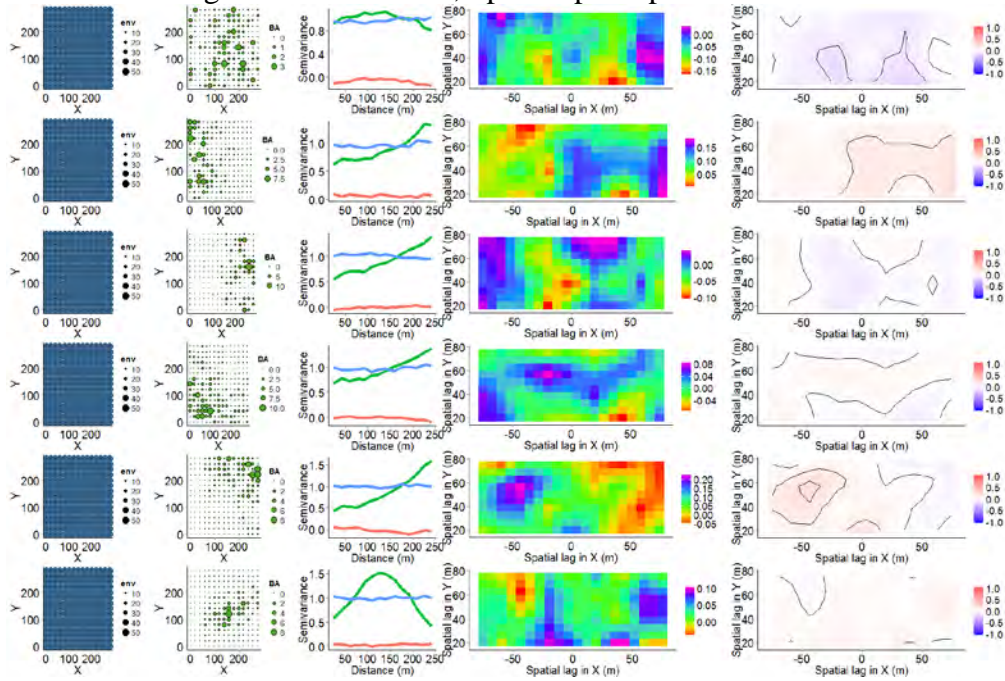
**Environmental gradient = CSR, Species point pattern = Thomas**



Environmental gradient = Uniform, Species point pattern = CSR

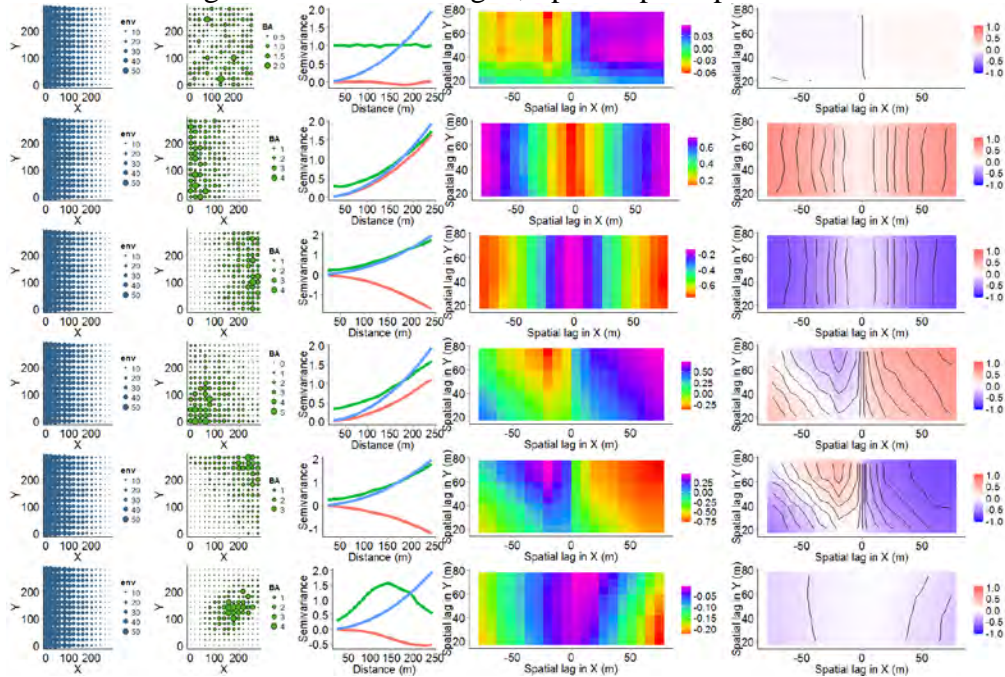


Environmental gradient = Uniform, Species point pattern = Thomas

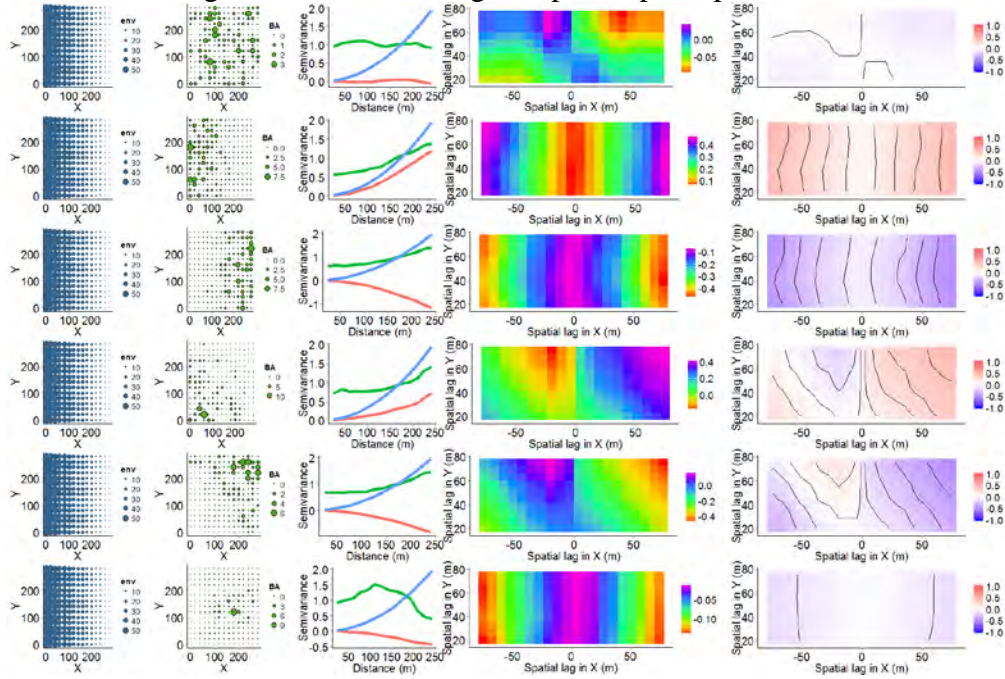




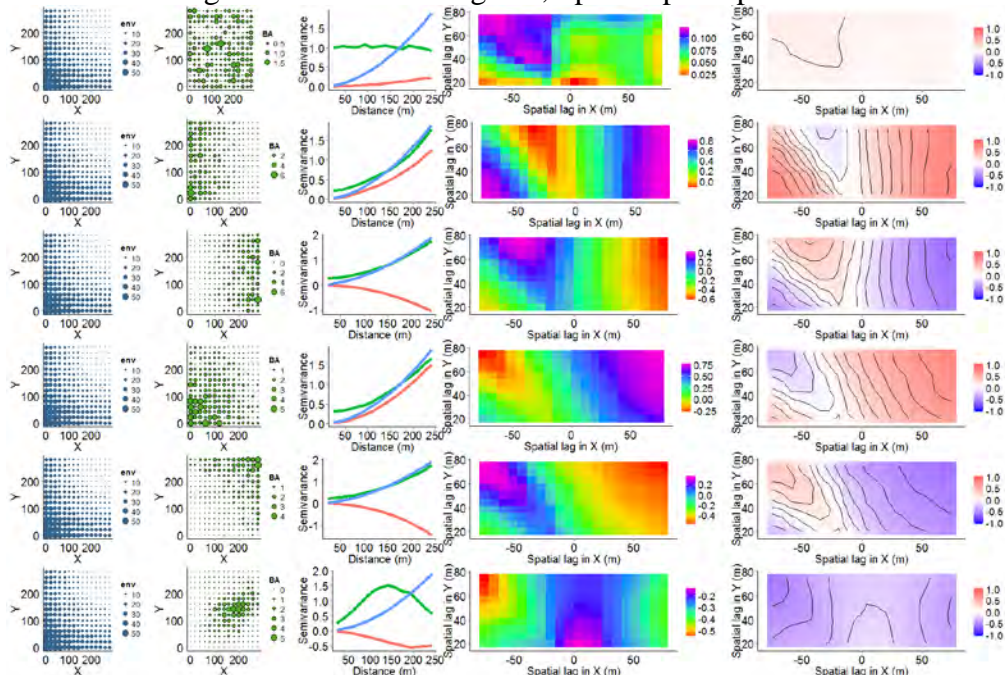
Environmental gradient = Decreasing X, Species point pattern = CSR



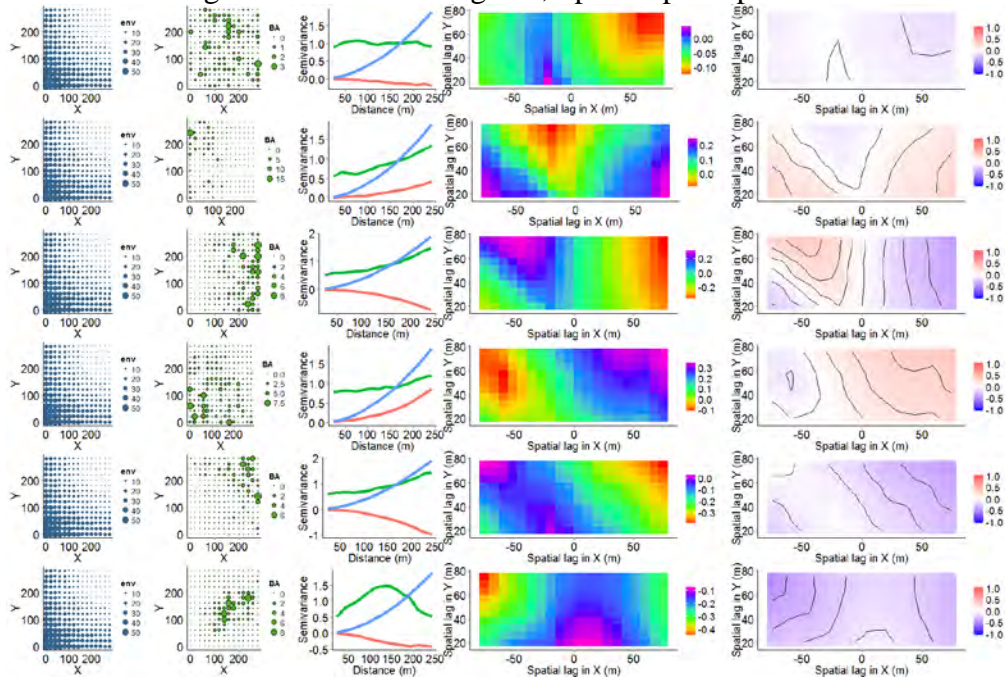
Environmental gradient = Decreasing X, Species point pattern = Thomas



Environmental gradient = Decreasing XY, Species point pattern = CSR

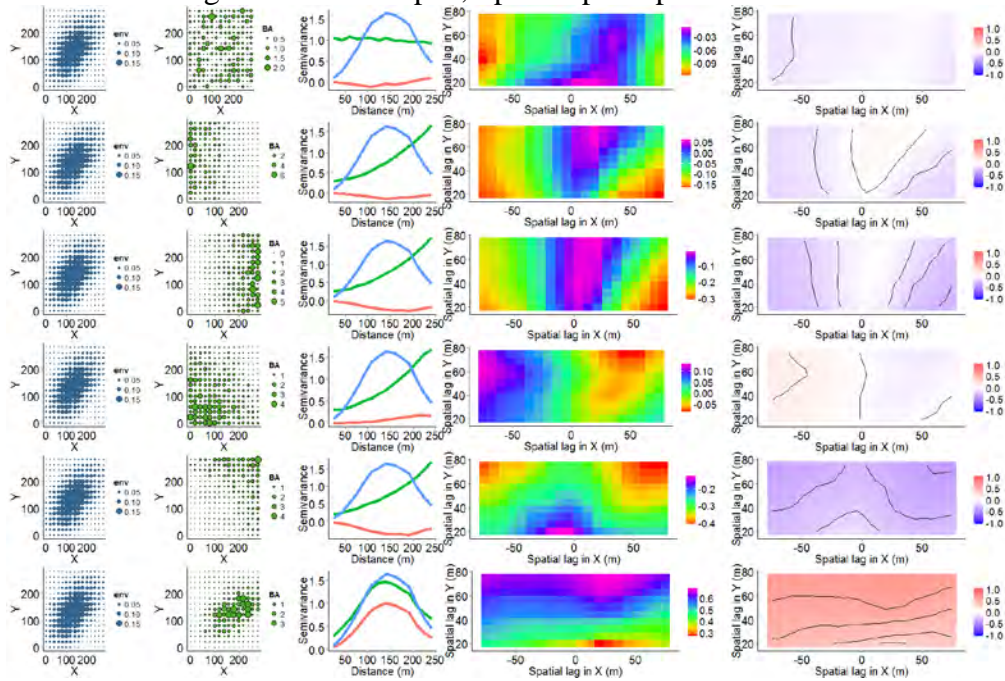


Environmental gradient = Decreasing XY, Species point pattern = Thomas

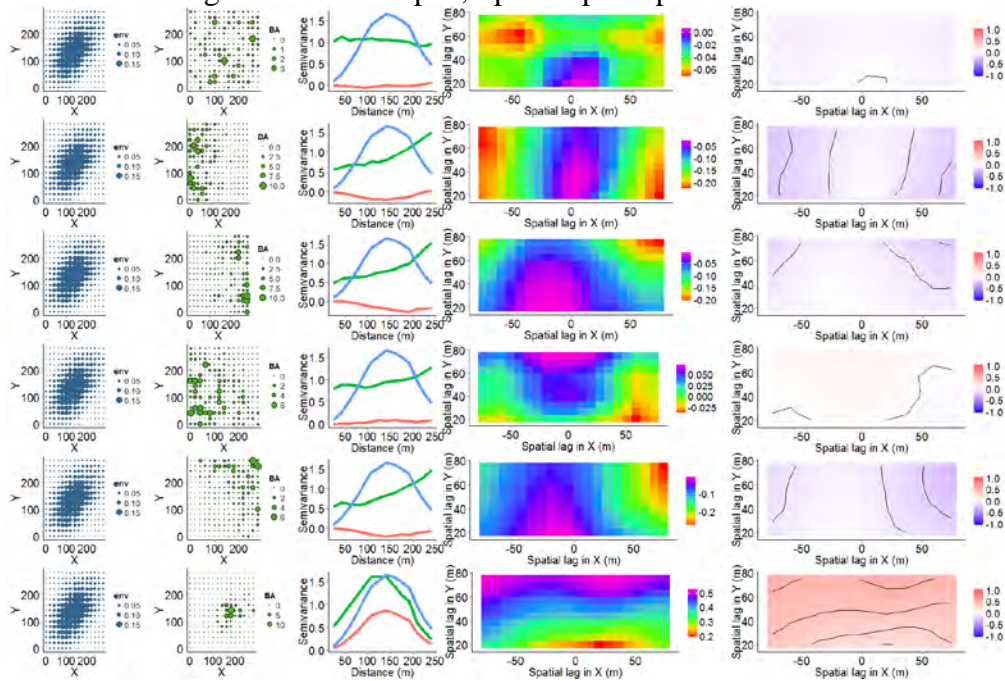




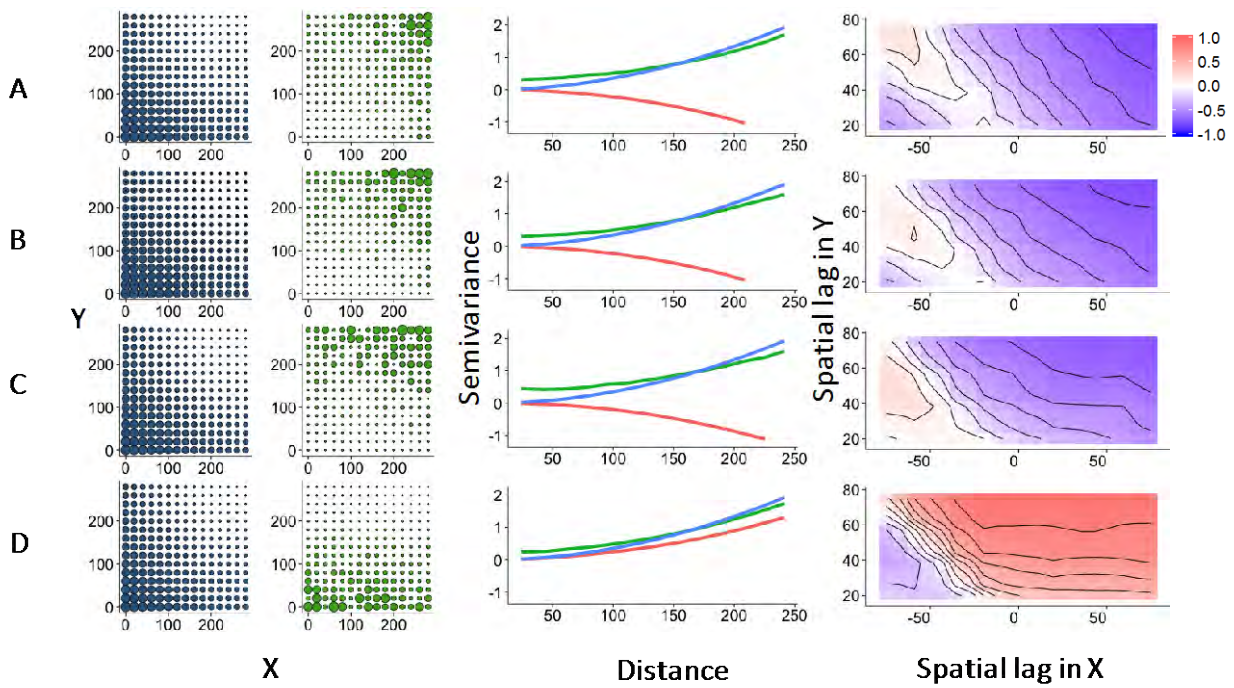
Environmental gradient = Clumped, Species point pattern = CSR



