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Assessing functional diversity: the influence of the number of the functional traits

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Abstract :

The impact of the variation of the number of functional traits on functional diversity assessment is still poorly known. Although the covariation between these two parameters may be desirable in some situations (e.g. if adding functional traits provides relevant new functional information), it may also result from mathematical artefacts and lead to misinterpretation of the results obtained. Here, we have tested the behaviour of a set of nine indices widely used for assessing the three main components of functional diversity (i.e. functional richness, evenness and divergence), according to the variation in the number of functional traits. We found that the number of functional traits may strongly impact the values of most of the indices considered, whatever the functional information they contain. The FRic, TOP and n-hypervolume indices that have been developed to characterize the functional richness component appeared to be highly sensitive to the variation in the number of traits considered. Regarding functional divergence, most of the indices considered (i.e. Q, FDis and FSpe) also showed a high degree of sensitivity to the number of traits considered. In contrast, we found that indices used to compute functional evenness (FEve and Ru), as well as one of the indices related to functional divergence (FDiv), are weakly influenced by the variation in the number of traits. All these results suggest that interpretation of most of the functional diversity indices considered cannot only be based on their values as they are, but requires taking into account the way in which they have been computed.

Keywords : Functional traits, Dissimilarity metric, Functional diversity, Index sensitivity, Trend analysis

Introduction

Functional diversity, based on the value and range of biological traits in ecosystems (Diaz & Cabido 2001), is becoming a major concept in ecology and ecosystem management in both the terrestrial and marine domains. An increasing body of literature suggests that functional diversity, rather than species diversity, enhances ecosystem functions such as productivity (Tilman et al. 1997, Diaz & Cabido 2001, Hooper & Dukes 2004, Petchey et al. 2004, Hooper et al. 2005), resilience to disturbances or invasion (Dukes 2001, Bellwood et al. 2004) and regulation in the flux of matter (Waldbusser et al. 2004, Villéger et al. 2008). It is therefore assumed that functional diversity may have the potential to link morphological, physiological and phenological variations at the individual level to ecosystem processes and patterns (Petchey et al. 2009).

In the current context of the acceleration of global change, there are increasing numbers of meta-analyses based on functional diversity aiming to understand and predict at global scale the responses of ecosystems in the face of disturbances (natural and/or anthropic, e.g. Devictor et al. 2010, Buisson et al. 2013, Stuart-Smith et al. 2013, D'agata et al. 2014, Parravicini et al. 2014, Mazel et al. 2014, Mouillot et al. 2014). The meta-analyses are generally based on the compilation of datasets which do not always share the same properties (e.g. number of species, number of functional traits or nature of functional traits; e.g.

Flynn et al. 2009, Aubin et al. 2013). For example, in their study, Flynn et al. (2009) used 5 functional traits for birds and 8 functional traits for plants to describe their ecological responses in a context of land use intensification. In order to correctly perform these meta-analyses, it is necessary to know the influence of the dataset properties on the values of the indices computed. The influence of the variation of species richness, for example, has been widely studied (see Mouchet et al. 2010) and suitable methods (e.g. use of nulls models, Mason et al. 2007) have been developed to counteract its effect. Although the number of functional traits is also reputed to influence the index values (Podani and Schmera 2006), no studies have assessed the shape (i.e. the trend) and the cause (i.e. the mathematical explanation) of this relation. However, good knowledge of the mathematical relations existing between the properties of the dataset and the indices used is necessary to properly perform meta-analysis.

In the present work, we investigated the influence of variations in the number of functional traits on the basis of a large set of functional indices describing the three major components of functional diversity (i.e. functional richness, functional evenness and functional divergence). We also tested the impact of the dissimilarity metric used on the trend observed between the functional diversity indices and the number of functional traits. The nine indices selected here are usually considered as among the most promising indices for assessing and monitoring functional diversity in both marine and terrestrial ecosystems (e.g. Mouillot et al. 2011, Pakeman et al. 2013, Buisson et al. 2013, Parravicini et al. 2014, Fontana et al. 2015). More specifically, we have addressed the following questions: (1) To what degree and how is each index affected by the number of traits considered? (2) Does the relation of each index with the number of traits vary according to the metric used (Euclidean distance vs Gower dissimilarity)? Finally, we regrouped the results of (1) and (2) in a table in order to help users to better interpret the results they obtained.

