Journal of Informetrics 13 (2019) 635–642

Contents lists available at ScienceDirect

Journal of Informetrics

journal homepage: www.elsevier.com/locate/joi

Regular article

Comparison of two article-level, field-independent citation metrics: Field-Weighted Citation Impact (FWCI) and Relative Citation Ratio (RCR)

Amrita Purkayastha[a], Eleonora Palmaro[a], Holly J. Falk-Krzesinski[b], Jeroen Baas[a,*]

[a] Research Intelligence, Elsevier B.V., The Netherlands
[b] Research Intelligence, Elsevier Inc., USA

ARTICLE INFO

Article history:
Received 10 October 2018
Received in revised form 24 March 2019
Accepted 25 March 2019
Available online 3 April 2019

Keywords:
Bibliometrics
FWCI
RCR
Citation impact
Article-level
Field-normalisation
Field-normalization
Research metrics

ABSTRACT

We reproduce the article-level, field-independent citation metric Relative Citation Ratio (RCR) using the Scopus database, and extend it beyond the biomedical field to all subject areas. We compare the RCR to the Field-Weighted Citation Impact (FWCI), also an article-level, field-normalised metric, and present the first results of correlations, distributions and application to research university benchmarking for both metrics. Our analyses demonstrate that FWCI and RCR of articles correlate with varying strengths across different areas of research. Additionally, we observe that both metrics are comparably stable across different subject areas of research. Moreover, at the level of universities, both metrics correlate strongly.

1. Introduction

The scientific research world of today has become increasingly competitive with greater demand for demonstrating a return on investment. Decision-makers in universities, funding bodies and government agencies are increasingly relying on quantitative approaches to support the process of research evaluation. Given the widely-acknowledged limitations of using traditional metrics such as raw citation counts, journal impact factor or h-index (Editorial, 2013; Seglen, 1997) – different fields cite at different rates, and citation counts rise and fall in the months to years after a publication appears – recent bibliometric research has been focused on developing advanced article-level metrics that measure citation impact while also accounting for field of study and time of publication. Extensive comparisons of field-normalisation methods can be found in Waltman and van Eck (2013), Bornmann and Marx (2015) and Ruiz-Castillo and Waltman (2015).

One such article-level, field-normalised metric is the Field-Weighted Citation Impact (FWCI) (Colledge, 2014; Colledge & Verlinde, 2014; Elsevier, 2017). FWCI is used by various research bodies (BEIS, 2016; BIS, 2013) and institutions to benchmark comparative research impact, regardless of differences in entity size, disciplinary profile, age, and publication-type composition. A formal description of the FWCI metric follows in Section 3.

* Corresponding author.
E-mail address: j.baas@elsevier.com (J. Baas).

https://doi.org/10.1016/j.joi.2019.03.012
1751-1577/

Recently, Hutchins, Yuan, Anderson, and Santangelo (2016) published a new article-level, field-independent metric called the Relative Citation Ratio (RCR), that they demonstrate to be correlated with expert opinion of influence measure for biomedical research. The authors make novel use of an article's cocitation network to field-normalise the number of citations it has received. The RCR of an article is calculated by dividing the number of citations the article received, by the expected number of citations of article. The expected number is derived by a quantile regression analysis of all articles funded by the National Institutes of Health (NIH), plotting the citations received by each article, against the field citation rate (FCR). FCR is determined by the average journal citation rate of articles in the same field. A critical discussion can be found in Waltman (2015), Janssens, Goodman, Powell, and Gwinn (2017) and Bloudoff-Indelicato (2015). Nonetheless, Bornmann and Haunschild (2017) found that the RCR correlates highly with three field-normalised indicators – the Mean Normalized Citation Score (MNCS), Citation Percentiles (CP) and source-normalized citation score 2 ($SNCS_2$) – for articles in biomedical research area. Our study builds on the recommendation therein to investigate RCR scores for publications in other areas of research, and compare the ability of RCR to field-normalise citation counts with that of other field-normalised indicators.

