Author citation metrics in paleontology: the h-index and the c-score

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Abstract

The "Stanford ranking" (SR) of standardized citation indicators calculates an individual scientist's composite c-score, addressing limitations of the h-index. Updated annually, the SR lists the top 100,000 scientists and the top 2% in each specialty. This study examines all 500 paleontologists included in the SR (SR-paleontologists), comparing their h-index, c-score and related productivity and citation variables. Analyses cover geographical distribution, statistical characterization and relationships among variables. SR-paleontologists are concentrated mainly in North America and central-northern Europe. An average SR-paleontologist has a 41-year career and 165 publications: 51 as first or single author (author), 69 as intermediate author (collaborator) and 45 as last author (manager). This imaginary scientist has received about 9400 citations (17% self-citations): 2734 as author, 4720 as collaborator, and 1948 as manager. The average h-index is 47, and the mean c-score is 3.65. These metrics show weak correlation and little dependence on career length. Rankings differ markedly depending on whether the h-index or c-score is applied. Paleontologists with high h-indices (h-paleontologists) typically have more papers and citations, especially as collaborators or managers, and higher self-citation rates. In contrast, those with high c-scores (c-paleontologists) generally produce fewer papers and citations overall, show lower self-citation rates and obtain a larger share of citations from work as authors rather than collaborators or managers. Expanding the database to include the broader paleontological community would enable a more comprehensive assessment of citation performance and better inform evaluation practices. To the author's knowledge, this is the first global, discipline-wide analysis conducted in the field of Earth Sciences using the SR.

Keywords: Citation metrics, individual assessment, h-index, c-score, Stanford ranking

Introduction

The h-index emerged as an alternative to crude measures of scientific productivity and impact, such as the number of papers published or the total citations received. As is well known, the h-index represents the intersection between the number of papers published by an author and the number of citations each paper has received, arranged in descending order (Hirsch, 2005). For example, an h-index of 70 indicates that a particular author has published 70 papers with at least 70 citations each. Despite its widely recognized flaws, the h-index remains the most widely used citation-based metric for evaluating the individual performance of scientists (Barnes, 2017).

The main drawbacks of the h-index include, among others, the difficulty of making interdisciplinary comparisons, its heavy reliance on highly cited papers, its failure to account for self-citations, its lack of consideration for career duration, the unfair allocation of credit in multi-authored papers, and its inability to detect irregular authorship practices, particularly fake authorship (Wuchty et al., 2007; Egghe, 2008; Schreiber, 2008; Alonso et al., 2009; Zhang, 2009; Bartneck & Kokkelmans, 2010; Gaster & Gaster, 2012; Barnes, 2017; Negahdary et al., 2018; Kolum & Haffner, 2021; Pöder, 2022; Bi, 2023; Stupnanova, 2024). In addition, the h-index is highly dependent on the database used. For example, Google Scholar considers all available citations and tends to inflate h-indices compared to other databases that apply quality filters (e.g., Clarivate or Scopus). These flaws make the h-index unsuitable for evaluating individual performance and may ultimately promote scientific misconduct (Rull, 2025). Some modifications of the h-index have been proposed (e.g., Egghe, 2008; Schreiber, 2008; Zang, 2009; Negahdary et al., 2018) but they have not been implemented in current evaluation practices.

Recently, a new index addressing the main limitations of the h-index has been developed. This composite index, called the *c*-score, is based on raw data from the Scopus database, which includes only the journals indexed in Scopus. The c-score accounts for specialty fields and career duration, excludes self-citations, employs fractional authorship to improve credit allocation, and gives more weight to single, first and last authorship (Ioannidis et al., 2016, 2019). The c-score for the top 100,000 scientists across disciplines is released annually in two versions: a single-year modality, reflecting the previous year, and a career-long modality, encompassing a researcher's entire career (Ioannidis et al., 2020). In addition to the top 100,000 scientists, those who fall within the top 2% of their specialty are also included in the ranking. All of this information is updated yearly and is publicly available in the Mendeley database since 2019.

