

Revisiting the Field Normalization Approaches/Practices

Xinyue Lu¹, Li Li², Zhesi Shen³

¹*luxinyue@mail.las.ac.cn*

Chinese Academy of Sciences, National Science Library; University of Chinese Academy of Sciences, Department of Information Resources Management, 33 Beisihuan West Road, 100190 Beijing (China)

²*lili2020@mail.las.ac.cn*, ³*shenzhs@mail.las.ac.cn*

Chinese Academy of Sciences, National Science Library, 33 Beisihuan West Road, 100190 Beijing (China)

Abstract

Field normalization plays a crucial role in scientometrics to ensure fair comparisons across different disciplines. In this paper, we revisit the effectiveness of several widely used field normalization methods. Our findings indicate that source-side normalization (as employed in SNIP) does not fully eliminate citation bias across different fields and the imbalanced paper growth rates across fields are a key factor for this phenomenon. To address the issue of skewness, logarithmic transformation has been applied. Recently, a combination of logarithmic transformation and mean-based normalization, expressed as $\ln(c+1)/\mu$, has gained popularity. However, our analysis shows that this approach does not yield satisfactory results. Instead, we find that combining logarithmic transformation ($\ln(c+1)$) with z-score normalization provides a better alternative. Furthermore, our study suggests that the best performance is achieved when combining both source-side and target-side field normalization methods.

Introduction

Citation and its derivative indicators are commonly used to reflect impact and are among the most important quantitative metrics in scientific evaluation (Garfield, 2006). However, differences in citation potential among fields result in field biases in citation-based indicators (Leydesdorff & Bornmann, 2011). The development and improvement of metrics which support cross-field comparison become a crucial issue in scientometrics.

Citation field normalization encompasses two important problems: how to treat the field difference and how to conduct the normalization. As for the first problem, there are two main streams of research aimed at addressing field bias: source-side normalization and target-side normalization.

Theoretical basis of source-normalized methods is that the varying citation density across fields is due to differences in the length of references (Mingers & Yang, 2017; Zitt & Small, 2008). In 2008, Zitt and Small proposed to normalize the raw citation by considering the reference length of citing source ($1/r$) (Zitt & Small, 2008). Later the concept of active reference ($1/a$) is introduced in 2011 (Leydesdorff & Bornmann, 2011) and journal's activity factor in 2012 (Waltman et al., 2013; Waltman & van Eck, 2013b), to account for the different accumulation rates of citations across different fields. The prerequisites for source-normalized methods to function fully are overly idealized and cannot be achieved in practice. Waltman

(Waltman & van Eck, 2013a) conducted a systematic large-scale empirical comparison among three source-normalized methods, but the evaluation framework he used does not support statistical tests. Meanwhile, how topic growth relates to citation counts and impacts citing-side normalization (Leydesdorff & Opthof, 2010; Waltman et al., 2013; Waltman & van Eck, 2013b) is not intuitive and still not well understood (Sjögårde & Didegah, 2022). This gap highlights the need for further research to explore how topic growth dynamics influence citation patterns and normalization practices.

The primary idea behind target-normalized methods is to calculate a relative citation performance given a comparable set for each publication or journal, which is commonly based on a field classification system (Leydesdorff & Bornmann, 2011). Therefore, the first issue of this normalized approach lies in the selection of field classification system (Bornmann, 2020). Recent studies have shown that a paper-level classification system performs better than journal-level classification system in reducing the citation bias (Ruiz-Castillo & Waltman, 2015; Shu et al., 2019; Strotmann & Zhao, 2010).

Once the classification system is determined, the second issue is selecting the normalization approaches which typically receives relatively less attention but is crucial. Currently, mean-based normalization (c/μ) (Abramo et al., 2012a, 2012b; Radicchi et al., 2008) and z-score transformation ($(c-\mu)/\text{std}$) are the widely used practices because they are intuitive and simple. Recently, the log transformation of citation is introduced to overcome the skewness of citation distribution (Brzezinski, 2015; Eom & Fortunato, 2011; Lundberg, 2007; Shen et al., 2018; Stringer et al., 2008). Furthermore, the normalization is applied to the transformed citation, especially the z-score normalization approach (Lundberg, 2007). A more detailed discussion of normalization approaches, including their applications and limitations, can be found in the review in 2016 (Waltman, 2016). Here leads to our second question, does this combination result better normalization performance (log-transformation + Z-score), or which type combination performs better?

