Interpreting bibliometric signals

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The last 10 years have seen a proliferation of metrics for journals — some useful, others merely curious. All provide points of departure to explore features associated with a title. In studying metrics, the objective is to identify meaningful measures that may inform editorial strategy and, ultimately, ensure that a journal is serving its community well.

As citation tracking options have expanded, SEG has participated in more projects designed to enrich scholarly metadata — from disambiguating author identities on papers via ORCID, enriching funder metadata by compliance with CHORUS, and democratizing access to citation data with the Initiative for Open Citations (Bakamjian, 2019). As of this writing, more than 58 million bibliographic records — including those from *Interpretation* — are open to researchers via the OpenCitations Index of Crossref (COCI, 2020).

More recently, SEG endorsed the San Francisco Declaration on Research Assessment (SEG, 2020), which advocates for the use of better methods to assess scholarly output. For publishers and editors, this means de-emphasizing reliance on standalone metrics, such as Journal Impact Factor or CiteScore, when evaluating journal performance. In accordance with best practice (Hicks et al., 2015), SEG also reports suites of indicators for every journal online (e.g., https://library.seg.org/page/inteio/about).

To support those ends, this article is meant to survey *Interpretation*'s current and historical performance across key indicators, as well as briefly explore related citation dynamics.

Citation sources

Journal metrics do not occur in a vacuum. They are derived from source data extracted from citation indexes. Likewise, not every journal is well represented across all databases, primarily due to differences in how source metadata are captured and curated.

Major databases in bibliometrics research include commercial sources such as Scopus and Web of Science (WoS), as well as free databases, including Google Scholar (established 2004, with metrics added in 2012), Microsoft Academic (2016), Crossref (2017), and Dimensions (2018).

The first large-scale meta-analysis of coverage across these sources recently was published, and the primary finding was that, overall, Google Scholar features the most comprehensive set of citations and bibliographic records (Martín-Martín et al., 2020). However, Google Scholar does not provide search or export functions to casual users. For those seeking fast export of data, results indicate that Microsoft Academic and Dimensions provide good alternatives.

For *Interpretation*, however, Microsoft Academic could not be used because its indexed records are intermingled with those of another publication. Correction was requested earlier this year, but resolution still is forthcoming. For that reason, only Crossref, Dimensions, Google Scholar, Scopus, and Web of Science were interrogated.

As seen in Figure 1, document counts across databases mostly are correct. The one outlier source is Scopus, which significantly deviates from published item counts between 2016 and 2019. Document counts in these years are incorrect (e.g. *Interpretation* published 171 articles in 2018, but Scopus indexed only 58 of them). When document counts are incomplete, aggregate citation counts will be inaccurate. As data from these years inform all Scopus-based metrics released in June 2020, they may not provide complete representations of *Interpretation*'s impact. Overall differentials between items published versus those indexed is –16.1% at Scopus, –10.5% in Web of Science, –6.4% at Dimensions, –1.1% at Google Scholar, and –0.25% in Crossref.

Just as journal item counts/identities can differ by database, so do citations. Google Scholar uses an automated approach to crawl the Web to track citing relationships, while other databases rely on their own pools of indexed items — these may be scholarly publishing outputs (e.g., Crossref), or expanded to include grants, patents, policy statements, and other types of gray literature (Dimensions includes some; Google Scholar, far more). In Figure 2, a comparison between citations to *Interpretation* by year across free databases provides evidence of the differences in approach. Recent reports suggest that Google Scholar is the most comprehensive database in terms of citation coverage (Harzing, 2019; Martín-Martín et al., 2020).

Journal-level metrics

Web of Science/Journal Citation Reports metrics

Journal Impact Factor

Arguably the most well-known of journal metrics is the Journal Impact Factor (JIF). Developed as a tool to

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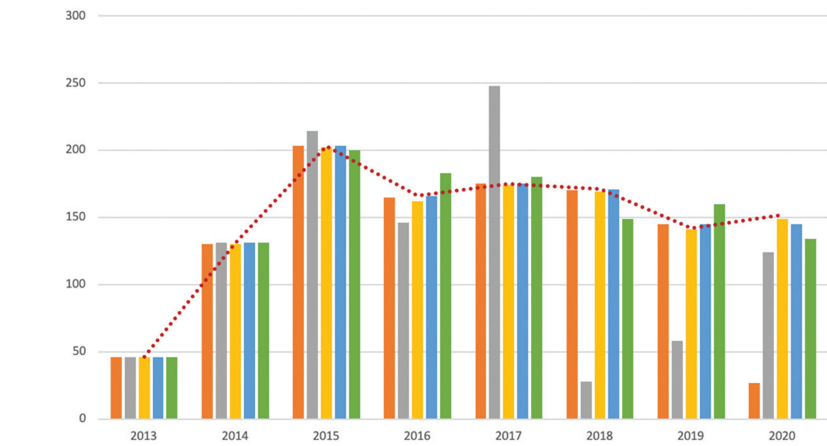
help libraries decide which journals to purchase (Garfield, 1972), JIF is a simple ratio of citations received in one year to the number of citable articles publishing within the previous two years. *Interpretation*'s latest JIF is 1.394, calculated as:

428 citations to all *Interpretation* articles published 2017–2018 / 392 citable articles published by *Interpretation* in 2017–2018.