Material and Methods

Selected functional indices

We tested here the most promising indices used to assess functional diversity and its three major components. More precisely, for assessing functional richness, which represents the amount of niche space occupied by the species within a community (Mouillot et al. 2013), we included FRic (Villéger et al. 2008), the TOP index (Fontana et al. 2015) and the n-hypervolume index (hereafter called HYPE, Blonder et al. 2014) that offer different insights into this general concept. Thus, the FRic index measures the volume of functional space occupied by the species and does not consider all the species present in the community for this (Villéger et al. 2008). In contrast, in considering all the species present in the community, the TOP index measures more specifically the overall range and composition of functional space (Fontana et al. 2015). Finally, the HYPE index represents the level of functional space filled by the community (Blonder et al. 2014). In short, although these 3 indices belong to the same concept (i.e. "functional richness), they do not measure exactly the same thing, and they do not have the same advantages and drawbacks (see Legras et al. 2018 for more details). For the same reason, we studied the functional evenness (i.e. the regularity of the distribution of the species in the functional space, Villéger et al. 2008), on the basis of two complementary indices: FEve (Villéger et al. 2008) and Ru (Ricotta et al. 2014). The main structural difference between these two indices is that the FEve index uses the Minimum Spanning Tree, MST) in its computation, which is not the case for the Ru index (Villéger et al. 2008, Ricotta et al. 2014). Finally, for the functional divergence component (i.e. the proportion of total abundance belonging to the most extreme functional species, Mouillot et al. 2013), we used FDiv (Villéger et al. 2008), FDis (Laliberté & Legendre 2010), Q (quadratic entropy of Rao, Botta-Dukat 2005) and FSpe (Villéger et al. 2010). As for the two previous components, all indices characterizing the functional divergence do not use the same mathematical tools to definite it. For example, FDis measures the mean distance of species from the centroid of community, whereas Q measures the pairwise distances between species (see Table 1 for further detail regarding the definitions and the mathematical formula of each index). Further information about the definition, the pros and the cons of each index can be found in Schleuter et al. 2010, Legras et al. 2018 and Legras & Gaertner 2018).

Although $FD_{P\&G}$ (index based on dendrogram construction, Petchey & Gaston 2002) is one of most widely used to characterize the functional richness, we have not selected this index for our study. Several studies have shown that the $FD_{P\&G}$. index suffers from several drawbacks. For instance, Maire et al. (2015) and Loiseau et al. (2017) have demonstrated that using a dendrogram-based method could lead to functional space of low quality and may alter the assessment of functional diversity and result in misleading ecological conclusions.

Simulated dataset

We simulated a pool of 50 species characterized by nine functional traits. The number of functionally different species was kept constant at 50, whatever the number of traits considered, because Mouchet et al. (2010) have demonstrated that this parameter could impact the functional diversity index values. Abundance matrices were simulated by random selection in the log normal distribution (a common pattern in nature; Preston 1948, Mouchet et al. 2010), and kept constant during the simulations. Thus, the abundance matrix had 1 row and 50 columns in order to simulate the results of a sample of 50 species at a single site. For the pool of 50 species, the values of traits for each species were obtained by a random selection in the normal distribution (μ=0 and σ= 1 – see further details on this rationale in Kraft et al. 2008 and in Mouchet et al. 2010).