The ranking based on the c-score is commonly known as the "Stanford ranking" (thereafter SR), as it was developed and is maintained by researchers at Stanford University. The c-score is not the ultimate measure of individual evaluation, but it addresses the main shortcomings of the h-index and is considered the best available method for assessing an author's impact based on their publications and corresponding citations (van der Aalst et al., 2023). The subdivision into specialties (22 fields and 176 subfields) allows analysis of the c-score ranking by fields of expertise. For example, Pan et al. (2024) tested the usefulness of the c-score in ophthalmology and Senior & Fazel (2020) did the same for mental health. It is also possible to conduct analyses by country or geographical area. For example, Jones (2023a, 2023b) conducted several analyses in forensic science for North American and Scandinavian researchers. The career duration of each scientist is also provided, which allows considering this variable in career-long analyses. The c-score is not the panacea but is the most robust index available to date for measuring individual scientific performance. The publicly available yearly updating of this index is an additional advantage for its potential use in routine evaluations. The c-score has also received some criticism, and a few modifications have been proposed to improve its performance (e.g., Moed, 2021; Forthmann et al., 2024; Scafetta, 2025). Other similar indices, such as the q-score (Banerjee et al., 2025) or the OnS (Onjia, 2025) have been developed. However, these proposals remain to be implemented for general use.

This paper focuses on paleontology, comparing the h-index and the c-score between them and with the career duration, as well as with other productivity and citation variables relevant for these indices, for paleontologists listed in the SR. All 500 paleontologists included in the career-long modality—whether among the top 100,000 scientists overall or the top 2% of paleontologists—are considered, and their records are analyzed. The use of the career-long modality ensures greater stability over time for h-index and c-score values, which are much less variable than the same measures calculated for single years.

In addition, scientists listed in the career-long modality are more consolidated in the SR, whereas those included in the single-year versions may show greater turnover, complicating comparisons. The SR encompasses most, if not all, of the best-known and most recognized paleontologists of recent decades and provides a global updated overview of the development of this field of knowledge. However, as emphasized by its creators, the SR is based on meeting the criteria derived from the composite c-score indicator, and absence from this ranking should not be interpreted as an assessment of research quality (Ioannidis et al., 2025). In other words, being included in the SR may be taken as a sign of quality, but the converse is not necessarily true.

It is important to emphasize that the comparison is between indices and variables within the specific field of paleontology, not between scientists. It should also be noted that the results of this paper pertain specifically to the field of paleontology and cannot be extrapolated to other disciplines or to the scientific community as a whole. In addition, the results obtained are valid only for the paleontologists included in the SR, as the others' c-scores remain unpublished. It is also important to stress that the comparisons presented here are not intended as an attempt to determine whether the h-index or the c-score is more suitable for evaluating the individual performance of paleontologists, a topic addressed elsewhere (Rull, 2025). The results provided are intended to support a more informed appraisal of individual performance in terms of productivity and citation metrics – alone or in combination with other complementary descriptors (e.g., Rull, 2026) – thereby contributing to the continuous improvement of evaluation practices. To the author's knowledge, this is the first global, discipline-wide analysis conducted in the fields of Earth Sciences and Biology using the SR.

Methods

As mentioned above, raw data were retrieved in the Mendeley database, version 8, released on September 2025 (Ioannidis et al., 2025). For the career-long modality, this version includes the papers published between 1960 and 2024 and the total citations received during the period 1996-2024. The raw data for this paper were extracted from the general database, filtered by 'paleontology' in the specialty subfield 1 column, corresponding mostly to the field of "Earth & Environmental Sciences" (95%), with the exception of 25 entries (5%) classified under "Biology". The extracted file is available as a spreadsheet in the Supplementary Material. This database includes two versions of the h-index — the raw h-index and the h-index corrected for the number of authors — as well as two versions of the c-score, with and without self-citations. In this paper, comparisons are made between the raw h-index, which is the most commonly used to classify scientists, and the c-score without self-citations, which is the metric used by Ioannidis et al. (2019, 2025) to assemble the SR.

The first part of the analysis is a worldwide geographical view of the distribution of SR-paleontologists across countries. The second part offer a general characterization of these paleontologists based on the variables listed in Table 1. Some of these variables were taken directly from the original dataset (Supplementary Material), while others—marked with an asterisk—were calculated from the same source. Some variables in Table 1 include author, collaborator and manager options. Author papers refer to first or sole authorship, manager papers refer to last authorship and collaborator papers refer to intermediate authorship. The use and misuse of these authorship strategies in relation to the h-index have been discussed in more detail elsewhere (Rull, 2025). These variables, together with the h-index and the c-score, were statistically characterized using conventional distribution parameters, namely range, mean, standard deviation, coefficient of variation, 95% confidence interval and skewness. Skewness was measured using the parameter G_1, which equals zero for symmetric distributions, is less than zero for left-skewed distributions, and greater than zero for right-skewed distributions (Joanes & Gill, 1998). Outliers were identified with the Grubbs (1950) test, which determines both the number of outliers and the distribution threshold used for their identification.