JIFs are released annually by Journal Citation Reports (JCR), a Clarivate Analytics product that draws from the Web of Science database (Collier, 2020). Articles considered "citable" in JIF generally are primary research or reviews; editorials, commentaries, and letters are not counted in the denominator of the calculation. All *Interpretation* articles were counted in the 2019 JIF (Appendix A). See Figure 3a for a recent JIF history.

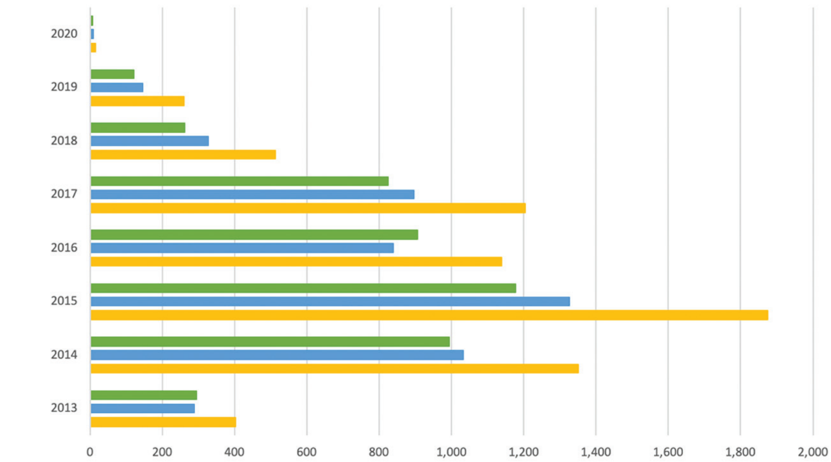
JIF is commonly, albeit inappropriately, used as a proxy for individual article quality. However, only a limited number of papers are responsible for increases, and skewed distributions are expected (Albarrán et al., 2011). To deter conflation of JIF with article quality, several publishers advocate reporting citation distribution frequencies (Larivière et al., 2016), provided for *Interpretation*'s latest JIF in Figure 3b.

There also are a number of well-known strategies to increase JIFs (Ioannidis and Thombs, 2019). Techniques range from the acceptable, such as frontloading content (publishing more articles earlier in the year) or publishing long review articles, to the unethical (e.g., coercing self-citations from authors, citation stacking). In those cases, it has been noted that JIF is a better measure of editorial effort than of content quality (Metze, 2010).



	2013	2014	2015	2016	2017	2018	2019	2020
Web of Science	46	130	203	165	175	170	145	27
Scopus	46	131	214	146	248	28	58	124
Google Scholar	46	130	202	162	174	169	141	149
Dimensions	46	131	203	166	175	171	145	145
Crossref	46	131	200	183	180	149	160	134
Published Items	46	131	203	166	175	171	142	152

Figure 1. *Interpretation*'s document counts by citation databases mostly is stable but with notable discrepancies in Scopus from 2016 through 2019.



	2013	2014	2015	2016	2017	2018	2019	2020
Crossref	293	994	1,177	905	824	262	121	6
Dimensions	287	1,032	1,325	839	895	327	145	9
Google Scholar	403	1,351	1,875	1,139	1,203	513	260	14

Figure 2. Open citation source counts (Crossref, Dimensions, Google Scholar) to articles in *Interpretation* (all years) as of 9 July 2020.

Five-year Impact Factor

JIF calculated with a five-year citation window is known as the Five-Year Impact Factor. *Interpretation* received its first true five-year score last year, when it became possible to calculate all data from its debut in 2013 through 2018. Although provided by JCR, the metric is based on partial data only from 2013 through 2017 (i.e., two years of published items are counted in the numerator for the 2015 Five-Year JIF, three years in 2016, and four years in 2017).

Immediacy Index

Not all journals reach citation maturity within the two-year window built into the JIF. Each discipline has particular norms surrounding peer-review and publication times, which affect possible citing behavior.

Immediacy Index is designed to provide early returns. It is calculated by dividing the number of citations to articles published in a given year by the number of articles published in the same year. Articles that publish earlier in the year or online well in advance of print have a greater chance of being cited and, thus, contributing to increases in immediate use.