In this paper, we want to answer the following questions:

- (1) Can the source-normalized methods entirely eliminate citation bias among fields?
- (2) For target-side normalization, among c/μ , $(c-\mu)/\text{std}$, $\ln(c)/\mu$, $\ln(c)-\mu/\text{std}$, which approach has better performance?
- (3) Will the combination of source-side and target-side normalization achieve better performance?

Data and Methods

Publication data and citation data

We collect articles and reviews indexed in the Web of Science (WoS) between 2020 and 2021 and their citations received in 2022. To ensure consistency in the data coverage, we focus exclusively on articles and reviews indexed in the Science Citation Index Expanded (SCIE) and Social Sciences Citation Index (SSCI)

categories. Finally, the dataset for 2020 and 2021 comprises a total of 450,810 papers, while the dataset for 2022 includes 2,221,501 papers. Additionally, the citation relationships in 2022 contain 118,294,005 citations, with 16,329,497 of these citations referencing core papers published in 2020 and 2021.

Classification systems

In this study, we leverage two distinct classification systems to categorize the collected publications, ensuring a more robust and unbiased approach to field normalization and evaluation. Specifically, we align the papers in our dataset with both the CWTS paper-level classification system, which provides hierarchical classification across three granularity levels—micro-level, meso-level, and macro-level topics (Waltman & van Eck, 2012)—and the SciSciNet subfield classification system, which is derived from the MAG (Microsoft Academic Graph) dataset and consists of 292 specific subfields (Lin et al., 2023). This dual-classification strategy addresses the potential issue of bias that may arise when using a single classification system for both normalization and evaluation, thus avoiding the “athlete and referee” situation, where the same classification system influences both the standardization and assessment processes.

Among the collected publications, 90.9% of publications can be matched to CWTS classification systems and 97.9% of publications can be matched to SciSciNet subfield classification system through DOI. For the unmatched papers, we generate embeddings based on title and abstract using SPECTER (Cohan et al., 2020) and apply the k-nearest neighbor algorithm(KNN) to find the most related classifications.

Citation Indicators

Building on the normalization approaches discussed earlier, the next step is to define the key bibliometric metrics that will be used in our analysis. These indicators are essential for evaluating the impact and performance of scientific publications, with citations being the most fundamental and widely-used measures.

In this section, we categorize the normalization methods into three distinct types: source-side metrics, target-side metrics, and dual-side metrics. Each category offers different approaches to adjust for field-specific biases.

Unnormalized metric

Citation count, c . The citation count refers to the citations received by paper i in a given year.

Source-side normalized metrics

- ① First source normalized citation count, $sc^{(1)}$. The $sc_i^{(1)}$ value of paper i is calculated as:

$$sc_i^{(1)} = \sum_{i=1}^{c_i} \left(\frac{1}{r_i} \right),$$

where r_i is the length of reference list in the paper from i^{th} citation. $sc^{(1)}$ would suppress citation bias among fields from source theoretically (Waltman et al., 2013).

- ② Second source normalized citation count, $sc^{(2)}$. The value $sc_i^{(2)}$ of paper i is calculated as:

$$sc_i^{(2)} = \sum_{i=1}^{c_i} \left(\frac{1}{a_i} \right),$$

where a_i is the number of active references in the paper from which i^{th} citation generates. Active reference is defined as papers in Web of Science, falling into the time window of analysis year (Waltman & van Eck, 2013b; Zitt & Small, 2008). For example, the active reference length for the 2-year time window of publications in 2022 refers to the number of references publishing between 2020 and 2021.

- ③ Third source normalized citation count, $sc^{(3)}$. The $sc_i^{(3)}$ value of paper i is calculated as:

$$sc_i^{(3)} = \sum_{i=1}^{c_i} \left(\frac{1}{a_i \times p_i} \right),$$

where the definition of a_i is the same as $sc^{(2)}$ and p_i is the proportion of publications which contains at least one active reference among all publications in journal of i^{th} citing publication (Waltman et al., 2013).