The third part of the survey aims to establish statistical relationships between the h-index and the c-score, considering the career duration (CD), as well as with the related productivity and citation variables (Table 1). The statistical relationships between the h-index, the c-score and related variables were examined using linear and non-linear correlation analysis. Non-linear models included quadratic (two-factor polynomial), power, exponential and logistic (sigmoidal) equations. The parameters considered were the linear (Pearson product-moment) correlation coefficient (r) and the linear determination coefficient (r^2), which measures the proportion of variance – or percentage when multiplied by 100 – explained by each model. For the non-linear models, the coefficient of determination (R^2) and the explained variance were computed. Variables with high skewness ($G_1 > 1$) were $\log_{10}$-transformed for centering and normalization before correlation analysis (Osborne, 2002; Ioannidis et al., 2016). When comparing the h-index and the c-score, the Spearman rank correlation coefficient (r_s) is also applied (Siegel & Castellan, 1988). This statistic quantifies the degree to which paleontologists retain similar rankings under both indices.

A comment is pertinent regarding the significance of linear correlation coefficients. In large samples, even very low correlations can be statistically significant, meaning that almost all calculated correlations reach significance. For example, in our case (n = 500), the significant correlation values are r = 0.088 ($p < 0.05$) and r = 0.115 ($p < 0.01$). According to Hammer & Harper (2024), interpreting correlation strength data should consider both statistical and contextual relevance. Therefore, in this study, significant correlations are interpreted in terms of the percentage of variance explained. Significant correlations below 0.500 are considered weak, as they explain 25% or less of the variance. Correlations between 0.500 and 0.710, which explain 25% to 50% of the variance, are considered moderate, while correlations above 0.710 (explaining more than 50% of the variance) are considered strong. This classification, based on the explanatory power, emphasizes the substantive strength of relationships and helps to distinguish statistically significant but weak relationships from those with greater explanatory importance. The software used for statistical analyses was PAST 4.16 (Hammer et al., 2001; Hammer & Harper, 2024).

Results

Geographical distribution

The current version of the database includes 22,513 paleontologists worldwide, of whom 500 (2.22%) meet the criteria for inclusion in the career-long modality of the SR. The geographical distribution of these authors, covering 34 countries, is shown in Fig. 1. Nearly half of them are from the USA (31%) and Great Britain (20%). Slightly less than a quarter (23%) are from Germany (8%), Australia, Canada, and France (5% each), while the remaining countries each account for 3% or less. Of them, only China, Sweden, Netherlands, Norway and Switzerland are above 1%.

General characterization

The most relevant statistical parameters for the variables considered are presented in Table 2. The least variable factors are the c-score (coefficient of variation ~6%), career duration (~23%), and the h-index (~27%). All other variables have coefficients of variation above 50%, with 13 ranging from ~70% to ~140%. This variation is significantly correlated (r = 0.836, $p < 0.01$) with distributional asymmetry, as measured by skewness. Career duration is approximately symmetric (G_1 ~0.3), whereas the c-score and h-index show moderately skewed distributions (G_1 ~1). The most variable factors have G_1 values between ~3 and ~6, indicating highly skewed distributions with long right tails. Skewness is also significantly correlated with the number of outliers (r = 0.721, $p < 0.01$), which are consistently located in the right tails of the distributions, with a maximum observed in TCns and AP (21 cases, or 4.2% of the distribution).

Correlations

The linear correlation coefficient between the h-index and the c-score is r=0.551. The coefficient of determination is $r^2 = 0.304$, indicating that approximately 30.36% of the variance is explained by this linear model (Fig. 2). Using non-linear regression models does not improve these values, as R^2 ranges from 0.303 (quadratic, exponential) to 0.305 (power, logistic), with the percentage of variance explained varying between 30.34% and 30.35% (moderate explanatory power). The Spearman rank correlation coefficient (r_s) between these two variables is 0.532 ($r_s^2 = 0.283$), with 28.30% of the variance explained. Despite the similarity and statistical significance of these correlations, the corresponding biplots display markedly different dispersion patterns. When actual values are used, most cases (i.e., authors) cluster within an elliptical region between approximately 30–60 for h and 3.3–3.8 for c; points lying beyond this region may be considered extreme values or outliers. In contrast, when ranks are used, the cases are widely dispersed across the entire plot area, with no concentration in any particular region. Therefore, despite the significant correlation and its moderate explanatory power, the h-index and the c-score classify palentologists in a very different fashion. Career duration (CD) shows a non-significant correlation with the h-index and a significant but weak correlation with the c-score. Thus, the h-index does not appear to be influenced by CD in SR-paleontologists, whereas the c-score is slightly, but statistically significantly, affected.