Interpretation does not artificially extend the time in which articles are available online in advance of print. Because the journal uses a "first in, first out" publishing protocol, its immediacy index history is stable (Figure 4). The boost seen in 2017 was due to several papers receiving higher-than-average same-year citations — all published in the second issue of the year.

Eigenfactor and Article Influence

Like JIF, Eigenfactor® scores use WoS citation data to assess and track influence. However, unlike JIF, the score concerns citation relationships within a predefined network of journals, in this case those included in JCR. The score is based on the number of times articles published in the past five years have been cited in one year. It also considers which journals have contributed these citations. Eigenfactor iteratively ranks all journals in the JCR network, giving more weight to a single citation from a highly rated journal than multiple citations from less-cited journals (Bergstrom et al., 2008).

Eigenfactor® scores can be normalized by the total number of journals included within any JCR year. Normalized scores are reported in JCR, including Article Influence (AI), which is calculated by multiplying the Eigenfactor score by 0.01 and dividing that by the number of articles in each journal. The mean AI for an article in JCR has score of 1.00.

See Figure 5 (or Appendix A) for five-year histories in *Interpretation* for Eigenfactor® and AI. The upward trajectory seen across these metrics is solid — the journal is referenced by a growing audience. Recent citations from highly ranked journals such as *Science Advances* and *Geology* contributed to the recent rise across both metrics.

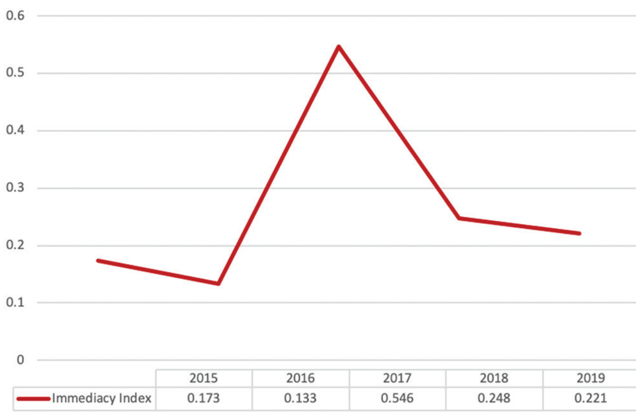


Figure 4. JCR/Web of Science-based metrics: Immediacy Index, calculated by dividing the number of citations received in a given year by the number of articles published, generally is stable on *Interpretation*.

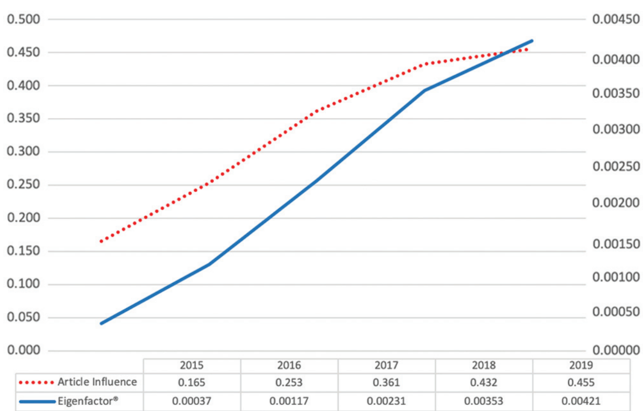


Figure 5. JCR/Web of Science-based metrics: Eigenfactor® and Article Influence scores for *Interpretation*.

