

1 Distance decay 2.0 – a global synthesis of taxonomic and functional turnover in ecological 2 communities

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161 **Abstract**

162 Understanding the variation in community composition and species abundances, i.e., β -diversity, is
163 at the heart of community ecology. A common approach to examine β -diversity is to evaluate
164 directional turnover in community composition by measuring the decay in the similarity among pairs
165 of communities along spatial or environmental distances. We provide the first global synthesis of
166 taxonomic and functional distance decay along spatial and environmental distance by analysing 149
167 datasets comprising different types of organisms and environments. We modelled an exponential
168 distance decay for each dataset using generalized linear models and extracted r^2 and slope to analyse
169 the strength and the rate of the decay. We studied whether taxonomic or functional similarity has
170 stronger decay across the spatial and environmental distances. We also unveiled the factors driving
171 the rate of decay across the datasets, including latitude, spatial extent, realm, and organismal features.
172 Taxonomic distance decay was stronger along spatial and environmental distances compared with
173 functional distance decay. The rate of taxonomic spatial distance decay was the fastest in the datasets
174 from mid-latitudes while the rate of functional decay increased with latitude. Overall, datasets
175 covering larger spatial extents showed a lower rate of decay along spatial distances but a higher rate
176 of decay along environmental distances. Marine ecosystems had the slowest rate of decay. This
177 synthesis is an important step towards a more holistic understanding of patterns and drivers of
178 taxonomic and functional β -diversity.

179 **Introduction**

180 Biodiversity on Earth is shrinking¹. Understanding its distribution is therefore paramount to inform
181 conservation efforts, and to evaluate the links between biodiversity, ecosystem functioning,
182 ecosystem services and human well-being^{2,3}. The variation in the occurrence and abundance of
183 species in space and time, i.e., β -diversity, is at the heart of community ecology and biogeography as
184 it provides a direct link between local (α) and regional (γ) diversity^{4,5}. Moreover, β -diversity has

185 become an essential currency in spatial^{6,7} and temporal⁸ comparisons of biodiversity patterns and their
186 underlying drivers. β -diversity is also informative in the context of biodiversity conservation and
187 practical management decisions in rapidly changing environments^{9,10}.

188 A common approach to examine spatial β -diversity is to consider directional turnover in community
189 composition with distance, i.e., distance decay^{4,11}. The similarity among the pairs of biological
190 communities typically decreases (“decays”) with increasing spatial or environmental distance^{11,12}.
191 This pattern stems mainly from dispersal limitation (related to physical barriers and dispersal
192 ability¹³) and species-specific responses to spatially structured environmental variation (related to
193 environmental filters and evolutionary processes¹⁴) and is well-documented in observational^{15–17} and
194 theoretical studies¹⁸ as well as meta-analyses¹⁹. Such studies offer interesting insights into the patterns
195 and drivers of spatial taxonomic β -diversity and often provide information about the effects of
196 environmental changes on ecosystem processes and associated functionality. Even if the patterns and
197 drivers of taxonomic β -diversity are relatively well-documented in the biogeographic literature, it is
198 much less understood whether the same patterns occur for functional β -diversity^{20–22}. Therefore,
199 functional biogeography emerges as a field to solve questions related to the distribution of forms and
200 functions of individuals, populations, communities, ecosystems, and biomes across spatial scales²³.

201 Understanding functional diversity relies on trait-based approaches, which are built on the idea that
202 the environment selects species based on their ecological requirements, and that functional traits
203 capture these requirements better than species identity²⁴. Thus, a trait-based approach should reflect
204 the functional response of biotic communities to environmental gradients better than an approach
205 based on species’ taxonomic identities only, and better predict how biotic communities respond to
206 environmental changes²⁵. Even if functional diversity has been investigated widely at the α -diversity
207 level^{26,27}, our understanding of functional β -diversity is much more limited and fragmented^{28–32}.
208 Comparing the patterns of functional and taxonomic β -diversity across different biotic groups,

209 ecosystems and geographic contexts has the potential to greatly contribute to a better mechanistic
210 understanding of the drivers behind the spatial variation in ecosystem functionality and shed further
211 light on how environmental change may affect ecological communities.

212 Niche filtering along environmental gradients induces coupling of taxonomic and functional diversity
213 patterns because dominant functional strategies dictate along the environmental gradient^{33,34}.
214 However, high taxonomic β -diversity does not necessarily mean high functional β -diversity^{25,35} (Fig.
215 1a), and the gain or loss of species does not inform about variations in functional β -diversity whenever
216 trait redundancy is high³⁶. For example, taxonomic homogenization does not lead to functional
217 homogenization if the newly introduced species in the assemblages are functionally similar to each
218 other^{30,37,38}. The most pressing question is whether functional features explain more of the distance
219 decay along environmental gradients than species identities, as suggested by some earlier studies^{39–}
220 43.

221 Hypotheses

222 Since the emergence of the first comprehensive distance decay meta-analysis¹⁹, our understanding of
223 community turnover along spatial and environmental gradients has increased notably. Here, based on
224 existing ecological literature and theory, and as an initial step towards synthesising knowledge, we
225 tested four hypotheses concerning the differences between taxonomic and functional distance decay
226 along the spatial and environmental distances. The master hypothesis is that the distance decay along
227 spatial gradients is stronger for taxonomic similarity than for functional similarity (**H_{1a}**). This is
228 because spatial factors relate with taxonomic more than functional composition as a result of dispersal
229 processes, dispersal history and speciation⁴². Such a hypothesis should be valid when functional traits
230 do not comprise dispersal related traits. In contrast, distance decay along environmental gradients is
231 stronger for functional similarity than for taxonomic similarity because functional composition
232 should respond more strongly to environmental variation^{27,39,40,42} (**H_{1b}**) (Fig. 1b).

233 *Latitudinal gradients*

234 We also generalize the effects of major geographic and environmental factors in the three hypotheses,
235 which are tested across the datasets. For example, latitudinal effect has been recognized as a relevant
236 factor in meta-analyses⁴⁴ and case studies^{45,46}, and these studies suggest that β -diversity should
237 decrease with increasing latitude (Fig. 1c). This is indicated by the faster latitudinal decline in γ -
238 diversity than in α -diversity^{47,48}, and the slopes of the species-area relationships (*proxy* for turnover)
239 decrease with latitude⁴⁹. Moreover, Rapoport's rule⁵⁰ postulates that species range sizes are larger at
240 high latitudes leading to lower β -diversity. Therefore, we hypothesize that the rate of taxonomic
241 distance decay along spatial gradients is generally slower in the datasets that originate from higher
242 latitudes (**H_{2a}**). In contrast, functional distance decay may show faster rates in the datasets from higher
243 latitudes. This is because the high diversity of tropical areas stems mainly from niche overlap⁵¹, which
244 increases the functional redundancy within communities and reduces the functional turnover⁵².
245 Regarding the environmental gradients, large-scale environmental heterogeneity tends to increase
246 towards poles^{19,53,54}, leading to a faster rate of functional distance decay along environmental
247 gradients at higher latitudes (**H_{2b}**). An alternative hypothesis is that extreme climatic conditions at
248 high latitudes decrease functional diversity because abiotic filtering limits the number of possible
249 ecological strategies found in a biotic community^{55,56}, resulting in relatively slow rate of functional
250 distance decay.

251 *Spatial extent*

252 Distance decay is also likely to be affected by the spatial extent of a given study⁵⁷. It has been shown
253 that distance decay has a power-law shape at spatial extents that do not exceed regional species pools
254 and exponential shape when extent encompasses multiple species pools¹². This suggests that the slope
255 of the relationship becomes flatter with increasing spatial extent^{11,19}, mainly because regional species
256 diversity is limited with a certain upper boundary⁵⁸. Furthermore, environmental heterogeneity affects

257 the diversity of species⁵⁹ and functional traits at regional level^{60,61}, but such effects are likely to be
258 scale-dependent^{62–64}. To summarize, we hypothesize that the rate of distance decay along spatial
259 gradients is generally slower in the datasets covering larger spatial extent (**H_{3a}**). In contrast, we
260 hypothesize that the rate of distance decay along environmental gradients is generally faster when
261 spatial extent is larger, especially for functional similarities, which are considered more sensitive to
262 environmental variation (**H_{3b}**).

263 *Realms*

264 We also expect that the patterns of distance decay vary among the realms. In general, marine
265 ecosystems are environmentally more homogeneous than terrestrial or freshwater ecosystems, at least
266 in the open ocean⁶⁵, and typically show weaker dispersal barriers than terrestrial or freshwater
267 ecosystems⁶⁶. Therefore, we hypothesize that the datasets from marine ecosystems have generally
268 slower rate of taxonomic and functional distance decay than the other ecosystems (**H₄**).

269 Here, we tested these hypotheses using datasets that cover a wide range of biotic groups from
270 unicellular diatoms to vascular plants, fungi, invertebrates, fish, birds, amphibians and mammals, and
271 that originate from marine, terrestrial and freshwater ecosystems spanning broad latitudinal gradients
272 (Fig. 2). To account for major biological differences in biotic groups, we also investigated if distance
273 decay varied among different sized taxa or among taxa with different dispersal mode^{67,68}. By using
274 such a comprehensive, multi-realm and multi-taxon dataset, we will explore patterns at more general
275 level, compared with case studies that have examined both taxonomic and functional β -diversity, but
276 only considered a single or few biotic groups.