The method for computing the considered indices differs according to the nature (quantitative or qualitative) of the functional traits (Laliberté & Legendre, 2010). If all studied traits are quantitative and no values are missing, indices are directly computed on the basis of their mathematical formula (see Table 1). For indices related to the functional space concept (i.e. FRic, TOP, HYPE, FEve and FDiv), the T trait values observed for each species are then used as T coordinates for projecting each species in the functional space (Villéger et al. 2008, Fontana et al. 2015). The other indices (i.e. Ru, FDis, Q and FSpe) are directly computed from the dissimilarity matrix (called hereafter DMatrix). This DMatrix is obtained by calculating the Euclidean distance between each pair of species. The greater the distance between two species, the more these two species can be considered as functionally distinct. Conversely, if all traits are either qualitative or represent a mix of both qualitative and quantitative variables, or if they are missing values, none of the indices considered can be computed, as previously explained. Regarding FRic, TOP, HYPE, FEve and FDiv, species cannot be projected according to their values in qualitative functional traits in a suitable manner. Similarly, for Ru, FDis, Q and FSpe, Euclidean distance cannot be used on qualitative data. In these cases, authors have to use an alternative method, which differs according to the indices considered. Regarding Ru, FDis, Q and FSpe, the alternative method consists in using the Gower distance rather than the Euclidean distance (Laliberté & Legendre, 2010; Podani & Schmera 2006). For FRic, TOP, HYPE, FEve and FDiv, the problem is solved by carrying out a factor analysis (a PCoA based on Gower distance for the dissimilarity matrix) on the functional traits matrix (Laliberté & Legendre, 2010). The factorial coordinate’s matrix can then be used for projecting species on the functional space. However, it is recommended by some authors to use a factor analysis (PCA or PCoA) and Gower dissimilarity even if all traits are quantitative (Villéger et al. 2008, Laliberté & Legendre 2010, Maire et al. 2015). In fact, this operation makes it possible to i) avoid the undesirable effect of traits correlation, and ii) reduce the dimensionality of the initial dataset (a high dimensionality leading to long computation time for some indices). Thus, we have chosen to apply a factor analysis in our study, even in this case, in order to be closer to the situations encountered in the case studies. For the sake of brevity, only results with the conservation of the two first factorial coordinates are presented here (we also simulated situations with 4 and 6 factorial coordinates that provided similar results, see Supplementary Material, Fig. S1). To test the impact of the metric used on the relation between functional index values and the number of functional traits, Euclidean vs Gower metrics (respectively hereafter called 'Euclidean-based Approach' and 'Gower-based Approach') were applied on the simulated data to compute DMatrix. To test the influence of the number of functional traits, we computed the functional indices for the number of traits varying from two to nine.

All these simulations were performed 999 times using the R software (R Development Core Team 2014) through FD package (Laliberté & Legendre 2010), *TOP.index* function (Fontana et al. 2015), *FeveR* function (Ricotta et al. 2014) and *fspe* function (Villéger et al. 2010). Moreover, it is important to note that due to our simulation procedure (i.e. functional traits were randomly selected and bootstrapped), results obtained remained independent of trait identity (i.e. they are not dependent on the functional information contained by traits). More specifically, this simulation procedure enables us to strictly evaluate the mathematical relationship (i.e. the trend) between the functional indices and the number of functional traits, whatever the functional information they contain. The relation between the functional index values and the number of functional traits for both metrics was tested by means of a trend analysis in an ANOVA framework.

Results

Euclidean-based Approach

When using the Euclidean-based approach, the three indices characterizing functional richness (i.e. FRic, TOP and HYPE indices) are influenced by the number of traits (t) used. More specifically, these indices increased with the number of functional traits and are characterized by a linear relationship for FRic and the TOP index (Table 2, adjusted R-squared (adj.R^2) =0.74 and 0.61 respectively), and a quartic relationship for the HYPE index (adj.R^2=0.85). For the evenness component, FEve and Ru remained stable relative to the number of functional traits (Fig 2), despite highlighting a cubic trend observed for the Ru index (Table 2, adj.R^2 for Ru index = 0.93). In contrast, for the divergence component, only the FDiv index was not influenced by the number of functional traits (adj.R^2 close to 0 and p-value = 0.17, Table 2). The three other indices (i.e. FDis, FSpe and Q) were both positively and closely correlated with the number of functional traits (Fig 2). Furthermore, these indices are mainly characterized by a cubic relationship with the number of functional traits for the FDis and FSpe indices (Table 2, both adj.R^2=0.99), and by a linear relationship for the Q index (Table 2, adj.R^2=1). We note that indices projected into functional space (i.e. FRic, TOP, HYPE, FEve and FDiv) showed the same trends whatever the number of dimensions of functional space (see Supplementary Material – Fig. S1).

Gower-based Approach

The FRic, TOP and HYPE indices strongly decreased with the increasing number of functional traits in a 2-D functional space (Fig 3). This trend is observed whatever the number of dimensions considered for the functional space (i.e. for 4 and 6 dimensions, see Supplementary Material – Fig. S2.). The FRic and TOP indices are respectively characterized by a significant cubic relationship with the number of functional traits (see Table 2, adj.R^2=0.95 and 0.93 respectively), whereas the HYPE index is characterized by a quartic relationship (adj.R^2= 0.96). For the evenness component, the number of functional traits very weakly influences both indices (i.e. FEve and Ru indices), as demonstrated by the trend analysis (Table 2, adj.R^2= 0.01 for FEve index and adj.R^2 = 0.02 for Ru index). For the divergence component, we also observed low adj.R^2 for FDiv index (Table 2, adj.R^2 = 0.02). Conversely, FDis, FSpe and Q decreased with the number of functional traits and they are characterized by a significant quartic relationship (see Table 2, adj.R^2= 0.82 for both FDis and FSpe and 0.78 for Q).This result implies that the number of functional traits strongly affects these three indices values when the Gower dissimilarity is used.

