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Bibliometric indicators of interdisciplinarity: the potential of the Leinster–Cobbold diversity indices to study disciplinary diversity

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Abstract In bibliometrics, interdisciplinarity is often measured in terms of the "diversity" of research areas in the references that an article cites. The standard indicators used are borrowed mostly from other research areas, notably from ecology (biodiversity measures) and economics (concentration measures). This paper argues that while the measures used in biodiversity research have evolved over time, the interdisciplinarity indicators used in bibliometrics can be mapped to a subset of biodiversity measures from the first and second generations. We discuss the third generation of biodiversity measures and especially the Leinster–Cobbold diversity indices (LCDiv) (Leinster and Cobbold in Ecology 93(3):477–489, 2012). We present a case study based on a previously published dataset of interdisciplinarity study in the field of bio-nano science (Rafols and Meyer in Scientometrics 82(2):263–287, 2010). We replicate the findings of this study to show that the various interdisciplinarity measures are in fact special cases of the LCDiv. The paper discusses some interesting properties of the LCDiv which make them more appealing in the study of disciplinary diversity than the standard interdisciplinary diversity indicators.

Keywords Interdisciplinarity · Disciplinary diversity · Leinster–Cobbold Indices · Hill numbers · Indicators of biodiversity

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Introduction

The concept of "interdisciplinary research" plays an increasingly important role in research policy debates (National Academies 2005). Virtually all research funding bodies and administrations of research institutions promote interdisciplinary research and often explicitly emphasise it in their funding conditions and recruitment or promotion of researchers. This is grounded in the belief that interdisciplinarity—as a mode of research—holds high promises not only to advance science but also to tackle pressing societal problems. Those who promote interdisciplinary research often argue that several, if not most, significant advances in science tend to come from the cross-fertilisation of different research fields. This is exemplified with the emergence of new research areas such as nanotechnology, bio-informatics, neuro-sciences which resulted from interactions and/or convergence between two or more "traditional" research fields. It is also often argued that the majority of societal challenges that research is expected to address transcend the boundaries of traditional research fields (see e.g. European Commission 2012).

Interdisciplinarity has also attracted the attention of science studies where considerable efforts have been made to operationalise and measure the concept of interdisciplinarity. A recent literature review (Wagner et al. 2011) on understanding and measuring interdisciplinarity has identified two approaches. The first approach is an approach which focuses on the interdisciplinary research as a social system and focuses on its systemic drivers as well as on the motives of and interactions among actors involved in interdisciplinary research. The second—bibliometric approach—takes another perspective. Rather than considering the processes and dynamics through which interdisciplinary research occurs, it focuses on the results of research (publications) and seeks to measure the extent to which a particular publication draws from and integrates different research disciplines. This approach has developed a set of indicators which are used to measure the interdisciplinary of a single paper or a body of research. The most commonly used indicators are borrowed from other research areas, notably from ecology (biodiversity measures) and economics (concentration measures).

This paper focuses on the bibliometric approach. Its purpose is to bring to discussion the Leinster–Cobbold diversity indices (LCDiv) which is part of a relatively new class of diversity indicators which are increasingly used in ecology but not widely used to investigate disciplinary diversity. Drawing from the literature in ecology, this paper argue that this new class of diversity measures have important properties which are relevant for the bibliometric study of interdisciplinarity and are lacking in commonly used indicators.

The paper is divided in three parts. The first section briefly discusses the concept of interdisciplinarity, as well as its definition and implementation in bibliometrics. The second section focuses on the development of diversity measures used in ecology and presents the Leinster–Cobbold diversity indices (LCDiv), highlighting its properties most relevant for bibliometric usage. The third section uses a previously published dataset in a case study which illustrates the potential of Leinster–Cobbold diversity indices (LCDiv) as an indicator for disciplinary diversity.

In the concluding remarks, we briefly outline directions of future work.

Interdisciplinarity as "knowledge integration"

The integrative nature of interdisciplinarity

Interdisciplinary research is an ambiguous term, the definition of which rests on a set of assumptions not only about what constitutes a "discipline" but also how they interact.

In current debates, interdisciplinarity is often discussed in connection with other concepts which describe different forms of interactions between research fields. Their definition can help clarify the definition of interdisciplinarity used in this paper.