Environmental gradient = Clumped, Species point pattern = Thomas



Environmental gradient = Decreasing XY, Species point pattern = CSR. The original species pattern (A) was rotated 15 degrees (B) and 30 degrees (C) anticlockwise. Directionality in the pattern in the Y dimension is detected by codispersion analysis (D).



**Notes S3** Results of principal components analysis of Tyson soil chemistry data.

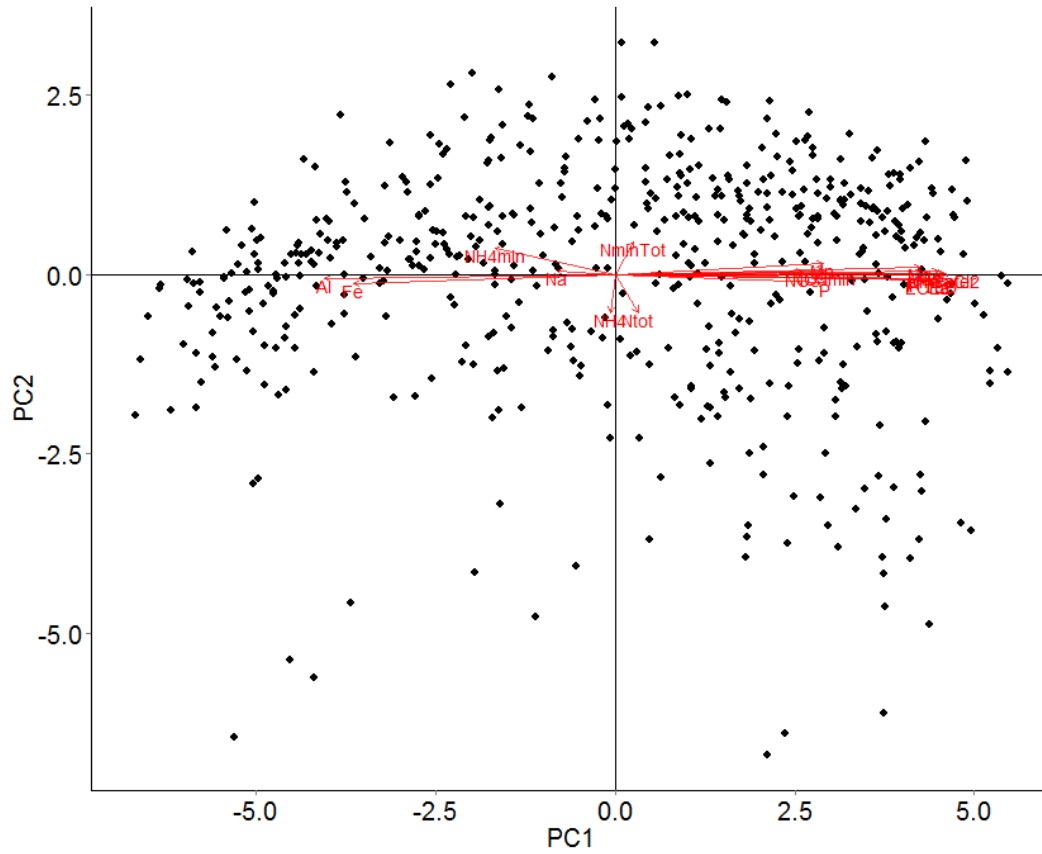


Figure S3.1 PCA biplot

Table S3. 1. Proportion of variance explained by the first two components.

	PC1	PC2
Standard deviation	3.131	1.5746
Proportion of variance	0.516	0.1305
Cumulative proportion	0.516	0.6465

Table S3. 2. Loadings for the first two components (|0.2| or greater are shown)

	<b>PC1 (fertility)</b>	<b>PC2 (nitrogen)</b>
pH <sub>Water</sub>	0.31	
Base Saturation	0.30	
Ca	0.30	
Effective Cation Exchange Capacity	0.29	
Mg	0.29	
K	0.28	
Al	-0.27	
Fe	-0.24	
N <sub>tot</sub>		-0.54
NH <sub>4</sub>		-0.54
N <sub>minTot</sub>		0.45
NH <sub>4min</sub>		0.36



**Notes S4** Type I error rates of the null models.

We estimated the type I error rate of the CSR, RLM and the toroidal shift models by comparing the observed codispersion values for (1) a CSR-distributed and (2) a Thomas-distributed species (with CSR diameters selected randomly from a truncated lognormal distribution with a minimum of 1 cm, a maximum of 80 cm, a mean of 40 cm and a standard deviation of  $\log(80/15)$  cm) and a CSR environmental variable in a  $300 \times 300$ -m plot divided into  $20 \times 20$ -m grid cells (Figure S3.1) with that expected under each of the null models. Here, we give the results from those comparisons. Graphs (Figure S3.2) show the observed-expected codispersion values and the significance for each cell under each null model for the two datasets. Tables give the raw output for each analysis (Table S3.1 and S3.2). Each line in the tables below represents one cell on the codispersion graph. Given are the observed and expected codispersion values, the 'P.value', which is the proportion of values that were the minimum of the number of expected values that were less than or greater than the observed value, the mean of the expected codispersion values and the difference between the observed codispersion value and that mean, and whether or not that difference was significant at the  $P < 0.05$  level (two-tailed).

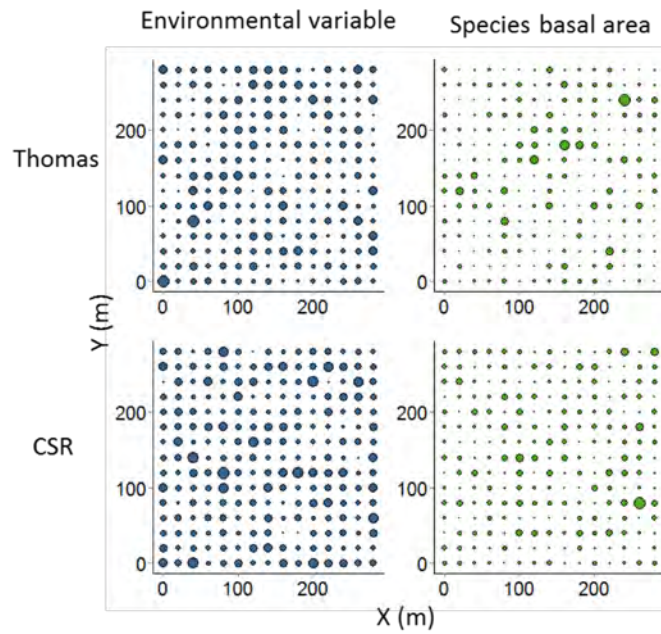


Figure S4.1: Spatial distributions of a simulated environmental variable and a species, where the species distribution was generated either using a Thomas process or was CSR.

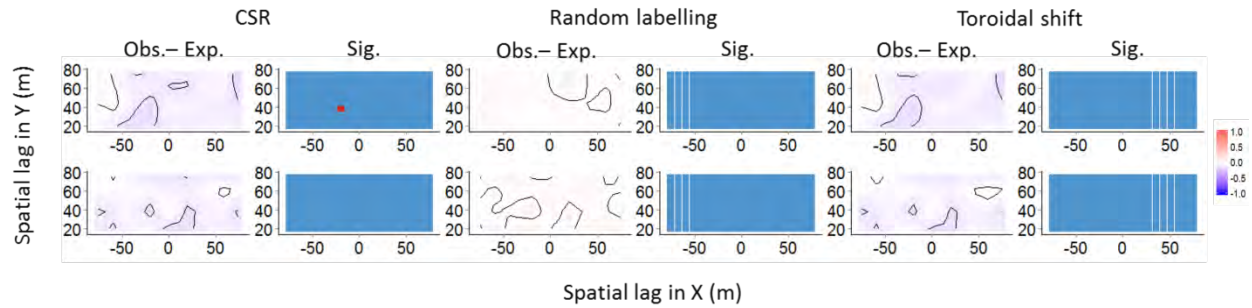


Figure S4.2: Observed – expected codispersion and significance (red) or not (blue) under the three null models calculated for two simulated species-environment relationships: CSR tree diameters distributed across points generated by a Thomas process (upper graphs) and a CSR process (lower graphs).

Table S4.1: Cell-level results for codispersion analysis of species-environmental relationship for tree distribution generated by a Thomas process under the (a) CSR, (b) random labelling and (c) toroidal shift null models.

(a) CSR null model							
cell	xx	yy	Codispersion	P.value	null_mean	diff	P.value.cat
1	-75	20	-0.029	0.382	-0.002	-0.027	Non-sig.
2	-67.1	20	-0.051	0.281	-0.004	-0.047	Non-sig.
3	-59.2	20	-0.087	0.186	-0.006	-0.081	Non-sig.
4	-51.3	20	-0.118	0.07	-0.003	-0.115	Non-sig.
5	-43.4	20	-0.142	0.035	-0.001	-0.142	Non-sig.
6	-35.5	20	-0.143	0.04	0.002	-0.145	Non-sig.
7	-27.6	20	-0.126	0.06	0.003	-0.129	Non-sig.
8	-19.7	20	-0.102	0.106	0.005	-0.107	Non-sig.
9	-11.8	20	-0.091	0.09	0.003	-0.094	Non-sig.
10	-3.9	20	-0.084	0.131	0.001	-0.086	Non-sig.
11	3.9	20	-0.08	0.126	-0.001	-0.08	Non-sig.
12	11.8	20	-0.082	0.136	-0.001	-0.08	Non-sig.
13	19.7	20	-0.084	0.161	-0.003	-0.081	Non-sig.
14	27.6	20	-0.074	0.156	0	-0.074	Non-sig.
15	35.5	20	-0.067	0.191	0.002	-0.069	Non-sig.
16	43.4	20	-0.052	0.236	0.004	-0.057	Non-sig.
17	51.3	20	-0.043	0.286	0.004	-0.047	Non-sig.
18	59.2	20	-0.031	0.352	0.004	-0.035	Non-sig.
19	67.1	20	-0.048	0.276	0.001	-0.049	Non-sig.
20	75	20	-0.064	0.236	-0.002	-0.063	Non-sig.
21	-75	26.1	-0.024	0.377	-0.001	-0.024	Non-sig.
22	-67.1	26.1	-0.031	0.352	-0.002	-0.03	Non-sig.
23	-59.2	26.1	-0.047	0.281	-0.003	-0.044	Non-sig.
24	-51.3	26.1	-0.077	0.161	-0.001	-0.075	Non-sig.
25	-43.4	26.1	-0.099	0.106	0	-0.099	Non-sig.
26	-35.5	26.1	-0.122	0.045	0.001	-0.123	Non-sig.
27	-27.6	26.1	-0.127	0.04	0.001	-0.128	Non-sig.
28	-19.7	26.1	-0.131	0.04	0.001	-0.132	Non-sig.
29	-11.8	26.1	-0.096	0.07	0.001	-0.097	Non-sig.
30	-3.9	26.1	-0.072	0.156	0.001	-0.074	Non-sig.
31	3.9	26.1	-0.055	0.211	0.001	-0.056	Non-sig.
32	11.8	26.1	-0.059	0.186	0.001	-0.06	Non-sig.
33	19.7	26.1	-0.065	0.216	0	-0.065	Non-sig.
34	27.6	26.1	-0.064	0.176	0.002	-0.066	Non-sig.
35	35.5	26.1	-0.064	0.176	0.002	-0.066	Non-sig.
36	43.4	26.1	-0.061	0.201	0.003	-0.064	Non-sig.
37	51.3	26.1	-0.058	0.201	0.002	-0.06	Non-sig.
38	59.2	26.1	-0.053	0.256	0.002	-0.055	Non-sig.
39	67.1	26.1	-0.065	0.211	-0.001	-0.065	Non-sig.
40	75	26.1	-0.075	0.196	-0.002	-0.073	Non-sig.
41	-75	32.2	-0.021	0.392	0	-0.022	Non-sig.
42	-67.1	32.2	-0.02	0.397	0	-0.019	Non-sig.
43	-59.2	32.2	-0.023	0.372	-0.001	-0.022	Non-sig.
44	-51.3	32.2	-0.053	0.251	0	-0.052	Non-sig.
45	-43.4	32.2	-0.075	0.166	0	-0.075	Non-sig.