Discussion

The choice of traits used is of primary importance for assessing functional diversity because it is dependent on both the ecological question addressed and the characteristics of the community studied (Petchey & Gaston 2006). Here, we present the first study strictly focused on the relation between the functional diversity indices and the number of functional traits according to the dissimilarity metrics used. Although the number of functional entities (i.e. species sharing the same combination of functional trait values) remains constant, our results showed that functional diversity indices values are influenced by the variations in the number of traits (independently of the functional information they contain) and by the dissimilarity metric used (Euclidean distance or Gower dissimilarity).

In our study, functional richness is investigated on the basis of the FRic, TOP and HYPE indices. These three indices are all based on the construction of a geometrical objet in a multidimensional space: the convex hull for the FRic and TOP indices (Villéger et al. 2008, Fontana et al. 2015) and the hypervolume for the HYPE index (Blonder et al. 2014). Here, we showed that these three indices strongly increased with the number of functional traits with Euclidean distance, while they decreased with Gower dissimilarity. This is due to the fact that the Euclidean distance is not normed and positively correlated with the number of functional traits (Mason et al. 2005, Podani & Schmera 2006, Mason et al. 2007). Using Euclidean distance, the more functional traits there are, the greater is the distance between species and the more widely spaced in the functional space the species are. Thus, the surface and volume of the geometric object built (i.e. convex hull or hypervolume) are greater and these three indices (i.e. FRic, TOP and HYPE) increase when the number of traits increases. The decrease of these three indices with Gower dissimilarity is explained by the fact that the distance between two points A and B decreases with the increase in the number of functional traits after projection in the n-dimensional space when we use Gower dissimilarity (with n constant, see Supplementary Material – Fig S3).

Regarding functional evenness, both indices (FEve and Ru) are weakly influenced by the number of functional traits, whatever the distance metric used. In addition, FEve and Ru are not – or only weakly - influenced by the species richness (Mouchet et al. 2010, Ricotta et al. 2014). Choosing between FEve and Ru should depend on the information sought by the user. FEve is focused on the regularity of the distances between each species (or individuals) and its nearest neighbour, weighted by their relative abundance (Villéger et al. 2008), whereas the Ru index measures the regularity of the distances between each species (or individuals) and all the remaining species (or individuals) of the community, weighted by their relative abundance (Ricotta et al. 2014).

Finally, functional divergence represents how spread-out or how clumped the species are in the niche space, weighted by the relative abundance (Mason et al. 2005), and is usually represented by FDiv, FDis and Q (Pavoine & Bonsall 2011). In addition, the aim of the FSpe index (i.e. quantifying how far apart the species are from the centre of gravity of the species pool, Villéger et al. 2010, Pla et al. 2012) suggests that this index can also be used for assessing this component. Our results showed that the FDiv index is weakly impacted when the number of functional traits increases, whatever the dissimilarity metric used (i.e.

Euclidean distance or Gower dissimilarity). In contrast, our work has demonstrated that FDis, FSpe and Q were positively correlated with the number of functional traits when we used Euclidean distance, whereas they are negatively correlated with this parameter when we used Gower dissimilarity. FDis, FSpe and Q being mathematically proportional to the dissimilarity metric (cf. Table 1), the patterns we observed for these indices are directly derived from the relation existing between the dissimilarity metric used and the number of functional traits (i.e. positive relationship for Euclidean metric (Podani & Schmera 2006) and negative relationship for Gower dissimilarity, see Supplementary Material – Fig S3.)