For the above four metrics, we also calculate their logarithmic form: $\ln(c_i + 1)$,

$\ln(sc_i^{(1)} + 1)$, $\ln(sc_i^{(2)} + 1)$ and $\ln(sc_i^{(3)} + 1)$, and respectively defined them as c^{\ln} ,

$sc^{(1)\ln}$, $sc^{(2)\ln}$ and $sc^{(3)\ln}$.

Target-side normalized metrics

For target-side normalized metrics, we consider two normalize approaches: relative ratio and z-score.

- ① Relative ratio, $ratio^f$, we define it as

$$ratio_i^f = \frac{m_i}{\mu^f},$$

where m_i refers to metric value of paper i and μ^f is average metric value of papers which belongs to the same field with paper i .

- ② z-score, z^f . We define it as

$$z_i^f = \frac{m_i - \mu^f}{\sigma^f},$$

where μ_i^f is average metric value of papers which belongs to the same field with paper i and σ^f is the standard deviation of metric value in field f .

Dual-side normalized metrics

By combining source-side and target-side normalization approaches, we have the dual-side normalized metrics as shown in Table 1.

Table 1 shows the total indicators we investigated in this work. We combine Citation count, c and three source-side metrics with two different normalized approaches, resulting in 24 metrics (Table 1). The structure of Table 1 can represent the categories to which the normalization methods used for each metric belongs (non-normalized, source-normalized, target-normalized or both).

Table 1. The combination of citation-based metrics and normalized approaches.

		None		Source side normalization					
		Original	Log	Original			Log		
None	-	C	c^{\ln}	$sc^{(1)}$	$sc^{(2)}$	$sc^{(3)}$	$sc^{(1)\ln}$	$sc^{(2)\ln}$	$sc^{(3)\ln}$
	Ratio	$R(c)$	$R(c^{\ln})$	$R(sc^{(1)})$	$R(sc^{(2)})$	$R(sc^{(3)})$	$R(sc^{(1)\ln})$	$R(sc^{(2)\ln})$	$R(sc^{(3)\ln})$
Target side Normalization	Z-score	$Z(c)$	$Z(c^{\ln})$	$Z(sc^{(1)})$	$Z(sc^{(2)})$	$Z(c^{\ln})$	$Z(sc^{(1)\ln})$	$Z(sc^{(2)\ln})$	$Z(sc^{(3)\ln})$

Evaluation Methodology

Evaluating bias among fields

We use two methods to assess whether the metrics correct bias among fields. The first qualitative method is based on a simple intuition: mean of the metric values in every meso-topic with field normalization effect should not have an obvious positive correlation with citation count that have not been normalized. So we will conduct scatter plots for each metric using field normalization methods against citation count to observe the relationship between them.

The second quantitative method is grounded in the following assumption: if the rankings derived from a given metric are not biased across scientific fields, then the proportion of publications from each field within the top $z\%$ of ranked publications should match the proportion of that field in the entire dataset (Dunaiski et al., 2019; Vaccario et al., 2017). In other words, publications from each field should be evenly distributed across every ranking interval. To quantitatively assess this deviation, we adopt the evaluation standard d_M proposed by Vaccario (Vaccario et al., 2017). Specifically, we compute the distributional inequality between the observed field

representation in the top $z\%$ and the expected distribution under field-neutral conditions. The greater this discrepancy, the poorer the effect of field normalization. For a given metric m , the expected number of papers from subfield i in the top $z\%$ under perfect field normalization is $\mu_i^{(m)} = (z/100) \cdot K_i$, where K_i is the total paper numbers in subfield i . The observed count $k_i^{(m)}$ represents the actual representation of subfield i in the top $z\%$. Then we can quantify the overall field bias using the Mahalanobis distance (d_M):

$$d_M^{(m)} = \sum_{i=1}^F \frac{(k_i^{(m)} - \mu_i^{(m)})^2}{\sigma_i^2} \cdot \left(1 - \frac{K_i}{N}\right),$$

where $\sigma_i^2 = \gamma \cdot K_i \cdot (N - K_i)$ is the expected variance and N is the total papers in the dataset. The finite-population correction factor $\gamma = \frac{n \cdot (N-n)}{N^2 \cdot (N-1)}$ accounts for the reduced variance in sampling without replacement, ensuring cross-sample comparability of bias measurements. The term $(1 - \frac{K_i}{N})$ dampens the disproportionate influence of dominant subfields on the aggregate bias metric, preventing overestimation from majority fields.