- *Multidisciplinarity* refers to the situation in which more than one discipline works on the same problem, each bringing its own perspective. Klein (1990, p. 58) cites the example of an Asian Studies centre which houses "*specialists from Oriental history, economics and sociology*". The characteristics of multidisciplinary research would be that—although they work together—"*scholars still work on problems posed by their disciplines*" Klein (1990). She describes this mode of research as "*additive and not integrative*".
- *Transdisciplinarity* refers to the organisation of interdisciplinary research by a grand unifying vision. Transdisciplinary approaches seek to "*transcend the narrow scope of disciplinary world views*" (Klein 1990, p. 66) and often use common conceptual frameworks. As an example of such frameworks, Klein (1990) cites "*general systems theory, structuralism or Marxism*"
- In this perspective, the distinctive feature of *inter-disciplinary research* is its "integrative"—as opposed to "additive" or "transcending"- nature of the cognitive content of research (Huutoniemi et al. 2010). A most commonly used definition in this context has been offered by the US National Academies in its report of the Committee on Facilitating Interdisciplinary Research and Committee on Science. According to this report, interdisciplinary research is defined as "*a mode of research by teams or individuals that integrates information, data, techniques, tools, perspectives, concepts, and/or theories from two or more disciplines or bodies of specialized knowledge to advance fundamental understanding or to solve problems whose solutions are beyond the scope of a single discipline or area of research practice* (National Academies 2005, p. 2). *As the report states further "research is truly interdisciplinary when it is not only just passing two disciplines together to create one product but rather an integration and synthesis of ideas and methods*" (National Academies 2005, p. 27).

From this definition, it is clear that the variety of potential integration level allows for multiple perspectives to describe and study interdisciplinarity and justifies different typologies of interdisciplinarity found in literature (Aboelela et al. 2007). An example of such a typology can be found in the study of a sample of researcher proposals submitted to the Academy of Finland, which distinguish between empirical, methodological and theoretical interdisciplinarity (Huutoniemi et al. 2010).

Bibliometric operationaliziation

Earlier attempts to develop indicators for interdisciplinary research in bibliometrics were frustrated by the lack of adequate data (Porter and Chubin 1985). In a project for the periodic Science Indicators report, Porter and his colleagues preferred to talk about '*cross-disciplinary research*' (Porter and Chubin 1985) and used the citations of scientific papers outside their subject categories as an indicator for cross-disciplinary research.

Table 1 Most common[a] indicators of interdisciplinarity in bibliometric studies

Indicators	Definition/description
Variety	The number of different disciplines that a given paper cites[b]
Shannon entropy	As measure of diversity the Shannon Entropy quantifies how diverse the subject categories in the references are.
Simpson diversity	It measures how references are distributed (or concentrated) in subject categories.
Rao-Stirling index	Can be understood as the Simpson diversity which takes into account distance/similarity (between disciplines)

Source: Rafols and Meyer (2010, p. 267)

[a] There is a growing interest in network-based indicators to measures interdisciplinarity but they are not further discussed here

[b] Its variants includes normalisation by the total numbers of subject categories or the shares of references outside a given subject category

The more recent approaches to measure interdisciplinary takes as a starting point the idea of integrating elements of different disciplines and seek to measure the extent to which it is reflected in the references that a particular paper cites. References in scientific papers are expected to reflect various aspects of interdisciplinarity because researchers normally credit what they are indebted to other disciplines in form of citations. This "debt" can be conceptual (concepts, ideas and approaches from other disciplines); analytical, (methods for defining, collecting and analyse data) and/or technical (tools developed in other fields).

Porter et al. (2007) developed the integration score as a measure of interdisciplinarity which takes into account not only the distribution of the cited references in different subject categories but also how closely related those subject categories are (see also Porter et al. (2006, 2008).

In line with Porter's conceptualisation, Rafols and Meyer (2006, 2010) introduced a new set of bibliometric indicators to quantify the disciplinary diversity of references as a proxy measure of interdisciplinarity. Those indicators are mostly based on the general framework for analysing diversity developed by Stirling (2007).

The most commonly used indicators are summarized in Table 1. Their formal notation will be discussed in subsequent sections. In varying combinations, those indicators have been used to investigate whether science is becoming more interdisciplinary (Porter and Rafols 2009), to study if interdisciplinarity is associated with higher impact (Yegros et al. 2013; Larivière and Gingras. 2010) or to characterise the interdisciplinary work of research organisations (Jensen and Lutkouskaya 2014).