46	-35.5	32.2	-0.111	0.06	0	-0.111	Non-sig.
47	-27.6	32.2	-0.127	0.045	0	-0.127	Non-sig.
48	-19.7	32.2	-0.147	0.025	0	-0.146	Non-sig.
49	-11.8	32.2	-0.098	0.065	0.001	-0.098	Non-sig.
50	-3.9	32.2	-0.066	0.186	0.001	-0.067	Non-sig.
51	3.9	32.2	-0.042	0.271	0.002	-0.043	Non-sig.
52	11.8	32.2	-0.046	0.246	0.002	-0.048	Non-sig.
53	19.7	32.2	-0.053	0.236	0.002	-0.055	Non-sig.
54	27.6	32.2	-0.058	0.196	0.002	-0.061	Non-sig.
55	35.5	32.2	-0.062	0.171	0.002	-0.065	Non-sig.
56	43.4	32.2	-0.066	0.156	0.002	-0.068	Non-sig.
57	51.3	32.2	-0.067	0.186	0.001	-0.068	Non-sig.
58	59.2	32.2	-0.067	0.181	0	-0.067	Non-sig.
59	67.1	32.2	-0.076	0.161	-0.002	-0.074	Non-sig.
60	75	32.2	-0.082	0.166	-0.003	-0.079	Non-sig.
61	-75	38.3	-0.017	0.427	0.002	-0.019	Non-sig.
62	-67.1	38.3	-0.003	0.487	0.002	-0.005	Non-sig.
63	-59.2	38.3	0.011	0.427	0.002	0.01	Non-sig.
64	-51.3	38.3	-0.02	0.362	0.001	-0.021	Non-sig.
65	-43.4	38.3	-0.042	0.266	0.001	-0.043	Non-sig.
66	-35.5	38.3	-0.096	0.111	0	-0.095	Non-sig.
67	-27.6	38.3	-0.128	0.05	-0.001	-0.127	Non-sig.
68	-19.7	38.3	-0.166	0.02	-0.003	-0.164	Sig.
69	-11.8	38.3	-0.101	0.08	0	-0.101	Non-sig.
70	-3.9	38.3	-0.057	0.226	0.001	-0.058	Non-sig.
71	3.9	38.3	-0.023	0.362	0.003	-0.026	Non-sig.
72	11.8	38.3	-0.028	0.317	0.004	-0.032	Non-sig.
73	19.7	38.3	-0.036	0.347	0.005	-0.041	Non-sig.
74	27.6	38.3	-0.05	0.256	0.003	-0.053	Non-sig.
75	35.5	38.3	-0.059	0.186	0.003	-0.062	Non-sig.
76	43.4	38.3	-0.075	0.156	0.001	-0.075	Non-sig.
77	51.3	38.3	-0.081	0.136	-0.001	-0.08	Non-sig.
78	59.2	38.3	-0.088	0.151	-0.002	-0.086	Non-sig.
79	67.1	38.3	-0.09	0.141	-0.003	-0.087	Non-sig.
80	75	38.3	-0.09	0.151	-0.003	-0.087	Non-sig.
81	-75	44.4	0.01	0.432	0.002	0.008	Non-sig.
82	-67.1	44.4	0.018	0.407	0.002	0.016	Non-sig.
83	-59.2	44.4	0.022	0.407	0.002	0.02	Non-sig.
84	-51.3	44.4	-0.01	0.447	0.001	-0.011	Non-sig.
85	-43.4	44.4	-0.033	0.342	0	-0.034	Non-sig.
86	-35.5	44.4	-0.081	0.146	-0.001	-0.079	Non-sig.
87	-27.6	44.4	-0.107	0.08	-0.002	-0.105	Non-sig.
88	-19.7	44.4	-0.139	0.035	-0.004	-0.136	Non-sig.
89	-11.8	44.4	-0.096	0.09	-0.001	-0.095	Non-sig.
90	-3.9	44.4	-0.066	0.191	0.001	-0.068	Non-sig.
91	3.9	44.4	-0.042	0.266	0.004	-0.046	Non-sig.
92	11.8	44.4	-0.044	0.246	0.005	-0.049	Non-sig.
93	19.7	44.4	-0.048	0.231	0.006	-0.053	Non-sig.
94	27.6	44.4	-0.052	0.211	0.003	-0.055	Non-sig.
95	35.5	44.4	-0.055	0.206	0.001	-0.056	Non-sig.
96	43.4	44.4	-0.066	0.191	-0.002	-0.064	Non-sig.
97	51.3	44.4	-0.075	0.171	-0.002	-0.073	Non-sig.
98	59.2	44.4	-0.087	0.131	-0.003	-0.084	Non-sig.
99	67.1	44.4	-0.096	0.136	-0.003	-0.092	Non-sig.
100	75	44.4	-0.101	0.131	-0.003	-0.098	Non-sig.

101	-75	50.6	0.03	0.357	0.002	0.028	Non-sig.
102	-67.1	50.6	0.027	0.387	0.001	0.026	Non-sig.
103	-59.2	50.6	0.017	0.402	0	0.017	Non-sig.
104	-51.3	50.6	-0.015	0.432	0	-0.015	Non-sig.
105	-43.4	50.6	-0.039	0.312	-0.001	-0.038	Non-sig.
106	-35.5	50.6	-0.074	0.166	-0.002	-0.073	Non-sig.
107	-27.6	50.6	-0.09	0.116	-0.003	-0.088	Non-sig.
108	-19.7	50.6	-0.111	0.06	-0.004	-0.107	Non-sig.
109	-11.8	50.6	-0.09	0.095	0	-0.09	Non-sig.
110	-3.9	50.6	-0.077	0.146	0.002	-0.079	Non-sig.
111	3.9	50.6	-0.065	0.176	0.004	-0.069	Non-sig.
112	11.8	50.6	-0.064	0.171	0.005	-0.069	Non-sig.
113	19.7	50.6	-0.064	0.181	0.005	-0.069	Non-sig.
114	27.6	50.6	-0.057	0.201	0.002	-0.06	Non-sig.
115	35.5	50.6	-0.053	0.236	0	-0.053	Non-sig.
116	43.4	50.6	-0.055	0.226	-0.003	-0.053	Non-sig.
117	51.3	50.6	-0.065	0.186	-0.003	-0.062	Non-sig.
118	59.2	50.6	-0.078	0.171	-0.003	-0.075	Non-sig.
119	67.1	50.6	-0.095	0.121	-0.003	-0.092	Non-sig.
120	75	50.6	-0.106	0.111	-0.003	-0.103	Non-sig.
121	-75	56.7	0.052	0.281	0.001	0.05	Non-sig.
122	-67.1	56.7	0.038	0.357	0	0.037	Non-sig.
123	-59.2	56.7	0.012	0.437	-0.001	0.013	Non-sig.
124	-51.3	56.7	-0.021	0.417	-0.001	-0.02	Non-sig.
125	-43.4	56.7	-0.045	0.271	-0.001	-0.043	Non-sig.
126	-35.5	56.7	-0.068	0.201	-0.002	-0.065	Non-sig.
127	-27.6	56.7	-0.072	0.181	-0.003	-0.069	Non-sig.
128	-19.7	56.7	-0.078	0.166	-0.004	-0.074	Non-sig.
129	-11.8	56.7	-0.084	0.126	0	-0.084	Non-sig.
130	-3.9	56.7	-0.089	0.106	0.002	-0.091	Non-sig.
131	3.9	56.7	-0.09	0.09	0.005	-0.095	Non-sig.
132	11.8	56.7	-0.087	0.09	0.005	-0.092	Non-sig.
133	19.7	56.7	-0.082	0.126	0.005	-0.087	Non-sig.
134	27.6	56.7	-0.064	0.191	0.001	-0.065	Non-sig.
135	35.5	56.7	-0.05	0.256	-0.001	-0.049	Non-sig.
136	43.4	56.7	-0.044	0.307	-0.004	-0.04	Non-sig.
137	51.3	56.7	-0.054	0.256	-0.003	-0.051	Non-sig.
138	59.2	56.7	-0.068	0.221	-0.003	-0.065	Non-sig.
139	67.1	56.7	-0.094	0.126	-0.003	-0.091	Non-sig.
140	75	56.7	-0.113	0.101	-0.003	-0.11	Non-sig.
141	-75	62.8	0.066	0.246	0.002	0.064	Non-sig.
142	-67.1	62.8	0.042	0.327	0.001	0.041	Non-sig.
143	-59.2	62.8	0.002	0.477	-0.001	0.003	Non-sig.
144	-51.3	62.8	-0.034	0.337	-0.002	-0.032	Non-sig.
145	-43.4	62.8	-0.06	0.211	-0.002	-0.058	Non-sig.
146	-35.5	62.8	-0.073	0.186	-0.003	-0.07	Non-sig.
147	-27.6	62.8	-0.067	0.181	-0.003	-0.064	Non-sig.
148	-19.7	62.8	-0.06	0.241	-0.004	-0.057	Non-sig.
149	-11.8	62.8	-0.08	0.141	-0.001	-0.08	Non-sig.
150	-3.9	62.8	-0.094	0.09	0.002	-0.095	Non-sig.
151	3.9	62.8	-0.104	0.05	0.004	-0.108	Non-sig.
152	11.8	62.8	-0.102	0.06	0.004	-0.106	Non-sig.
153	19.7	62.8	-0.098	0.111	0.004	-0.102	Non-sig.
154	27.6	62.8	-0.072	0.176	0.001	-0.073	Non-sig.
155	35.5	62.8	-0.052	0.281	0	-0.051	Non-sig.

156	43.4	62.8	-0.035	0.347	-0.002	-0.033	Non-sig.
157	51.3	62.8	-0.042	0.317	-0.002	-0.04	Non-sig.
158	59.2	62.8	-0.051	0.281	-0.002	-0.048	Non-sig.
159	67.1	62.8	-0.094	0.141	-0.002	-0.092	Non-sig.
160	75	62.8	-0.126	0.08	-0.002	-0.123	Non-sig.
161	-75	68.9	0.056	0.296	0.003	0.053	Non-sig.
162	-67.1	68.9	0.034	0.377	0.002	0.032	Non-sig.
163	-59.2	68.9	-0.004	0.477	0	-0.004	Non-sig.
164	-51.3	68.9	-0.043	0.276	-0.001	-0.042	Non-sig.
165	-43.4	68.9	-0.071	0.171	-0.001	-0.07	Non-sig.
166	-35.5	68.9	-0.089	0.121	-0.002	-0.087	Non-sig.
167	-27.6	68.9	-0.086	0.121	-0.003	-0.083	Non-sig.
168	-19.7	68.9	-0.082	0.156	-0.004	-0.078	Non-sig.
169	-11.8	68.9	-0.083	0.136	-0.002	-0.082	Non-sig.
170	-3.9	68.9	-0.084	0.126	0	-0.084	Non-sig.
171	3.9	68.9	-0.088	0.085	0.002	-0.09	Non-sig.
172	11.8	68.9	-0.091	0.101	0.002	-0.093	Non-sig.
173	19.7	68.9	-0.096	0.121	0.003	-0.099	Non-sig.
174	27.6	68.9	-0.074	0.176	0.003	-0.076	Non-sig.
175	35.5	68.9	-0.057	0.241	0.002	-0.059	Non-sig.
176	43.4	68.9	-0.039	0.312	0.001	-0.04	Non-sig.
177	51.3	68.9	-0.041	0.281	-0.001	-0.04	Non-sig.
178	59.2	68.9	-0.043	0.296	-0.002	-0.04	Non-sig.
179	67.1	68.9	-0.095	0.116	-0.002	-0.093	Non-sig.
180	75	68.9	-0.134	0.07	-0.002	-0.132	Non-sig.
181	-75	75	0.047	0.332	0.005	0.042	Non-sig.
182	-67.1	75	0.026	0.382	0.003	0.023	Non-sig.
183	-59.2	75	-0.01	0.442	0.001	-0.011	Non-sig.
184	-51.3	75	-0.051	0.236	0	-0.051	Non-sig.
185	-43.4	75	-0.081	0.161	0	-0.081	Non-sig.
186	-35.5	75	-0.104	0.095	-0.002	-0.102	Non-sig.
187	-27.6	75	-0.103	0.095	-0.003	-0.1	Non-sig.
188	-19.7	75	-0.101	0.116	-0.004	-0.097	Non-sig.
189	-11.8	75	-0.086	0.146	-0.002	-0.083	Non-sig.
190	-3.9	75	-0.075	0.161	-0.001	-0.073	Non-sig.
191	3.9	75	-0.072	0.161	0	-0.073	Non-sig.
192	11.8	75	-0.081	0.136	0.001	-0.082	Non-sig.
193	19.7	75	-0.093	0.131	0.003	-0.096	Non-sig.
194	27.6	75	-0.076	0.161	0.004	-0.079	Non-sig.
195	35.5	75	-0.062	0.211	0.004	-0.066	Non-sig.
196	43.4	75	-0.043	0.302	0.003	-0.047	Non-sig.
197	51.3	75	-0.04	0.312	0.001	-0.041	Non-sig.
198	59.2	75	-0.036	0.332	-0.002	-0.034	Non-sig.
199	67.1	75	-0.096	0.136	-0.002	-0.094	Non-sig.
200	75	75	-0.14	0.045	-0.001	-0.139	Non-sig.

**(b) Random labelling null model**

cell	xx	yy	Codispersion	P.value	null_mean	diff	P.value.cat
1	-75	20	-0.029	0.131	-0.081	0.052	Non-sig.
2	-67.1	20	-0.051	0.156	-0.097	0.046	Non-sig.
3	-59.2	20	-0.087	0.241	-0.123	0.036	Non-sig.
4	-51.3	20	-0.118	0.256	-0.146	0.028	Non-sig.
5	-43.4	20	-0.142	0.296	-0.164	0.022	Non-sig.
6	-35.5	20	-0.143	0.327	-0.16	0.017	Non-sig.

7	-27.6	20	-0.126	0.337	-0.142	0.016	Non-sig.
8	-19.7	20	-0.102	0.352	-0.117	0.015	Non-sig.
9	-11.8	20	-0.091	0.362	-0.107	0.016	Non-sig.
10	-3.9	20	-0.084	0.367	-0.101	0.017	Non-sig.
11	3.9	20	-0.08	0.377	-0.093	0.013	Non-sig.
12	11.8	20	-0.082	0.462	-0.089	0.008	Non-sig.
13	19.7	20	-0.084	0.467	-0.084	0	Non-sig.
14	27.6	20	-0.074	0.392	-0.089	0.015	Non-sig.
15	35.5	20	-0.067	0.296	-0.093	0.026	Non-sig.
16	43.4	20	-0.052	0.196	-0.085	0.033	Non-sig.
17	51.3	20	-0.043	0.246	-0.07	0.027	Non-sig.
18	59.2	20	-0.031	0.296	-0.05	0.02	Non-sig.
19	67.1	20	-0.048	0.447	-0.055	0.006	Non-sig.
20	75	20	-0.064	0.482	-0.061	-0.003	Non-sig.
21	-75	26.1	-0.024	0.131	-0.072	0.047	Non-sig.
22	-67.1	26.1	-0.031	0.136	-0.074	0.042	Non-sig.
23	-59.2	26.1	-0.047	0.211	-0.081	0.034	Non-sig.
24	-51.3	26.1	-0.077	0.271	-0.105	0.028	Non-sig.
25	-43.4	26.1	-0.099	0.276	-0.123	0.023	Non-sig.
26	-35.5	26.1	-0.122	0.377	-0.138	0.015	Non-sig.
27	-27.6	26.1	-0.127	0.397	-0.139	0.012	Non-sig.
28	-19.7	26.1	-0.131	0.442	-0.139	0.008	Non-sig.
29	-11.8	26.1	-0.096	0.392	-0.109	0.014	Non-sig.
30	-3.9	26.1	-0.072	0.337	-0.09	0.018	Non-sig.
31	3.9	26.1	-0.055	0.337	-0.075	0.02	Non-sig.
32	11.8	26.1	-0.059	0.367	-0.076	0.017	Non-sig.
33	19.7	26.1	-0.065	0.392	-0.077	0.012	Non-sig.
34	27.6	26.1	-0.064	0.367	-0.081	0.016	Non-sig.
35	35.5	26.1	-0.064	0.322	-0.083	0.019	Non-sig.
36	43.4	26.1	-0.061	0.307	-0.08	0.019	Non-sig.
37	51.3	26.1	-0.058	0.342	-0.073	0.015	Non-sig.
38	59.2	26.1	-0.053	0.417	-0.063	0.01	Non-sig.
39	67.1	26.1	-0.065	0.442	-0.07	0.005	Non-sig.
40	75	26.1	-0.075	0.452	-0.078	0.002	Non-sig.
41	-75	32.2	-0.021	0.141	-0.066	0.045	Non-sig.
42	-67.1	32.2	-0.02	0.146	-0.06	0.04	Non-sig.
43	-59.2	32.2	-0.023	0.181	-0.056	0.033	Non-sig.
44	-51.3	32.2	-0.053	0.251	-0.08	0.028	Non-sig.
45	-43.4	32.2	-0.075	0.291	-0.098	0.023	Non-sig.
46	-35.5	32.2	-0.111	0.367	-0.125	0.015	Non-sig.
47	-27.6	32.2	-0.127	0.407	-0.137	0.01	Non-sig.
48	-19.7	32.2	-0.147	0.477	-0.151	0.005	Non-sig.
49	-11.8	32.2	-0.098	0.412	-0.111	0.013	Non-sig.
50	-3.9	32.2	-0.066	0.367	-0.085	0.019	Non-sig.
51	3.9	32.2	-0.042	0.302	-0.065	0.023	Non-sig.
52	11.8	32.2	-0.046	0.291	-0.068	0.022	Non-sig.
53	19.7	32.2	-0.053	0.327	-0.073	0.02	Non-sig.
54	27.6	32.2	-0.058	0.327	-0.075	0.017	Non-sig.
55	35.5	32.2	-0.062	0.342	-0.077	0.015	Non-sig.
56	43.4	32.2	-0.066	0.362	-0.077	0.011	Non-sig.
57	51.3	32.2	-0.067	0.422	-0.074	0.008	Non-sig.
58	59.2	32.2	-0.067	0.472	-0.071	0.003	Non-sig.
59	67.1	32.2	-0.076	0.452	-0.08	0.004	Non-sig.
60	75	32.2	-0.082	0.437	-0.088	0.006	Non-sig.
61	-75	38.3	-0.017	0.181	-0.058	0.041	Non-sig.