The aim of this study is to extend the RCR metric to all subject areas of research by reproducing it using the Scopus database (RCR_{Scopus}), and comparing with the RCR metric using PubMed data (RCR_{PubMed}, Section 4). Prior to this article, the RCR metric was calculated using a number of data sources (Digital Science, 2018; Hutchins et al., 2016). A description of all data sources used in our study is provided in Section 2. In this study, we extend RCR to Scopus and compare, for the first time, two article-level, field independent citation metrics across multiple subject areas. Specifically, we compare the FWCI and RCR metrics in terms of correlations of absolute value, stability across disciplines and their application for the purpose of benchmarking entities, the results of which are presented in Section 5. A brief discussion of the differences between the two metrics is described in Section 6 and finally our conclusions in Section 7.

2. Data sources

PubMed, a database maintained by the National Center for Biotechnology Information (NCBI) at the National Institutes of Health (NIH), comprises more than 28 million citations for biomedical literature from MEDLINE, life science journals, and online books. Citations may include links to full-text content from PubMed Central and publisher web sites (NCBI, 2018).

Scopus, maintained by Elsevier, is a curated abstract and citation database of peer-reviewed literature, covering over 78 million documents published in over 22,000 journals, book series, and conference proceedings by over 5000 publishers. Scopus covers 27 subject areas (All Science Journal Classification Codes, ASJC) (Elsevier, 2018b).

SciVal, a solution maintained by Elsevier, provides access to the research performance information for over 9000 research institutions (institutes) globally. SciVal includes tools to visualise institute research performance and benchmark across performance and collaboration activities (Elsevier, 2018a).

3. Field-Weighted Citation Impact

Field-Weighted Citation Impact (FWCI) is an indicator of mean citation impact, and compares the actual number of citations received by a document with the expected number of citations for documents of the same document type (article, review, book, or conference proceeding), publication year, and subject area. The metric is always defined with a reference to a global baseline of 1.0 and intrinsically accounts for differences in citation accrual over time, differences in citation rates for different document types (e.g., reviews typically attract more citations than articles), as well as subject-specific difference in citation frequencies overall and over time and document types. It is therefore a sophisticated normalised bibliometric. The FWCI builds on the field-normalisation method suggested by Lundberg (2007) and Waltman, van Eck, van Leeuwen, Visser, and van Raan (2011), normalising for differences among document types, publication ages and fields. Like the MNCS indicator (Waltman et al., 2011), the FWCI uses harmonic rather than arithmetic averages to calculate the expected number of citations of a publication that belongs to multiple fields.

Mathematically, the FWCI of an article i is defined as:

$$\mathrm{FWCI}_i = \frac{c_i}{e_i} \tag{1}$$

where c_i = citations received by publication i in the publication year plus following 3 years and e_i = expected number of citations per publication received in the same time period by similar publications.

Similar publications to publication i is defined by all publications that are in the same All Science Journal Classification (ASJC) category as i (Berkvens, 2012), of the same document type as i, and published in the same year as i. If an article belongs to more than one ASJC (334 level) category, fractional document count and fractional citation count are used. This means if publication i belongs to 2 categories A and B, it will be counted 0.5 times in each of A and B, and the citations will also be equally shared between the two categories. Next e_i is calculated by taking the harmonic mean of resulting citation per document in each category:

$$\frac{1}{e_i} = \frac{1}{2}\left(\frac{1}{e_A} + \frac{1}{e_B}\right) \tag{2}$$

where e_A, e_B = citations per document in ASJC category A and B, respectively.

Table 1
Coefficients of correlation of FWCI and RCR_{Scopus} and % of missing RCR values where FWCI larger than 0.