The next section will show that those measures are in fact a subset of indicators used in the field of ecology for the study of biodiversity.

Diversity measures in ecology

With the recognition of the essential role that diversity play in the healthy function of the ecosystem and increasing concerns that it is threatened by human activities, the field of ecology has developed sophisticated measures to quantify biodiversity. A good overview of those measures is provided in Chao and Jost (2012) and Gotelli and Chao (2013). The diversity indicators used in ecology are too numerous to be listed and explained here but they can however be categorised according to the information content.

In the following sections we present diversity measures used in ecology. Looking at how they evolved over time, we can distinguish three "ideal types" of generations of diversities measures. To emphasise the wide context in which those measures are used and following Stirling (2007), we adopt the terms "element" and "systems" instead of the respective terms used in ecology: 'species' and 'assemblage' or 'community'.

The first generation of diversity measures: the distribution sensitive measures

As noted by Chao and Jost (2012), the simplest measure of diversity is the number of distinct elements which exists in a system. A system with only two distinct elements will be said to be more diverse than one with only one element. An obvious limitation of this measure is that it ignores the distribution of the elements. It would not allow to discriminate between systems in which few elements dominate and systems in which the elements are evenly distributed.

The first generation of diversity measures has been developed to take the frequencies of elements into account. The two most popular indicators are the Gini-Simpson Index and the Shannon entropy (Gotelli and Chao 2013 p. 202). Simply put, both assess the distribution of the elements as a starting point and calculate (a) the probability that two chosen individuals belong to different species (in the case of the Gini-Simpson Index) and (b) the uncertainty of the identity of the element of a randomly chosen individual in the system (in the case of Shannon Entropy).

Their formal notation is provided in Eqs. 1 and 2 respectively for the Gini-Simpson Index and Shannon entropy.

$$H_{GS} = 1 - \sum_{i=1}^{S} p_i^2 \quad (1)$$

$$H_{SH} = -\sum_{i=1}^{S} p_i \log p_i \quad (2)$$

where p_i is the proportion of elements in a system and S the number of elements in the system.

It should be noted that for Shannon Entropy, the natural logarithm is conventionally used but one could also use a different base.

Those measures—although they are sensitive to the distribution of elements in the system—have been criticised as they assume that all elements having nothing in common (are "perfectly distinct"). Two systems with equally frequent elements will have the same values even if one contains elements which are more closely related than the other.

Distribution and similarity sensitive measures

The limitation of the distribution-sensitive measures has led to the development of diversity measures which show lower diversity for systems of elements which are closely related and higher diversity for systems of elements which are very different. In context of ecology, those measures would account for taxonomic or phylogenetic differences between the species.

The most commonly similarity sensitive measure is the Rao Quadratic Entropy (see Eq. 3) which extends the Gini–Simpson Index by taking the 'similarity of elements' into consideration.

$$Q = \sum_{i,j} d_{i,j} p_i p_j \tag{3}$$

where $d_{i,j}$ is the distance between the ith and jth element in the distance matrix and p_i is the proportion of element I and S the number of elements in the system.

Ricotta and Szeidl (2006), p. 239) provides a formulation of a measure which extends the Shannon entropy by including distance between elements. In ecology this measure has been further developed into a diversity measure for species difference by Allen et al. (2009) and is referred to as phylogenetic entropy by Chao and Jost (2012, p. 206). The phylogenetic entropy uses a phylogenetic tree to account for the distance/similarity between species. We use the original formulation by Ricotta and Szeidl (2006) which is based on a distance matrix and we refer to this measure here as the Ricota-Szeidl Entropy (Eq. 4).

$$H_d = -\sum_{j=1}^{S} p_j \log\left(1 - \sum_{i\neq j}^{S} d_{ij} p_i\right) \tag{4}$$

The third generation of diversity measures: effective numbers of diversity and their generalisation measures

While the usefulness of diversity measures which are sensitive to both the distribution of elements in a system and the similarity of those elements between them is widely recognised, they have drawn strong criticisms in the biodiversity literature.