277 **Material and methods**

278 **Data collection.** We gathered our data by directly contacting data owners or using the existing data
279 sources, such as sPlot⁶⁹ and CESTES⁷⁰. We included datasets that provided raw data of species
280 abundances, functional traits, environmental variables and spatial coordinates of the study sites. A
281 few datasets (n = 6) provided only species occurrence rather than abundance information (Appendix
282 S1). The traits included in the datasets were chosen by data owners from a suite of traits that should
283 respond well to environmental variation. For plant datasets compiled from the sPlot database, trait
284 information was commonly derived from the TRY database⁷¹. Regarding the CESTES database, we
285 compiled 48 datasets, specifically from: fish communities^{22,72–74}, terrestrial vascular plants^{75–86},
286 aquatic macroinvertebrates^{87–89}, terrestrial arthropods^{86,90–98}, birds^{83,90,99–102}, bats^{102,103}, bryophytes⁸⁵,
287 butterflies^{98,104}, corals¹⁰⁵, and foraminifera¹⁰⁶. We only included datasets with at least ten sites, two
288 environmental variables and three traits or trait categories. In some cases, more than one dataset
289 representing different taxonomic groups with different responses to environment and dispersal
290 abilities (e.g., stream macroinvertebrates and diatoms) were collected in the same study area. In total,
291 149 datasets representing 17 major biotic groups from terrestrial (n = 87), freshwater (n = 41) and
292 marine (n = 21) environments were assembled amounting to over 17,000 study sites around the globe
293 (Fig. 2). From the 149 datasets, 118 were published in peer reviewed journals (Appendix S1). Taxa
294 were mostly identified to species or morphospecies level but, in a few cases, we used data at genus
295 level if existing taxonomic knowledge did not allow distinguishing individual species. Finally, each
296 dataset included (i) a sites-by-species abundances matrix, (ii) a species-by-trait table, (iii) a sites-by-
297 spatial coordinates table, and (iv) a sites-by-environmental variables table (Fig. 3a). Detailed
298 information about collected datasets can be found in Appendix S1.

299 **Data curation.** For each dataset, we removed the sites with less than two observed species, and the
300 species with lower than three traits considered. Trait data included ordered, categorical and

301 continuous traits, the latter of which were log transformed (Log_{10}) when needed. Environmental
302 variables were log-transformed (Log_{10}) to approximate normality (except for e.g., temperature, pH
303 and variables given as eigenvectors), and the environmental variables showing strong inter-
304 correlations (pairwise $r_p < 0.7$) were excluded from further analyses¹⁰⁷. Spatial coordinates were
305 converted to the World Geodetic System 1984 (WGS84) datum and geographic coordinate system
306 and expressed in decimal degrees with an accuracy up to five decimals. All the data curation and
307 further analyses were performed in the software R v.4.0.2 (ref.¹⁰⁸) using the appropriate R packages.
308 We will consistently refer to the functions used and their respective packages from here on.

309 **Taxonomic and functional similarities.** Pairwise between-site taxonomic and functional similarities
310 were obtained for each dataset following the tree-based approach implemented in the function beta
311 in the package ‘BAT’ v.2.1.0 (ref.¹⁰⁹). We used the tree-based approach because it provides an
312 unequivocal comparison of taxonomic and functional similarities¹¹⁰. Community similarity (S) ranges
313 between zero and one and is commonly calculated for the pairs of communities as the sum of the
314 unique features of each community over the sum of the shared features between communities and the
315 unique features of each community. In the tree-based approach, these features are edges, which may
316 have different lengths and be shared by different species that may be present in different
317 communities¹¹⁰. Taxonomic and functional similarities were calculated for species occurrences and
318 abundances based on a Podani family of Sørensen-based indices¹¹¹. Here, we estimated S between
319 communities j and k as $S_{jk} = 1 - \frac{b+c}{2a+b+c}$ (1), where a is the sum of the length of the edges shared
320 between the communities j and k , b is the sum of the length of the edges unique to the community j ,
321 and c is the sum of the length of the edges unique to the community k .

322 When estimating taxonomic similarities, each species is a unique entity that share no edges with
323 others and, therefore, all the edges of the tree have same length (Fig. 3b). Thus, the sum of the length
324 of the edges equals the sum of the number of the observed species. For functional similarities, the

325 length of the edge shared between two species depends on how similar species are with respect to
326 their traits. To estimate the length of the edges shared by species, we first construct a global (i.e.
327 considering all the species within the dataset) matrix of species similarities by applying the Gower
328 similarity index¹¹² to the species-by-trait table using the function `gowdis` of the package ‘FD’ v.1.0
329 (ref.^{113,114}). We used a modified version of the Gower index extended to accommodate variables in
330 ordinal scales¹¹⁵. Using the species similarity matrix, we built a global tree of species similarities
331 based on an unweighted pair group method with arithmetic mean (UPGMA) hierarchical cluster using
332 function `hclust` of package ‘stats’ v.4.0.2 (ref.¹⁰⁸). The length of the edge shared by two species was
333 estimated as the distance between the intersection of two species in the global tree to the root of the
334 tree (Fig. 3b). Based on the length of those edges, functional similarities between the pairs of
335 communities were estimated using the equation 1. Therefore, even if two communities do not share
336 any species, taxonomic similarity would be lower than functional similarity in case of the comparison
337 of a continuous functional trait (e.g., body size; Fig. 3b). Note that the calculation of similarities was
338 carried out within each dataset separately. Details of the calculation of similarities using the Sørensen-
339 based indices for occurrence and abundance (i.e., percentage differences index) data can be found in
340 the Appendix S2. We used both occurrence and abundance data because occurrences should be very
341 informative about the drivers and patterns of communities along geographic gradients while
342 abundances should inform well patterns along environmental gradients¹¹⁶. Main results are given for
343 occurrence data in the main text, and abundance-based results can be found in Appendix S3.

344 **Spatial and environmental distances.** We estimated the spatial and environmental distances
345 between all the pairs of sites separately for each dataset. Spatial distances within each dataset were
346 calculated as the geographic distance in kilometres between the pairs of sites using the function
347 `earth.dist` of the package ‘fossil’ v.0.4.0 (ref.¹¹⁷; Fig. 3b). To estimate environmental distances, we
348 first standardized the environmental variables to $\mu = 0$ and $\sigma = 1$. Then, we calculated the
349 environmental distance between sites as the Euclidean distance using the measured and standardized

350 environmental variables for all the pairs of sites within each dataset (Fig. 3b) using the function
351 `vegdist` of the package ‘`vegan`’ v.2.5-6 (ref.¹¹⁸). Because the datasets comprised different number and
352 types of environmental variables, the values of environmental distance were context-dependent and
353 not very informative for comparison across datasets. We therefore assumed that the environmental
354 gradient scaled positively with spatial extent and rescaled the actual environmental distance to range
355 between zero and one in each dataset by dividing actual values by the average environmental distance
356 of the dataset.

357 **Distance decay of similarity.** We modelled the distance decay of similarity following a negative
358 exponential curve between the community similarity and distance¹². This is because maximum spatial
359 distances within our datasets were on average 795.5 kilometres; 95% CI [506.08, 1084.95], and
360 therefore, it is highly likely that many of the datasets encompassed multiple species pools. One of the
361 main assumptions of the distance decay is that $S_{ij} > S_{jk}$ if the distance between the sites i and j is
362 shorter than the distance between j and k ¹². That is, the slope of the relationship should be negative,
363 and positive slopes suggest either periodicity in the environmental gradient or a mismatch between
364 the communities and the measured environmental variables¹¹. Here, we calculated distance decay
365 separately for taxonomic and functional similarities along spatial and environmental distance using a
366 generalized linear model (GLM) following a binomial distribution of errors with a log link¹¹⁹ (Fig.
367 3c). Following Latombe et al.¹²⁰, we included a negative constraint in GLMs such that the slopes are
368 forced to be negative (i.e., slope ≤ 0). Besides, we included a negative constraint to the intercept of
369 the model such that intercept ≤ 0 . Therefore, because $e^0 = 1$, we avoided intercept values that fall
370 outside the range of taxonomic and functional similarities. We forced the negative coefficients via a
371 non-positive least-square regression^{121,122} within the iterative re-weighted least-square algorithm¹²³
372 implemented in the function `glm.cons` of the package ‘`zetadiv`’ v.1.2.0 (ref.^{120,124}). We estimated a
373 pseudo- R^2 (hereafter r^2) as $r^2 = 1 - \frac{\text{model deviance}}{\text{model null-deviance}}$ (2). Because of the pairwise structure of the

374 data, similarities are non-independent, so we performed a leave-one-out Jack knife procedure to
375 obtain the mean and confidence interval of the intercepts and slopes for each model¹¹⁹. Within such
376 framework, the slope represents the *rate of decay*, that is, the proportion of similarity loss per unit
377 distance, and the r^2 represents the *strength of the relationship* between similarity and distance.
378 Although it can be argued that slopes and r^2 are highly correlated, the correlation between slopes and
379 r^2 in this study was small (Pearson's $r = 0.10$; p -value = 0.240).