ASJC subject	Pearson	Spearman	% of RCR missing
Biomedical	0.96	0.98	
Scopus	0.66	0.84	4.8%
Engineering	0.67	0.79	13.6%
Medicine	0.71	0.89	1.2%
Social Sciences	0.68	0.83	11.0%
Physics &Astronomy	0.74	0.85	8.0%

4. The RCR metric using Scopus data

We computed a Relative Citation Ratio (RCR) for all articles in the Scopus database following the methodology described in Hutchins et al. (2016). In addition, there are a few methodological modifications since the publication of Hutchins et al. (2016), suggested by the developers of RCR Hutchins and Santangelo, National Institutes of Health, personal communication, that have been implemented in the calculation of RCR on the NIH public web tool called *iCite* (https://icite.od.nih.gov) and in the methodology used in this article for comparison with the values from the *iCite* platform. In the following description of the RCR metric, we have pointed out the methodological modifications wherever applicable.

The RCR of a publication i published in year Y is defined as:

$$\mathrm{RCR}_i = \frac{\mathrm{ACR}_i}{\mathrm{ECR}_i^Y} \tag{3}$$

ACR (article citation rate) is the number of citations of publication i, divided by the number of years since publication:

$$\mathrm{ACR}_i = \frac{\text{total citations to the article}}{\text{last year in the database} - Y} \tag{4}$$

ECR (expected citation rate) of publication i is derived by fitting the FCR (field citation rate) of publication i to the equation obtained by regression of the FCR and ACR values of a benchmark article set published in year Y. The original ECR was derived using an ordinary least squares (OLS) approach and the benchmark article set was NIH R01-funded publications. This is now a quantile regression with inequality constraints, of all NIH-funded publications. An important difference between these approaches is that linear regression estimates the conditional mean, while quantile regression estimates the conditional median. The resulting slope and intercept used to estimate ECR from FCR values are calculated using the R function rq (Koenker & Ng, 2005): rq(ACR~FCR, tau=0.5, data, R=diag(2), r=c(0,0), method="fnc")

The selection of a publication set to use for the benchmark in the regression analysis is customizable Hutchins et al. (2016). In order to align with the values produced by *iCite* and to not introduce another flavour of RCR which cannot be compared directly to values available online at *iCite*, the approach of selecting NIH-funded publications for the benchmark is similarly applied in this analysis. The implication is that RCR values above 1 for a given FCR have a citation count above expectations for NIH funded publications for such FCR.

FCR of publication i is the average JCR (journal citation rate) of all articles in the cocitation network of i and can be defined as:

$$\mathrm{FCR} = \frac{\sum \mathrm{JCR}}{N} \tag{5}$$

where N is the number of publications representing the field of publication i and are those co-cited with i, meaning all publications that have a citing publication in common.

JCR associated with a publication is the 2-year(n) synchronous citation rate of the journal J of the publication in year Y (Rousseau & Leydesdorff, 2011):

$$\mathrm{JCR}_n(J, Y) = \frac{\sum_{i=1}^{n} \mathrm{Cit}(Y, Y-i)}{\sum_{i=1}^{n} \mathrm{Pub}(Y-i)} \tag{6}$$

Cit(Y,X) denotes the citations from publications in year Y to publications in journal J published in year X. Similarly, Pub(X) denotes the number of articles in journal J in year X. The 2 year synchronous implies that the numerator is the sum of citations given in year Y to publications published in J in 2 years before year Y, and the denominator equals the sum of publications in the journal in the same 2 years preceding year Y.

In further modification to the original RCR, the set of publications in Eq. (6) is restricted to only publications of types Article, Review, and Conference Paper, and only citations to those publications are taken into consideration. Additionally, journals with less than 50 publications and JCR values below 0.25 are ignored. The thresholds on JCR resulted in some publications in the database having no RCR value, as JCR, FCR and ECR for these publications are missing (see Table 1). For additional details about the original methodology of the RCR metric, refer to Hutchins et al. (2016).