The main charge is that those measures fail to satisfy the most basic property that an ecologist would expect from a meaningful measure of diversity, namely the *replication principle*. In simple terms, the "replication principle" states that if you have two completely distinct communities (i.e. without any overlap in the species) with each community having a diversity measure X, one would expect that combining those two communities would result in a community with a diversity measure $2X$. Jost (2006, 2007, 2009) argues that other measures (referred to in this paper as second-generation of diversity measures) do in fact calculate the entropy and cannot be considered measures of the diversity.

One category of diversity measures which satisfy this replication principle is the so called "Hill numbers". The Hill-numbers are a family of diversity measures which "*quantify the diversity in units of equivalents numbers of equally abundant specifies*" (Gotelli and Chao 2013, p. 195). They are also called "effective numbers of species" and can be interpreted as the "*number of equally abundant specifies that are needed to give the same value of the diversity measure*" (Chao and Jost 2012, p. 204).

It should be noted that Hill numbers are also used in other research areas where they support the interpretation of concentration measures like in economics (Adelman 1969) and in political sciences (Laakso and Taagepera 1979).

As measures of diversity, the Hill numbers have some properties that other measures of diversity based on entropy do not have:

- They satisfy the replication principles i.e. two communities with each 4 effective numbers of species will—if pooled together—result in a community whose effective number equal 8. They therefore give logically consistent answers.
- Their linear scale makes it easier to interpret the magnitude of their change. To illustrate this advantage Jost (2006) gives the example of a researcher who finds change from Shannon entropy from 4.5 to 4.1. In that case, researchers would "*go no further than say that the difference is small, and then fall back to statistical tests to see if the difference is*

statistical significant". By using the effective numbers instead, the difference is from 90 to 60 effective numbers of species. This large change of easier to interpret as the "*the question of the real magnitude (is distinguished…) from its statistical significance. (…) It is essential to have informative, interpretable diversity and similarity measures, so that we can go beyond mere statistical conclusions*" (Jost 2006, p. 369).

- In addition to this advantage of intuitive consistency, another interesting property they have is that practically all traditional measures of diversity can be easily converted to "Hill numbers/"effective numbers". Jost (2006) provides an overview of how entropy-based measures can be derived from the traditional, basic entropy measures. Chao el al (2010) developed a new measure of phylogenetic diversity measures based on Hill numbers. This measure—called here Chao's phylogenetic diversity—combines the advantages of (1) taking into account both the frequencies of elements and their similarity (defined as phylogenetic distances) and (2) belonging to the class of Hill numbers and thus satisfying important properties which diversity measures are expected to have. In addition, their measure generalizes and unifies many existing measures.
- Another advantage of the Hill numbers is that, because they are defined by their 'order'—which is a parameter which specifies how their numbers should be sensitive to the distribution of elements—they give the researchers the flexibility to decide how much emphasis is placed on the less frequent elements. Chao's phylogenetic diversity can be computed for several values of 'order' and used to create 'diversity profiles'. In comparing the systems (ecological communities), the diversity profiles show the effect of taking into consideration the rarity/dominance of elements (species) and therefore would convey more information about the diversity of species in the communities than a single diversity number (Chao et al. 2010, p. 3607).

Chao's phylogenetic diversity makes use of the evolutional path of the species to quantify the similarity/dissimilarity between them. As such it is a measure specifically tailored for ecological analysis and cannot be directly used for other contexts.

Leinster and Cobbold (2012) developed a measure which extends the Hill numbers to include the similarities/differences between species. Their measure—called here the Leinster–Cobbold Diversity Indices—can be used with any similarity coefficient between each pair of the species. This extends the scope of its usage to other contexts such disciplinary diversity in bibliometrics.

In the following, we first provide its formal definition and discuss its properties as well as its relation to other diversity measures. In the next section we provide a case study of its use in the study of disciplinary diversity.

Consider a system with S elements with relative frequencies translating in estimated probabilities $p = (p_1, \ldots, p_S)$ so that $\sum_{i=1}^{S} p_i = 1$.

The similarity between the elements is encoded in an $S \times S$ matrix $Z = \left(Z_{i,j}\right)$. The element $Z_{i,j}$ measures the similarity between the ith and jth elements. The similarity lies between 0 and 1, whereby 0 indicates total dissimilarity and 1 indicates identical elements.