The strongest correlations with the h-index correspond to total citations (TC) and total citations excluding self-citations (TCns) (Table 3). Notably, these two variables show a very strong correlation with each other (r = 0.985; ~97% variance explained), indicating that the number of citations for SR-paleontologists is heavily influenced by non-self-citations. However, the correlation between TC and self-citations (SC) remains strong, emphasizing the importance of this factor for the h-index. The total number of papers has a moderately significant impact on the h-index, whereas the number of citations per paper, when including or excluding self-citations (TC/TP, TCns/TP), shows weaker influence. When authorship strategies are considered, the strongest correlations are found for the collaborator variables, including the number of citations, either in total (CC) or excluding self-citations (CCns), and the number of papers (CP, moderate). The manager variables (MP, MC, and MCns) show moderate correlations, while he author variables show weak (AC, ACns) or non-significant correlations (AP). In summary, collaborator and manager strategies strongly influence the h-index, whereas variables associated with the author strategy have a substantially lower impact.

Table 3 also shows that the linear model is not the best-fitting model in any case. The largest differences in the percentage of variance explained range from ~4% to ~9% and occur among the most strongly correlated variables (Fig. 3), whereas in other cases the differences are below 1%. The overall average difference is 2.68%, which is very small. In addition, the patterns of statistical significance do not differ between the linear and the best-fitting non-linear models. Therefore, the interpretations provided above using the linear correlations remain valid.

In the case of the c-score, the strongest correlations occur with author paper citations, both including and excluding self-citations (AC and ACns) (Table 4). Correlations with other authorship strategies are significant but much lower, falling within the weak category, except for CP, which is non-significant. This indicates that the c-score is heavily influenced by author citations, whereas the collaborator and manager strategies have a much smaller impact. Correlations with total citations (TC and TCns) and with citations per paper excluding self-citations (TCns/TP) are moderate. In this case, the relationship with self-citations (SC), though significant, is weak. Productivity variables, whether overall or by authorship strategy, show very low correlations, falling within the weak category. Therefore, citation—particularly to author papers—rather than productivity in any of its forms, is the main factor influencing the c-score.

As in the case of the h-index, non-linear models provided better fits than linear models (Fig. 3), with maximum differences in the percentage of variance explained ranging from ~4% to ~6%, and minimum differences close to zero (average 2.17%). Once again, the patterns of statistical significance did not differ between the linear and the best-fitting non-linear models, with two exceptions: citations per paper (TC/TP) and citations to manager papers excluding self-citations (MCns), which lie on the weak–moderate boundary when using the quadratic and power models, respectively. Therefore, the interpretations based on the linear regression analyses remain valid. The results presented in Tables 3 and 4 are summarized and synthesized in Fig. 4.

Conclusions and discussion

SR-paleontologists are mainly concentrated in North America and central-northern Europe, with a similar pattern observed in Australia. Other regions of the world show little to no presence of SR-paleontologists, except for China, where the numbers are comparable to those in northern Europe. Unfortunately, data on the total number of paleontologists in each country are not available, preventing percentage-based estimates.

Based on the parameter estimates in Table 2, rounded to the nearest integer, a hypothetical average SR paleontologist has a career duration of 41 ± 1 years and has published 165 ± 8 papers, of which 51 ± 4 (31%) are as first/single author, 69 ± 5 (42%) as intermediate author, and 45 ± 3 (27%) as last author. According to these figures, there is no distinct author, collaborator, or manager strategy (sensu Rull, 2025), although the collaborator role is more prevalent. This imaginary paleontologist has received 9402 ± 690 citations (61 ± 3 per paper), 1656 ± 110 (17%) of which are self-citations, and has an h-index of 47 ± 1 and a c-score of 3.65 ± 0.02.

The h-index and the c-score produce markedly different rankings of SR-paleontologists. For example, the eminent Stephen Jay Gould† is ranked 283rd by the h-index but rises to 5th position when ranked by the *c*-score. This is an extreme, though not uncommon, example of paleontologists with low h-index ranks appearing much higher when the c-score is used. The opposite pattern is less extreme but also common; for example, another paleontologist is ranked 23rd by the h-index and 313th by the c-score. Cases showing better agreement between the two classifications also exist. For instance, a third paleontologist is ranked 4th by both the h and c ranks, whereas a fourth is ranked 498th by the h-index and 499th by the *c*-score. These examples, together with numerous intermediate cases, explain the high dispersion observed (Fig. 2) and the absence of a strong direct or inverse statistical association.