Generating the cocitation network for the entire set of Scopus articles led to over 72 billion distinct pairs of articles. This required heavy computation which was performed on a Spark infrastructure. NIH has published the RCR metric for PubMed

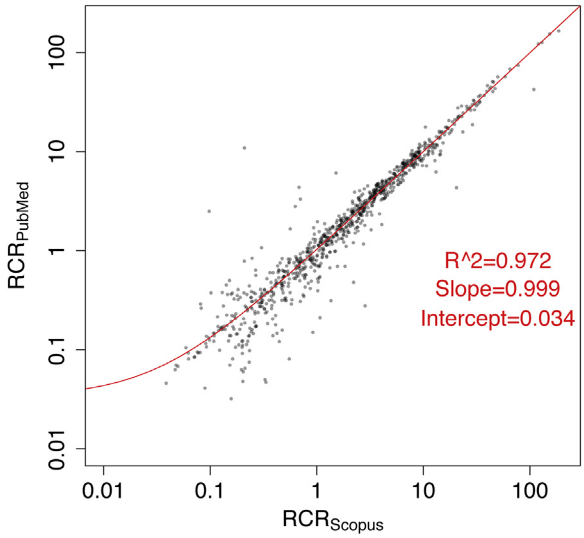

Fig. 1. Correlation of RCR_{PubMed} and RCR_{Scopus} ($n = 1000$, scale = log–log, 0 values omitted). The correlation coefficient is 0.97, showing that the values for the two metrics are strongly correlated.

articles on *iCite*. We queried *iCite* to obtain RCR values for 1000 articles published between 2009 and 2013. We correlated these values with the values we obtained using Scopus. Fig. 1 shows a scatter plot of RCR using PubMed (RCR_{PubMed}) vs. RCR using Scopus (RCR_{Scopus}), fitted to a weighted linear model. The Spearman rank correlation coefficient is 0.97, showing that the values are strongly correlated.

Going forward, for all our comparative analyses of RCR and FWCI, we have used RCR values using Scopus, RCR_{Scopus}. All datasets generated for this study are openly available online (Purkayastha, Palmaro, & Baas, 2019).

5. Results

5.1. Correlations of FWCI and RCR_{Scopus}

Firstly, we correlate FWCI and RCR_{Scopus} for the sample we used in Section 4, which represents the biomedical field. Normally FWCI is computed using citations within a 3-year window after the year of publication, as described in Eq. (1). In this study, however, we have chosen to use FWCI without any expected citation window in order to minimize differences in citation from RCR_{Scopus}. This is to ensure that we can compare the two metrics based on the same starting point. Next, we draw random samples of 10,000 Scopus articles, published between 1996 and 2016, from each of the following categories of the ASJC scheme: all Scopus, Engineering, Medicine, Social Sciences, and Physics & Astronomy. Some articles have a missing RCR_{Scopus} value (as explained in Section 4) but a valid FWCI value (see Table 1).

Table 1 gives a summary of all the correlation coefficients, both Pearson and Spearman indices. As citation distribution is not normal but highly skewed, we use the Spearman index to assess the strength of these correlations. We find that FWCI correlates with RCR_{Scopus} with varying strengths across different subject areas. The correlation is more monotonic than linear, which means that when FWCI increases, RCR_{Scopus} also increases but not at the same rate. Fig. 2

shows scatter plots fitted to weighted linear models for each of the categories. We note that due to the highly skewed nature of citation data, we use a log–log scale to present all plots in this article.

5.2. Stability of the metrics across disciplines

Across different fields of research, how stable are the values of RCR_{Scopus} and FWCI? To investigate this, we chose a third subject classification scheme, one that is different from the subject categories that go into the normalisation of each metric. We chose four fields of the existing Organisation for Economic Co-operation and Development (OECD) classifications (OECD, 2015): Engineering and technology, Medical and health sciences, Social sciences, and Natural sciences. OECD follows a journal-level, content-based classification scheme like ASJC, but the definition of fields are based on some specific selection criteria as laid out in OECD (2015). The resulting top-level fields are broader, and hence we will be sampling from a larger pool. Again, from all articles published between 1996 and 2016, we drew samples of size 10,000 per OECD field.