The 95% confidence interval for the simulated unbiased selection process using all publications represents the minimum standard to accomplish the task of field normalization, and d_M based on citation count represents a benchmark with no effect at all. It is worth noting that we utilized the micro-level topics from CWTS to standardize various metrics on the target side, while meso-level topics was employed to compute d_M to evaluate the effectiveness of the standardization. Additionally, we also used the subfield classification system from SciSciNet to recalculate d_M as a robustness check.

Benchmark of quantitative evaluation

We analyse the distribution of d_M using subfield classification of SciSciNet through a simulated unbiased selection process as a statistical null model. Specifically, we extract 10% of the total publications to calculate d_M . Figure 1 illustrates the distribution of d_M with 500,000 simulations, with the upper bound of the 95% confidence interval estimated to be approximately 329.83. All rankings generated by the metrics described above will compute d_M and compare it with the value of 329.83.

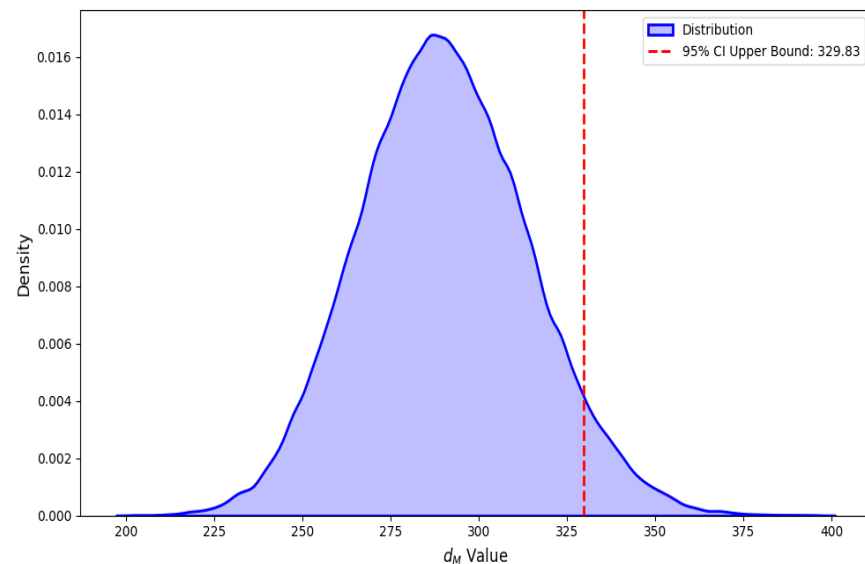


Figure 1. the distribution of d_M .

Results

RQ1: Can the source-normalized methods entirely eliminate citation bias among fields?

To address the question of which one of source-normalized methods can better correct the citation bias among fields, we construct scatter plots of several original metrics ($sc^{(1)}$, $sc^{(2)}$ and $sc^{(3)}$) against citation count c , without applying any normalized methods (Figure 2(a) – (c)). Among these, $sc^{(1)}$ with the smallest slope shows the best performance, but the differences in performance among the three source-normalized methods are not significant.

To better account for the influence of outliers and reflect the overall relationship between indicators, we rank the papers based on the values of the indicators and calculate the correlation among the rankings (Figure 2(d) – (f)). In ranking correlations, $sc^{(3)}$ exhibits the most effective correction for field bias. However, all three source-normalized methods ($sc^{(1)}$, $sc^{(2)}$ and $sc^{(3)}$) still show a strong positive correlation with citation count (c), suggesting that none of the three source-normalized indicators fully eliminate the field biases. Overall, $sc^{(3)}$ demonstrates the best performance in addressing citation bias among three source-normalized methods.