62	-67.1	38.3	-0.003	0.181	-0.04	0.037	Non-sig.
63	-59.2	38.3	0.011	0.206	-0.02	0.031	Non-sig.
64	-51.3	38.3	-0.02	0.246	-0.046	0.027	Non-sig.
65	-43.4	38.3	-0.042	0.291	-0.065	0.023	Non-sig.
66	-35.5	38.3	-0.096	0.367	-0.109	0.013	Non-sig.
67	-27.6	38.3	-0.128	0.437	-0.135	0.007	Non-sig.
68	-19.7	38.3	-0.166	0.487	-0.166	0	Non-sig.
69	-11.8	38.3	-0.101	0.417	-0.112	0.011	Non-sig.
70	-3.9	38.3	-0.057	0.342	-0.077	0.02	Non-sig.
71	3.9	38.3	-0.023	0.241	-0.052	0.029	Non-sig.
72	11.8	38.3	-0.028	0.201	-0.058	0.029	Non-sig.
73	19.7	38.3	-0.036	0.246	-0.067	0.031	Non-sig.
74	27.6	38.3	-0.05	0.347	-0.068	0.018	Non-sig.
75	35.5	38.3	-0.059	0.392	-0.069	0.009	Non-sig.
76	43.4	38.3	-0.075	0.472	-0.073	-0.002	Non-sig.
77	51.3	38.3	-0.081	0.482	-0.077	-0.004	Non-sig.
78	59.2	38.3	-0.088	0.457	-0.083	-0.005	Non-sig.
79	67.1	38.3	-0.09	0.457	-0.093	0.004	Non-sig.
80	75	38.3	-0.09	0.437	-0.101	0.01	Non-sig.
81	-75	44.4	0.01	0.196	-0.029	0.039	Non-sig.
82	-67.1	44.4	0.018	0.171	-0.021	0.038	Non-sig.
83	-59.2	44.4	0.022	0.166	-0.014	0.036	Non-sig.
84	-51.3	44.4	-0.01	0.201	-0.04	0.03	Non-sig.
85	-43.4	44.4	-0.033	0.266	-0.059	0.026	Non-sig.
86	-35.5	44.4	-0.081	0.327	-0.098	0.018	Non-sig.
87	-27.6	44.4	-0.107	0.382	-0.121	0.014	Non-sig.
88	-19.7	44.4	-0.139	0.452	-0.148	0.008	Non-sig.
89	-11.8	44.4	-0.096	0.377	-0.109	0.013	Non-sig.
90	-3.9	44.4	-0.066	0.337	-0.084	0.017	Non-sig.
91	3.9	44.4	-0.042	0.357	-0.06	0.018	Non-sig.
92	11.8	44.4	-0.044	0.397	-0.059	0.014	Non-sig.
93	19.7	44.4	-0.048	0.407	-0.057	0.009	Non-sig.
94	27.6	44.4	-0.052	0.437	-0.057	0.005	Non-sig.
95	35.5	44.4	-0.055	0.492	-0.057	0.003	Non-sig.
96	43.4	44.4	-0.066	0.452	-0.063	-0.003	Non-sig.
97	51.3	44.4	-0.075	0.432	-0.07	-0.005	Non-sig.
98	59.2	44.4	-0.087	0.417	-0.079	-0.008	Non-sig.
99	67.1	44.4	-0.096	0.462	-0.1	0.004	Non-sig.
100	75	44.4	-0.101	0.407	-0.113	0.012	Non-sig.
101	-75	50.6	0.03	0.181	-0.009	0.039	Non-sig.
102	-67.1	50.6	0.027	0.151	-0.013	0.04	Non-sig.
103	-59.2	50.6	0.017	0.156	-0.023	0.041	Non-sig.
104	-51.3	50.6	-0.015	0.181	-0.049	0.033	Non-sig.
105	-43.4	50.6	-0.039	0.241	-0.067	0.028	Non-sig.
106	-35.5	50.6	-0.074	0.281	-0.096	0.022	Non-sig.
107	-27.6	50.6	-0.09	0.296	-0.11	0.02	Non-sig.
108	-19.7	50.6	-0.111	0.362	-0.128	0.017	Non-sig.
109	-11.8	50.6	-0.09	0.367	-0.106	0.016	Non-sig.
110	-3.9	50.6	-0.077	0.362	-0.092	0.015	Non-sig.
111	3.9	50.6	-0.065	0.452	-0.072	0.007	Non-sig.
112	11.8	50.6	-0.064	0.482	-0.063	-0.001	Non-sig.
113	19.7	50.6	-0.064	0.362	-0.05	-0.014	Non-sig.
114	27.6	50.6	-0.057	0.422	-0.051	-0.007	Non-sig.
115	35.5	50.6	-0.053	0.467	-0.052	-0.001	Non-sig.
116	43.4	50.6	-0.055	0.497	-0.058	0.003	Non-sig.

117	51.3	50.6	-0.065	0.482	-0.063	-0.002	Non-sig.
118	59.2	50.6	-0.078	0.437	-0.071	-0.007	Non-sig.
119	67.1	50.6	-0.095	0.447	-0.099	0.004	Non-sig.
120	75	50.6	-0.106	0.402	-0.119	0.013	Non-sig.
121	-75	56.7	0.052	0.201	0.012	0.039	Non-sig.
122	-67.1	56.7	0.038	0.151	-0.005	0.043	Non-sig.
123	-59.2	56.7	0.012	0.141	-0.034	0.046	Non-sig.
124	-51.3	56.7	-0.021	0.191	-0.058	0.037	Non-sig.
125	-43.4	56.7	-0.045	0.236	-0.075	0.03	Non-sig.
126	-35.5	56.7	-0.068	0.256	-0.094	0.026	Non-sig.
127	-27.6	56.7	-0.072	0.241	-0.099	0.027	Non-sig.
128	-19.7	56.7	-0.078	0.226	-0.106	0.028	Non-sig.
129	-11.8	56.7	-0.084	0.332	-0.103	0.018	Non-sig.
130	-3.9	56.7	-0.089	0.387	-0.101	0.012	Non-sig.
131	3.9	56.7	-0.09	0.442	-0.085	-0.005	Non-sig.
132	11.8	56.7	-0.087	0.302	-0.069	-0.018	Non-sig.
133	19.7	56.7	-0.082	0.151	-0.043	-0.039	Non-sig.
134	27.6	56.7	-0.064	0.302	-0.044	-0.02	Non-sig.
135	35.5	56.7	-0.05	0.422	-0.046	-0.004	Non-sig.
136	43.4	56.7	-0.044	0.437	-0.052	0.008	Non-sig.
137	51.3	56.7	-0.054	0.487	-0.056	0.002	Non-sig.
138	59.2	56.7	-0.068	0.482	-0.062	-0.006	Non-sig.
139	67.1	56.7	-0.094	0.442	-0.099	0.005	Non-sig.
140	75	56.7	-0.113	0.392	-0.125	0.013	Non-sig.
141	-75	62.8	0.066	0.201	0.029	0.037	Non-sig.
142	-67.1	62.8	0.042	0.181	0.002	0.04	Non-sig.
143	-59.2	62.8	0.002	0.176	-0.04	0.042	Non-sig.
144	-51.3	62.8	-0.034	0.186	-0.07	0.036	Non-sig.
145	-43.4	62.8	-0.06	0.236	-0.092	0.032	Non-sig.
146	-35.5	62.8	-0.073	0.236	-0.102	0.029	Non-sig.
147	-27.6	62.8	-0.067	0.221	-0.096	0.029	Non-sig.
148	-19.7	62.8	-0.06	0.256	-0.09	0.029	Non-sig.
149	-11.8	62.8	-0.08	0.367	-0.096	0.016	Non-sig.
150	-3.9	62.8	-0.094	0.412	-0.101	0.007	Non-sig.
151	3.9	62.8	-0.104	0.332	-0.088	-0.016	Non-sig.
152	11.8	62.8	-0.102	0.191	-0.068	-0.034	Non-sig.
153	19.7	62.8	-0.098	0.07	-0.037	-0.061	Non-sig.
154	27.6	62.8	-0.072	0.176	-0.04	-0.032	Non-sig.
155	35.5	62.8	-0.052	0.387	-0.043	-0.009	Non-sig.
156	43.4	62.8	-0.035	0.352	-0.049	0.013	Non-sig.
157	51.3	62.8	-0.042	0.417	-0.051	0.009	Non-sig.
158	59.2	62.8	-0.051	0.452	-0.053	0.002	Non-sig.
159	67.1	62.8	-0.094	0.442	-0.099	0.004	Non-sig.
160	75	62.8	-0.126	0.432	-0.132	0.007	Non-sig.
161	-75	68.9	0.056	0.226	0.022	0.034	Non-sig.
162	-67.1	68.9	0.034	0.211	0.001	0.033	Non-sig.
163	-59.2	68.9	-0.004	0.231	-0.035	0.031	Non-sig.
164	-51.3	68.9	-0.043	0.216	-0.074	0.031	Non-sig.
165	-43.4	68.9	-0.071	0.211	-0.102	0.031	Non-sig.
166	-35.5	68.9	-0.089	0.241	-0.115	0.026	Non-sig.
167	-27.6	68.9	-0.086	0.266	-0.107	0.021	Non-sig.
168	-19.7	68.9	-0.082	0.357	-0.097	0.015	Non-sig.
169	-11.8	68.9	-0.083	0.417	-0.092	0.009	Non-sig.
170	-3.9	68.9	-0.084	0.462	-0.089	0.005	Non-sig.
171	3.9	68.9	-0.088	0.332	-0.073	-0.014	Non-sig.

172	11.8	68.9	-0.091	0.186	-0.06	-0.031	Non-sig.
173	19.7	68.9	-0.096	0.08	-0.039	-0.056	Non-sig.
174	27.6	68.9	-0.074	0.171	-0.043	-0.03	Non-sig.
175	35.5	68.9	-0.057	0.377	-0.047	-0.01	Non-sig.
176	43.4	68.9	-0.039	0.377	-0.052	0.013	Non-sig.
177	51.3	68.9	-0.041	0.412	-0.053	0.012	Non-sig.
178	59.2	68.9	-0.043	0.422	-0.053	0.01	Non-sig.
179	67.1	68.9	-0.095	0.467	-0.099	0.004	Non-sig.
180	75	68.9	-0.134	0.462	-0.133	0	Non-sig.
181	-75	75	0.047	0.246	0.016	0.031	Non-sig.
182	-67.1	75	0.026	0.266	0	0.026	Non-sig.
183	-59.2	75	-0.01	0.362	-0.03	0.02	Non-sig.
184	-51.3	75	-0.051	0.281	-0.078	0.027	Non-sig.
185	-43.4	75	-0.081	0.236	-0.112	0.03	Non-sig.
186	-35.5	75	-0.104	0.291	-0.127	0.023	Non-sig.
187	-27.6	75	-0.103	0.352	-0.118	0.014	Non-sig.
188	-19.7	75	-0.101	0.497	-0.104	0.002	Non-sig.
189	-11.8	75	-0.086	0.497	-0.088	0.003	Non-sig.
190	-3.9	75	-0.075	0.497	-0.077	0.002	Non-sig.
191	3.9	75	-0.072	0.352	-0.06	-0.013	Non-sig.
192	11.8	75	-0.081	0.196	-0.052	-0.028	Non-sig.
193	19.7	75	-0.093	0.106	-0.041	-0.052	Non-sig.
194	27.6	75	-0.076	0.201	-0.047	-0.029	Non-sig.
195	35.5	75	-0.062	0.372	-0.051	-0.011	Non-sig.
196	43.4	75	-0.043	0.412	-0.055	0.012	Non-sig.
197	51.3	75	-0.04	0.367	-0.054	0.014	Non-sig.
198	59.2	75	-0.036	0.372	-0.053	0.017	Non-sig.
199	67.1	75	-0.096	0.472	-0.099	0.003	Non-sig.
200	75	75	-0.14	0.402	-0.134	-0.006	Non-sig.

**(c) Toroidal shift null model**

cell	xx	yy	Codispersion	P.value	null_mean	diff	P.value.cat
1	-75	20	-0.029	0.402	-0.004	-0.026	Non-sig.
2	-67.1	20	-0.051	0.362	-0.003	-0.048	Non-sig.
3	-59.2	20	-0.087	0.201	-0.001	-0.086	Non-sig.
4	-51.3	20	-0.118	0.06	-0.002	-0.116	Non-sig.
5	-43.4	20	-0.142	0.04	-0.003	-0.14	Non-sig.
6	-35.5	20	-0.143	0.03	-0.005	-0.139	Non-sig.
7	-27.6	20	-0.126	0.05	-0.006	-0.12	Non-sig.
8	-19.7	20	-0.102	0.131	-0.007	-0.094	Non-sig.
9	-11.8	20	-0.091	0.136	-0.006	-0.085	Non-sig.
10	-3.9	20	-0.084	0.181	-0.005	-0.08	Non-sig.
11	3.9	20	-0.08	0.246	-0.003	-0.077	Non-sig.
12	11.8	20	-0.082	0.211	-0.002	-0.08	Non-sig.
13	19.7	20	-0.084	0.246	-0.001	-0.083	Non-sig.
14	27.6	20	-0.074	0.266	0	-0.074	Non-sig.
15	35.5	20	-0.067	0.276	0	-0.067	Non-sig.
16	43.4	20	-0.052	0.332	-0.002	-0.051	Non-sig.
17	51.3	20	-0.043	0.382	-0.003	-0.04	Non-sig.
18	59.2	20	-0.031	0.437	-0.006	-0.025	Non-sig.
19	67.1	20	-0.048	0.342	-0.003	-0.046	Non-sig.
20	75	20	-0.064	0.296	0	-0.064	Non-sig.
21	-75	26.1	-0.024	0.457	-0.006	-0.019	Non-sig.
22	-67.1	26.1	-0.031	0.407	-0.004	-0.028	Non-sig.