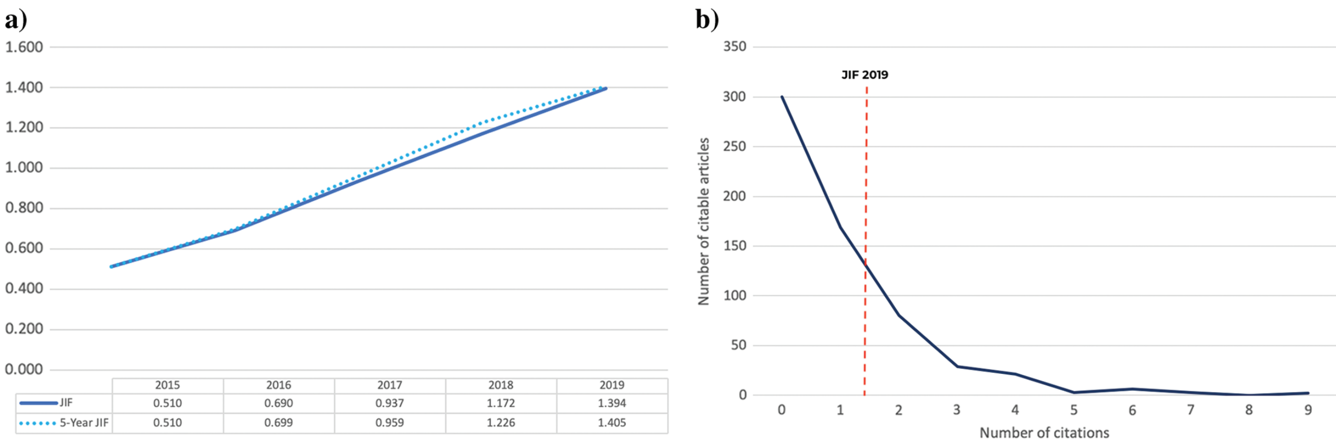


Figure 3. JCR/Web of Science-based metrics. (a) JIF and Five-Year JIF scores. (b) Citation distribution of *Interpretation*, showing that most papers feature citation rates lower than that of the current JIF. Citations are to "citable" documents only, which include research articles and reviews. The distributions contain citations garnered in 2019 to citable documents published in 2017 and 2018 in order to be comparable to the 2019 JIF.

Scopus metrics

CiteScore

As with JIF, CiteScore measures the ratio of citations to articles published. These metrics differ in terms of which incoming citations are counted (and when). While JIF counts *all* incoming citations received in one year divided by the number of research/review articles published over two years, CiteScore includes citations and counts to peer-reviewed articles over four years in both numerator and denominator (Elsevier, 2020).

Limiting counts to only peer-reviewed document types is a new feature of CiteScore for 2019. This change addresses a common complaint leveled against JIF — that it counts citations to "noncitable items" in the numerator but does not count the same documents in the denominator, giving an advantage to journals with news and commentary sections (e.g., *Nature*, *Science*). Most society-owned titles do not employ dedicated news staff, so their journals tend to score more highly on CiteScore than JIF.

Interpretation's latest CiteScore of 2.9 is based on the number of citations received in 2016–2019 divided by the number of documents published in the same time period, i.e.:

1,264 citations to peer-reviewed articles published 2016–2019 (count as of June 2020) / 437 peer-reviewed articles published 2016–2019

As we saw in Figure 1, this calculation is based on incomplete data. It is likely that *Interpretation*'s CiteScore would rise if all documents were indexed completely in Scopus. To that end, SEG has requested correction, but a timeline for resolution has not been provided. Appendix B summarizes all current Scopus-based metrics.

SCImago Journal Rank

SCImago Journal Rank (SJR) is a prestige metric that assigns relative scores to all of the sources in Scopus. SJR is developed from Google's PageRank algorithm, which ranks websites by their links from other influential websites. Similarly, a citation from a journal with a high SJR is weighted more than a citation from a journal with a lower SJR (SCImago Research Group, 2007).

SJR also considers number of articles in a journal, making it similar to the JCR/WoS-based AI score. In addition to source used, the difference is time — SJR draws on three years of data, while AI uses five years. The score is reported with CiteScore (Scopus, 2020) and also is available directly from SCImago with a variety of other derivative calculations (SCImago Journal Rank, 2020).

In the end, the coverage gaps in Scopus render SJR and its corollary metrics currently invalid for *Interpretation*. It is, however, interesting to see the rise across both — even if based on limited data — as shown in Figure 6.

SNIP and IPP

Source Normalized Impact per Paper (SNIP) and Impact per Publication (IPP) are metrics developed by the Centre for Science and Technology Studies (CWTS) at Leiden University.

SNIP measures the average citation impact of a journal and corrects for differences in citation practices between subjects (hence, source normalized). IPP measures the average citation impact of articles in a journal. Like the JIF, IPP does not correct for differences in citation practices between scientific fields.

Journal-specific SNIP scores are reported with CiteScore and SJR in Scopus; IPP is currently available only on the CWTS Web site (CWTS, 2020). Like CiteSource and SJR, these measurements are calculated using Scopus data. With the familiar caveat that SNIP and IPP do not reflect *Interpretation*'s complete record, scores are provided in Figure 7.

Google Scholar metrics

Google Scholar 2020 metrics were released on 7 July 2020 (Acharya, 2020). Coverage includes articles

	2018	2019
CiteScore	2.5	2.9
SCImago Journal Rank	0.434	0.585

Figure 6. Scopus-based metrics: CiteScore and SCImago Journal Rank scores from Elsevier and SCImago.

	2015	2016	2017	2018	2019
SNIP	1.56	0.98	1.09	0.63	0.71
IPP	0.63	0.96	1.18	0.93	1.20

Figure 7. Scopus-based metrics: SNIP and IPP scores from the Centre for Science and Technology Studies.

published in 2015–2019 and includes citations from all articles that were indexed in Google Scholar as of June 2020.