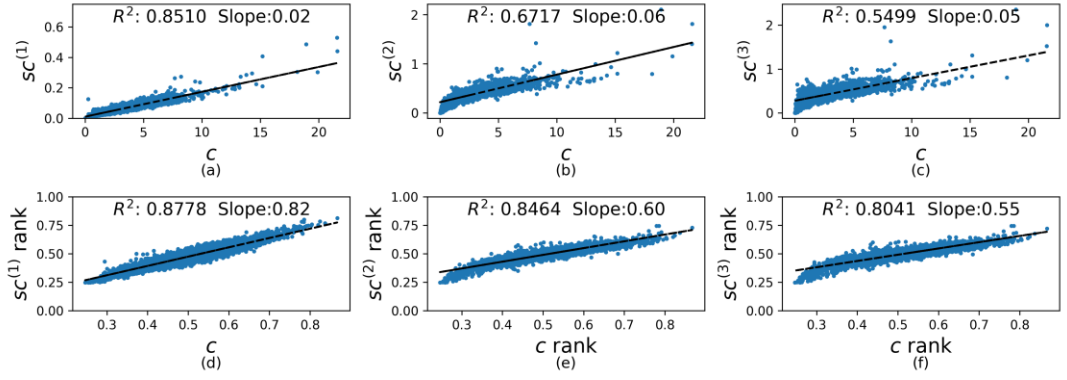


Figure 2. Correlation between citation count and source-normalized metrics.

We further validate the conclusion through a quantitative evaluation method based on d_M . The smaller the d_M , the better the normalization effect of metric among fields. As shown in Figure 3, $sc^{(3)}$ achieves the smallest d_M value across all percentiles, followed by $sc^{(2)}$, and then $sc^{(1)}$. All three methods perform better than the benchmark c , demonstrating a certain degree of effectiveness of the source-normalized methods in reducing field bias.

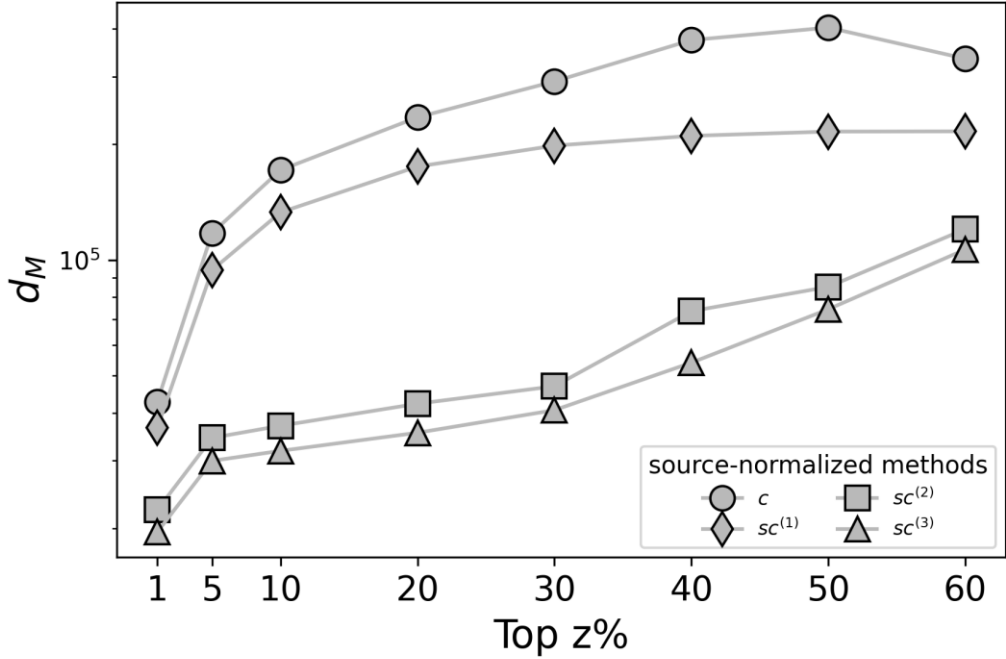


Figure 3. Field bias of source-normalized metrics.

We further investigate why source-side normalization methods fail to fully eliminate field bias in the normalization process. According to Waltman’s 2013 paper on SNIP

(Waltman et al., 2013), there are three key assumptions for ensuring the effectiveness of source-side normalization:

- (1) the same number of papers are published annually within each field, i.e., $M_{2020}^f = M_{2021}^f = M_{2022}^f$;
- (2) there is no citation overlap between journals from different fields;
- (3) each journal has at least one paper with an active reference.