23	-59.2	26.1	-0.047	0.332	-0.001	-0.046	Non-sig.
24	-51.3	26.1	-0.077	0.171	-0.002	-0.075	Non-sig.
25	-43.4	26.1	-0.099	0.106	-0.003	-0.097	Non-sig.
26	-35.5	26.1	-0.122	0.045	-0.003	-0.119	Non-sig.
27	-27.6	26.1	-0.127	0.05	-0.003	-0.123	Non-sig.
28	-19.7	26.1	-0.131	0.08	-0.004	-0.127	Non-sig.
29	-11.8	26.1	-0.096	0.146	-0.004	-0.092	Non-sig.
30	-3.9	26.1	-0.072	0.246	-0.004	-0.069	Non-sig.
31	3.9	26.1	-0.055	0.317	-0.003	-0.053	Non-sig.
32	11.8	26.1	-0.059	0.307	-0.002	-0.058	Non-sig.
33	19.7	26.1	-0.065	0.291	0	-0.065	Non-sig.
34	27.6	26.1	-0.064	0.271	0	-0.064	Non-sig.
35	35.5	26.1	-0.064	0.261	0	-0.064	Non-sig.
36	43.4	26.1	-0.061	0.271	-0.002	-0.059	Non-sig.
37	51.3	26.1	-0.058	0.296	-0.003	-0.054	Non-sig.
38	59.2	26.1	-0.053	0.342	-0.005	-0.048	Non-sig.
39	67.1	26.1	-0.065	0.276	-0.004	-0.062	Non-sig.
40	75	26.1	-0.075	0.231	-0.002	-0.073	Non-sig.
41	-75	32.2	-0.021	0.457	-0.007	-0.014	Non-sig.
42	-67.1	32.2	-0.02	0.447	-0.004	-0.015	Non-sig.
43	-59.2	32.2	-0.023	0.442	-0.001	-0.022	Non-sig.
44	-51.3	32.2	-0.053	0.296	-0.002	-0.051	Non-sig.
45	-43.4	32.2	-0.075	0.171	-0.003	-0.072	Non-sig.
46	-35.5	32.2	-0.111	0.07	-0.003	-0.108	Non-sig.
47	-27.6	32.2	-0.127	0.04	-0.002	-0.125	Non-sig.
48	-19.7	32.2	-0.147	0.045	-0.002	-0.145	Non-sig.
49	-11.8	32.2	-0.098	0.146	-0.003	-0.095	Non-sig.
50	-3.9	32.2	-0.066	0.276	-0.003	-0.062	Non-sig.
51	3.9	32.2	-0.042	0.372	-0.003	-0.039	Non-sig.
52	11.8	32.2	-0.046	0.362	-0.001	-0.045	Non-sig.
53	19.7	32.2	-0.053	0.302	0.001	-0.054	Non-sig.
54	27.6	32.2	-0.058	0.276	0	-0.059	Non-sig.
55	35.5	32.2	-0.062	0.251	0	-0.062	Non-sig.
56	43.4	32.2	-0.066	0.256	-0.002	-0.065	Non-sig.
57	51.3	32.2	-0.067	0.236	-0.003	-0.063	Non-sig.
58	59.2	32.2	-0.067	0.286	-0.005	-0.062	Non-sig.
59	67.1	32.2	-0.076	0.216	-0.004	-0.071	Non-sig.
60	75	32.2	-0.082	0.196	-0.003	-0.078	Non-sig.
61	-75	38.3	-0.017	0.477	-0.009	-0.008	Non-sig.
62	-67.1	38.3	-0.003	0.482	-0.005	0.002	Non-sig.
63	-59.2	38.3	0.011	0.432	0	0.012	Non-sig.
64	-51.3	38.3	-0.02	0.432	-0.002	-0.018	Non-sig.
65	-43.4	38.3	-0.042	0.352	-0.003	-0.04	Non-sig.
66	-35.5	38.3	-0.096	0.111	-0.002	-0.094	Non-sig.
67	-27.6	38.3	-0.128	0.065	0	-0.127	Non-sig.
68	-19.7	38.3	-0.166	0.035	0.001	-0.168	Non-sig.
69	-11.8	38.3	-0.101	0.166	-0.001	-0.1	Non-sig.
70	-3.9	38.3	-0.057	0.302	-0.003	-0.055	Non-sig.
71	3.9	38.3	-0.023	0.427	-0.003	-0.02	Non-sig.
72	11.8	38.3	-0.028	0.417	-0.001	-0.027	Non-sig.
73	19.7	38.3	-0.036	0.342	0.001	-0.038	Non-sig.
74	27.6	38.3	-0.05	0.296	0	-0.05	Non-sig.
75	35.5	38.3	-0.059	0.271	0	-0.059	Non-sig.
76	43.4	38.3	-0.075	0.221	-0.002	-0.073	Non-sig.
77	51.3	38.3	-0.081	0.196	-0.003	-0.077	Non-sig.

78	59.2	38.3	-0.088	0.181	-0.005	-0.083	Non-sig.
79	67.1	38.3	-0.09	0.166	-0.005	-0.085	Non-sig.
80	75	38.3	-0.09	0.171	-0.005	-0.085	Non-sig.
81	-75	44.4	0.01	0.402	-0.008	0.018	Non-sig.
82	-67.1	44.4	0.018	0.392	-0.005	0.023	Non-sig.
83	-59.2	44.4	0.022	0.407	-0.001	0.023	Non-sig.
84	-51.3	44.4	-0.01	0.462	-0.002	-0.008	Non-sig.
85	-43.4	44.4	-0.033	0.372	-0.003	-0.031	Non-sig.
86	-35.5	44.4	-0.081	0.171	-0.001	-0.079	Non-sig.
87	-27.6	44.4	-0.107	0.101	0	-0.107	Non-sig.
88	-19.7	44.4	-0.139	0.065	0.002	-0.142	Non-sig.
89	-11.8	44.4	-0.096	0.161	-0.001	-0.095	Non-sig.
90	-3.9	44.4	-0.066	0.266	-0.003	-0.063	Non-sig.
91	3.9	44.4	-0.042	0.357	-0.003	-0.039	Non-sig.
92	11.8	44.4	-0.044	0.327	-0.002	-0.043	Non-sig.
93	19.7	44.4	-0.048	0.291	0.001	-0.049	Non-sig.
94	27.6	44.4	-0.052	0.286	0	-0.052	Non-sig.
95	35.5	44.4	-0.055	0.256	-0.001	-0.054	Non-sig.
96	43.4	44.4	-0.066	0.246	-0.002	-0.064	Non-sig.
97	51.3	44.4	-0.075	0.191	-0.003	-0.072	Non-sig.
98	59.2	44.4	-0.087	0.186	-0.005	-0.082	Non-sig.
99	67.1	44.4	-0.096	0.151	-0.005	-0.091	Non-sig.
100	75	44.4	-0.101	0.126	-0.005	-0.096	Non-sig.
101	-75	50.6	0.03	0.362	-0.007	0.037	Non-sig.
102	-67.1	50.6	0.027	0.397	-0.005	0.032	Non-sig.
103	-59.2	50.6	0.017	0.412	-0.002	0.019	Non-sig.
104	-51.3	50.6	-0.015	0.452	-0.003	-0.013	Non-sig.
105	-43.4	50.6	-0.039	0.337	-0.003	-0.036	Non-sig.
106	-35.5	50.6	-0.074	0.191	-0.001	-0.073	Non-sig.
107	-27.6	50.6	-0.09	0.146	0	-0.091	Non-sig.
108	-19.7	50.6	-0.111	0.106	0.002	-0.113	Non-sig.
109	-11.8	50.6	-0.09	0.166	-0.001	-0.089	Non-sig.
110	-3.9	50.6	-0.077	0.221	-0.003	-0.074	Non-sig.
111	3.9	50.6	-0.065	0.261	-0.004	-0.061	Non-sig.
112	11.8	50.6	-0.064	0.261	-0.002	-0.062	Non-sig.
113	19.7	50.6	-0.064	0.241	0	-0.064	Non-sig.
114	27.6	50.6	-0.057	0.276	0	-0.057	Non-sig.
115	35.5	50.6	-0.053	0.266	-0.001	-0.052	Non-sig.
116	43.4	50.6	-0.055	0.286	-0.002	-0.053	Non-sig.
117	51.3	50.6	-0.065	0.211	-0.003	-0.062	Non-sig.
118	59.2	50.6	-0.078	0.196	-0.005	-0.073	Non-sig.
119	67.1	50.6	-0.095	0.151	-0.004	-0.091	Non-sig.
120	75	50.6	-0.106	0.116	-0.003	-0.103	Non-sig.
121	-75	56.7	0.052	0.291	-0.006	0.058	Non-sig.
122	-67.1	56.7	0.038	0.372	-0.005	0.042	Non-sig.
123	-59.2	56.7	0.012	0.472	-0.003	0.015	Non-sig.
124	-51.3	56.7	-0.021	0.412	-0.003	-0.018	Non-sig.
125	-43.4	56.7	-0.045	0.302	-0.003	-0.042	Non-sig.
126	-35.5	56.7	-0.068	0.226	-0.001	-0.067	Non-sig.
127	-27.6	56.7	-0.072	0.216	0	-0.072	Non-sig.
128	-19.7	56.7	-0.078	0.216	0.002	-0.08	Non-sig.
129	-11.8	56.7	-0.084	0.176	-0.001	-0.083	Non-sig.
130	-3.9	56.7	-0.089	0.186	-0.004	-0.085	Non-sig.
131	3.9	56.7	-0.09	0.176	-0.004	-0.086	Non-sig.
132	11.8	56.7	-0.087	0.171	-0.003	-0.084	Non-sig.

133	19.7	56.7	-0.082	0.196	0	-0.082	Non-sig.
134	27.6	56.7	-0.064	0.226	-0.001	-0.063	Non-sig.
135	35.5	56.7	-0.05	0.281	-0.001	-0.049	Non-sig.
136	43.4	56.7	-0.044	0.332	-0.003	-0.041	Non-sig.
137	51.3	56.7	-0.054	0.276	-0.003	-0.051	Non-sig.
138	59.2	56.7	-0.068	0.231	-0.004	-0.063	Non-sig.
139	67.1	56.7	-0.094	0.166	-0.003	-0.091	Non-sig.
140	75	56.7	-0.113	0.111	-0.002	-0.111	Non-sig.
141	-75	62.8	0.066	0.251	-0.005	0.071	Non-sig.
142	-67.1	62.8	0.042	0.352	-0.005	0.047	Non-sig.
143	-59.2	62.8	0.002	0.487	-0.005	0.006	Non-sig.
144	-51.3	62.8	-0.034	0.367	-0.004	-0.03	Non-sig.
145	-43.4	62.8	-0.06	0.261	-0.003	-0.056	Non-sig.
146	-35.5	62.8	-0.073	0.216	-0.001	-0.072	Non-sig.
147	-27.6	62.8	-0.067	0.221	0.001	-0.068	Non-sig.
148	-19.7	62.8	-0.06	0.261	0.003	-0.064	Non-sig.
149	-11.8	62.8	-0.08	0.176	0	-0.08	Non-sig.
150	-3.9	62.8	-0.094	0.166	-0.003	-0.091	Non-sig.
151	3.9	62.8	-0.104	0.126	-0.004	-0.1	Non-sig.
152	11.8	62.8	-0.102	0.131	-0.003	-0.099	Non-sig.
153	19.7	62.8	-0.098	0.151	-0.002	-0.097	Non-sig.
154	27.6	62.8	-0.072	0.211	-0.002	-0.069	Non-sig.
155	35.5	62.8	-0.052	0.296	-0.003	-0.049	Non-sig.
156	43.4	62.8	-0.035	0.362	-0.003	-0.032	Non-sig.
157	51.3	62.8	-0.042	0.347	-0.004	-0.038	Non-sig.
158	59.2	62.8	-0.051	0.281	-0.004	-0.047	Non-sig.
159	67.1	62.8	-0.094	0.186	-0.002	-0.093	Non-sig.
160	75	62.8	-0.126	0.101	0	-0.126	Non-sig.
161	-75	68.9	0.056	0.291	-0.005	0.061	Non-sig.
162	-67.1	68.9	0.034	0.372	-0.005	0.039	Non-sig.
163	-59.2	68.9	-0.004	0.492	-0.005	0.001	Non-sig.
164	-51.3	68.9	-0.043	0.327	-0.005	-0.038	Non-sig.
165	-43.4	68.9	-0.071	0.231	-0.004	-0.067	Non-sig.
166	-35.5	68.9	-0.089	0.136	-0.001	-0.088	Non-sig.
167	-27.6	68.9	-0.086	0.126	0.002	-0.088	Non-sig.
168	-19.7	68.9	-0.082	0.156	0.005	-0.087	Non-sig.
169	-11.8	68.9	-0.083	0.156	0.001	-0.084	Non-sig.
170	-3.9	68.9	-0.084	0.186	-0.001	-0.083	Non-sig.
171	3.9	68.9	-0.088	0.186	-0.003	-0.084	Non-sig.
172	11.8	68.9	-0.091	0.171	-0.003	-0.088	Non-sig.
173	19.7	68.9	-0.096	0.156	-0.003	-0.093	Non-sig.
174	27.6	68.9	-0.074	0.216	-0.003	-0.07	Non-sig.
175	35.5	68.9	-0.057	0.286	-0.004	-0.053	Non-sig.
176	43.4	68.9	-0.039	0.377	-0.004	-0.035	Non-sig.
177	51.3	68.9	-0.041	0.357	-0.004	-0.037	Non-sig.
178	59.2	68.9	-0.043	0.332	-0.003	-0.039	Non-sig.
179	67.1	68.9	-0.095	0.171	-0.001	-0.094	Non-sig.
180	75	68.9	-0.134	0.101	0	-0.134	Non-sig.
181	-75	75	0.047	0.312	-0.005	0.052	Non-sig.
182	-67.1	75	0.026	0.367	-0.005	0.032	Non-sig.
183	-59.2	75	-0.01	0.492	-0.006	-0.004	Non-sig.
184	-51.3	75	-0.051	0.327	-0.005	-0.046	Non-sig.
185	-43.4	75	-0.081	0.201	-0.005	-0.076	Non-sig.
186	-35.5	75	-0.104	0.106	-0.001	-0.103	Non-sig.
187	-27.6	75	-0.103	0.09	0.002	-0.106	Non-sig.

188	-19.7	75	-0.101	0.095	0.006	-0.108	Non-sig.
189	-11.8	75	-0.086	0.131	0.003	-0.088	Non-sig.
190	-3.9	75	-0.075	0.221	0	-0.075	Non-sig.
191	3.9	75	-0.072	0.236	-0.003	-0.07	Non-sig.
192	11.8	75	-0.081	0.196	-0.003	-0.078	Non-sig.
193	19.7	75	-0.093	0.161	-0.004	-0.089	Non-sig.
194	27.6	75	-0.076	0.226	-0.005	-0.071	Non-sig.
195	35.5	75	-0.062	0.302	-0.005	-0.057	Non-sig.
196	43.4	75	-0.043	0.377	-0.005	-0.038	Non-sig.
197	51.3	75	-0.04	0.372	-0.004	-0.036	Non-sig.
198	59.2	75	-0.036	0.367	-0.003	-0.033	Non-sig.
199	67.1	75	-0.096	0.181	-0.001	-0.095	Non-sig.
200	75	75	-0.14	0.106	0.001	-0.141	Non-sig.

Table S4.2: Cell-level results for codispersion analysis of species-environmental relationship for tree distribution generated by a CSR process under the (a) CSR, (b) random labelling and (c) toroidal shift null models.

(a) CSR null model							
cell	xx	yy	Codispersion	P.value	null_mean	diff	P.value.cat
1	-75	20	-0.064	0.186	0.004	-0.068	Non-sig.
2	-67.1	20	-0.089	0.126	0.002	-0.092	Non-sig.
3	-59.2	20	-0.117	0.085	0	-0.118	Non-sig.
4	-51.3	20	-0.073	0.131	0.001	-0.074	Non-sig.
5	-43.4	20	-0.043	0.271	0.001	-0.044	Non-sig.
6	-35.5	20	-0.022	0.377	0.002	-0.024	Non-sig.
7	-27.6	20	-0.022	0.417	0.003	-0.025	Non-sig.
8	-19.7	20	-0.025	0.402	0.004	-0.029	Non-sig.
9	-11.8	20	-0.074	0.141	0.003	-0.077	Non-sig.
10	-3.9	20	-0.107	0.07	0.002	-0.109	Non-sig.
11	3.9	20	-0.135	0.025	0.001	-0.136	Non-sig.
12	11.8	20	-0.134	0.03	0	-0.133	Non-sig.
13	19.7	20	-0.132	0.06	-0.002	-0.13	Non-sig.
14	27.6	20	-0.094	0.085	0.002	-0.096	Non-sig.
15	35.5	20	-0.066	0.186	0.005	-0.07	Non-sig.
16	43.4	20	-0.04	0.286	0.007	-0.046	Non-sig.
17	51.3	20	-0.047	0.246	0.005	-0.053	Non-sig.
18	59.2	20	-0.057	0.246	0.004	-0.061	Non-sig.
19	67.1	20	-0.069	0.206	0.004	-0.073	Non-sig.
20	75	20	-0.077	0.191	0.004	-0.081	Non-sig.
21	-75	26.1	-0.083	0.141	0.003	-0.085	Non-sig.
22	-67.1	26.1	-0.093	0.085	0.002	-0.095	Non-sig.
23	-59.2	26.1	-0.1	0.07	0	-0.1	Non-sig.
24	-51.3	26.1	-0.063	0.151	0	-0.063	Non-sig.
25	-43.4	26.1	-0.038	0.312	0	-0.037	Non-sig.
26	-35.5	26.1	-0.035	0.312	0	-0.035	Non-sig.
27	-27.6	26.1	-0.05	0.216	0	-0.05	Non-sig.
28	-19.7	26.1	-0.07	0.166	0.001	-0.071	Non-sig.
29	-11.8	26.1	-0.072	0.136	0.002	-0.074	Non-sig.