380 **Statistical analysis.** We tested our hypothesis using two different approaches. Firstly, we
381 investigated whether taxonomic or functional distance decay is stronger along spatial and
382 environmental distances (H_1) by performing a pairwise t-test to compare r^2 drawn from GLMs using
383 taxonomic similarity and the GLMs using functional similarity for each dataset (Fig. 3d). Totally, we
384 carried out two pairwise t-tests, one considering the r^2 from the models using spatial distances, and a
385 second considering the r^2 from the models using environmental distances.

386 We also investigated the ecological and geographical factors driving the rate of the distance decay
387 across datasets. Each dataset was characterized with respect to (i) latitude, recorded as the absolute
388 mean value of all the sites of the dataset; (ii) spatial extent, expressed as the largest pairwise distance
389 (in km) between study sites; (iii) realm, classified into freshwater, marine and terrestrial
390 environments; (iv) body size, estimated at organism-level as the log transformed fresh weight (g)
391 drawn from literature^{47,125}; (v) dispersal mode, classified as active and passive modes and organisms
392 dispersed by seeds; (vi) taxonomic γ -diversity expressed as the total number of species in the dataset;
393 (vii) functional γ -diversity, measured as the total volume of the union of the n-dimensional
394 hypervolumes estimated within the dataset; (viii) total number of study sites in the dataset and (ix)
395 the number of environmental variables in the dataset. For body sizes, we note that although the size
396 range within the biotic group may be large (up to five orders of magnitude), it is small compared to
397 the overall variation obtained across organism groups (twelve orders of magnitude). For more details

398 on body size approximations, see refs.^{47,49}. The taxonomic γ -diversity was included to study if there
399 is a typical positive relationship between γ -diversity (taxonomic and functional) and β -diversity^{7,52}.
400 Functional γ -diversity was estimated based on geometrical n-dimensional hypervolumes^{126,127}. We
401 used the species functional similarity matrix based on Gower's index (see the 'taxonomic and
402 functional similarities' section) to extract orthogonal synthetic trait axes through a principal
403 coordinate analysis¹²⁸. Then, the hypervolume of each site within the dataset was calculated using a
404 gaussian kernel density estimate via the function kernel.alpha of the package 'BAT'¹²⁹. The
405 hypervolume of all sites were sequentially merged using the function hypervolume_set of the package
406 'hypervolume' v.2.0.12 (ref.¹³⁰), and the united-hypervolume was used to estimate the total amount
407 of functional space occupied by all the species within the dataset using the function get_volume of
408 the package 'hypervolume'. Because trait dimensionality affects the accuracy of the functional
409 separation of species^{131,132}, we standardized the number of dimensions to seven synthetic traits axes
410 for all datasets. Hypervolumes are expressed in units of SDs to the power of the number of trait
411 dimensions used (i.e., seven). The number of study sites and the number of environmental variables
412 for each dataset were included to explore their potential effect on distance decay.

413 Finally, we used boosted regression trees (BRT) to test the effects of latitude (H_2), spatial extent (H_3)
414 and realm (H_4) on the rate of taxonomic and functional distance decay along spatial and
415 environmental distance across the datasets. In addition, we included dispersal mode, body size,
416 taxonomic and functional γ -diversity, number of sites, and number of environmental variables in the
417 dataset as predictors in the BRTs (Fig. 3d). BRT is a regression modelling technique able to fits
418 nonlinear relationships between predictor and response variables, including interaction among
419 variables by using a boosting strategy to combine results from a large number (usually thousands) of
420 simple regression tree models¹³³. Our BRT outputs included graphs of the shapes of relationships
421 between predictors and the response variable (e.g., linear, curvilinear and sigmoidal response shapes)
422 and a relative importance of predictor variables. We also plotted a LOESS line on these plots to allow

423 for easy visualization of the central tendency of the predicted values. Relative importance is
424 constructed by counting the number of times a variable is selected for splitting in each tree, weighted
425 by the squared improvement of the model as a result of each split, and averaged over all trees (see
426 ref.^{133–135} for more details). BRT parameters were selected to amplify the deviance explained by the
427 model. We tested interaction depth between 2 and 5, and the learning rates of 0.1, 0.01, and 0.001.
428 The best models were the ones with learning rate of 5 and interaction depth of 0.001. We performed
429 a 50–50 cross-validation procedure and estimated the model performance ($D^2 =$
430 $\frac{\text{Deviance}_{\text{Total}} - \text{Deviance}_{\text{Cross-validation}}}{\text{Deviance}_{\text{Total}}}$) following Leathwick et al.¹⁰⁷. As the datasets in this study have
431 not always followed the same sampling methodology, and show different functional traits and
432 environmental variables, we fitted the BRT models following a Laplace distribution of the errors to
433 reduce the absolute error loss from the variation among datasets. BRT models were fitted using the
434 function gbm.step of the package ‘dismo’ v.1.1-4 (ref.¹³⁶).

435 Main results show the distance decay results based on total similarities (equation 1), but we also
436 partitioned the similarities into replacement and richness difference components following the
437 methodology described in the Appendix S2. Replacement gives the variation as a result of the
438 substitution of species (turnover) or functional traits (functional replacement), and richness
439 differences accounts for the variation as a result of net differences induced by the loss/gain of species
440 or traits¹³⁷. We only show the results of the partitioned components using occurrence data for
441 simplicity. The final figures were prepared using the tools from the tidyverse environment¹³⁸ in the
442 R software v.4.0.2 (ref.¹⁰⁸).

443 Results

444 *Strength of the distance decay*

445 The taxonomic and functional similarities had a mean correlation of 0.74 ($sd \pm 0.20$) within datasets.
446 The distance decays showed a wide range of shapes, from very steep decays to almost flat
447 relationships (Fig. 4). The average r^2 using occurrence data for taxonomic similarities was 0.099 (sd
448 ± 0.129) and 0.061 ($sd \pm 0.091$) for functional similarities. Spatial distance decays of taxonomic
449 similarities were significantly stronger than the distance decays of functional similarities when
450 considering both occurrence (Fig 4a; $t = 6.330$, $p < 0.001$, $df = 148$) and abundance data (Appendix
451 S3, Fig. S1), supporting **H_{1a}** – spatial distance decay is stronger for taxonomic than functional
452 similarities (Fig. 4a).

453 However, our results did not support **H_{1b}** as the distance decay for taxonomic similarities (mean $r^2 =$
454 0.103, $sd \pm 0.095$) were also, on average, stronger than for functional similarities (mean $r^2 = 0.076$,
455 $sd \pm 0.086$) along environmental distances (Fig 4b; $t = 6.935$, $p < 0.001$, $df = 148$). Note, however,
456 that 41 out of 149 datasets had stronger distance decay of functional similarities than taxonomic
457 similarities along environmental gradients. Most of the biotic groups had at least one dataset with a
458 stronger relationship for functional similarities than for taxonomic similarities, except for corals,
459 foraminifera, lichens, amphibians and fungi each of which comprised only one dataset.

460 *Rate of the distance decay*

461 The mean slope of the spatial distance decay was 0.009 ($sd \pm 0.027$) for taxonomic similarities, and
462 0.004 ($sd \pm 0.015$) for functional similarities (Fig 4a). For environmental distances, the mean slope
463 of the distance decay was 1.073 ($sd \pm 1.063$) for taxonomic similarities and 0.365 ($sd \pm 0.361$) for
464 functional similarities (Fig 4b). Regarding the biotic groups, terrestrial plants had the steepest slopes
465 along spatial distance both for taxonomic and functional similarities (Fig. 5). Along environmental
466 distance, corals had the steepest slopes (Fig. 5). Similar patterns were found for abundance-based

467 similarities, except for the biotic groups, where aquatic plants had the steepest slopes along spatial
468 distances (Appendix S3).

469 Across datasets, BRT explained 36.51% of the deviance of the slopes of the spatial distance decay
470 for taxonomic similarities, and 36.86% for functional similarities using occurrence data. For the
471 distance decay along environmental distances, BRT explained 14.43% of the deviance of the slopes
472 of the decay of taxonomic similarities and 20.40% for functional similarities. Spatial extent and γ -
473 diversity contributed most to the variation in slopes along either spatial or environmental distance
474 using both occurrence and abundance-based similarities (Fig. 6 – 7a, Appendix S3).

475 Latitudinal patterns

476 The slopes of spatial distance decay of both taxonomic and functional similarities were the steepest
477 in datasets centred at ca. 35–45°, partly supporting **H_{2a}** that distance decay was flatter at high latitudes
478 (Fig. 6a). However, note that taxonomic spatial distance decay sharply decreased towards the poles.
479 The slopes of environmental distance decay were flatter in the datasets from high latitudes (Fig. 6b),
480 providing no support to hypothesis **H_{2b}**.

481 Spatial extent

482 The distance decay of taxonomic and functional similarities was flatter in the datasets that covered
483 larger spatial extent both for occurrence (Fig. 6a) and abundance data (Appendix S3, Fig. S3a),
484 supporting hypothesis **H_{3a}** – distance decay becomes flatter with increasing spatial extent. For
485 environmental distances, distance decay was steeper in the datasets that covered larger spatial extents
486 for both taxonomic and functional similarities, agreeing thus with **H_{3b}** that distance decay would
487 become steeper with larger spatial extent.