The selection of indices to be used for properly assessing the main facets of functional diversity of a given community is a complex issue (Loiseau & Gaertner 2015). It primarily depends on the aims of each study and the nature of the available data. With this choice is associated the choice of both the identity and the number of traits to select. Although of primordial importance, this choice could be difficult because it implies very good knowledge of (i) the level of implication of each functional trait in the role of the species in ecosystem, and (ii) the number of functional traits to select to correctly describe a given function. For example, for the food acquisition and locomotion of fishes, Villéger et al. (2010) suggested using 16 morphometric traits to take into account these functions. In another study, Mouillot et al. (2014) used only six functional traits (with only one related to morphometry) to describe the same two functions. This example illustrates that the choice of the number of functional traits to be used for describing a given function is not universal (even for identical species), but based on a partly subjective rationale (Hortal et al. 2015, De Bello et al. 2017). Moreover, this point is particularly difficult to deal with because it gives rise to the dilemma of choosing between "select enough traits to describe a given function" and "select too many traits for a given function", that could generate an overestimation of this function compared to the other functions (overestimation generated by a trivial correlation between traits). A method of ordination (e.g. PCA or PCoA) will avoid these correlations, but ordination entails the risk of a loss of information (since the ordination axes can only capture a proportion of the variation in functional trait values across species, Villéger et al. 2008).

Furthermore, series of sensitivity can be applied to test the robustness of values of functional diversity indices against the number (and the identity) of functional traits (see Mouillot et al. 2014). This can be done by rerunning analyses using all combinations of *(n-1)* traits out of *n*. The results obtained might serve as a basis for the differentiation of the effects due to ecological phenomena from those due to the mathematical artefacts. An alternative solution to overcome this sensitivity might be to compare beforehand the values of indices to null models respecting the same conditions as those used to compute the indices (e.g. same number of functional traits, same dissimilarity metric used). To date, the use of null models has been recommended by several authors (Mason et al. 2007, Mason et al. 2008, Villéger et al. 2008, 2010) to get around the problem of the sensitivity of these indices to the variation of species richness (Mouchet et al. 2010). With the aim of helping ecologists to build proper null models, we have summarized in Table 3 the sensitivity to these factors of the most widely used functional diversity indices on the basis of the results of our study.

To sum up, three operations can be envisaged once the best set of functional traits has been chosen by the users according to the aim of the study. Firstly, a series of sensitivities tests can be applied on the set of traits to avoid some misinterpretation due to the mathematical artefacts. Secondly, a factor analysis (as PCA or PCoA) can be performed to reduce the number of dimensions of functional space. For some indices, a large number of dimensions can entail extensive computation time. Thirdly, to get around the sensitivity of indices to the data used for their computation (e.g. number of functional traits, dissimilarity metric used, species richness), we can compare the value of the index to the values obtained under null models.

Our study is of primarily theoretical importance in providing a better understanding of the mathematical properties of functional diversity indices that may impact the interpretation of results obtained by the ecologists in the field. For example, our study highlights the fact that is highly hazardous to compare the functional diversity values of i) studies which do not exactly share the same number of functional traits, or ii) studies in which functional diversity values are not computed with the same dissimilarity metric. By improving and clarifying the theoretical properties of these indices, our study could help ecologists to better estimate both the diversity patterns and the role of the taxa studied in ecosystem functioning.

Finally, many studies have recently focused on the development of new functional diversity indices (Villéger et al. 2008, Laliberté & Legendre 2010, Fontana et al. 2015). While this domain of research is necessary, our study strongly supports the need to devote a significant methodological effort to the assessment of the mathematical properties of indices already developed in order to better assess their limits and constraints. This would be not only a major step towards avoiding any misinterpretation of the results obtained by the users, but would also provide a methodological basis for orientating future research focused on the development of new indices.

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Table 1: Functional diversity measures. From Mouchet et al. 2010, modified.