30	-3.9	26.1	-0.073	0.131	0.003	-0.076	Non-sig.
31	3.9	26.1	-0.088	0.08	0.003	-0.091	Non-sig.
32	11.8	26.1	-0.104	0.065	0.001	-0.106	Non-sig.
33	19.7	26.1	-0.128	0.055	-0.001	-0.127	Non-sig.
34	27.6	26.1	-0.097	0.101	0.002	-0.099	Non-sig.
35	35.5	26.1	-0.072	0.151	0.003	-0.075	Non-sig.
36	43.4	26.1	-0.047	0.241	0.005	-0.052	Non-sig.
37	51.3	26.1	-0.052	0.216	0.005	-0.057	Non-sig.
38	59.2	26.1	-0.058	0.186	0.005	-0.063	Non-sig.
39	67.1	26.1	-0.076	0.156	0.004	-0.081	Non-sig.
40	75	26.1	-0.089	0.116	0.003	-0.093	Non-sig.
41	-75	32.2	-0.094	0.09	0.002	-0.096	Non-sig.
42	-67.1	32.2	-0.095	0.07	0.001	-0.096	Non-sig.
43	-59.2	32.2	-0.09	0.085	0	-0.09	Non-sig.
44	-51.3	32.2	-0.058	0.166	-0.001	-0.057	Non-sig.
45	-43.4	32.2	-0.034	0.317	-0.001	-0.033	Non-sig.
46	-35.5	32.2	-0.044	0.261	-0.001	-0.042	Non-sig.
47	-27.6	32.2	-0.068	0.156	-0.001	-0.067	Non-sig.
48	-19.7	32.2	-0.098	0.07	-0.001	-0.097	Non-sig.
49	-11.8	32.2	-0.07	0.156	0.002	-0.072	Non-sig.
50	-3.9	32.2	-0.051	0.221	0.003	-0.054	Non-sig.
51	3.9	32.2	-0.059	0.181	0.004	-0.062	Non-sig.
52	11.8	32.2	-0.086	0.121	0.002	-0.088	Non-sig.
53	19.7	32.2	-0.125	0.055	0	-0.126	Non-sig.
54	27.6	32.2	-0.099	0.085	0.002	-0.1	Non-sig.
55	35.5	32.2	-0.076	0.131	0.002	-0.078	Non-sig.
56	43.4	32.2	-0.052	0.231	0.004	-0.056	Non-sig.
57	51.3	32.2	-0.055	0.216	0.005	-0.06	Non-sig.
58	59.2	32.2	-0.059	0.186	0.005	-0.064	Non-sig.
59	67.1	32.2	-0.081	0.126	0.004	-0.085	Non-sig.
60	75	32.2	-0.097	0.085	0.003	-0.1	Non-sig.
61	-75	38.3	-0.11	0.07	0.001	-0.111	Non-sig.
62	-67.1	38.3	-0.098	0.08	0	-0.099	Non-sig.
63	-59.2	38.3	-0.077	0.136	0	-0.077	Non-sig.
64	-51.3	38.3	-0.05	0.221	-0.002	-0.048	Non-sig.
65	-43.4	38.3	-0.03	0.347	-0.003	-0.028	Non-sig.
66	-35.5	38.3	-0.056	0.231	-0.003	-0.053	Non-sig.
67	-27.6	38.3	-0.093	0.111	-0.004	-0.09	Non-sig.
68	-19.7	38.3	-0.138	0.03	-0.003	-0.135	Non-sig.
69	-11.8	38.3	-0.068	0.201	0.001	-0.069	Non-sig.
70	-3.9	38.3	-0.019	0.407	0.004	-0.023	Non-sig.
71	3.9	38.3	-0.016	0.412	0.005	-0.021	Non-sig.
72	11.8	38.3	-0.06	0.201	0.004	-0.064	Non-sig.
73	19.7	38.3	-0.122	0.065	0.001	-0.123	Non-sig.
74	27.6	38.3	-0.101	0.09	0.001	-0.102	Non-sig.
75	35.5	38.3	-0.082	0.141	0.001	-0.083	Non-sig.
76	43.4	38.3	-0.059	0.236	0.003	-0.062	Non-sig.
77	51.3	38.3	-0.059	0.201	0.004	-0.064	Non-sig.
78	59.2	38.3	-0.06	0.206	0.006	-0.066	Non-sig.
79	67.1	38.3	-0.087	0.121	0.004	-0.091	Non-sig.
80	75	38.3	-0.107	0.095	0.003	-0.11	Non-sig.
81	-75	44.4	-0.086	0.131	-0.001	-0.086	Non-sig.
82	-67.1	44.4	-0.076	0.156	-0.001	-0.075	Non-sig.
83	-59.2	44.4	-0.058	0.221	-0.001	-0.056	Non-sig.
84	-51.3	44.4	-0.037	0.307	-0.001	-0.036	Non-sig.



85	-43.4	44.4	-0.022	0.392	-0.001	-0.021	Non-sig.
86	-35.5	44.4	-0.045	0.286	-0.002	-0.043	Non-sig.
87	-27.6	44.4	-0.076	0.136	-0.002	-0.074	Non-sig.
88	-19.7	44.4	-0.116	0.065	-0.003	-0.113	Non-sig.
89	-11.8	44.4	-0.055	0.236	0.001	-0.055	Non-sig.
90	-3.9	44.4	-0.013	0.417	0.003	-0.016	Non-sig.
91	3.9	44.4	-0.01	0.432	0.005	-0.015	Non-sig.
92	11.8	44.4	-0.047	0.256	0.004	-0.051	Non-sig.
93	19.7	44.4	-0.097	0.095	0.003	-0.1	Non-sig.
94	27.6	44.4	-0.081	0.131	0.003	-0.083	Non-sig.
95	35.5	44.4	-0.065	0.211	0.003	-0.068	Non-sig.
96	43.4	44.4	-0.043	0.337	0.003	-0.046	Non-sig.
97	51.3	44.4	-0.039	0.347	0.004	-0.043	Non-sig.
98	59.2	44.4	-0.034	0.337	0.004	-0.038	Non-sig.
99	67.1	44.4	-0.059	0.196	0.003	-0.062	Non-sig.
100	75	44.4	-0.079	0.156	0.002	-0.081	Non-sig.
101	-75	50.6	-0.061	0.206	-0.001	-0.06	Non-sig.
102	-67.1	50.6	-0.056	0.251	-0.001	-0.055	Non-sig.
103	-59.2	50.6	-0.046	0.281	-0.002	-0.045	Non-sig.
104	-51.3	50.6	-0.03	0.387	0	-0.029	Non-sig.
105	-43.4	50.6	-0.018	0.437	0.001	-0.018	Non-sig.
106	-35.5	50.6	-0.03	0.357	0.001	-0.031	Non-sig.
107	-27.6	50.6	-0.051	0.236	0	-0.051	Non-sig.
108	-19.7	50.6	-0.079	0.131	-0.001	-0.078	Non-sig.
109	-11.8	50.6	-0.045	0.281	0.001	-0.046	Non-sig.
110	-3.9	50.6	-0.022	0.382	0.003	-0.025	Non-sig.
111	3.9	50.6	-0.023	0.387	0.004	-0.028	Non-sig.
112	11.8	50.6	-0.047	0.286	0.004	-0.051	Non-sig.
113	19.7	50.6	-0.079	0.181	0.004	-0.083	Non-sig.
114	27.6	50.6	-0.063	0.196	0.004	-0.067	Non-sig.
115	35.5	50.6	-0.05	0.251	0.004	-0.054	Non-sig.
116	43.4	50.6	-0.028	0.372	0.004	-0.032	Non-sig.
117	51.3	50.6	-0.021	0.412	0.003	-0.024	Non-sig.
118	59.2	50.6	-0.012	0.432	0.003	-0.015	Non-sig.
119	67.1	50.6	-0.034	0.332	0.002	-0.036	Non-sig.
120	75	50.6	-0.052	0.216	0.002	-0.054	Non-sig.
121	-75	56.7	-0.033	0.377	-0.002	-0.031	Non-sig.
122	-67.1	56.7	-0.034	0.402	-0.002	-0.032	Non-sig.
123	-59.2	56.7	-0.034	0.372	-0.002	-0.032	Non-sig.
124	-51.3	56.7	-0.021	0.437	0.001	-0.022	Non-sig.
125	-43.4	56.7	-0.013	0.452	0.003	-0.015	Non-sig.
126	-35.5	56.7	-0.015	0.437	0.003	-0.018	Non-sig.
127	-27.6	56.7	-0.023	0.392	0.002	-0.025	Non-sig.
128	-19.7	56.7	-0.036	0.337	0.001	-0.036	Non-sig.
129	-11.8	56.7	-0.033	0.327	0.002	-0.035	Non-sig.
130	-3.9	56.7	-0.031	0.342	0.002	-0.034	Non-sig.
131	3.9	56.7	-0.038	0.322	0.004	-0.042	Non-sig.
132	11.8	56.7	-0.046	0.286	0.004	-0.051	Non-sig.
133	19.7	56.7	-0.058	0.251	0.005	-0.063	Non-sig.
134	27.6	56.7	-0.045	0.276	0.005	-0.05	Non-sig.
135	35.5	56.7	-0.033	0.322	0.006	-0.039	Non-sig.
136	43.4	56.7	-0.012	0.442	0.005	-0.017	Non-sig.
137	51.3	56.7	-0.001	0.477	0.003	-0.004	Non-sig.
138	59.2	56.7	0.013	0.442	0.001	0.012	Non-sig.
139	67.1	56.7	-0.005	0.472	0.001	-0.006	Non-sig.

140	75	56.7	-0.021	0.382	0.001	-0.023	Non-sig.
141	-75	62.8	-0.008	0.482	-0.001	-0.007	Non-sig.
142	-67.1	62.8	-0.01	0.487	-0.001	-0.009	Non-sig.
143	-59.2	62.8	-0.012	0.467	-0.001	-0.011	Non-sig.
144	-51.3	62.8	-0.011	0.457	0.003	-0.014	Non-sig.
145	-43.4	62.8	-0.01	0.447	0.006	-0.016	Non-sig.
146	-35.5	62.8	-0.014	0.427	0.006	-0.02	Non-sig.
147	-27.6	62.8	-0.017	0.407	0.005	-0.022	Non-sig.
148	-19.7	62.8	-0.024	0.392	0.003	-0.027	Non-sig.
149	-11.8	62.8	-0.044	0.256	0.003	-0.047	Non-sig.
150	-3.9	62.8	-0.057	0.216	0.003	-0.059	Non-sig.
151	3.9	62.8	-0.064	0.191	0.003	-0.067	Non-sig.
152	11.8	62.8	-0.06	0.216	0.004	-0.064	Non-sig.
153	19.7	62.8	-0.054	0.251	0.006	-0.06	Non-sig.
154	27.6	62.8	-0.04	0.302	0.007	-0.047	Non-sig.
155	35.5	62.8	-0.03	0.347	0.007	-0.038	Non-sig.
156	43.4	62.8	-0.011	0.422	0.006	-0.018	Non-sig.
157	51.3	62.8	-0.003	0.447	0.004	-0.006	Non-sig.
158	59.2	62.8	0.008	0.477	0	0.008	Non-sig.
159	67.1	62.8	-0.001	0.452	0.002	-0.002	Non-sig.
160	75	62.8	-0.009	0.417	0.003	-0.012	Non-sig.
161	-75	68.9	-0.014	0.447	0.001	-0.015	Non-sig.
162	-67.1	68.9	-0.008	0.462	0.001	-0.009	Non-sig.
163	-59.2	68.9	-0.002	0.457	0.002	-0.003	Non-sig.
164	-51.3	68.9	-0.009	0.432	0.005	-0.013	Non-sig.
165	-43.4	68.9	-0.013	0.397	0.007	-0.02	Non-sig.
166	-35.5	68.9	-0.032	0.307	0.007	-0.038	Non-sig.
167	-27.6	68.9	-0.046	0.246	0.005	-0.051	Non-sig.
168	-19.7	68.9	-0.065	0.186	0.003	-0.068	Non-sig.
169	-11.8	68.9	-0.071	0.141	0.003	-0.074	Non-sig.
170	-3.9	68.9	-0.075	0.126	0.003	-0.078	Non-sig.
171	3.9	68.9	-0.078	0.151	0.004	-0.082	Non-sig.
172	11.8	68.9	-0.077	0.151	0.004	-0.082	Non-sig.
173	19.7	68.9	-0.076	0.196	0.005	-0.082	Non-sig.
174	27.6	68.9	-0.06	0.191	0.006	-0.066	Non-sig.
175	35.5	68.9	-0.047	0.236	0.007	-0.054	Non-sig.
176	43.4	68.9	-0.032	0.312	0.007	-0.039	Non-sig.
177	51.3	68.9	-0.031	0.312	0.005	-0.036	Non-sig.
178	59.2	68.9	-0.03	0.317	0.003	-0.033	Non-sig.
179	67.1	68.9	-0.033	0.302	0.004	-0.037	Non-sig.
180	75	68.9	-0.035	0.307	0.005	-0.041	Non-sig.
181	-75	75	-0.02	0.397	0.002	-0.022	Non-sig.
182	-67.1	75	-0.007	0.457	0.003	-0.01	Non-sig.
183	-59.2	75	0.007	0.467	0.004	0.003	Non-sig.
184	-51.3	75	-0.007	0.437	0.006	-0.013	Non-sig.
185	-43.4	75	-0.016	0.387	0.008	-0.024	Non-sig.
186	-35.5	75	-0.048	0.241	0.007	-0.054	Non-sig.
187	-27.6	75	-0.069	0.141	0.005	-0.074	Non-sig.
188	-19.7	75	-0.097	0.075	0.003	-0.1	Non-sig.
189	-11.8	75	-0.094	0.08	0.003	-0.097	Non-sig.
190	-3.9	75	-0.091	0.106	0.004	-0.095	Non-sig.
191	3.9	75	-0.091	0.116	0.004	-0.095	Non-sig.
192	11.8	75	-0.093	0.08	0.005	-0.098	Non-sig.
193	19.7	75	-0.096	0.111	0.005	-0.101	Non-sig.
194	27.6	75	-0.077	0.146	0.006	-0.083	Non-sig.

195	35.5	75	-0.063	0.176	0.007	-0.069	Non-sig.
196	43.4	75	-0.051	0.216	0.007	-0.058	Non-sig.
197	51.3	75	-0.058	0.196	0.006	-0.063	Non-sig.
198	59.2	75	-0.066	0.186	0.004	-0.071	Non-sig.
199	67.1	75	-0.062	0.191	0.006	-0.069	Non-sig.
200	75	75	-0.058	0.221	0.008	-0.066	Non-sig.
<b>(b) Random labelling null model</b>							
<b>cell</b>	<b>xx</b>	<b>yy</b>	<b>Codispersion</b>	<b>P.value</b>	<b>null_mean</b>	<b>diff</b>	<b>P.value.cat</b>
1	-75	20	-0.064	0.482	-0.07	0.006	Non-sig.
2	-67.1	20	-0.089	0.347	-0.067	-0.022	Non-sig.
3	-59.2	20	-0.117	0.211	-0.063	-0.054	Non-sig.
4	-51.3	20	-0.073	0.407	-0.061	-0.012	Non-sig.
5	-43.4	20	-0.043	0.397	-0.06	0.017	Non-sig.
6	-35.5	20	-0.022	0.186	-0.072	0.05	Non-sig.
7	-27.6	20	-0.022	0.141	-0.084	0.062	Non-sig.
8	-19.7	20	-0.025	0.146	-0.101	0.076	Non-sig.
9	-11.8	20	-0.074	0.256	-0.112	0.038	Non-sig.
10	-3.9	20	-0.107	0.412	-0.12	0.013	Non-sig.
11	3.9	20	-0.135	0.432	-0.123	-0.012	Non-sig.
12	11.8	20	-0.134	0.432	-0.119	-0.015	Non-sig.
13	19.7	20	-0.132	0.372	-0.113	-0.019	Non-sig.
14	27.6	20	-0.094	0.467	-0.099	0.005	Non-sig.
15	35.5	20	-0.066	0.357	-0.089	0.023	Non-sig.
16	43.4	20	-0.04	0.181	-0.09	0.05	Non-sig.
17	51.3	20	-0.047	0.181	-0.106	0.058	Non-sig.
18	59.2	20	-0.057	0.176	-0.127	0.07	Non-sig.
19	67.1	20	-0.069	0.201	-0.13	0.061	Non-sig.
20	75	20	-0.077	0.241	-0.129	0.052	Non-sig.
21	-75	26.1	-0.083	0.437	-0.078	-0.005	Non-sig.
22	-67.1	26.1	-0.093	0.372	-0.077	-0.016	Non-sig.
23	-59.2	26.1	-0.1	0.307	-0.072	-0.028	Non-sig.
24	-51.3	26.1	-0.063	0.447	-0.056	-0.007	Non-sig.
25	-43.4	26.1	-0.038	0.457	-0.045	0.008	Non-sig.
26	-35.5	26.1	-0.035	0.372	-0.055	0.02	Non-sig.
27	-27.6	26.1	-0.05	0.342	-0.072	0.021	Non-sig.
28	-19.7	26.1	-0.07	0.337	-0.094	0.024	Non-sig.
29	-11.8	26.1	-0.072	0.357	-0.091	0.019	Non-sig.
30	-3.9	26.1	-0.073	0.372	-0.089	0.016	Non-sig.
31	3.9	26.1	-0.088	0.462	-0.091	0.003	Non-sig.
32	11.8	26.1	-0.104	0.447	-0.096	-0.008	Non-sig.
33	19.7	26.1	-0.128	0.337	-0.102	-0.026	Non-sig.
34	27.6	26.1	-0.097	0.487	-0.094	-0.003	Non-sig.
35	35.5	26.1	-0.072	0.392	-0.087	0.015	Non-sig.
36	43.4	26.1	-0.047	0.281	-0.086	0.039	Non-sig.
37	51.3	26.1	-0.052	0.271	-0.093	0.041	Non-sig.
38	59.2	26.1	-0.058	0.281	-0.103	0.045	Non-sig.
39	67.1	26.1	-0.076	0.332	-0.108	0.031	Non-sig.
40	75	26.1	-0.089	0.377	-0.11	0.021	Non-sig.
41	-75	32.2	-0.094	0.432	-0.083	-0.011	Non-sig.
42	-67.1	32.2	-0.095	0.397	-0.082	-0.013	Non-sig.
43	-59.2	32.2	-0.09	0.407	-0.077	-0.014	Non-sig.
44	-51.3	32.2	-0.058	0.497	-0.053	-0.004	Non-sig.
45	-43.4	32.2	-0.034	0.472	-0.037	0.002	Non-sig.