488 Realms

489 Marine ecosystems had flatter slopes compared to freshwater or terrestrial ecosystems considering
490 environmental distances, but not for spatial distances, thus partly agreeing with **H₄** (Fig. 6). However,
491 the importance of the realms in BRTs was overall low. A similar pattern emerged for abundance-
492 based similarities (Appendix S3, Fig. S3).

493 Organismal variables and dataset features

494 The slopes of both spatial and environmental distance decays were steeper for larger-bodied
495 organisms in taxonomic and functional similarity (Fig. 7a–b). Organisms relying on seed dispersal
496 had steeper slopes along spatial and environmental distances than other dispersal types, but the overall
497 importance of dispersal mode was low (Fig. 7b). Taxonomic γ -diversity had a U-shaped relationship
498 with slopes for distance decay along spatial and environmental distances (Fig. 7b). Slopes of distance
499 decay had an overall decreasing trend for functional γ -diversity for both spatial and environmental
500 distances (Fig. 7a–b). Generally, slopes were steeper in the datasets where the number of study sites
501 was higher (Fig. 7a), and flatter when datasets comprised only a few environmental variables (Fig
502 7b).

503 Replacement and richness differences

504 The slopes of taxonomic replacement along spatial distance decreased rapidly in the datasets above
505 35° while the functional replacement peaked at ca. 45° (Appendix S4, Fig. S1a). Along environmental
506 distance, the taxonomic replacement increased towards higher latitudes while the functional
507 replacement did not vary notably along latitude (Appendix S4, Fig. S1b). For the richness differences
508 component, the slopes of both taxonomic and functional similarities were the steepest in the datasets
509 at ca. 45° degrees for the spatial distance decay (Appendix S4, Fig. S2a). For environmental distances,
510 slopes became flatter from low to high latitudes up to ca. 50° degrees for taxonomic similarities while
511 for functional similarities, slopes did not vary along latitude (Appendix S4, Fig. S2b). Both

512 replacement and richness differences showed flatter spatial slopes with increasing spatial extent
513 (Appendix S4, Fig S1-S2). In contrast, environmental slopes increased with spatial extent only
514 replacement (Appendix S4, Fig. S1b) while the effects of spatial extent for the slopes of richness
515 differences along environment was very low (Appendix S4, Fig. S2b). Furthermore, marine
516 ecosystems showed the flattest slopes of replacement along environmental gradients (Appendix S4,
517 Fig. S1b) while freshwater ecosystems had the flattest slopes of richness differences (Appendix S4,
518 Fig. S2b). Details about the organismal variables and datasets features can be found in the Appendix
519 S4.

520 **Discussion**

521 Community ecology and biogeography have lacked a comprehensive evaluation of functional β -
522 diversity across different taxa and ecosystems globally. Earlier studies suggest that functional β -
523 diversity better reflects environmental variability compared with taxonomic β -diversity, and that
524 focusing on functional β -diversity may help, for example, understand how humans impact ecosystems
525 by modifying the local environment^{33,39-41}. This is because functional traits should reflect best the
526 ecological requirements of species. Using a comparative analysis across biotic groups, ecosystem
527 types and realms, we show here that (i) taxonomic distance decay is generally stronger along spatial
528 gradients than functional distance decay, and that (ii) the decay of functional similarities along
529 environmental gradients is typically not stronger than the decay of taxonomic similarities, unlike
530 previously suggested.

531 *The strength of the distance decay of taxonomic and functional similarities*

532 The stronger taxonomic than functional distance decay along space provides empirical evidence for
533 the idea that the taxonomic distance decay is a robust approach for ecological and biogeographical
534 studies, supporting **H_{1a}**. Compositional differences effectively summarize dispersal-related factors as

535 well as species responses to climatic and other spatially structured environmental variables. However,
536 spatial distance decay of functional similarities may not reflect well geographic differences in biotic
537 communities. This probably stems from the different roles played by deterministic and stochastic
538 drivers when shaping taxonomic and functional composition: functional composition mirrors mostly
539 local environmental filtering and typically does not strongly reflect dispersal limitations or species
540 pool effects that influence stronger taxonomic composition⁴². Yet, the specific outcomes of any
541 analysis of functional diversity depends on the functional traits included in the analysis¹³⁹ and how
542 researchers handle individual trait variability¹⁴⁰. Also, some morphological or size-related traits with
543 no clear functional meaning may turn out informative when exploring geographic patterns in
544 functional composition⁴². For example, functional traits rather than species identities explained more
545 variability of tree communities along broad spatial gradients¹⁴¹ or the variation of phytoplankton
546 communities along a large South America gradient¹⁴². Such findings point to the fact that the
547 decisions about which functional traits to include in the analysis is critical.

548 Our analysis suggests that, overall, functional distance decay is also somewhat weaker than
549 taxonomic distance decay along environmental gradients. However, this result is likely context-
550 dependent, and the stronger functional than taxonomic distance decay depends on whether the species
551 replaced from one community to another are a random subsample of functionally redundant species
552 from the regional pool or not³⁴. In fact, in 40 datasets, distance decay of functional similarities was
553 stronger than taxonomic similarities along environmental gradients. The datasets with stronger
554 distance decay of functional than taxonomic similarities spanned a broad range of latitudes, number
555 of study sites and environmental variables. Therefore, for using such heterogeneous datasets, we are
556 not able to provide any strict guidance on the choice of functional traits or environmental variables
557 to be measured in future studies. For example, the dataset on grassland arthropods from the
558 Biodiversity exploratories project had standardized traits and environmental variables, but only
559 Homoptera out of four different taxa showed stronger functional than taxonomic distance decay along

560 environmental gradients. One explanation is that the whole organisms are susceptible to
561 environmental filtering, and each species comprises a set of traits that cannot be physically filtered
562 as a response to the environment. Therefore, environmental filtering on a given trait of a species may
563 also filter other traits simultaneously, or a given species may comprise a trait not filtered by the
564 environment, which tends to increase the community similarity among sites. Yet, we emphasize that
565 the variation in the rate of distance decay of functional similarities along environmental gradients
566 across datasets was better explained in BRT than the variation in the rate of the distance decay of
567 taxonomic similarities. This suggests that the taxonomic metrics may be more context dependent than
568 the functional metrics along environmental gradients and that functional features may be more useful
569 to generalize across taxa and ecosystems²⁴. Furthermore, functional distance decay should not be
570 much affected by dispersal effects and regional species pools as compared to taxonomic distance
571 decay.

572 *The effects of latitude on the rate of distance decay*

573 In addition to our master hypothesis, we investigated whether the rate of distance decay showed
574 consistent variation across ecosystems, along geographic gradients and among major taxonomic
575 groups. We did not find slower rates of decay in the datasets at higher latitudes, but rather, concurring
576 with the recent meta-analysis of species turnover¹⁴³, we found that taxonomic similarities decayed
577 the fastest at mid latitudes, above which the rate lowered down. Traditionally, this pattern has been
578 explained with the Rapoport's rule, whereby there is an increase in species range size at higher
579 latitudes¹⁴⁴ and hence lower taxonomic turnover. Yet, such finding may also stem from landscape
580 fragmentation that increases β -diversity¹⁴⁵, especially at mid latitudes prone to strong human impact
581 and at local spatial scales⁵⁰. We also observed a faster rate of functional spatial distance decay towards
582 poles, agreeing with our hypothesis. This may reflect the fact that the high species diversity of the
583 tropics is mainly due to niche overlap⁵¹, which increases the functional redundancy and reduces the

584 functional turnover⁵². Furthermore, the latitudinal decrease in the rate of abundance-based functional
585 distance decay (Appendix S3, Fig. S1) suggests an optimal utilization of the functional space, as have
586 been observed earlier exclusively for marine organisms¹⁴⁶.

587 Taxonomic and functional distance decay along environmental gradients exhibited a clear minimum
588 in the datasets near 50° while increasing notably from 60° towards the poles especially for taxonomic
589 similarities. This result points to a breakpoint in total similarities that stems from richness differences,
590 as the replacement component did not have similar breakpoints but, rather, had similar replacement
591 levels in the tropics with decreasing trend at mid- and high latitudes. Latitudinal breakpoints in
592 turnover have been found earlier¹⁴⁷ in terrestrial vertebrates at ca. 30°, where turnover decreased
593 substantially, while nestedness component increased. Soininen et al.¹⁴³ found a breakpoint for
594 turnover component at 41°, whereas there was no breakpoint in nestedness component. Present results
595 suggest that the rate of distance decay is relatively similar through the extensive tropical region,
596 whereas it either increases or decreases rapidly at mid latitudes, depending on β -diversity metric or
597 whether this phenomenon is examined along spatial or environmental gradients.

598 *The effect of spatial extent on the rate of distance decay*

599 The rate of spatial distance decay was slower in the datasets covering larger spatial extent as we
600 hypothesized, perhaps suggesting that regional species pools are limited, and new species are not
601 found constantly at the same frequency when extent is larger. Lower decay rates in larger study areas
602 could also result from repeated patterns in environmental variation, that is, environmental patchiness
603 or natural periodicity in the environment¹¹. Agreeing with our hypothesis, we also found that the rate
604 of decay along environmental distance was higher in the datasets covering larger spatial extent. These
605 findings indicate that spatial distance decay is more affected by species pool effects and dispersal
606 processes than environmental distance decay, possibly because the latter reflects more strongly the
607 level of local deterministic environmental filtering processes. Similar evidence has accumulated from

608 case studies conducted in various ecosystems^{33,39,41,148}. The finding that the rate of distance decay
609 along environmental distance was higher in the datasets covering larger extents indicates the stronger
610 environmental filtering at larger study areas. We also note that, in our BRT models, extent and γ -
611 diversity had by far the largest relative importance, suggesting that their interplay plays a key role in
612 shaping distance decay.