The Leinster–Cobbold diversity indices (LCDiv) are defined as

$$
{}^{q}D^{Z}(\boldsymbol{p}) = \begin{cases} \left(\sum\limits_{i:p_i > 0} p_i (Z\boldsymbol{p})_i^{q-1} \right)^{\frac{1}{1-q}} & q \neq 1, \\ \prod\limits_{i:p_i > 0} (Z\boldsymbol{p})_i^{-p_i} & q = 1, \\ \min\limits_{i:p_i > 0} \dfrac{1}{(Z\boldsymbol{p})_i} & q = \infty \end{cases} . \tag{5}
$$

where

$$\left(Z_p\right)i = \sum_{j=1}^{S} Z_{i,j} p_i \tag{6}$$

The quantity $\left(Z_p\right)i$ in Eq. 6 represents the expected similarity between an element of the category i and an element in the system chosen at random. In this sense it measure how "ordinary" the category i is within the system.

q is in number in range $0 \leq q \leq$ Infinity. It is called *a sensitivity parameter* and control the relative emphasise that the user wishes to place on common and rare elements.

Using the Leinster-Cobbold diversity indices (LCDiv) as a measure of disciplinary diversity

Diversity measures in ecology and bibliometrics

A comparison of the diversity measures in ecology and in bibliometrics shows that the bibliometric indicators can be mapped to a subset of the first two generations of diversity measures used in ecology.

Distribution sensitive measures are a class of measures that takes into account not only the number of elements in a system but also their distribution. The bibliometric indicators Shannon and Simpson fall into this category.

Distribution and distance sensitive, are a category of measures which also take into account the similarity or dissimilarity between the elements. The rationale is that, other things being equal, the assemblage of closely related species would be less phylogenetically diverse than a set if distantly related species. This is the category in which the Rao-Stiring index belongs.

To our knowledge, the third generations of diversity measures, the *effective numbers/generalisation measures* has not been until very recently (Zhang et al. 2015; Mugabushaka et al. 2015) been discussed in the bibliometric literature.

We argue that the interesting properties which make the (LCDiv) appealing for biodiversity study are equally relevant also for the study of disciplinary diversity in bibliometrics. Table 2 below provides an overview of diversity indicators in ecology and the names under which they are used in the bibliometric literature.

First, as Leinster and Cobbold (2012) have shown the most commonly used measures of disciplinary diversity in bibliometic and several others diversity measures used in the field of biodiversity can be seen as special cases of the Leinster–Cobbold diversity indices (LCDiv). The advantage in bibliometrics is obvious: not only would one have a single formula which would replace the Shannon entropy, the Simpson Diversity and the Rao-Stirling Index, but it would also to explore other diversity measures which are not used in bibliometrics. Table 3 below shows how the Leinster–Cobbold diversity indices (LCDiv) can be converted to those indicators and vice versa.

Second: because the Leinster–Cobbold diversity indices (LCDiv) produce "effective numbers" which satisfy the replication principle gives, they give diversity value which can be easily interpreted and compared. This is also relevant when studying their patterns and trends.

Third: by quantifying the diversity on a spectrum of the sensitivity parameter q (which specifies how much emphasis should be given to relatively rare elements in the system),

Table 2 Overview of diversity indicators in ecology and in bibliometric studies

	Indicators	Advantages	Limitations	Usage in bibliometrics
Simple	Number of elements		Ignore the distribution of elements, would not detect dominance by few elements	Variety
First generation of diverity measures: distribution sensitive measures	Shannon Entropy	Takes into account frequencies of elements and their distribution	Ignore the similarity or dissimilarity between the elements	Shannon Entropy
	Gini-Simpson Diversity			Simpson Diversity
Second generation of diverity measures: distance sensitive measures	Rao-Quadrartic Entropy	Takes into consideration the distance/similarity between categories	Does not satisfy the "replication principle" and thus lacks intuitive consistency	Rao–Stirling Index
	Ricota-Szeidl Entropy	Rao-Quadratic entropy generalizes the Gini-Simpson entropy while the Ricota-Szeidl entropy generalises the Shannon entropy		–
Third generation of diverity measures: unifying frameworks	Hill numbers/ Effective numbers	Satisfy the replication principle	Do not take into account distance/ similarity between elements	–
	Leinster–Cobbold diversity indices (LCDiv)	Satisfy the replication principles Take into account distance/ similarity between elements Use a sensitivity parameter Generalise all other measures listed above		–

the Leinster–Cobbold diversity indices (LCDiv) provide potentially more information than measures which consider only one arbitrary chosen value of this sensitivity parameter.