Fig. 3 shows box and whisker plots for each of the metrics, for all four OECD fields. The top whiskers of all distributions are not in the range of the plot, as the maximum value of each metric in each field is very high. The bottom whiskers (minimum value) are all 0. For RCR_{Scopus}, the maximum difference in first quartile is between Engineering and Social sciences (4.1%), the maximum difference in median is between Engineering and Natural sciences (11%), and the maximum difference in

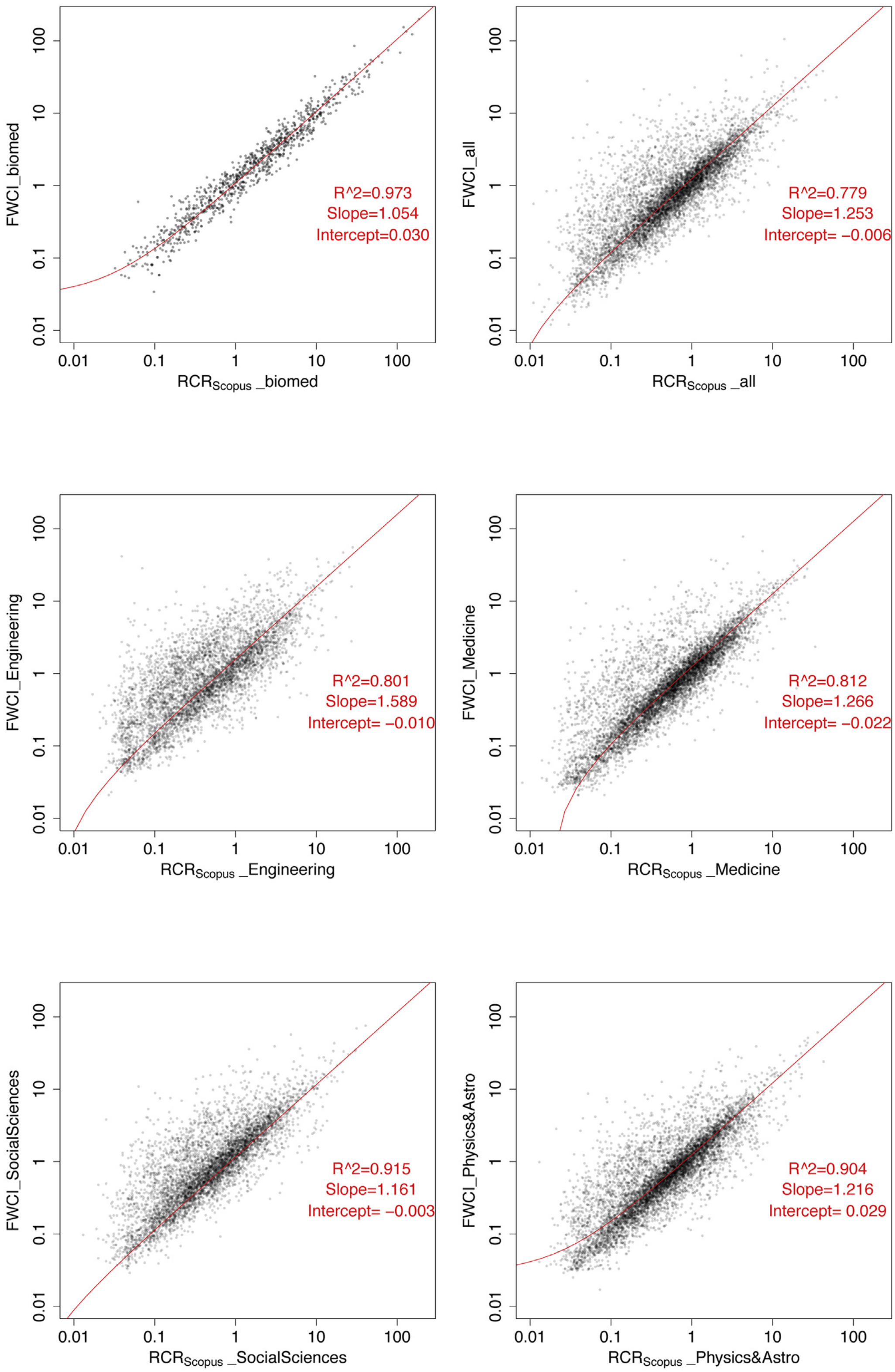