613 *The effect of realm on the distance decay*

614 We found evidence for a lower rate of distance decay in marine versus terrestrial or freshwater
615 ecosystems. Moreover, we found very comparable distance decay slopes for terrestrial and
616 freshwaters, and the factor ‘realm’ showed low relative importance in the BRT models. Overall, this
617 finding agrees with earlier meta-review on β -diversity¹⁹, suggesting that large-scale diversity patterns
618 are generally weaker in marine ecosystems¹⁴⁹. However, marine ecosystems would have lower
619 species turnover than freshwater or terrestrial systems⁴⁹. As connectivity, energy flows, dispersal
620 modes, body size structure and trophic dynamics differ substantially between dry and wet
621 ecosystems¹⁵⁰, it would be vital to investigate possible differences in turnover among the realms more
622 closely.

623 *Organismal variables and dataset features*

624 Organism size did seem to affect taxonomic or functional distance decay along spatial and
625 environmental gradients as the slopes typically increased with organism body size. This may be
626 because β -diversity should be low among the small microbial taxa with efficient passive dispersal¹⁹.
627 The rationale behind such idea is that efficient dispersal homogenizes communities among sites
628 resulting in lower β -diversity¹⁵¹. Body size is also a key driver of organisms’ biological complexity¹⁵²,
629 and it may be that smaller organisms show a much more limited set of trait combinations than
630 macroorganisms, leading to a lower functional redundancy among larger species. Furthermore, our

631 knowledge about the taxonomy and functional traits of organisms is typically size-dependent. For
632 example, the identification of larger species is much easier than that of microorganisms, which also
633 applies to the identification and measurement of soft functional traits^{153,154}. Therefore, the values of
634 β-diversity of small organisms may be typically underestimated.

635 Patterns in environmental distance decay were relatively congruent with spatial distance decay
636 regarding dispersal mode, suggesting that taxa which disperse passively do not seem to track
637 environmental gradients more efficiently compared with less dispersive taxa. It may also be that
638 small-sized taxa were filtered along some unmeasured spatially-structured environmental gradients,
639 and the pattern was thus detected as spatial turnover even if caused by some underlying unmeasured
640 environmental factors. Forthcoming studies would greatly benefit from disentangling the signal of
641 unmeasured environmental variables from true dispersal limitation¹⁵⁵.

642 *Study design*

643 There are also some possibly influential aspects in our study design that should be discussed.

644 Although the study is global in its extent, the availability of datasets was not evenly distributed
645 geographically. This is a well-known problem in biodiversity research¹⁵⁶ that calls for
646 complementary studies to verify that these trends hold true in poorly sampled regions.

647 Also, we relied on the suite of traits and environmental variables included in the original datasets
648 and, thus, the collection of traits and environmental variables used differed somewhat among
649 datasets even for the same focal taxonomic groups. This increases the uncertainty on how
650 environmental variables filter the functional structure of communities in different contexts and how
651 strong the taxonomic community-environment relationships are. An alignment of key traits and
652 environmental variables is therefore desirable, but requires a suite of sister studies following the
653 same protocol, which is unfortunately not yet available. Moreover, the fact that some of the biotic

654 groups (e.g., corals, foraminifera) were underrepresented in our analysis with only one dataset
655 included (Fig. 2), or the total lack of some taxa (e.g. aquatic and terrestrial mammals, bacteria),
656 makes it more difficult to generalize distance decay across taxa.

657 *Concluding remarks*

658 In summary, we believe our analysis is an important step towards a more comprehensive
659 understanding of patterns and drivers of functional β -diversity, particularly in comparison with the
660 patterns and drivers of taxonomic β -diversity that have so far attracted much more research interest
661 compared with functional β -diversity. Here, we found that functional distance decay is scale-
662 dependent and a product of large-scale geographic factors (latitude) and taxonomic and functional
663 γ -diversity, but is also driven by organisms' biology to some degree. In general, taxonomic distance
664 decay provides a better tool for many aspects of biogeographical research, because it reflects
665 dispersal-related factors as well as species responses to climatic and other typically spatially-
666 structured environmental variables. However, functional distance decay may be a cost-effective
667 option for investigating how humans impact ecosystems via modifying the environment. Overall,
668 the present findings and data shed light into the congruence between the functional and taxonomic
669 diversity patterns and provide useful new information to the field of functional biogeography.

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673 compilation from the sPlot database and commented on the first draft, Martin Gossner coordinated
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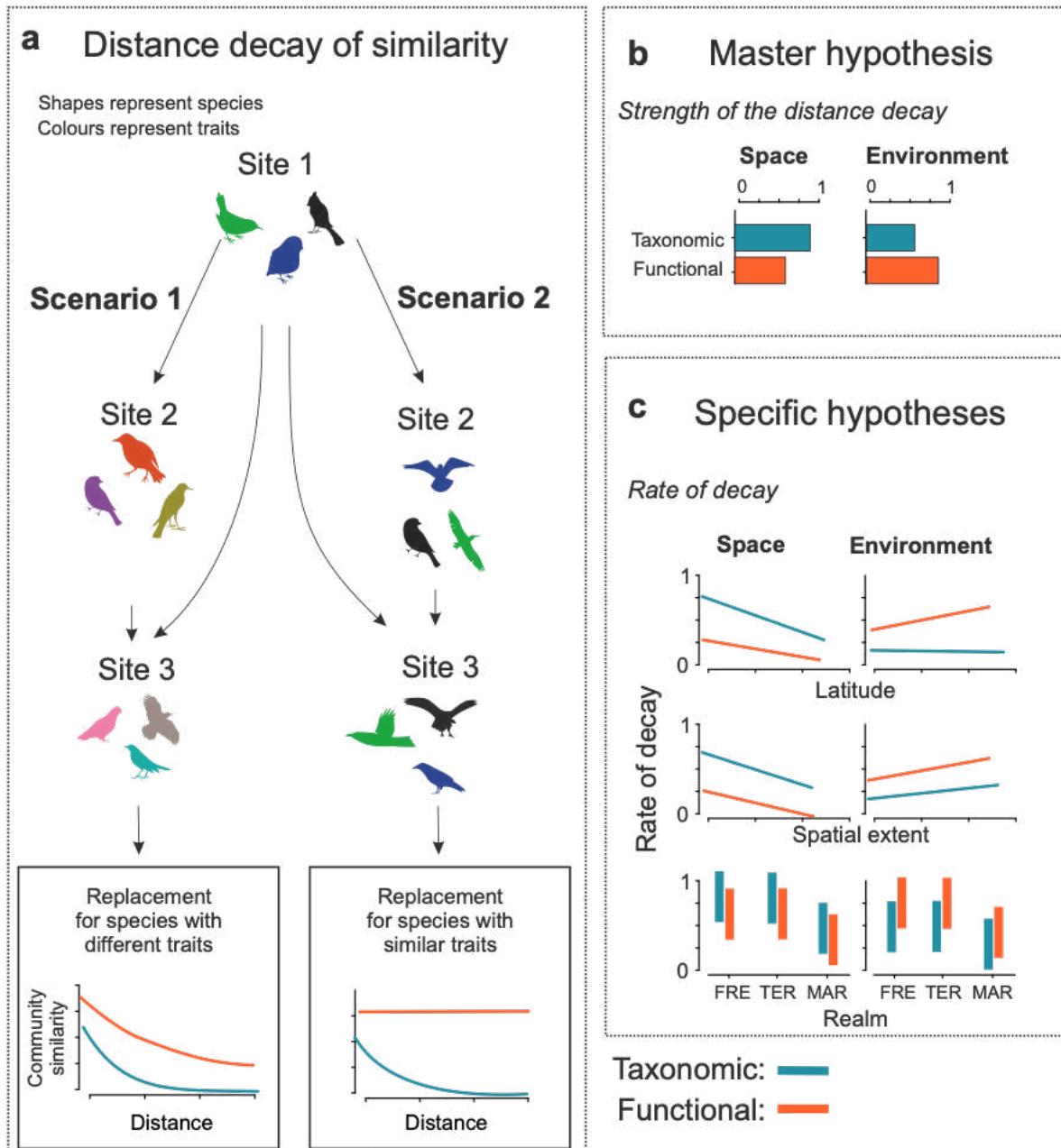
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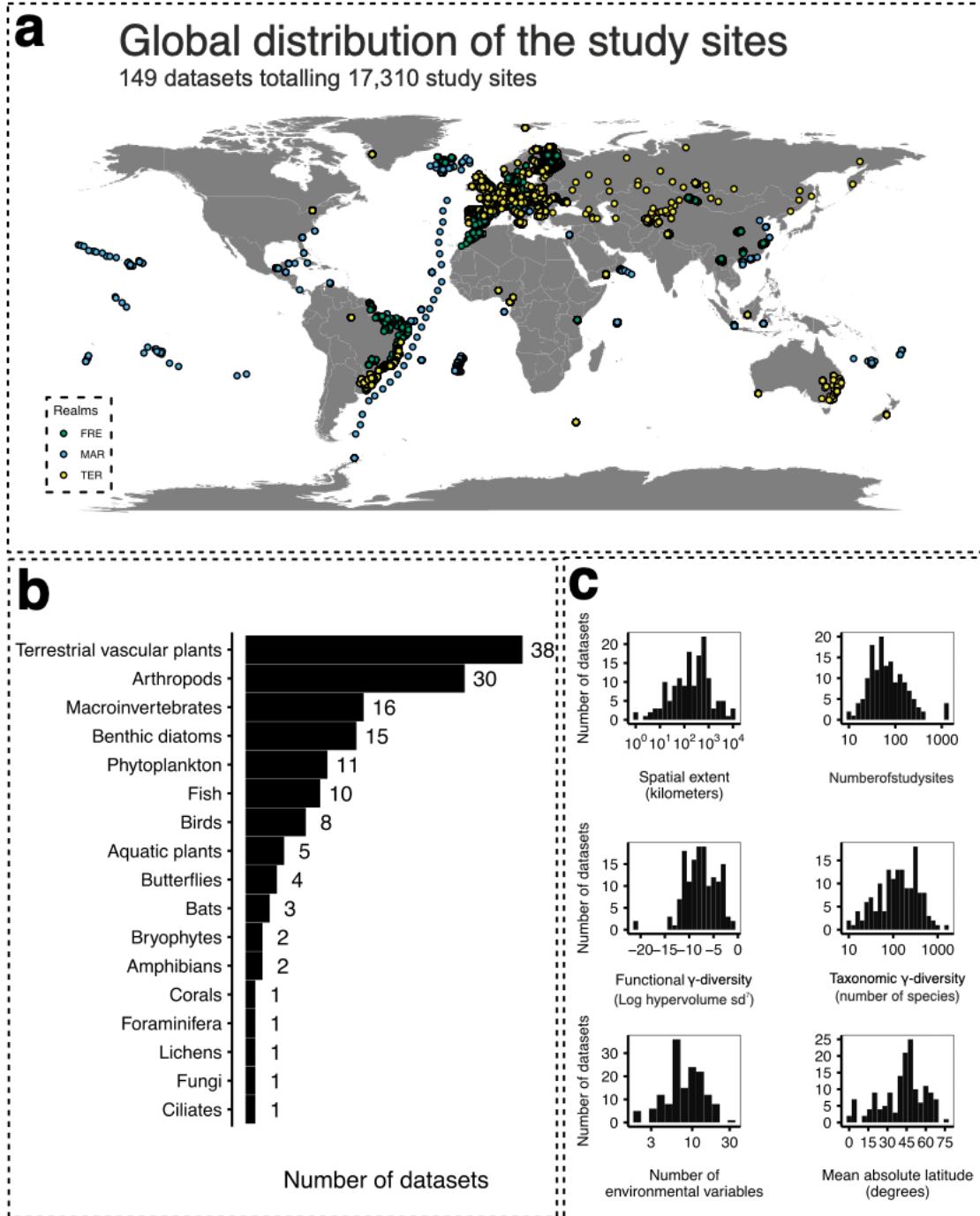
1067 **Figures**