46	-35.5	32.2	-0.044	0.482	-0.045	0.001	Non-sig.
47	-27.6	32.2	-0.068	0.492	-0.064	-0.004	Non-sig.
48	-19.7	32.2	-0.098	0.467	-0.089	-0.009	Non-sig.
49	-11.8	32.2	-0.07	0.417	-0.078	0.008	Non-sig.
50	-3.9	32.2	-0.051	0.322	-0.07	0.019	Non-sig.
51	3.9	32.2	-0.059	0.367	-0.072	0.013	Non-sig.
52	11.8	32.2	-0.086	0.497	-0.082	-0.004	Non-sig.
53	19.7	32.2	-0.125	0.337	-0.096	-0.03	Non-sig.
54	27.6	32.2	-0.099	0.487	-0.091	-0.008	Non-sig.
55	35.5	32.2	-0.076	0.407	-0.087	0.011	Non-sig.
56	43.4	32.2	-0.052	0.317	-0.084	0.032	Non-sig.
57	51.3	32.2	-0.055	0.322	-0.086	0.031	Non-sig.
58	59.2	32.2	-0.059	0.337	-0.089	0.03	Non-sig.
59	67.1	32.2	-0.081	0.427	-0.095	0.014	Non-sig.
60	75	32.2	-0.097	0.472	-0.099	0.002	Non-sig.
61	-75	38.3	-0.11	0.377	-0.089	-0.021	Non-sig.
62	-67.1	38.3	-0.098	0.447	-0.09	-0.009	Non-sig.
63	-59.2	38.3	-0.077	0.407	-0.084	0.006	Non-sig.
64	-51.3	38.3	-0.05	0.472	-0.049	-0.001	Non-sig.
65	-43.4	38.3	-0.03	0.487	-0.025	-0.005	Non-sig.
66	-35.5	38.3	-0.056	0.377	-0.031	-0.025	Non-sig.
67	-27.6	38.3	-0.093	0.266	-0.054	-0.039	Non-sig.
68	-19.7	38.3	-0.138	0.191	-0.083	-0.055	Non-sig.
69	-11.8	38.3	-0.068	0.467	-0.06	-0.008	Non-sig.
70	-3.9	38.3	-0.019	0.312	-0.043	0.025	Non-sig.
71	3.9	38.3	-0.016	0.307	-0.045	0.029	Non-sig.
72	11.8	38.3	-0.06	0.467	-0.062	0.002	Non-sig.
73	19.7	38.3	-0.122	0.322	-0.086	-0.036	Non-sig.
74	27.6	38.3	-0.101	0.447	-0.087	-0.015	Non-sig.
75	35.5	38.3	-0.082	0.452	-0.086	0.004	Non-sig.
76	43.4	38.3	-0.059	0.377	-0.081	0.022	Non-sig.
77	51.3	38.3	-0.059	0.392	-0.076	0.016	Non-sig.
78	59.2	38.3	-0.06	0.417	-0.07	0.009	Non-sig.
79	67.1	38.3	-0.087	0.482	-0.077	-0.01	Non-sig.
80	75	38.3	-0.107	0.412	-0.083	-0.024	Non-sig.
81	-75	44.4	-0.086	0.427	-0.072	-0.014	Non-sig.
82	-67.1	44.4	-0.076	0.462	-0.069	-0.006	Non-sig.
83	-59.2	44.4	-0.058	0.452	-0.061	0.003	Non-sig.
84	-51.3	44.4	-0.037	0.452	-0.038	0.001	Non-sig.
85	-43.4	44.4	-0.022	0.462	-0.022	0	Non-sig.
86	-35.5	44.4	-0.045	0.457	-0.029	-0.016	Non-sig.
87	-27.6	44.4	-0.076	0.312	-0.046	-0.03	Non-sig.
88	-19.7	44.4	-0.116	0.221	-0.07	-0.046	Non-sig.
89	-11.8	44.4	-0.055	0.462	-0.055	0	Non-sig.
90	-3.9	44.4	-0.013	0.296	-0.044	0.031	Non-sig.
91	3.9	44.4	-0.01	0.276	-0.048	0.038	Non-sig.
92	11.8	44.4	-0.047	0.382	-0.063	0.016	Non-sig.
93	19.7	44.4	-0.097	0.447	-0.083	-0.014	Non-sig.
94	27.6	44.4	-0.081	0.427	-0.085	0.004	Non-sig.
95	35.5	44.4	-0.065	0.377	-0.085	0.02	Non-sig.
96	43.4	44.4	-0.043	0.312	-0.073	0.03	Non-sig.
97	51.3	44.4	-0.039	0.392	-0.057	0.018	Non-sig.
98	59.2	44.4	-0.034	0.477	-0.036	0.003	Non-sig.
99	67.1	44.4	-0.059	0.442	-0.045	-0.014	Non-sig.
100	75	44.4	-0.079	0.387	-0.055	-0.025	Non-sig.

101	-75	50.6	-0.061	0.457	-0.056	-0.005	Non-sig.
102	-67.1	50.6	-0.056	0.442	-0.05	-0.006	Non-sig.
103	-59.2	50.6	-0.046	0.452	-0.04	-0.006	Non-sig.
104	-51.3	50.6	-0.03	0.487	-0.031	0.001	Non-sig.
105	-43.4	50.6	-0.018	0.427	-0.024	0.007	Non-sig.
106	-35.5	50.6	-0.03	0.442	-0.032	0.002	Non-sig.
107	-27.6	50.6	-0.051	0.492	-0.044	-0.007	Non-sig.
108	-19.7	50.6	-0.079	0.397	-0.062	-0.018	Non-sig.
109	-11.8	50.6	-0.045	0.367	-0.059	0.014	Non-sig.
110	-3.9	50.6	-0.022	0.276	-0.056	0.035	Non-sig.
111	3.9	50.6	-0.023	0.251	-0.063	0.039	Non-sig.
112	11.8	50.6	-0.047	0.347	-0.072	0.025	Non-sig.
113	19.7	50.6	-0.079	0.452	-0.085	0.006	Non-sig.
114	27.6	50.6	-0.063	0.362	-0.085	0.022	Non-sig.
115	35.5	50.6	-0.05	0.291	-0.085	0.035	Non-sig.
116	43.4	50.6	-0.028	0.291	-0.068	0.04	Non-sig.
117	51.3	50.6	-0.021	0.342	-0.046	0.025	Non-sig.
118	59.2	50.6	-0.012	0.457	-0.017	0.005	Non-sig.
119	67.1	50.6	-0.034	0.477	-0.027	-0.007	Non-sig.
120	75	50.6	-0.052	0.432	-0.038	-0.014	Non-sig.
121	-75	56.7	-0.033	0.482	-0.037	0.005	Non-sig.
122	-67.1	56.7	-0.034	0.442	-0.028	-0.006	Non-sig.
123	-59.2	56.7	-0.034	0.382	-0.017	-0.016	Non-sig.
124	-51.3	56.7	-0.021	0.487	-0.023	0.001	Non-sig.
125	-43.4	56.7	-0.013	0.407	-0.026	0.014	Non-sig.
126	-35.5	56.7	-0.015	0.362	-0.036	0.021	Non-sig.
127	-27.6	56.7	-0.023	0.367	-0.042	0.019	Non-sig.
128	-19.7	56.7	-0.036	0.392	-0.052	0.017	Non-sig.
129	-11.8	56.7	-0.033	0.307	-0.063	0.03	Non-sig.
130	-3.9	56.7	-0.031	0.276	-0.07	0.039	Non-sig.
131	3.9	56.7	-0.038	0.246	-0.079	0.041	Non-sig.
132	11.8	56.7	-0.046	0.271	-0.082	0.035	Non-sig.
133	19.7	56.7	-0.058	0.337	-0.086	0.028	Non-sig.
134	27.6	56.7	-0.045	0.291	-0.086	0.041	Non-sig.
135	35.5	56.7	-0.033	0.251	-0.085	0.052	Non-sig.
136	43.4	56.7	-0.012	0.266	-0.062	0.051	Non-sig.
137	51.3	56.7	-0.001	0.322	-0.034	0.033	Non-sig.
138	59.2	56.7	0.013	0.447	0.005	0.008	Non-sig.
139	67.1	56.7	-0.005	0.492	-0.005	0	Non-sig.
140	75	56.7	-0.021	0.477	-0.019	-0.003	Non-sig.
141	-75	62.8	-0.008	0.452	-0.018	0.01	Non-sig.
142	-67.1	62.8	-0.01	0.477	-0.01	0	Non-sig.
143	-59.2	62.8	-0.012	0.452	-0.004	-0.008	Non-sig.
144	-51.3	62.8	-0.011	0.397	-0.026	0.015	Non-sig.
145	-43.4	62.8	-0.01	0.302	-0.041	0.031	Non-sig.
146	-35.5	62.8	-0.014	0.266	-0.054	0.041	Non-sig.
147	-27.6	62.8	-0.017	0.296	-0.055	0.038	Non-sig.
148	-19.7	62.8	-0.024	0.312	-0.058	0.034	Non-sig.
149	-11.8	62.8	-0.044	0.302	-0.074	0.03	Non-sig.
150	-3.9	62.8	-0.057	0.342	-0.084	0.028	Non-sig.
151	3.9	62.8	-0.064	0.312	-0.095	0.031	Non-sig.
152	11.8	62.8	-0.06	0.276	-0.096	0.037	Non-sig.
153	19.7	62.8	-0.054	0.266	-0.099	0.044	Non-sig.
154	27.6	62.8	-0.04	0.201	-0.096	0.056	Non-sig.
155	35.5	62.8	-0.03	0.191	-0.094	0.064	Non-sig.

156	43.4	62.8	-0.011	0.236	-0.068	0.057	Non-sig.
157	51.3	62.8	-0.003	0.291	-0.038	0.035	Non-sig.
158	59.2	62.8	0.008	0.452	0.003	0.005	Non-sig.
159	67.1	62.8	-0.001	0.457	-0.005	0.004	Non-sig.
160	75	62.8	-0.009	0.442	-0.017	0.008	Non-sig.
161	-75	68.9	-0.014	0.477	-0.018	0.004	Non-sig.
162	-67.1	68.9	-0.008	0.457	-0.016	0.007	Non-sig.
163	-59.2	68.9	-0.002	0.432	-0.017	0.015	Non-sig.
164	-51.3	68.9	-0.009	0.312	-0.04	0.032	Non-sig.
165	-43.4	68.9	-0.013	0.251	-0.057	0.043	Non-sig.
166	-35.5	68.9	-0.032	0.251	-0.072	0.04	Non-sig.
167	-27.6	68.9	-0.046	0.337	-0.074	0.028	Non-sig.
168	-19.7	68.9	-0.065	0.437	-0.077	0.011	Non-sig.
169	-11.8	68.9	-0.071	0.437	-0.081	0.01	Non-sig.
170	-3.9	68.9	-0.075	0.437	-0.084	0.009	Non-sig.
171	3.9	68.9	-0.078	0.372	-0.094	0.016	Non-sig.
172	11.8	68.9	-0.077	0.312	-0.102	0.025	Non-sig.
173	19.7	68.9	-0.076	0.286	-0.113	0.037	Non-sig.
174	27.6	68.9	-0.06	0.241	-0.109	0.049	Non-sig.
175	35.5	68.9	-0.047	0.186	-0.105	0.058	Non-sig.
176	43.4	68.9	-0.032	0.231	-0.082	0.05	Non-sig.
177	51.3	68.9	-0.031	0.327	-0.059	0.028	Non-sig.
178	59.2	68.9	-0.03	0.492	-0.028	-0.002	Non-sig.
179	67.1	68.9	-0.033	0.492	-0.033	-0.001	Non-sig.
180	75	68.9	-0.035	0.452	-0.041	0.005	Non-sig.
181	-75	75	-0.02	0.492	-0.019	-0.001	Non-sig.
182	-67.1	75	-0.007	0.427	-0.021	0.014	Non-sig.
183	-59.2	75	0.007	0.291	-0.029	0.036	Non-sig.
184	-51.3	75	-0.007	0.261	-0.053	0.047	Non-sig.
185	-43.4	75	-0.016	0.201	-0.071	0.054	Non-sig.
186	-35.5	75	-0.048	0.286	-0.086	0.039	Non-sig.
187	-27.6	75	-0.069	0.392	-0.089	0.02	Non-sig.
188	-19.7	75	-0.097	0.492	-0.092	-0.005	Non-sig.
189	-11.8	75	-0.094	0.472	-0.087	-0.007	Non-sig.
190	-3.9	75	-0.091	0.452	-0.083	-0.008	Non-sig.
191	3.9	75	-0.091	0.482	-0.093	0.002	Non-sig.
192	11.8	75	-0.093	0.392	-0.107	0.013	Non-sig.
193	19.7	75	-0.096	0.307	-0.126	0.03	Non-sig.
194	27.6	75	-0.077	0.241	-0.12	0.043	Non-sig.
195	35.5	75	-0.063	0.211	-0.114	0.052	Non-sig.
196	43.4	75	-0.051	0.241	-0.095	0.044	Non-sig.
197	51.3	75	-0.058	0.362	-0.079	0.021	Non-sig.
198	59.2	75	-0.066	0.447	-0.056	-0.01	Non-sig.
199	67.1	75	-0.062	0.497	-0.057	-0.005	Non-sig.
200	75	75	-0.058	0.467	-0.062	0.003	Non-sig.

**(c) Toroidal shift null model**

cell	xx	yy	Codispersion	P.value	null_mean	diff	P.value.cat
1	-75	20	-0.064	0.181	0	-0.064	Non-sig.
2	-67.1	20	-0.089	0.121	-0.002	-0.087	Non-sig.
3	-59.2	20	-0.117	0.095	-0.004	-0.114	Non-sig.
4	-51.3	20	-0.073	0.156	-0.003	-0.07	Non-sig.
5	-43.4	20	-0.043	0.256	-0.002	-0.041	Non-sig.
6	-35.5	20	-0.022	0.397	-0.002	-0.019	Non-sig.