Fig. 2. RCR_{Scopus} vs. FWCI plotted in log–log scale for different categories (0 values omitted): Biomedical field (top-left, $n = 1000$), all Scopus (top-right, $n = 10,000$), Engineering (middle-left, $n = 10,000$), Medicine (middle-right, $n = 10,000$), Social Sciences (bottom-left, $n = 10,000$), and Physics and Astronomy (bottom-right, $n = 10,000$). FWCI and RCR_{Scopus} correlate with varying strengths, and more so monotonically than linearly.

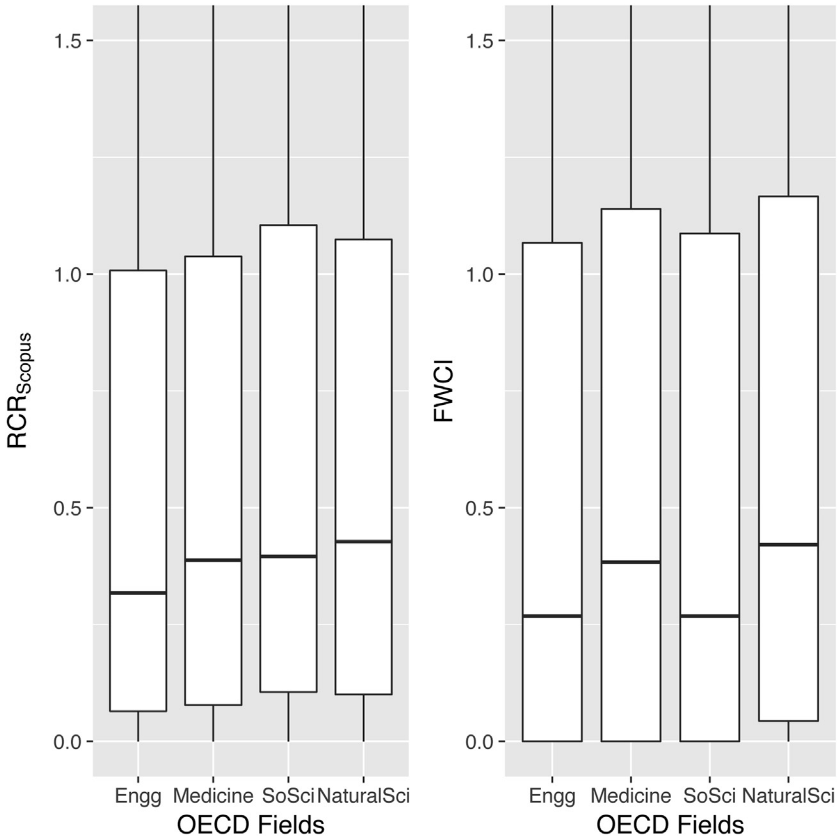

Fig. 3. Distribution of RCR_{Scopus} and FWCI across four OECD fields (n = 10, 000). For both metrics, the values across fields show similar distribution statistics.