Journals are ranked by Google Scholar according to h5-index, which is the h-index for all articles published in the last five complete years. Analogous to Hirsch's original proposal of an h-index for researchers (Hirsch, 2005), the h5-index is largest number h such that h articles published in 2015–2019 have received at least h citations each.

Interpretation's current h5-index is 25; its h5-median is 34 (Google Scholar, 2020a). Histories of these metrics are shown in Figure 8 (also Appendix C). The slight, recent drop in h5-median is due to two highly cited 2014 papers aging out of the calculation. Google's metrics still include the most-cited paper in the journal's history, which published in 2015. See Appendix D for top-cited papers in *Interpretation* to date.

Google Scholar data can be used for additional calculations, either by journal, issue, or any other set of research papers. To illustrate using *Interpretation*, h-index and AW-index histories were compiled using Publish or Perish software (Harzing, 2007) (Figure 9). AW-index adjusts for age of articles, showing that 2017 articles currently are receiving increased citation. Source data set is available online (Mavzer, 2020).

Ranking across databases

Mapping journals to field-specific categories is a feature of commercial citation databases. Curation of subjects is handled by in-house classifiers (Scopus) or editors (Web of Science). These subjects facilitate ranking of titles according to associated scores, despite the fact that the journals within each category may vary wildly in scope and type.

Interpretation is included in one category in WoS (Geochemistry and Geophysics) and two categories at Scopus (Geophysics, Geology). See Table 1 for ranking within each subject according to latest CiteScore and JIF scores.

Note that ranks may change as databases are refreshed. Scopus will restore GEOPHYSICS to the Geophysics category later this year. Google Scholar ranks the top 20 journals according to h5-index in its subject listings (e.g., GEOPHYSICS is currently placed fifth in Google Scholar's Geophysics category) (Google Scholar, 2020b).

Some databases provide subject rankings only at the article level. Dimensions, for example, has tagged *Interpretation*'s articles across four fields of research. Two years after publication, each article receives a field citation ratio, calculated by dividing the number of citations a paper has received by the average received by documents published in the same year and in the same field of research (Bode et al., 2019).

Table 1. Subject rankings for *Interpretation* across WoS and Scopus.

Source	Subject(s)	Rank
JCR/WoS	Geochemistry and Geophysics	56/85
Scopus	Geophysics	49/116
	Geology	82/235
Dimensions	Geophysics	n/a
	Geology	n/a
	Geochemistry	n/a
	Physical Geography & Environmental Geoscience	n/a

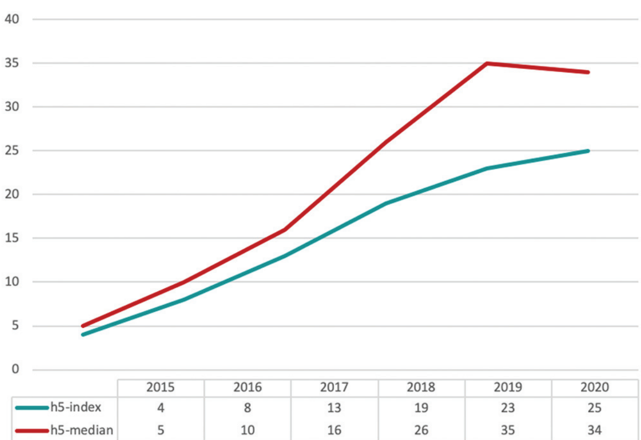


Figure 8. Google Scholar-based metrics: h5-index and h5-median histories. Increases in these five-year windows have been driven by several highly cited articles listed in Appendix D.

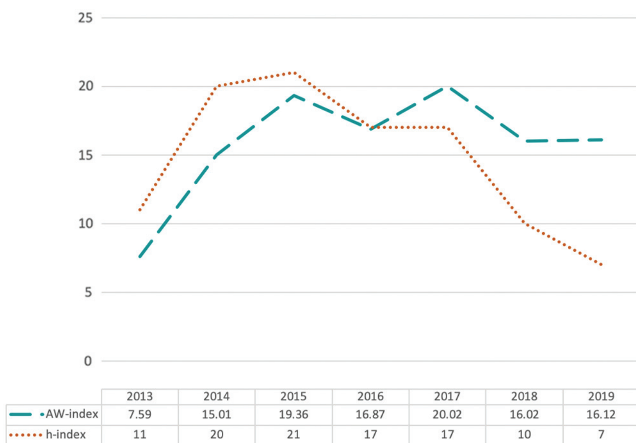


Figure 9. Google Scholar-based metrics: h- and AW-index calculated for each year of *Interpretation* articles using citation counts captured on 7 July 2020.