In the following we use a case study to illustrate why the properties of this class of diversity measures is of interest in the context of disciplinary diversity and which additional advantages they offer in comparison to the diversity measures used hitherto in bibliometrics.

Case study: disciplinary diversity of selected papers in bio-nanoscience

The case study is based on a dataset of 12 journal articles from a group of five researchers from the bio-nano science described and published by Rafols and Meyer (2010). For those 12 papers, Rafols and Meyers published the distribution of their references in Web of Science Categories (Rafols and Meyers, 2010 Table 3, p. 276) as well as the scores on various indicators of diversity (ibid. Table 4, p. 277). The similarity/distance measures

Table 3 Conversion between Leinster–Cobbold diversity indices (LCDiv) and selected diversity measures

	Given the Leinster–Cobbold diversity indices ${}^qD^Z$(p) where Z = similarity matrix Z_1 = identity matrix, q sensitivity parameter and p the probability vector of elements in a system ${}^qD^Z(p)$ can be transformed in selected diversity measures according to formula given below		
	Variety	Gini–Simpson and Rao-quadratic entropy	Shannon entropy and Ricotta-Szeidl entropy
Without considering distance/similarity of categories	Variety $= {}^qD^Z(p)$ with $Z = Z_1$ and $q = 0$	Gini-Simpson $= 1 - (1/{}^qD^Z(p))$ with $Z = Z_1$ and $q = 2$	Shannon $= \ln({}^qD^Z(p))$ with $Z = Z_1$ and $q = 1$
Taking into account distance/similarities of categories		Rao-quadratic entropy = 1 $(1/({}^qD^Z(p)))$ With $q = 2$	Ricotta-szeidl = $\ln({}^qD^Z(p))$ $q = 1$

between the Web of Science subject categories are taken from the supplementary materials[1] to the paper by Chavarro et al. (2014).

This case study has two objectives:

- to illustrate that the various diversity measures are in fact special cases of the Leinster–Cobbold diversity indices (LCDiv). Here we replicate the diversity measures computed by Rafols and Meyer 2010 using the Leinster–Cobbold diversity profiles.
- to show that the diversity profiles offer more information than single numbers diversity indicators. To this end, we compare the diversity profiles of three papers computed at different values of the sensitivity parameters q.

Replicating measures of diversity in Rafols and Meyer (2010)

We first compute the values of the Leinster–Cobbold diversity indices (LCDiv) using different values for the sensitivity parameters (0, 1, 2, 3, 4 and infinity) and in two variants: without taking into account the distance/similarity between the subject categories (i.e. with Z as an identity matrix) and by taking into account the distance/similarity between the subject categories (using the data described above).

The Table 4 show the values of the Leinster–Cobbold diversity indices (LCDiv). The left part of the table show values of the measures assuming that the categories are perfectly distinct, while the right part include values which take into account the proximity of various subject categories.

We then use the conversion formulas provided in Table 3 to derive, from the values of Leinster–Cobbold diversity indices (LCDiv) the various diversity measures provided in Rafols and Meyer (2010, Table 4 on p. 277). The results are shown in Table 5. We note some differences which are due to rounding. In case of the Shannon Entropy, the results differ because this indicator is in Rafols and Meyer (2010) is given in a normalized form.

[1] http://www.interdisciplinaryscience.net/topics/interdisciplinarity-and-local-knowledge.

Table 4 Leinster–Cobbold diversity indices (LCDiv)[a] for the 12 papers in Rafols and Meyer (2010)