third quartile is between Engineering and Social sciences (9.7%). The mean RCR_{Scopus} for the four fields from left to right are 0.886, 0.911, 1.011 and 0.935, and the maximum difference in mean is between Engineering and Social Sciences (12.5%). On the other hand, for FWCI, the maximum difference in first quartile is between Engineering and Natural sciences (4.4%), the maximum difference in median is also between Engineering and Natural sciences (15.3%), and the maximum difference in third quartile is again also between Engineering and Natural sciences (9.9%). The mean FWCI for the four fields from left to right are 1.004, 1.066, 1.011 and 1.074, and the maximum difference in mean is between Engineering and Natural Sciences (7%). These observations show that for both metrics, the values across disciplines show similar distribution statistics, as the differences within fields are low for both – within 13% for RCR_{Scopus} and within 15% for FWCI. This indicates that FWCI and RCR_{Scopus} both perform well in normalising data across different areas of research. We note that due to the highly skewed nature of citation data, in each field most of the papers have a value lower than the mean value reported above, and a handful of papers have a value far larger than the mean.

5.3. Measuring citation impact of universities

In practice, aggregated field-weighted citation indicators are often used at the level of entities like universities to compare research outputs. In popular benchmarking tools such as Elsevier's SciVal solution (Elsevier, 2018a), scholarly impact of a university is indicated by averaging FWCI of all articles affiliated with the university in the last 5 years. We investigate how RCR_{Scopus} compares with FWCI as an indicator for benchmarking scholarly output of universities. To this end, for all universities available in SciVal, we calculate the average value of FWCI and RCR_{Scopus} per university, using all publications per university in Scopus published in a 5 year period (between 2009 and 2013) and document types Article, Review and Conference Papers. We exclude universities with less than 100 total publications to date, as citation metrics for these may not be meaningful.

Fig. 4 shows a scatter plot of FWCI vs. RCR of 6424 universities available in SciVal, fitted to a weighted linear model. We observe that at the institution-level the metrics are strongly correlated with a Pearson correlation coefficient of 0.92 and Spearman correlation coefficient of 0.93. This indicates that RCR_{Scopus} performs as well as FWCI for the purpose of benchmarking scholarly output of universities.

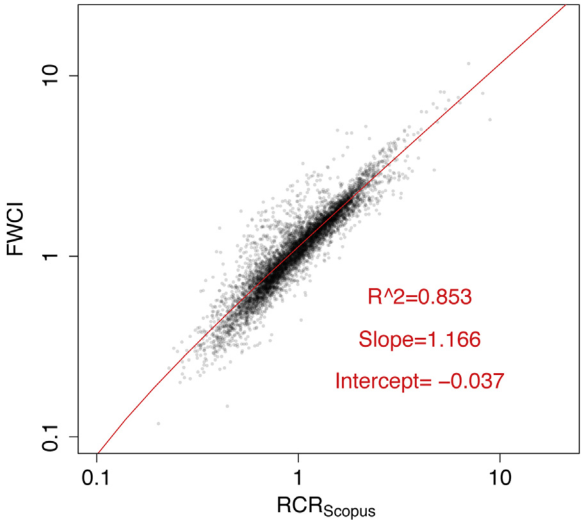

Fig. 4. Correlation of RCR_{Scopus} and FWCI of all universities within SciVal that have more than 100 publications ($n = 6424$, scale = log–log). The correlation coefficient is 0.93, showing that the values for the two metrics are strongly correlated.

6. Discussion

In Section 5, we presented a comparison of the FWCI and the RCR_{Scopus} across multiple subject areas. We provided evidence of statistical correlations with varying strengths between FWCI and RCR_{Scopus}, both at the article-level across different disciplines, and at the level of universities. While Fig. 4 shows small differences in the values of the outliers at the level of universities, we note that Fig. 2 shows the existence of some outliers at the level of individual articles that behave very differently from the rest of the population sample. Initial attempts to study these outliers have shown that it is not trivial to uncover one or more major explanations for the deviations between the two metrics. Since these are large differences and have significant implications at the individual level, the focus of future work will be to conduct further investigations using these outliers. We also note that the biomedical field shows a much higher correlation between the two metrics (Table 1 and Fig. 2) than all ASJC.