7	-27.6	20	-0.022	0.362	-0.003	-0.018	Non-sig.
8	-19.7	20	-0.025	0.377	-0.005	-0.02	Non-sig.
9	-11.8	20	-0.074	0.151	-0.006	-0.068	Non-sig.
10	-3.9	20	-0.107	0.101	-0.007	-0.1	Non-sig.
11	3.9	20	-0.135	0.055	-0.007	-0.127	Non-sig.
12	11.8	20	-0.134	0.055	-0.007	-0.126	Non-sig.
13	19.7	20	-0.132	0.07	-0.007	-0.125	Non-sig.
14	27.6	20	-0.094	0.111	-0.008	-0.087	Non-sig.
15	35.5	20	-0.066	0.226	-0.008	-0.058	Non-sig.
16	43.4	20	-0.04	0.322	-0.008	-0.031	Non-sig.
17	51.3	20	-0.047	0.271	-0.008	-0.039	Non-sig.
18	59.2	20	-0.057	0.256	-0.007	-0.05	Non-sig.
19	67.1	20	-0.069	0.166	-0.003	-0.067	Non-sig.
20	75	20	-0.077	0.146	0	-0.077	Non-sig.
21	-75	26.1	-0.083	0.106	0	-0.082	Non-sig.
22	-67.1	26.1	-0.093	0.09	-0.002	-0.091	Non-sig.
23	-59.2	26.1	-0.1	0.07	-0.003	-0.097	Non-sig.
24	-51.3	26.1	-0.063	0.186	-0.002	-0.061	Non-sig.
25	-43.4	26.1	-0.038	0.266	-0.002	-0.036	Non-sig.
26	-35.5	26.1	-0.035	0.286	-0.003	-0.033	Non-sig.
27	-27.6	26.1	-0.05	0.211	-0.004	-0.046	Non-sig.
28	-19.7	26.1	-0.07	0.156	-0.007	-0.064	Non-sig.
29	-11.8	26.1	-0.072	0.146	-0.007	-0.065	Non-sig.
30	-3.9	26.1	-0.073	0.151	-0.006	-0.066	Non-sig.
31	3.9	26.1	-0.088	0.106	-0.006	-0.082	Non-sig.
32	11.8	26.1	-0.104	0.08	-0.006	-0.098	Non-sig.
33	19.7	26.1	-0.128	0.045	-0.006	-0.122	Non-sig.
34	27.6	26.1	-0.097	0.085	-0.006	-0.091	Non-sig.
35	35.5	26.1	-0.072	0.166	-0.006	-0.066	Non-sig.
36	43.4	26.1	-0.047	0.266	-0.007	-0.041	Non-sig.
37	51.3	26.1	-0.052	0.236	-0.007	-0.045	Non-sig.
38	59.2	26.1	-0.058	0.231	-0.007	-0.051	Non-sig.
39	67.1	26.1	-0.076	0.141	-0.005	-0.072	Non-sig.
40	75	26.1	-0.089	0.116	-0.002	-0.087	Non-sig.
41	-75	32.2	-0.094	0.09	0	-0.094	Non-sig.
42	-67.1	32.2	-0.095	0.09	-0.001	-0.094	Non-sig.
43	-59.2	32.2	-0.09	0.085	-0.003	-0.088	Non-sig.
44	-51.3	32.2	-0.058	0.176	-0.002	-0.056	Non-sig.
45	-43.4	32.2	-0.034	0.296	-0.001	-0.033	Non-sig.
46	-35.5	32.2	-0.044	0.236	-0.003	-0.041	Non-sig.
47	-27.6	32.2	-0.068	0.141	-0.005	-0.063	Non-sig.
48	-19.7	32.2	-0.098	0.111	-0.008	-0.09	Non-sig.
49	-11.8	32.2	-0.07	0.151	-0.007	-0.063	Non-sig.
50	-3.9	32.2	-0.051	0.241	-0.006	-0.045	Non-sig.
51	3.9	32.2	-0.059	0.211	-0.005	-0.053	Non-sig.
52	11.8	32.2	-0.086	0.106	-0.005	-0.081	Non-sig.
53	19.7	32.2	-0.125	0.05	-0.005	-0.121	Non-sig.
54	27.6	32.2	-0.099	0.085	-0.005	-0.094	Non-sig.
55	35.5	32.2	-0.076	0.141	-0.005	-0.071	Non-sig.
56	43.4	32.2	-0.052	0.216	-0.006	-0.046	Non-sig.
57	51.3	32.2	-0.055	0.206	-0.007	-0.049	Non-sig.
58	59.2	32.2	-0.059	0.246	-0.008	-0.051	Non-sig.
59	67.1	32.2	-0.081	0.131	-0.006	-0.075	Non-sig.
60	75	32.2	-0.097	0.085	-0.004	-0.093	Non-sig.
61	-75	38.3	-0.11	0.065	0	-0.109	Non-sig.

62	-67.1	38.3	-0.098	0.085	-0.001	-0.097	Non-sig.
63	-59.2	38.3	-0.077	0.146	-0.002	-0.075	Non-sig.
64	-51.3	38.3	-0.05	0.236	-0.001	-0.049	Non-sig.
65	-43.4	38.3	-0.03	0.332	-0.001	-0.029	Non-sig.
66	-35.5	38.3	-0.056	0.201	-0.003	-0.053	Non-sig.
67	-27.6	38.3	-0.093	0.116	-0.006	-0.087	Non-sig.
68	-19.7	38.3	-0.138	0.045	-0.01	-0.129	Non-sig.
69	-11.8	38.3	-0.068	0.186	-0.007	-0.061	Non-sig.
70	-3.9	38.3	-0.019	0.412	-0.006	-0.013	Non-sig.
71	3.9	38.3	-0.016	0.422	-0.004	-0.011	Non-sig.
72	11.8	38.3	-0.06	0.216	-0.004	-0.056	Non-sig.
73	19.7	38.3	-0.122	0.06	-0.004	-0.118	Non-sig.
74	27.6	38.3	-0.101	0.075	-0.004	-0.097	Non-sig.
75	35.5	38.3	-0.082	0.101	-0.003	-0.078	Non-sig.
76	43.4	38.3	-0.059	0.201	-0.004	-0.054	Non-sig.
77	51.3	38.3	-0.059	0.186	-0.006	-0.053	Non-sig.
78	59.2	38.3	-0.06	0.246	-0.008	-0.052	Non-sig.
79	67.1	38.3	-0.087	0.136	-0.007	-0.079	Non-sig.
80	75	38.3	-0.107	0.075	-0.006	-0.101	Non-sig.
81	-75	44.4	-0.086	0.116	0	-0.086	Non-sig.
82	-67.1	44.4	-0.076	0.146	-0.001	-0.075	Non-sig.
83	-59.2	44.4	-0.058	0.231	-0.002	-0.056	Non-sig.
84	-51.3	44.4	-0.037	0.302	-0.002	-0.035	Non-sig.
85	-43.4	44.4	-0.022	0.422	-0.001	-0.021	Non-sig.
86	-35.5	44.4	-0.045	0.271	-0.004	-0.041	Non-sig.
87	-27.6	44.4	-0.076	0.156	-0.006	-0.07	Non-sig.
88	-19.7	44.4	-0.116	0.06	-0.01	-0.106	Non-sig.
89	-11.8	44.4	-0.055	0.231	-0.007	-0.048	Non-sig.
90	-3.9	44.4	-0.013	0.442	-0.005	-0.008	Non-sig.
91	3.9	44.4	-0.01	0.472	-0.004	-0.006	Non-sig.
92	11.8	44.4	-0.047	0.261	-0.004	-0.043	Non-sig.
93	19.7	44.4	-0.097	0.116	-0.004	-0.093	Non-sig.
94	27.6	44.4	-0.081	0.131	-0.004	-0.076	Non-sig.
95	35.5	44.4	-0.065	0.196	-0.004	-0.061	Non-sig.
96	43.4	44.4	-0.043	0.276	-0.005	-0.038	Non-sig.
97	51.3	44.4	-0.039	0.327	-0.007	-0.032	Non-sig.
98	59.2	44.4	-0.034	0.377	-0.008	-0.026	Non-sig.
99	67.1	44.4	-0.059	0.256	-0.009	-0.05	Non-sig.
100	75	44.4	-0.079	0.166	-0.009	-0.07	Non-sig.
101	-75	50.6	-0.061	0.206	0	-0.061	Non-sig.
102	-67.1	50.6	-0.056	0.226	-0.001	-0.055	Non-sig.
103	-59.2	50.6	-0.046	0.276	-0.002	-0.044	Non-sig.
104	-51.3	50.6	-0.03	0.352	-0.002	-0.028	Non-sig.
105	-43.4	50.6	-0.018	0.422	-0.001	-0.016	Non-sig.
106	-35.5	50.6	-0.03	0.387	-0.003	-0.027	Non-sig.
107	-27.6	50.6	-0.051	0.276	-0.006	-0.046	Non-sig.
108	-19.7	50.6	-0.079	0.126	-0.009	-0.071	Non-sig.
109	-11.8	50.6	-0.045	0.261	-0.007	-0.038	Non-sig.
110	-3.9	50.6	-0.022	0.382	-0.005	-0.016	Non-sig.
111	3.9	50.6	-0.023	0.387	-0.004	-0.019	Non-sig.
112	11.8	50.6	-0.047	0.256	-0.005	-0.042	Non-sig.
113	19.7	50.6	-0.079	0.156	-0.005	-0.074	Non-sig.
114	27.6	50.6	-0.063	0.216	-0.006	-0.058	Non-sig.
115	35.5	50.6	-0.05	0.261	-0.006	-0.044	Non-sig.
116	43.4	50.6	-0.028	0.362	-0.007	-0.021	Non-sig.



117	51.3	50.6	-0.021	0.437	-0.007	-0.014	Non-sig.
118	59.2	50.6	-0.012	0.482	-0.008	-0.004	Non-sig.
119	67.1	50.6	-0.034	0.372	-0.009	-0.025	Non-sig.
120	75	50.6	-0.052	0.266	-0.01	-0.042	Non-sig.
121	-75	56.7	-0.033	0.337	0.001	-0.033	Non-sig.
122	-67.1	56.7	-0.034	0.327	-0.001	-0.033	Non-sig.
123	-59.2	56.7	-0.034	0.342	-0.002	-0.031	Non-sig.
124	-51.3	56.7	-0.021	0.402	-0.002	-0.019	Non-sig.
125	-43.4	56.7	-0.013	0.452	-0.002	-0.011	Non-sig.
126	-35.5	56.7	-0.015	0.462	-0.003	-0.011	Non-sig.
127	-27.6	56.7	-0.023	0.422	-0.005	-0.018	Non-sig.
128	-19.7	56.7	-0.036	0.327	-0.008	-0.027	Non-sig.
129	-11.8	56.7	-0.033	0.312	-0.006	-0.027	Non-sig.
130	-3.9	56.7	-0.031	0.337	-0.005	-0.026	Non-sig.
131	3.9	56.7	-0.038	0.317	-0.005	-0.033	Non-sig.
132	11.8	56.7	-0.046	0.266	-0.005	-0.041	Non-sig.
133	19.7	56.7	-0.058	0.241	-0.006	-0.052	Non-sig.
134	27.6	56.7	-0.045	0.322	-0.007	-0.038	Non-sig.
135	35.5	56.7	-0.033	0.347	-0.007	-0.026	Non-sig.
136	43.4	56.7	-0.012	0.482	-0.008	-0.004	Non-sig.
137	51.3	56.7	-0.001	0.442	-0.008	0.007	Non-sig.
138	59.2	56.7	0.013	0.392	-0.008	0.02	Non-sig.
139	67.1	56.7	-0.005	0.472	-0.01	0.004	Non-sig.
140	75	56.7	-0.021	0.462	-0.011	-0.01	Non-sig.
141	-75	62.8	-0.008	0.462	-0.001	-0.008	Non-sig.
142	-67.1	62.8	-0.01	0.467	-0.002	-0.008	Non-sig.
143	-59.2	62.8	-0.012	0.462	-0.003	-0.009	Non-sig.
144	-51.3	62.8	-0.011	0.452	-0.003	-0.008	Non-sig.
145	-43.4	62.8	-0.01	0.457	-0.003	-0.007	Non-sig.
146	-35.5	62.8	-0.014	0.477	-0.004	-0.009	Non-sig.
147	-27.6	62.8	-0.017	0.432	-0.006	-0.012	Non-sig.
148	-19.7	62.8	-0.024	0.397	-0.008	-0.017	Non-sig.
149	-11.8	62.8	-0.044	0.261	-0.007	-0.037	Non-sig.
150	-3.9	62.8	-0.057	0.211	-0.006	-0.05	Non-sig.
151	3.9	62.8	-0.064	0.201	-0.006	-0.058	Non-sig.
152	11.8	62.8	-0.06	0.231	-0.007	-0.053	Non-sig.
153	19.7	62.8	-0.054	0.256	-0.007	-0.047	Non-sig.
154	27.6	62.8	-0.04	0.342	-0.008	-0.032	Non-sig.
155	35.5	62.8	-0.03	0.397	-0.009	-0.021	Non-sig.
156	43.4	62.8	-0.011	0.497	-0.009	-0.002	Non-sig.
157	51.3	62.8	-0.003	0.452	-0.008	0.005	Non-sig.
158	59.2	62.8	0.008	0.417	-0.006	0.015	Non-sig.
159	67.1	62.8	-0.001	0.437	-0.008	0.007	Non-sig.
160	75	62.8	-0.009	0.497	-0.01	0	Non-sig.
161	-75	68.9	-0.014	0.452	-0.003	-0.012	Non-sig.
162	-67.1	68.9	-0.008	0.472	-0.003	-0.005	Non-sig.
163	-59.2	68.9	-0.002	0.482	-0.004	0.002	Non-sig.
164	-51.3	68.9	-0.009	0.437	-0.004	-0.005	Non-sig.
165	-43.4	68.9	-0.013	0.442	-0.004	-0.009	Non-sig.
166	-35.5	68.9	-0.032	0.367	-0.005	-0.026	Non-sig.
167	-27.6	68.9	-0.046	0.281	-0.006	-0.039	Non-sig.
168	-19.7	68.9	-0.065	0.216	-0.008	-0.058	Non-sig.
169	-11.8	68.9	-0.071	0.166	-0.008	-0.063	Non-sig.
170	-3.9	68.9	-0.075	0.151	-0.008	-0.067	Non-sig.
171	3.9	68.9	-0.078	0.136	-0.008	-0.07	Non-sig.

172	11.8	68.9	-0.077	0.151	-0.008	-0.069	Non-sig.
173	19.7	68.9	-0.076	0.196	-0.008	-0.068	Non-sig.
174	27.6	68.9	-0.06	0.226	-0.009	-0.051	Non-sig.
175	35.5	68.9	-0.047	0.307	-0.009	-0.038	Non-sig.
176	43.4	68.9	-0.032	0.372	-0.008	-0.024	Non-sig.
177	51.3	68.9	-0.031	0.357	-0.007	-0.025	Non-sig.
178	59.2	68.9	-0.03	0.377	-0.005	-0.026	Non-sig.
179	67.1	68.9	-0.033	0.377	-0.006	-0.027	Non-sig.
180	75	68.9	-0.035	0.377	-0.007	-0.028	Non-sig.
181	-75	75	-0.02	0.422	-0.004	-0.015	Non-sig.
182	-67.1	75	-0.007	0.482	-0.004	-0.003	Non-sig.
183	-59.2	75	0.007	0.402	-0.004	0.011	Non-sig.
184	-51.3	75	-0.007	0.487	-0.005	-0.002	Non-sig.
185	-43.4	75	-0.016	0.462	-0.005	-0.011	Non-sig.
186	-35.5	75	-0.048	0.291	-0.007	-0.041	Non-sig.
187	-27.6	75	-0.069	0.196	-0.007	-0.062	Non-sig.
188	-19.7	75	-0.097	0.095	-0.008	-0.089	Non-sig.
189	-11.8	75	-0.094	0.111	-0.009	-0.085	Non-sig.
190	-3.9	75	-0.091	0.116	-0.009	-0.082	Non-sig.
191	3.9	75	-0.091	0.126	-0.009	-0.081	Non-sig.
192	11.8	75	-0.093	0.121	-0.009	-0.084	Non-sig.
193	19.7	75	-0.096	0.146	-0.009	-0.087	Non-sig.
194	27.6	75	-0.077	0.196	-0.009	-0.068	Non-sig.
195	35.5	75	-0.063	0.231	-0.009	-0.053	Non-sig.
196	43.4	75	-0.051	0.286	-0.008	-0.043	Non-sig.
197	51.3	75	-0.058	0.291	-0.006	-0.052	Non-sig.
198	59.2	75	-0.066	0.236	-0.003	-0.063	Non-sig.
199	67.1	75	-0.062	0.221	-0.004	-0.059	Non-sig.
200	75	75	-0.058	0.261	-0.004	-0.054	Non-sig.