	Not considering distance/similarity						Considering distance/similarity					
Sensitivity parameter q	0	1	2	3	4	Inf	0	1	2	3	4	Inf
Column no.	1	2	3	4	5	6	7	8	9	10	11	12
Papers												
Fun95	16	6.452	4.553	3.989	3.740	3.106	1.656	1.422	1.329	1.288	1.266	1.188
Koj97	17	5.526	4.232	3.848	3.652	2.880	1.479	1.284	1.225	1.203	1.192	1.143
Ish98	15	5.003	3.499	2.990	2.741	2.156	1.342	1.229	1.192	1.176	1.167	1.108
Noj97	16	4.532	3.120	2.665	2.447	1.967	1.280	1.172	1.141	1.128	1.122	1.077
Yas98	16	4.466	3.003	2.537	2.327	1.890	1.231	1.158	1.133	1.122	1.115	1.072
Oka99	16	4.857	3.814	3.557	3.439	3.062	1.253	1.190	1.165	1.154	1.148	1.108
Kik01	14	4.944	3.857	3.534	3.364	2.673	1.251	1.195	1.169	1.155	1.148	1.102
Sak99	14	5.103	4.040	3.764	3.641	3.184	1.245	1.181	1.159	1.149	1.143	1.098
Bur03	14	4.697	3.536	3.230	3.086	2.571	1.178	1.142	1.127	1.120	1.115	1.082
Tom00	15	4.841	3.846	3.625	3.530	3.028	1.227	1.165	1.145	1.136	1.132	1.095
Tom02	14	4.849	3.864	3.630	3.531	3.192	1.242	1.180	1.159	1.149	1.143	1.103
Yil04	16	5.358	4.128	3.858	3.753	3.418	1.377	1.232	1.190	1.173	1.164	1.120

[a] Generally for effective numbers the decimals after the comma are not meaningful. We keep them here for the conversion in other diversity measures (see Table 5)

Table 5 Deriving diversity measures commonly used in bibliometrics from the values of the Leinster–Cobbold diversity indices (LCDiv)

Computation	Variety Col 1	Gini–Simpson 1 − (1/Col 3)	Shannon ln(Col 2)	Rao 1 − (1/Col 9)	Ricotta–Seidl[a] ln(Col 7)
Papers					
Fun95	16	0.780	1.864	0.247	0.352
Koj97	17	0.764	1.709	0.184	0.250
Ish98	15	0.714	1.610	0.161	0.206
Noj97	16	0.679	1.511	0.124	0.159
Yas98	16	0.667	1.496	0.118	0.147
Oka99	16	0.738	1.581	0.142	0.174
Kik01	14	0.741	1.598	0.144	0.178
Sak99	14	0.752	1.630	0.137	0.166
Bur03	14	0.717	1.547	0.113	0.133
Tom00	15	0.740	1.577	0.127	0.152
Tom02	14	0.741	1.579	0.137	0.166
Yil04	16	0.758	1.679	0.159	0.209

[a] Although this measure is not used in bibliometric analysis, it is given here to illustrate that this class of diversity measures can be derived from the Leinster–Cobbold diversity indices (LCDiv)

Charting measures of diversity profiles

The 12 papers in the dataset have in fact diversity scores which are very close and it is difficult to say which ones have a higher “diversity” than others. Yet to illustrate how the diversity

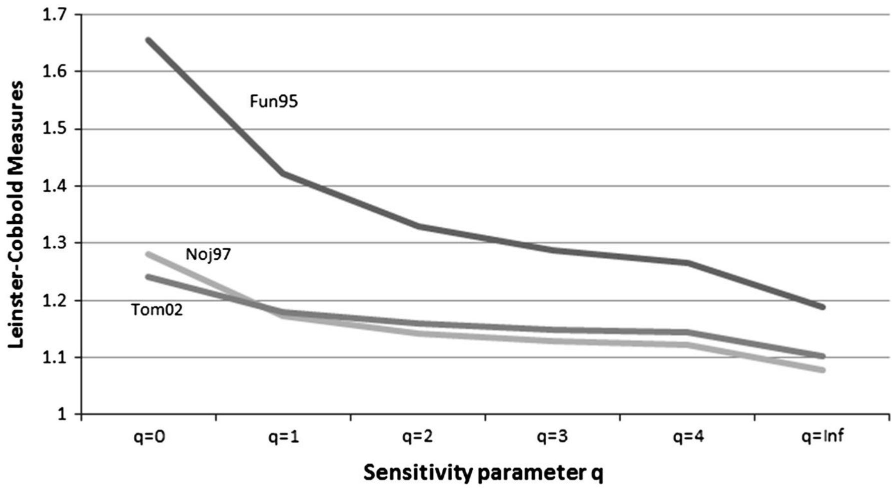

Fig. 1 Leinster–Cobbold diversity profiles of three selected papers

profiles conveys more information than a single number we use the diversity measures (taken at a various values of the sensitivity parameter q), to compare three selected papers.