If these three assumptions hold, the mean value (μ) of $sc^{(3)}$ for each field can be calculated as shown in the following formula (for details, see paper (Waltman et al., 2013)):

$$\mu = \frac{2(M_{2020} + M_{2021})}{M_{2022}} = 1.$$

The first two assumptions are difficult to achieve in practice and may help explain why these metrics fail to perform as expected. To further explore this issue, we test the validity of the first two assumptions.

The core of assumption 1 is that $M_{2022} = \frac{1}{2}(M_{2020} + M_{2021})$, implying that the number of papers published in a given field in 2022 should be equal to half of the total number of papers published in 2020 and 2021. However, in reality, the number of papers published in each field fluctuates every year, with varying degrees of change across different fields. This variation results in a mean value for $sc^{(3)}$, that deviates from 1. To quantify this variation, we define the *growth rate* of a field as $\frac{(M_{2020} + M_{2021})}{M_{2022}}$. A higher growth rate corresponds to a larger μ value for that field.

Assumption 2 posits that there is no citation overlap between journals from different fields. The core of source-normalized methods is the adjustment of citation counts by dividing them by the citation density of the corresponding field. If a paper is cited by journals from other fields, the citation density is either overestimated or underestimated, leading to normalization failure. To test this assumption, we define the *citation density* of a field.

The citation density of a field f , denoted as D_f , is defined as the total number of active references generated by all papers within the field. For a given paper i , its actual citation density AD_i is calculated as the weighted average of the citation densities of the fields that cite it:

$$AD_i = \sum_{k \in CitingFields_i} w_{i,k} \cdot D_k,$$

where $w_{i,k}$ is the proportion of citations received by paper i from field k and D_k is the citation density of field k . The expected citation density of paper i is the citation density of its own field f , denoted as D_f . Based on these, the density ratio for paper i is defined as:

$$DR_i = \frac{AD_i}{D_f},$$

this ratio greater than 1 indicates that the citation density of paper i is overestimated, potentially underestimating the paper's true impact. Conversely, a ratio less than 1 suggests that the citation density is underestimated, potentially overestimating the paper's impact.

Figure 4(a) shows the mean value of $sc^{(3)}$ for each meso-field in the CWTS classification against the growth rate. The colour of each data point represents the citation density ratio. We observe a clear positive correlation between the growth rate and the mean $sc^{(3)}$, and we find that when the citation density ratio is higher, the mean $sc^{(3)}$ tends to be smaller. Figure 4(b) demonstrates a positive correlation between the mean value of $sc^{(3)}$ and the growth rate, while showing a negative correlation with the citation density ratio. Further residual analysis reveals that the growth rate explains 63.7% of the variance in the mean value of $sc^{(3)}$, suggesting that it is a primary factor contributing to the failure of field normalization.