1068

1069 Figure 1. (a) Taxonomic and functional distance decay. Two scenarios of distance decay of
1070 taxonomic and functional similarities along spatial and environmental distances. In scenario 1 (for
1071 simplicity, we consider here replacement only), the replacement occurs among species that have
1072 different traits (i.e., colours), which leads to both taxonomic and functional distance decay. In
1073 scenario 2, the replacement occurs among species that have similar traits, which leads to zero
1074 functional distance decay measured by the slope. (b) Master hypothesis: spatial distance decay is
1075 stronger for taxonomic similarities than for functional similarities, while environmental distance

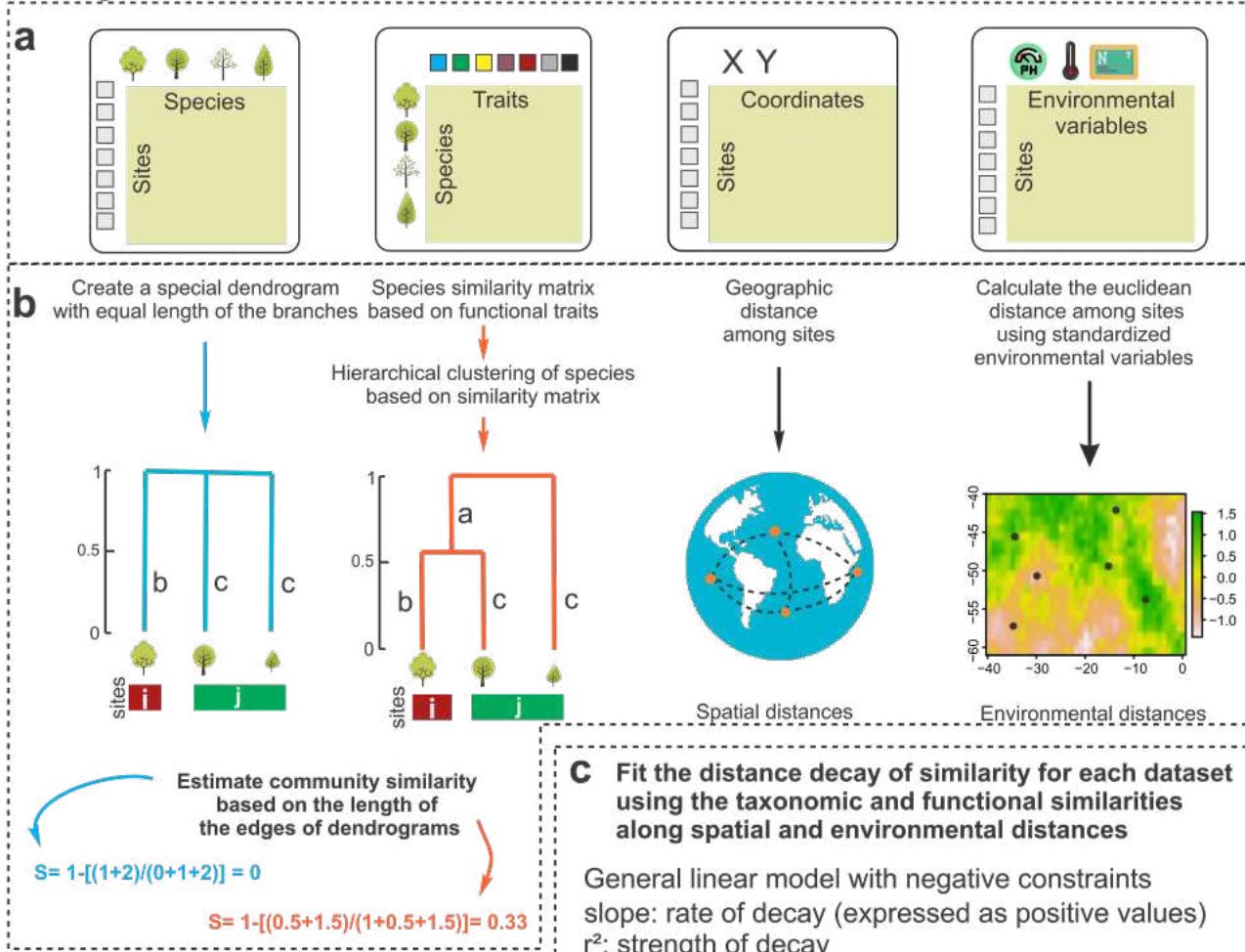
1076 decay is stronger for functional similarities. (c) Specific hypotheses (higher values indicate steeper
1077 slopes) across datasets: Latitude: spatial distance decay is flatter in the datasets from higher latitude
1078 and more notably for taxonomic similarities than for functional similarities. Environmental distance
1079 decay is steeper in datasets from higher latitude for functional similarities, while it does not vary
1080 notably with latitude for taxonomic similarities. Spatial extent: Both taxonomic and functional
1081 spatial distance decay are flatter in the datasets covering larger spatial extent, while environmental
1082 distance decay is steeper in datasets covering larger extent. Realm: Marine ecosystems show flatter
1083 spatial and environmental distance decay than terrestrial and freshwater systems. FRE= freshwater
1084 systems, TER = terrestrial systems, MAR = marine systems.