Consider the Leinster–Cobbold values of the three papers Fun95, Noj97 and Tom02 at different values of the sensitivity parameter q.

We note that the differences are in fact very small and want to caution the reader not to over-interpret them. The point we want to illustrate here is diversity profiles offer more information than single numbers.

The Fig. 1 shows that for all values of q considered, the first paper is characterized by a higher disciplinary diversity in its references that the two other papers. However, for the two other papers, the situation is not that clear. For $q = 0$, the diversity of references of the Noj97 is higher than for Tom02. If we use the diversity measures at this given sensitivity parameter q, we may reach the conclusion that the references in Noj97 are more diverse than those of Tom02. However, for all other values considered, the situation is reversed. As Leinster and Cobbold (2012, p. 13) point out, when the diversity profiles cross, we cannot conclude that one system is more diverse than another. In that case, the "*locations of the crossings*" can however still give meaningful information about the differences in the two systems whose diversity is considered, for example with respect to the role that relatively rare elements play.

We note that Stirling (2007, p. 712) has also introduced two parameters for denoted α and β and Beta which at various values (all possible permutations of the values 0 and 1) lead to different variants of this diveryity entropy. From this he derived four different "facets" of diversity namely: variety, balance, disparity and diversity.

Concluding remarks

In bibliometrics, interdisciplinarity is operationalised in terms of the diversity of the references in a scholarly article. The most commonly used indicators are derived from the fields of ecology (biodiversity measures) and from the fields of economics (concentration measures). In this paper we argue that, while discussions on accurate and informative measures of biodiversity study have evolved over the last years, the bibliometric study of disciplinary diversity still use mainly a subset of the "second generation" of ecologic diversity measures. We discuss the "third generation" of biodiversity measures—the "effective numbers"—which not only generalise most of the other diversity measures but also have some proprieties which make their interpretation intuitively consistent with the concept of diversity Jost (2006). They were further developed by Leinster and Cobbolod (2012) to take into account the similarity/distance of elements (species) in a system (community). We discuss the potential of the Leinster–Cobbold diversity indices (LCDiv) for the study of disciplinary diversity and provide an example to illustrate how the commonly used bibliometric indicators of interdisciplinarity are in fact special cases of these more general Leinster–Cobbold diversity indices (LCDiv).

While we believe that operationalisation of interdisciplinarity as "diversity of references" is theoretically sound, we see however a number of issues which need to be addressed before we can confidently establish this approach as a measure of interdisciplinarity.

First, to our knowledge, the reliability of diversity measures as indicators of interdisciplinary has not yet been extensively tested. The paper by Zhang et al. (2015) shows that the diversity measure (LCDiv using $q = 2$) varies according to the level of the granularity of subject classification. But because their paper use the Leuven-Budapest subject classification (ECOOM) developed by Glänzel and Schubert 2003) which is based on Thomson Reuters Web of Science Subject Categories and most research interdisciplinarity use Thomson Reuters Web of Science Subject Categories, further research is needed to understand how diversity indicators might behave when using other subject classifications.

Second, although there are already some studies which address the validity of bibliometric indicators of interdisciplinary (Roessner et al. 2013), we think that more need to be done to have conclusive results on whether the diversity of references do indeed detect truly interdisciplinary research. In this context, the objection raised by Huutoniemi et al. (2010, p. 80) who argues that measures which "*use information that is attached to the researcher or to the proposals and publications he or she produces (…) cannot properly identify research that is interdisciplinary in an epistemological or cognitive sense, let alone differentiate between the various types of interdisciplinarity.*" should be addressed.

A third issue, of more technically nature, is the choice of the distance/similarity measures. In bibliometric studies of interdisciplinarity, the distance/similarities between research fields are usually computed on the basis of direct citations using the cosine similarity. In biodiversity studies however Pavoine et al. (2005) have shown that the choice of distance/similarities measures impact the behaviour of diversity measures. There is a need in bibliometrics, to investigate to which extent the interdisciplinarity scores depends on the choice not only of the similarity basis (direct citation, bibliographic coupling etc. …) but also of the distance/proximity measures used.

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