From a methodological standpoint in general, it is instructive to understand where the difference between the two metrics arises. The numerator of RCR is Article Citation Rate (ACR) which is the number of citation received per year, and the denominator is Expected Citation Rate (ECR), which is the expected number of citation per year. The ECR is always calculated based on the same number of years as the ACR. In essence, therefore, the numerators of both the RCR and FWCI metrics (total citation count) are identical, while the denominators (expected citation in the field) are different. The expected citation in the field for both metrics is based on the citation rate in a collection of journals. In case of RCR, this collection of journals is defined by the journals in the cocitation network of each article. On the other hand, in case of FWCI, this collection of journals is defined by the ASJC category to which the article belongs.

Another major difference between the two metrics is that FWCI normalises citations across publication year, field and document types, while RCR normalises citations across fields and years but not across document types. This can have implications in assessing the impact of books written by an author, as opposed to articles published by an author, as the two document types have different citation patterns. Further studies will be necessary to fully elucidate differences between both metrics.

From a computational standpoint, as mentioned in Section 4, the RCR is computationally complex, primarily in the step of generating a cocitation network for each article in Scopus, in order to calculate a Field Citation Rate (FCR). In comparison, the FWCI is computationally simpler and computes faster.

There is a large amount of ongoing research on stable clustering algorithms that define research areas, *Topics of Prominence* being the most recent effort (Klavans & Boyack, 2017). Others have also investigated citations normalisation across algorithmically constructed clusters (Perianes-Rodriguez & Ruiz-Castillo, 2016). In a future study, we plan to use Topics at various clustering levels to define an article's field at a more granular level than ASJC, compute a *topic-weighted* citation impact metric, and compare with RCR_{Scopus} and FWCI.

7. Conclusion

We calculated RCR for all publications in the Scopus database and demonstrated that the RCR metric can be extended beyond biomedical research to a broad range of subject areas. We also demonstrated that RCR_{Scopus} of an article correlates with an article's FWCI with varying strengths across different fields of research. Moreover, FWCI and RCR_{Scopus} perform equally well in normalising citations across research fields. Lastly, at the level of universities, FWCI and RCR_{Scopus} correlate strongly, indicating that RCR performs as well as FWCI for the purpose of benchmarking scholarly output of universities. Additional studies are necessary to fully evaluate RCR_{Scopus} for research evaluation purposes.

Author contributions

Amrita Purkayastha: Conceptualization Ideas, Methodology, Software Programming, Formal Analysis, Investigation, Data Curation Management, Writing – Original Draft Preparation, Writing – Review & Editing Preparation, Visualization Preparation.

Eleonora Palmaro: Conceptualization Ideas, Methodology, Software Programming, Formal Analysis, Investigation, Data Curation Management, Writing – Review & Editing Preparation, Visualization Preparation.

Holly J. Falk-Krzesinski: Conceptualization Ideas, Writing – Original Draft Preparation, Writing – Review & Editing Preparation, Project Administration Management.

Jeroen Baas: Conceptualization Ideas, Validation Verification, Formal Analysis, Investigation, Data Curation Management, Writing – Review & Editing Preparation, Supervision Oversight.

Acknowledgement

We thank B. Ian Hutchins and George Santangelo, Office of Portfolio Analysis (OPA), Division of Program Coordination, Planning, and Strategic Initiatives (DPCPSI) at the National Institutes of Health (NIH), for their expert input and guidance in the process of reproducing RCR using Scopus data; Julius Donnert, School of Physics and Astronomy, University of Minnesota (USA) and INAF-Istituto di Radioastronomia (Italy), for his insightful comments on the plots; Bamini Jayabalasingham, Analytical Services at Elsevier, for reviewing and providing feedback on the manuscript.

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