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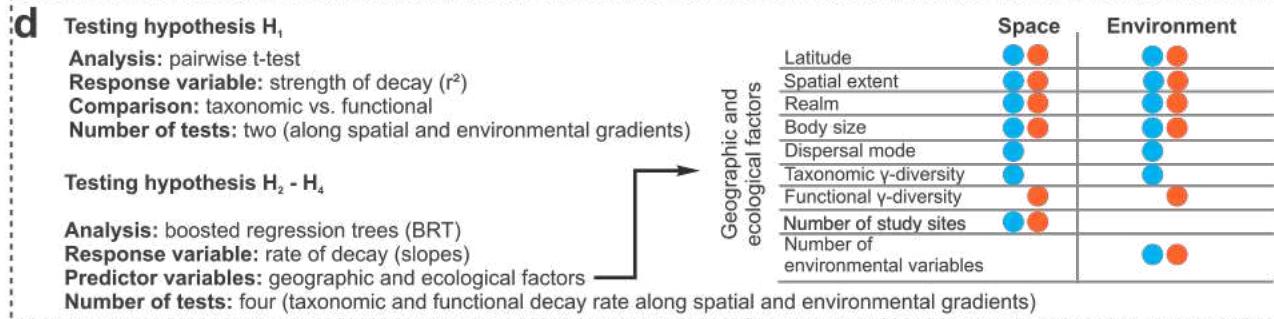
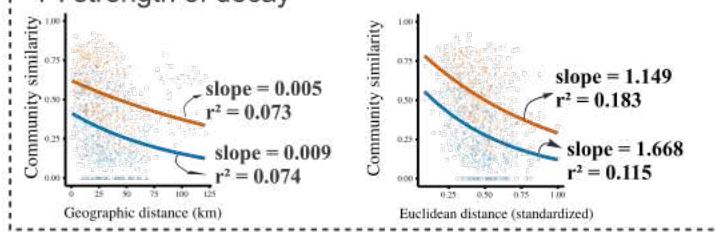
1086 Figure 2. Study design highlighting (a) map of the study sites coloured according to the realms
1087 (FRE = Freshwater, TER = Terrestrial, MAR = Marine); (b) the number of data sets for major biotic
1088 groups; and (c) the distribution of the datasets with respect to spatial extent, number of study sites,
1089 functional γ -diversity (log hypervolume sd^7), taxonomic γ -diversity (number of species), number of
1090 environmental variables, and latitude.

Analyses within datasets



Analyses across datasets

Compile the rate (slopes) and the strength (r^2) of the decay from all datasets for hypothesis testing.



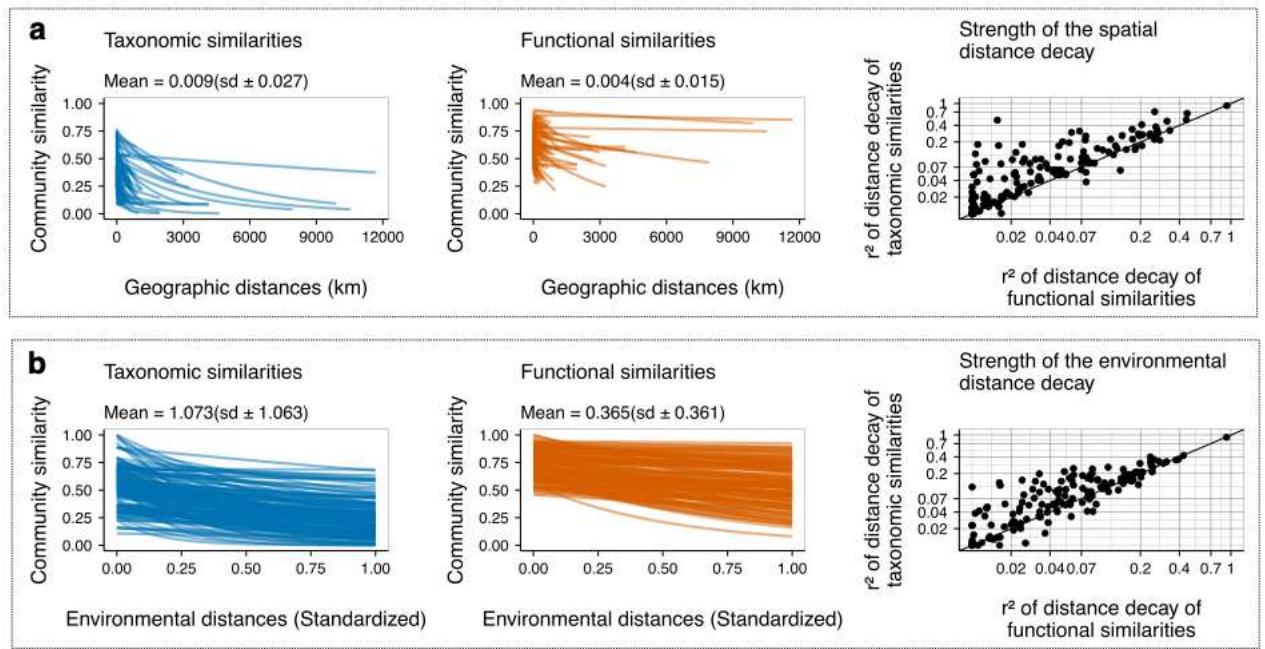
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1092 Figure 3. The analytical framework described step-wisely. The blocks a-c hierarchically describe
1093 the methods performed at dataset level, including the estimation of similarities and distances as well
1094 as the distance decay models of each dataset. The block d describes the tests performed after the

1095 compilation of the metrics from all datasets. The first block (a) shows the four objects used in the
1096 analyses: a species-by-trait table, a sites-by-species matrix, a sites-by-coordinates table and a sites-
1097 by-environment table. The second block (b) illustrates the calculation of taxonomic and functional
1098 similarities, and spatial and environmental distances. In the first example, only species identities are
1099 taken into account and as sites i and j do not share any species, community similarity (blue) equals
1100 zero. In the second example, sites i and j do not share any species, but as two species have same
1101 body size, community similarity (orange) is higher than zero. Similarity is estimated using the
1102 length of the edge of the dendograms as $S = 1 - [(b+c)/(2a+b+c)]$. The third example shows how
1103 spatial distances were calculated as the geographic distances among sites using spatial coordinates.
1104 The fourth example illustrates how sites far from each other may show similar environmental
1105 conditions and therefore small environmental distance. Environmental distances were calculated as
1106 the Euclidean distances of standardized environmental variables. The third block (c) illustrates the
1107 metrics extracted to study the distance decay across datasets. The strength (r^2) and rate (slope) of
1108 decay were extracted from each dataset using log-binomial generalized linear models (GLM). The
1109 models were built separately for each response variable (taxonomic or functional similarity) and
1110 explanatory variables (spatial or environmental distance), totalling four r^2 values and four slopes.
1111 Also, the data of marine fish from the Mediterranean Sea is shown as an example where the
1112 distance decay of similarity along environmental distance is stronger (higher r^2) for functional
1113 similarity than for taxonomic similarity, irrespectively of the rate of decay (slope). The fourth block
1114 (d) describes the analyses used to test the hypotheses and which metrics were considered for each
1115 analysis. The strength (r^2) of decay was used to test hypothesis H_1 while the rate of decay (slope)
1116 was used to hypotheses H_2-H_4 .

The shape and strength of the distance decay

Using occurrence-based total similarities



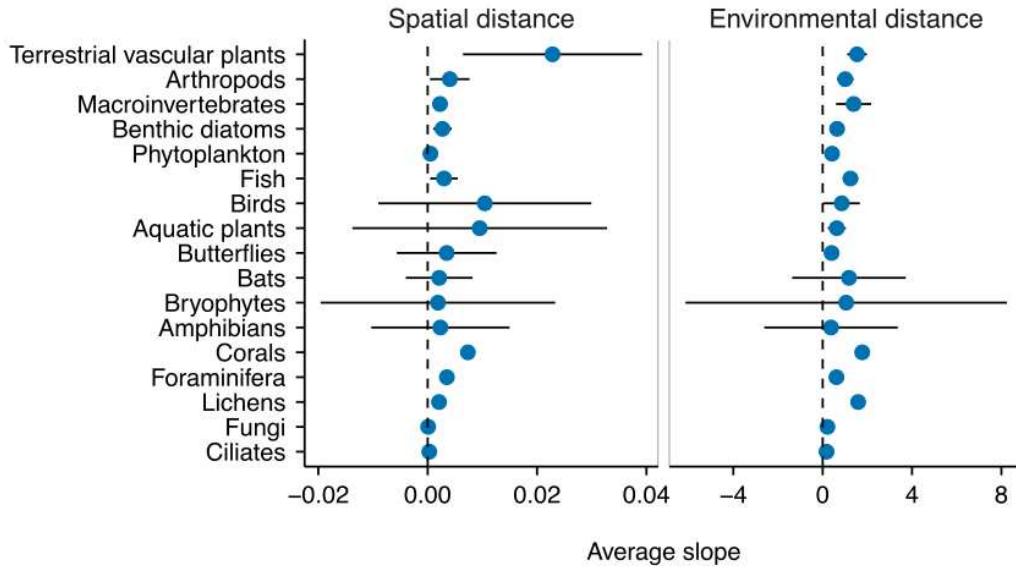
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1118 Figure 4. The distance decay along (a) spatial distance, and (b) environmental distance. Each line in
1119 the panels of left and middle columns shows the shape of the distance decay of an individual
1120 dataset. The mean and standard deviation of slopes are given in the plots. The blue lines show the
1121 distance decay of taxonomic similarity while the orange lines show the distance decay of functional
1122 similarity. The panels on the right column show the strength of the distance decay of taxonomic (y-
1123 axis) and functional (x-axis) similarity. The 1:1 line marks the equivalence of r^2 between taxonomic
1124 and functional similarities. The dots below the line indicate a dataset with stronger decay of
1125 functional than taxonomic similarity, whereas circles above the line indicates stronger decay of
1126 taxonomic than functional similarities.