Citation dynamics

Journal-level metrics can give us a snapshot of *Interpretation* at one point in citation time, but they lack the ability to tell us more about the journal's interaction with other sources, authors, or topics. The bibliographic map in Figure 10 is meant to provide an overview of the structure of citation trails for *Interpretation*.

This map was constructed using VOSviewer and bibliographic records from WoS. It illustrates on co-citation data (minimum number of citations = 4) for all published articles in the journal from 2013 through 2019. Of the 756 journals in this network, GEOPHYSICS is cited most often, followed by the *AAPG Bulletin*, and *Marine and Petroleum Geology* (see detail in Figure 10b).

When mapped using bibliographic records from Dimensions, the same parameters give us an expanded view of *Interpretation*'s citing universe (Figure 11a). Of the 1,308 source titles included, GEOPHYSICS is still the most-cited source, followed by *The Leading Edge*, *AAPG Bulletin*, and then *Marine and Petroleum Geology* (Figure 11b).

Just as social networks can be mined for relationships between people, citation network mapping can reveal the outlines of a journal's activity. While it is good practice to check on metrics, they are of limited use, regardless of the source. In the end, metrics are not report cards — echoing Goodhart's Law, the moment a journal indicator becomes a goal, it ceases to be meaningful.

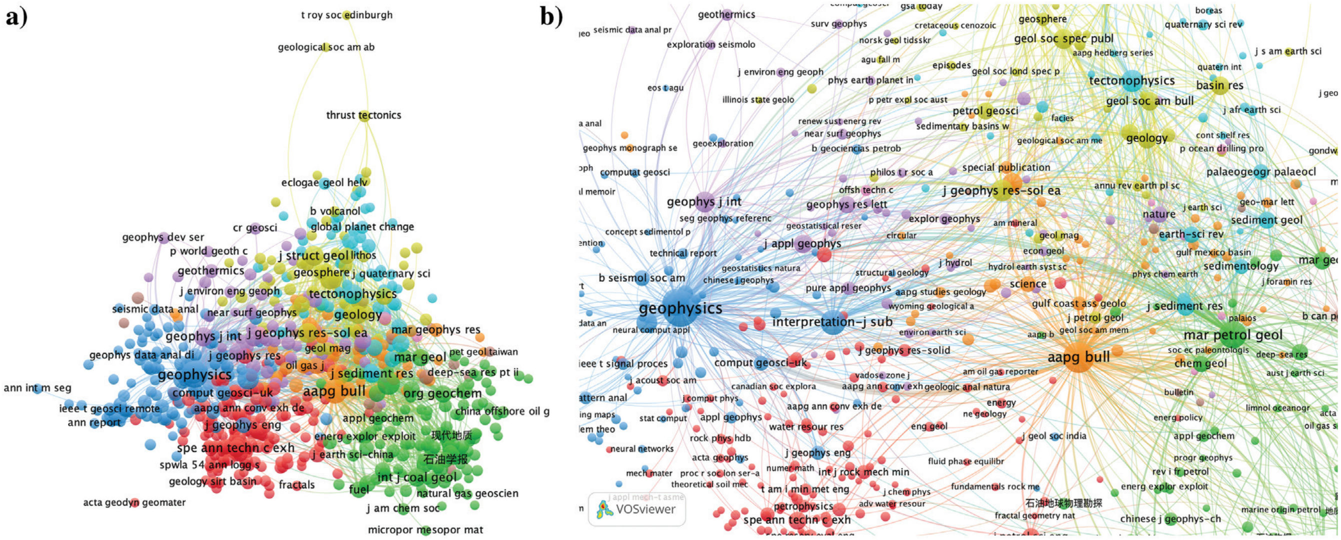


Figure 10. (a) Web of Science-based co-citation network map of *Interpretation* sources (date of capture: 23 June 2020; minimum number of citations to a source = 4) using VOSviewer v. 1.6.10. (b) Detailed view.