Functional diversity Component	**Functional diversity Index**	**Authors**	**Mathematical formula**	**Description**	**Data needed**
Functional richness	TOP	Fontana *et al*. 2015	Quickhull algorithm	Sum of successive convex hull area. Density of functional space filled by the community.	Trait values or factorial coordinates
	FRic	Villéger *et al*. 2008	Quickhull algorithm	Convex Hull Volume. Amount of functional space filled by the community.	Trait values or factorial coordinates
	HYPE	Blonder *et al*. 2014	Computation of n-hypervolume	Level of functional space filled by the community	Trait values or factorial coordinates
Functional evenness	FEve	Villéger *et al*. 2008	$FEve = \frac{\sum_{l=1}^{S-1} \min\left(PEW_l, \frac{1}{S-1}\right) - (\frac{1}{S-1})}{1 - \frac{1}{S-1}}$	Sum of MST branch length *(l)* weighted by relative abundance.	Trait values or factorial coordinates
	Ru	Ricotta et al. 2014	$Ru = \frac{\sum_i^S \min\left\{\left[\frac{\left(p_i * \sum_{j \neq i}^{S} \frac{p_j}{1-p_i} * d_{ij}\right)}{\sum_i^S p_i \sum_{j \neq i}^{S} \frac{p_j}{1-p_i}} * d_{ij}, \frac{1}{S}\right]\right\} - 1/s}{1 - 1/S}$	Regularity with which species are distributed along the tree, together with the evenness in their abundances	Trait values or factorial coordinates
Functional divergence	FDiv	Villéger *et al*. 2008	$FDiv = \frac{\Delta d + \overline{dG}}{\Delta \lvert d \rvert + dG}$	Species deviance from the mean distance to the center of gravity weighted by relative abundance.	Trait values or factorial coordinates
	FDis	Laliberté & Legendre 2010	$FDis = \frac{\sum p_i z_i}{\sum p_i}$	Mean distance of individual species to the centroid of all species to the community.	Dissimilarity matrix

	Q	Rao (1982) & Botta-Dukat (2005)	$Q = \sum_{i=1}^{S}\sum_{j=1}^{S} p_i\, p_j d_{ij}$	Sum of pairwise distances between species weighted by relative abundance.	Dissimilarity matrix
	FSpe	Villéger *et al*. 2010	$FSpe = \sum_{i=1}^{S}(p_i * dG_i)$	Euclidean distance of species to the center of gravity of all the species weighted by relative abundance.	Dissimilarity matrix

d_{ij} : dissimilarity between species i and j. S : total species richness. p_i : relative abundance of species i. dG : mean distance of species to the center of gravity. Δd : sum of abundance-weighted deviances. $\Delta|d|$: absolute abundance-weighted deviances from the center of gravity (see Villéger et al. 2008 for more explanations about computations of $dG, \Delta d$ and $\Delta|d|$) . PEW_l : partial weighted evenness ($PEW_l = \frac{dist(i,j)}{w_i+w_j} \Big/ \sum_{l=1}^{S-1}\frac{dist(i,j)}{w_i+w_j}$, for each branch l of the MST) z_i : distance of individual species to the centroid of the community.

Table 2: Relationship observed between functional diversity indices and number of functional traits by a trend analysis in an ANOVA framework when Euclidean distance or Gower dissimilarity is used for index computation. Code, formula and a short description of each functional diversity index is given in Table 1.

Functional diversity index	Type of relation	p-value associated	Adjusted R-squared
	using Euclidean distance		
FRic	Linear	<2,2e-16	0,74
TOP	Linear	<2,2e-16	0,61
HYPE	Quartic	<2,2e-16	0,85
FEve	Quadratic	0,04	0,003
Ru	Cubic	<2,2e-16	0,93
FDiv	Quadratic	0,17	0,001
FDis	Cubic	<2,2e-16	0,99
FSpe	Cubic	<2,2e-16	0,99
Q	Linear	<2,2e-16	1
	using Gower dissimilarity		
FRic	Cubic	< 2,2e-16	0,95
TOP	Cubic	< 2,2e-16	0,93
HYPE	Quartic	<2,2e-16	0,96
FEve	Linear	0,002	0,01
Ru	linear	3,57e-05	0,02
FDiv	Quadratic	0,001	0,02
FDis	Quartic	4,67e-05	0.82
FSpe	Quartic	5,02e-05	0,82
Q	Quartic	2e-07	0,78

Table 3: Sensitivity of functional diversity indices to the main factors of variation between different datasets. Mathematical formulas of indices are given in Table 1. For the number of traits factor (between 2 to 9), we tested whether the functional diversity values remain the same (insensitive) or not (sensitive) with the increase in this factor. For the dissimilarity metric used (Euclidean vs Gower), we tested whether the patterns of functional diversity indices between the two datasets remain the same (insensitive) or not (sensitive) according to trend analysis in an ANOVA framework (α=0.05).