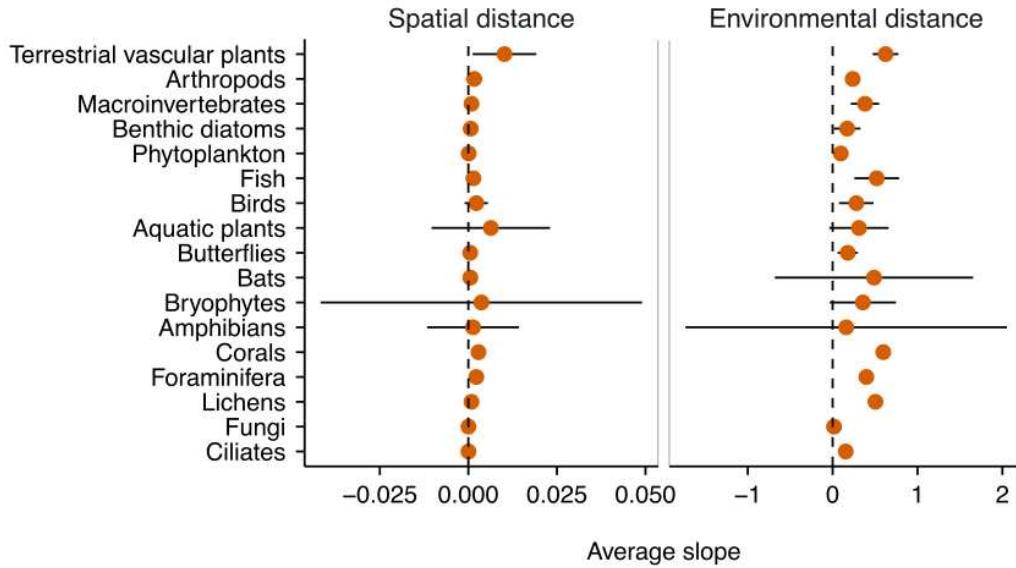
Rate of decay of biotic groups

Using occurrence-based total similarities

Taxonomic similarities



Functional similarities

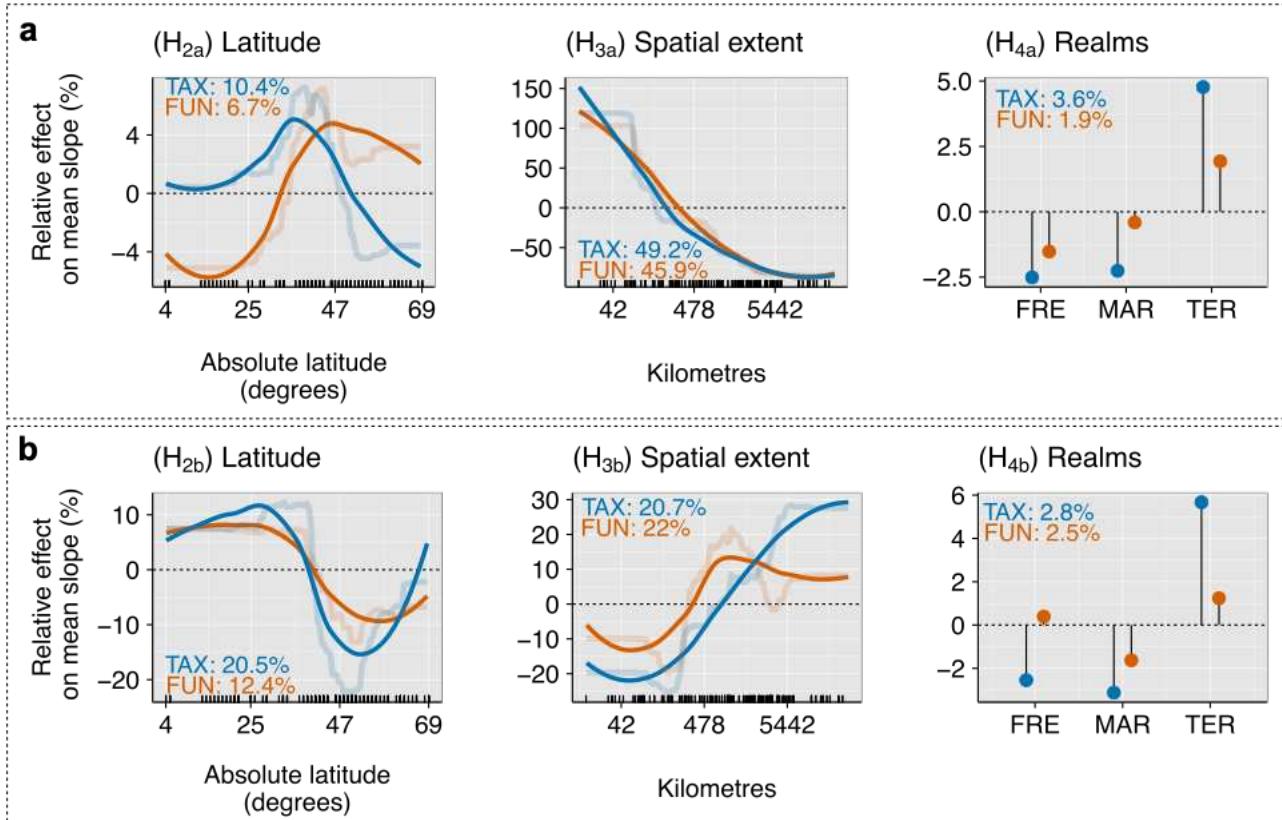


1127

1128 Figure 5. The average rate of decay of biotic groups using occurrence data along spatial and
1129 environmental distance. The vertical dotted lines highlight the zero rate (absence of decay) and the
1130 horizontal lines indicate the standard deviation of the mean. The blue circles show the rate of decay
1131 of taxonomic similarities while the orange circles show the rate of decay of functional similarities.

Effects of geographic factors on the rate of decay

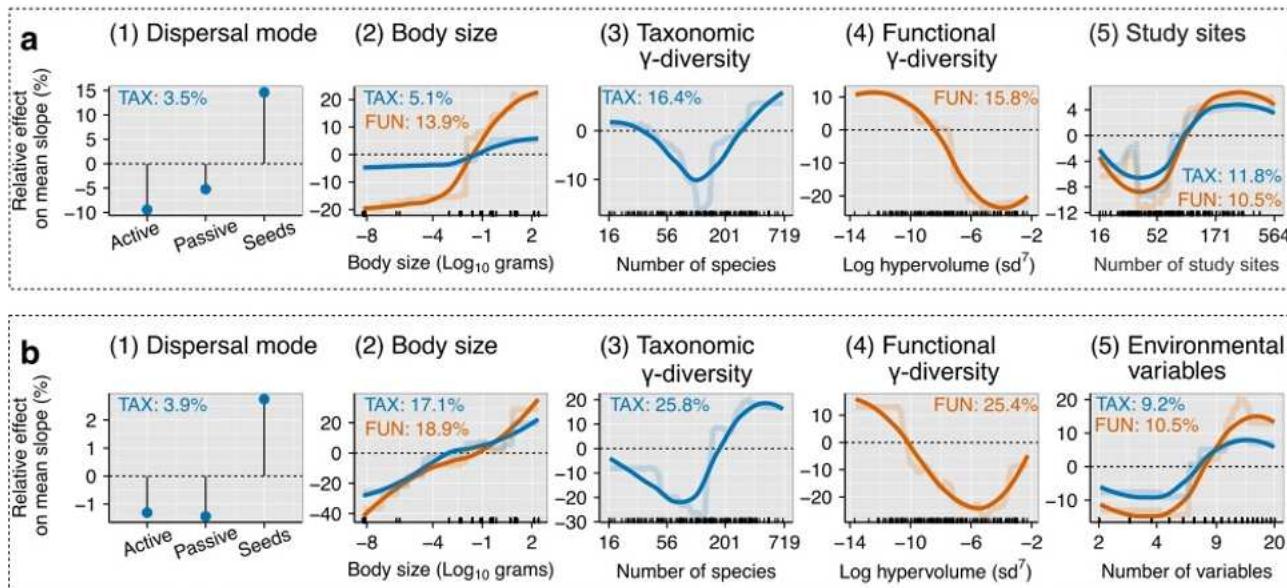
Using occurrence-based total similarities



1133 Figure 6. Relative effects (%) of geographic factors on the rate of decay along spatial (a) and
1134 environmental (b) distance decay of the total component of taxonomic (TAX - blue) and functional
1135 (FUN - orange) similarities using occurrence data across datasets. Partial dependence plots show the
1136 effects of a predictor variable on the response variable after accounting for the average effects of all
1137 other variables in the model. Semi-transparent lines represent the actual predicted effects; solid lines
1138 represent LOESS fits to predicted values from BRT. We show here only the variables related to the
1139 specific hypotheses, i.e., latitude, spatial extent, and realms (FRE = Freshwater, TER = Terrestrial,
1140 MAR = Marine).

Effects of organismal variables and dataset features on the rate of decay

Using occurrence-based total similarities



1142 Figure 7. Relative effects (%) of organismal variables and dataset features on the rate of decay
1143 along spatial (a) and environmental (b) distance considering the total component of taxonomic (blue
1144 lines) and functional (orange lines) similarities using occurrence data across datasets. Partial
1145 dependence plots show the effects of a predictor variable on the response variable after accounting
1146 for the average effects of all other variables in the model. Semi-transparent lines represent the actual
1147 predicted effects; solid lines represent LOESS fits to predicted values from BRT. We show here the
1148 organismal variables and the variables related to the dataset features.