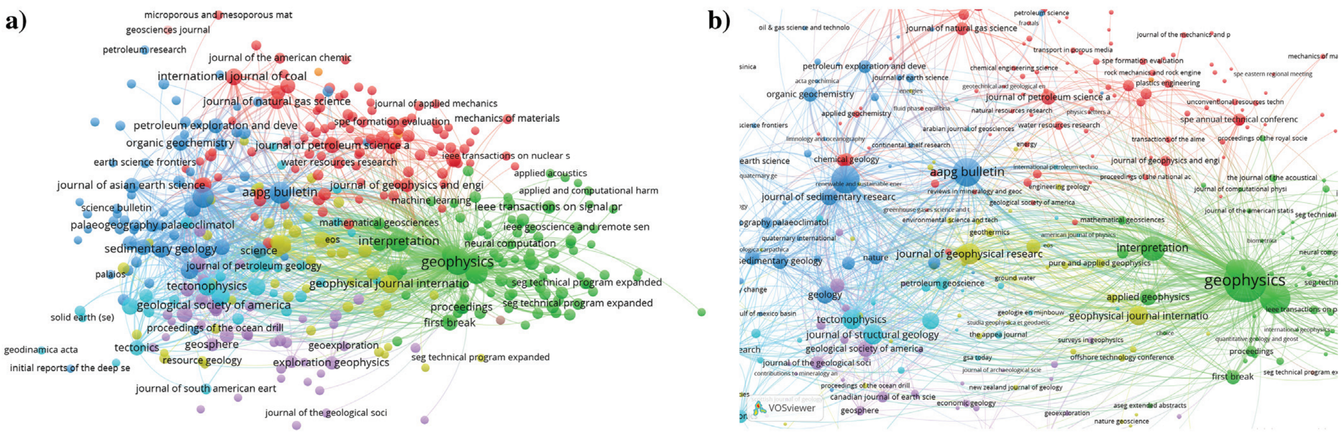


Figure 11. (a) Dimensions-based co-citation network map of *Interpretation* sources (date of capture: 30 June 2020; minimum number of citations to a source = 4) using VOSviewer v. 1.6.10. (b) Detailed view.

Appendix A

Table A-1. Summary table of metrics derived from Web of Science data as reported in Journal Citation Reports; calculated by Clarivate.

	2015	2016	2017	2018	2019
Journal Impact Factor	0.51	0.69	0.937	1.172	1.394
Geochemistry and Geophysics category rank	76/81	73/84	69/85	62/84	56/85
Total citations counted by JIF	106	244	529	797	1,096
JIF without self-citations	0.289	0.525	0.699	0.929	1.192
Five-year JIF	0.51	0.699	0.959	1.226	1.405
Immediacy index	0.173	0.133	0.546	0.248	0.221
Citable documents	173	143	152	153	131
Total articles	173	143	152	153	131
Total reviews	0	0	0	0	0
Cited Half-Life	1.5	2.1	2.4	3.1	3.4
Citing Half-Life	>10.0	>10.0	10.5	10.4	9.6
Eigenfactor Score	0.00037	0.00117	0.00231	0.00353	0.00421
Article Influence Score	0.165	0.253	0.361	0.432	0.455
% Articles in Citable Items	100	100	100	100	100
Normalized Eigenfactor	0.04235	0.1343	0.27	0.41993	0.51452
Average JIF Percentile	6.79	13.69	19.412	26.786	34.706

Appendix B

Table B-1. Summary table of metrics derived from Scopus data; reported by Elsevier (CiteScore, subject ranking), SCImago (SJR, citations, collaboration rate), and the Centre for Science and Technology Studies (SNIP, IPP).

	2013	2014	2015	2016	2017	2018	2019
CiteScore	-	-	-	-	-	2.5	2.9
SCImago Journal Rank	-	-	-	-	-	0.434	0.585
Geology category rank	-	-	-	-	-	83/224	82/235
Geophysics category rank	-	-	-	-	-	51/107	49/116
Cited documents	-	20	76	180	236	283	221
Uncited documents	-	26	101	211	255	325	201
Total number of citations	-	43	156	420	582	629	600
Self-citations	-	13	36	64	123	6	20
% Self-cited	-	0.00%	0.00%	14.70%	26.30%	1.20%	4.30%
External citations per document (average)	-	0.75	0.795	1.063	1.05	1.141	1.487
Total citations per document (average)	-	1.075	1.033	1.254	1.332	1.152	1.538
Number of citable documents	-	40	151	335	437	546	390
Number of noncitable documents	-	6	26	56	54	62	32
Cites/document (4-year window)	-	1.075	1.033	1.254	1.319	1.199	1.516
Cites/document (3-year window)	-	1.075	1.033	1.254	1.332	1.152	1.538
Cites/document (2-year window)	-	1.075	1.033	1.281	1.282	0.997	1.411
% International collaboration	17.39	28.24	30.84	31.51	37.1	32.14	24.14
Impact per publication (IPP)	0.54	0.54	0.63	0.96	1.18	0.93	1.2
Source-normalized impact per publication (SNIP)	1.45	1.45	1.56	0.98	1.09	0.63	0.71

Appendix C

Table C-1. Summary table of metrics derived from Google Scholar data.