		Sensitivity to…	
Functional diversity component	Functional diversity index	Number of traits	Distance metric used
Functional richness	FRic	Yes	Yes
	TOP	Yes	Yes
	HYPE	Yes	Yes
Functional evenness	FEve	No	No
	Ru	No	No
Functional divergence	FDiv	No	No
	FDis	Yes	Yes
	FSpe	Yes	Yes
	Q	Yes	Yes

Figures

Fig 1: General framework to compute the nine functional diversity indices studied through the two approaches considered in this study. Modified from Villéger et al. 2008. Tr_i = i^{th} functional trait, Sp j= j^{th} species. PC = Principal component (resulting from a PCoA or a PCA). Comm = Community. Code, formula and a short description of each functional diversity index is given in Table 1.

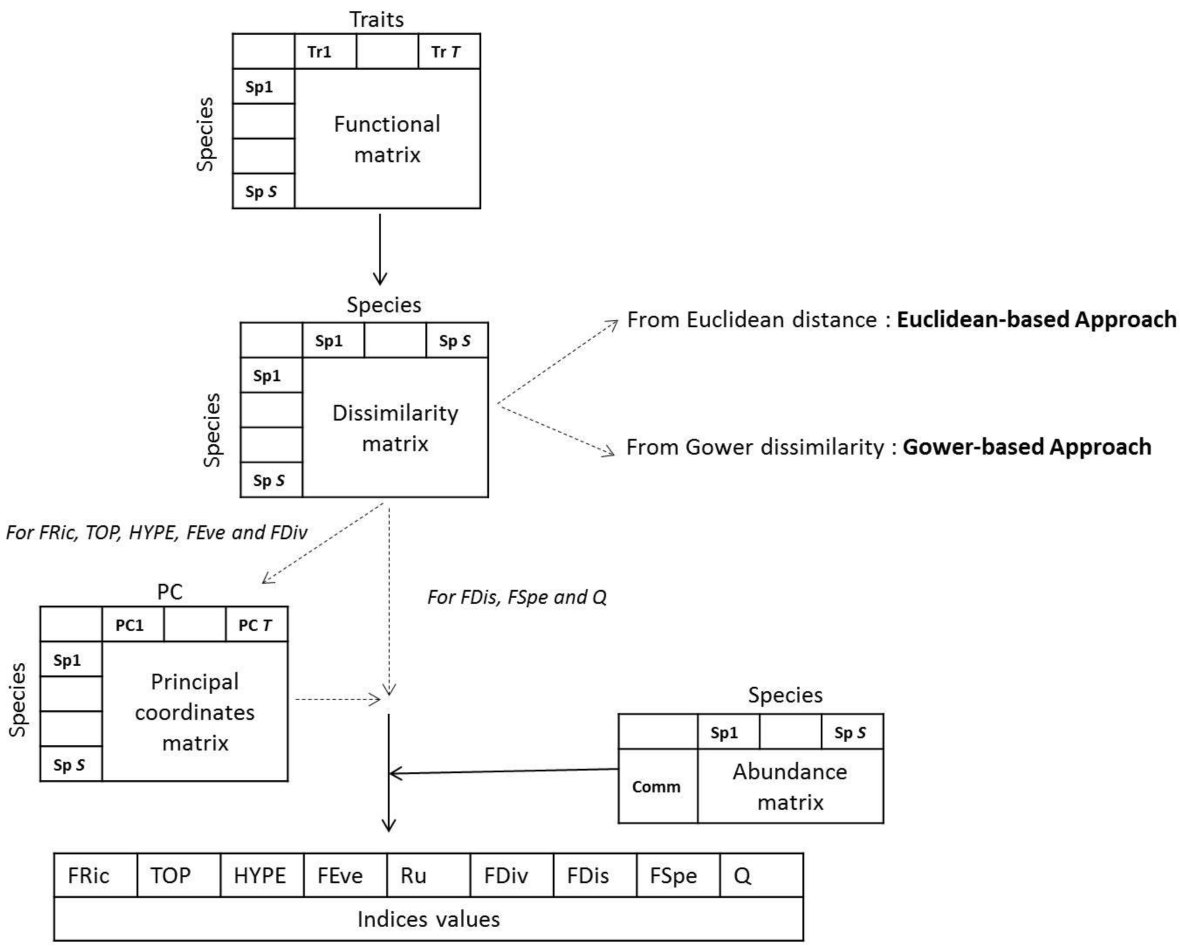

Fig 2: Influence of the number of functional traits on the estimation of functional diversity indices with the Euclidean-based Approach (i.e. computing functional indices from the Euclidean distance matrix). Curves are mean values of indices and vertical bars, associated standard errors. Code, formula and a short description of each functional diversity index is given in Table 1.