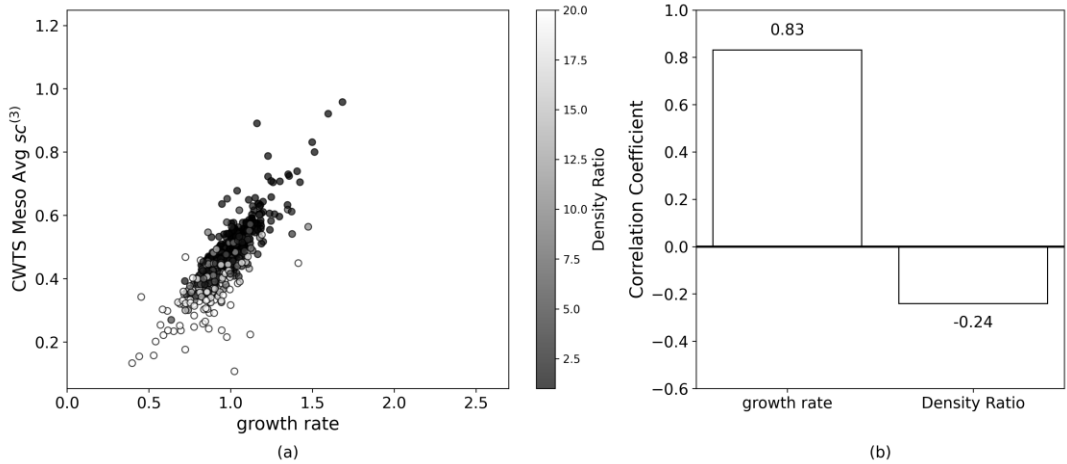


Figure 4. Factors affecting the effectiveness of source-side normalization. (a) Correlation between growth rate and average c for CWTS meso fields. (b) Strength of Correlation between Growth Rate/Density Ratio and Average $sc^{(3)}$ by CWTS meso fields.

RQ2: Among c/μ , $c-\mu/std$, $\ln(c)/\mu$, $\ln(c)-\mu/std$, which approach has better performance?

To explore this question, we calculate the original form c , ratio-normalized original form $R(c)$, z-score-normalized original form $Z(c)$, ratio-normalized logarithmic form $R(c^{\ln})$, and z-score-normalized logarithmic form $Z(c^{\ln})$. According to the recommendation of previous research, we conduct the field normalization at the micro-level. Meanwhile, we evaluate the normalization performance at both CWTS meso-level and SciSciNet subfields. As shown in Fig.5, the results suggest that, under both evaluation schemes, no single method consistently outperforms others across all scenarios. However, overall, retaining the original citation counts and applying ratio normalization ($R(c)$) or using the logarithmic form combined with z-score normalization ($Z(c^{\ln})$) tend to yield relatively better outcomes.

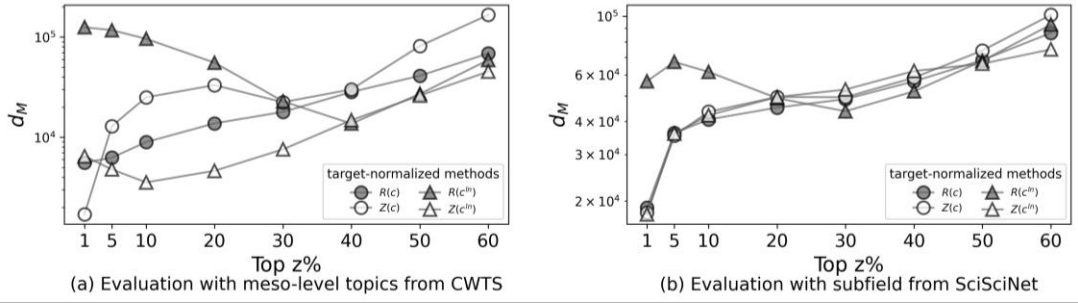


Figure 5. Field bias of different normalization approaches.

Strictly proving the effectiveness of these normalization metrics is challenging, but we can provide an intuitive explanation. Citation distributions are often approximated as log-normal distributions (Stringer et al., 2008). Under the logarithmic transformation, there is a natural connection between $\log(c) - \mu$ and $\log(c/\mu)$, leading to similar performance for $R(c)$ and $Z(c^{\ln})$. Additionally, since the variance across distributions is also considered for $Z(c^{\ln})$, the normalization performance is further improved. However, for $\log(c)$, which is already approximately normally distributed, using $\log(c)/\mu$, while aligning the means across different fields, tends to amplify the variance in fields with smaller means. This amplification gives these fields an advantage in top rankings and decreases the normalization performance.

RQ3: Will the combination of source-side and target-side normalization achieve better performance?

To address the question of whether combining source-side and target-side normalization can yield better performance than using source-side normalization alone, we leveraged the conclusions from *RQ1* and *RQ2*. *RQ1* demonstrated that $sc^{(3)}$ is the most effective source-normalized metric, while *RQ2* showed that applying ratio normalization to the original citation counts or using log-transformed z-score normalization generally yields better results. Building on these findings, we combined with the ratio normalization and log-transformed z-score methods to create two new indicators: $R(sc^{(3)})$ (ratio-normalized) and $Z(sc^{(3)\ln})$ (log-transformed z-score-normalized). These newly constructed indicators were then compared against existing indicators, including c , $R(c)$, and $Z(c^{\ln})$, to evaluate their relative effectiveness in normalizing citation data and reflecting a paper's impact within its field.