	2013	2014	2015	2016	2017	2018	2019	2020
h5-index	-	-	4	8	13	19	23	25
h5-median	-	-	5	10	16	26	35	34
Total number of papers in Google Scholar	46	130	202	162	174	169	141	149
Total number of citations	403	1351	1875	1139	1203	513	260	14
Average number of citations per paper	8.76	10.39	9.28	7.03	6.91	3.04	1.84	14
Average number of authors per paper	2.59	3.12	3.31	3.41	4.18	4.01	3.85	4.54
h-index	11	20	21	17	17	10	7	2
g-index	17	31	32	23	21	13	11	2
Age-weighted citation rate (AWCR)	57.57	225.17	375	284.75	401	256.5	260	14
AW-index	7.59	15.01	19.36	16.87	20.02	16.02	16.12	3.74

Appendix D

Table D-1. Top-cited papers from *Interpretation* (2013–2019) in Google Scholar as of 7 July 2020.

Cites	Authors	Title	Pub Year
127	T Zhao, V Jayaram, A Roy, KJ Marfurt	A comparison of classification techniques for seismic facies recognition	2015
117	IF Jones, I Davison	Seismic imaging in and around salt bodies	2014
92	R Perez Altamar, K Marfurt	Mineralogy-based brittleness prediction from surface seismic data: Application to the Barnett Shale	2014
73	BS Hart, JHS Macquaker, KG Taylor	Mudstone (“shale”) depositional and diagenetic processes: Implications for seismic analyses of source-rock reservoirs	2013
71	R Roden, T Smith, D Sacrey	Geologic pattern recognition from seismic attributes: Principal component analysis and self-organizing maps	2015
70	KJ Marfurt, TM Alves	Pitfalls and limitations in seismic attribute interpretation of tectonic features	2015
56	F Li, W Lu	Coherence attribute at different spectral scales	2014
53	YE Aimene, A Ouenes	Geomechanical modeling of hydraulic fractures interacting with natural fractures — Validation with microseismic and tracer data from the Marcellus and Eagle Ford	2015
52	J Qi, T Lin, T Zhao, F Li, K Marfurt	Semisupervised multiattribute seismic facies analysis	2016
52	S Ishutov, FJ Hasiuk, C Harding, JN Gray	3D printing sandstone porosity models	2015
50	T Guo	The Fuling Shale Gas Field — A highly productive Silurian gas shale with high thermal maturity and complex evolution history, southeastern Sichuan Basin, China	2015
48	R Boswell, C Shipp, T Reichel, D Shelander, T Saeki, M Frye, W Shedd, TS Collett, DR McConnell	Prospecting for marine gas hydrate resources	2016
46	JE Downton, B Roure	Interpreting azimuthal Fourier coefficients for anisotropic and fracture parameters	2015
46	Y Yang, MD Zoback	The role of preexisting fractures and faults during multistage hydraulic fracturing in the Bakken Formation	2014
42	A Johnson, H Daigle	Nuclear magnetic resonance secular relaxation measurements as a method of extracting internal magnetic field gradients and pore sizes	2016
40	T Zhao, J Zhang, F Li, KJ Marfurt	Characterizing a turbidite system in Canterbury Basin, New Zealand, using seismic attributes and distance-preserving self-organizing maps	2016

Table D-1. Top-cited papers from *Interpretation* (2013–2019) in Google Scholar as of 7 July 2020. (continued)

Cites	Authors	Title	Pub Year
40	A Biswas, A Mandal, SP Sharma, WK Mohanty	Delineation of subsurface structures using self-potential, gravity, and resistivity surveys from South Purulia Shear Zone, India: Implication to uranium mineralization	2014
40	L MacGregor, J Tomlinson	Marine controlled-source electromagnetic methods in the hydrocarbon industry: A tutorial on method and practice — Tutorial on marine CSEM method and practice	2014
39	J Qi, B Zhang, H Zhou, K Marfurt	Attribute expression of fault-controlled karst — Fort Worth Basin, Texas: A tutorial	2014
38	AK Furre, A Kiær, O Eiken	CO_2-induced seismic time shifts at Sleipner	2015
35	T Schmiedel, S Kjoberg, S Planke, C Magee, O Galland, N Schofield, CA-L Jackson, DA Jerram	Mechanisms of overburden deformation associated with the emplacement of the Tulipan sill, mid-Norwegian margin	2017
35	I Lecomte, PL Lavadera, I Anell, SJ Buckley, DW Schmid, M Heeremans	Ray-based seismic modeling of geologic models: Understanding and analyzing seismic images efficiently	2015
35	A Roy, AS Romero-Peláez,TJ Kwiatkowski, KJ Marfurt	Generative topographic mapping for seismic facies estimation of a carbonate wash, Veracruz Basin, southern Mexico	2014
34	N Pham, S Fomel, D Dunlap	Automatic channel detection using deep learning	2019
34	HS Nance, H Rowe	Eustatic controls on stratigraphy, chemostratigraphy, and water mass evolution preserved in a Lower Permian mudrock succession, Delaware Basin, west Texas, USA	2015
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