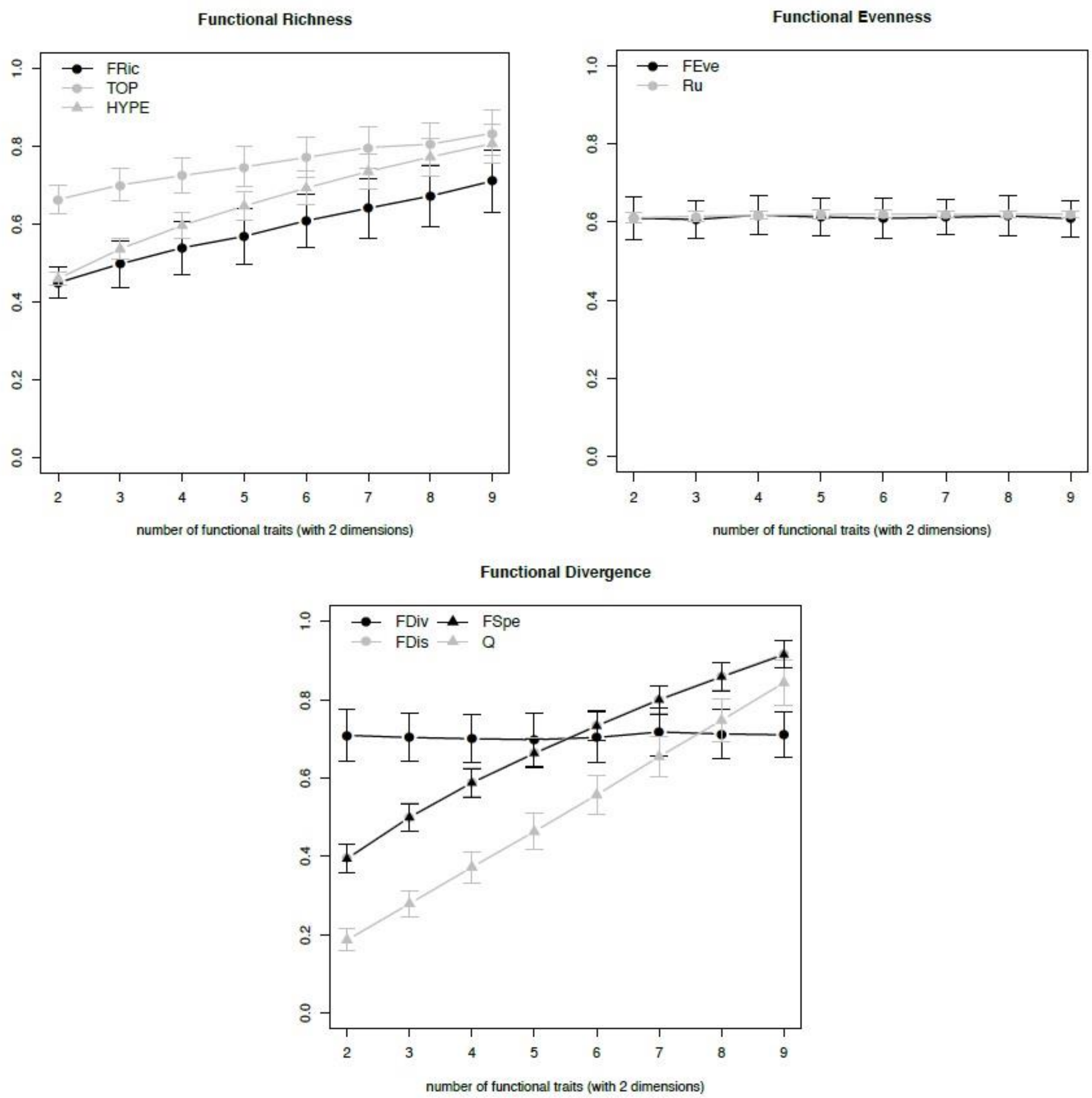

Fig 3: Influence of the number of functional traits on the estimation of functional diversity indices with a Gower-based Approach (i.e. computing functional indices from the Gower dissimilarity matrix). Curves are mean values of indices and vertical bars, associated standard errors. Code, formula and a short description of each functional diversity index is given in Table 1.