As illustrated in Figure 6(a), evaluation using the meso-level topics from CWTS indicates that combining source-side normalization with target-side normalization methods yields better results than using target-side normalization alone, with the Z-score method demonstrating superior performance for the field normalization task. Figure 6(b) presents the combination of source-normalized and target-normalized

methods ($R(sc^{(3)})$ and $Z(sc^{(3)\ln})$), demonstrating significantly better performance compared to other single-method approaches when subfields from SciSciNet was used as evaluation classification system. Among these, the combination of z-score normalization with the logarithmic form of $sc^{(3)}$, represented as $Z(sc^{(3)\ln})$, always emerges as the most effective.

These findings underscore the advantages of integrating source-side and target-side normalization methods. By leveraging their complementary strengths, the combined metrics provide a more effective and robust solution for addressing field-specific biases.

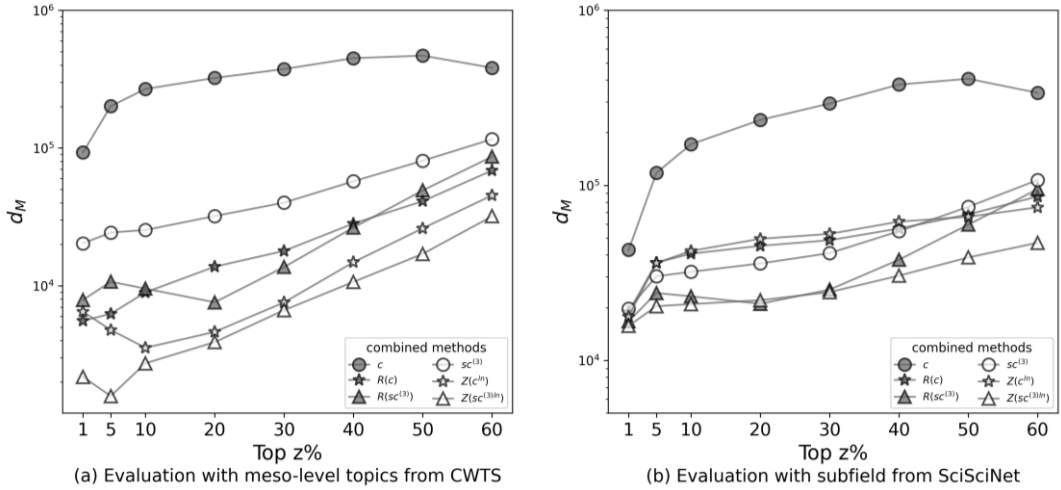


Figure 6. Field normalization performance for combining source and target-side approaches.

Conclusion

In this paper, we evaluated various source-normalized methods and found that while they achieve some success in reducing bias across fields, they are all unable to fully eliminate it. Our analysis, including residual analysis, indicates that imbalanced paper growth rates across fields are a key factor contributing to the limitations of these methods, which not only addresses the puzzle of why these methods are unable to fully eliminate field bias (Sjögårde & Didegah, 2022) but also opens avenues for future research to develop more refined normalization approaches that can better account for such dynamic factors.

We also found that using ratio normalization on original citation counts and log-transformation followed by z-score normalization both yields relatively strong results. However, directly applying ratio normalization after log-transformation is not a theoretically sound method. As a result, some studies that rely on this method should critically re-evaluate their findings.

Furthermore, by combining source-normalized and target-normalized methods, we found that the indicators constructed with ratio normalization ($R(sc^{(3)})$) and log-

transformed z-score normalization ($Z(sc^{(3)\ln})$) demonstrated relatively better performance compared to single-method approaches. However, these combinations still do not fully eliminate field differences within the 95% confidence interval. This suggests that while these combinations show promise, further refinement is needed to reduce biases more effectively.

These findings offer insights for the practical application of field normalization. Developing more robust normalization evaluation frameworks and exploring more effective ways to combine source-side and target-side normalization methods, along with their mathematical justification, will be crucial for enhancing the comparability across disciplines and improving citation metrics evaluation.

Acknowledgments

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