Considering the variables that most strongly affect the h-index and the c-score (Fig. 4), it could be said that paleontologists with high h-indices (h-paleontologists) have more citations—both with and without self-citations—higher self-citation rates, and more citations as collaborators and managers than as authors. Conversely, paleontologists with higher c-scores (c-paleontologists) have fewer total citations, lower self-citation rates, and many more citations as authors than as collaborators and managers. In terms of productivity, h-paleontologists have published many more papers—regardless of authorship strategy—than c-paleontologists, and the inverse relationship observed with respect to citations and authorship is maintained. The number of citations per paper is always higher for c-paleontologists, although the correlations in this case are weak. Interestingly, being an h-paleontologist or a c-paleontologist appears to be independent of career duration.

The creators of the c-score highlighted that only 322 of the top 1000 scientists based on total citations were also included in the top 1000 according to the c-score (version 2013; 84,116 scientists). This discrepancy likely reflects that the former group were not first or single authors of their papers (Ioannidis et al., 2016). They also noted that many Nobel laureates and other highly influential scientists ranked among the top 1000 with the c-score but would rank much lower when using total citations. In paleontology, it is not possible to estimate comparable figures due to the unavailability of data for researchers not included in the SR and the absence (to the author's knowledge) of Nobel laureates among SR-paleontologists.

Ioannidis et al. (2016) – using linear correlation on log-transformed data for the entire database – analyzed the correlations between the h-index, the c-score, and seven selected variables. Two of these—the total number of citations (NC) and the number of citations to single or first author papers (NSF)—correspond to the variables analyzed in the present work (TC and AC, respectively). The strongest correlation was between total citations and the h-index (r = 0.88), suggesting that these variables convey similar information. Conversely, they reported a negative correlation between total citations and citations as first/single author (r = –0.22). In the present work, it was found that the first correlation (h-index vs. TC) is very similar for paleontology (r = 0.864, ~75% of the variance explained), whereas the second correlation (TC vs. AC), not previously estimated, is positive and significant (r = 0.423) but has weak explanatory power (~18%). For the total database, this indicates that top authors in terms of total citations and h-index have relatively few highly influential papers as first or single authors. In contrast, among SR-paleontologists, author citations contributed more substantially to the total number of citations.

The correlation between the h-index and the c-score was weaker in the entire database (r = 0.25) than among SR-paleontologists (r = 0.551), likely due to the high variability of this parameter across disciplines and specialties in the former case. The strong correlation found in this work between the c-score and author citations (r = 0.746)—interpreted as the high contribution of AC to c values—was even higher when using the total database (r = 0.83). Therefore, this relationship is reinforced when all research fields are considered. Ioannidis et al. (2016) explored the correlations between total citations and their seven variables within the 12 scientific fields available at the time, which included “Earth & Environmental Sciences” (EES), to which almost all SR-paleontologists belong. Their results were consistent with those from the entire database for the h-index ($r > 0.80$) but not for the c-score ($r \approx 0.7$ for EES and $r < -0.1$ for the total). A similar discrepancy was observed for single/first author citations ($r > 0.2$ for EES and $r < -0.2$ for the total). Unfortunately, no more detailed studies are available within the EES field to situate paleontology within this framework.

Some similar data exist for other disciplines very different from paleontology, mainly from the medical sciences. For example, Pan et al. (2024) reported a strong linear correlation ($r = 0.73$) between the h-index and the c-score in the clinical ophthalmology and optometry subfields (4603 authors). The correlation between h and c with citations to first/single author papers are also strong but lower in the first case ($r = 0.56$ and $r = 0.69$, respectively). The investigation was aimed at evaluating the best citation index to predict winners of the prestigious Weisenfeld award, and it was concluded that the c-score was the better suited for this task.

Jones (2023a) analyzed the USA forensic scientists ($n = 93$) and provided a general characterization of the main variables relevant to their citation metrics. For example, the average number of papers published was ~96 with the total number of citations of 2467 (with ~9% being self-citations). The average number of papers as single/first author was ~38 and the average number of cites to these papers was 789. The mean h-index was ~13 and the average c-score was 3.13. The same author conducted a similar analysis for the Nordic countries (Denmark, Finland, Norway and Sweden), where 34 SR forensic scientists conduct their research (Jones, 2023b). In this case, the mean number of papers was 135 and the total number of citations was 3467 (13% self-citations), in average. The mean number of papers with single or first authorship was 39, and the mean number of citations to these papers was 823. The average h-index was ~28, and the mean c-score was 3.18. Other analyses do not provide comparable quantitative data but report the position of scientists from a given specialty within the SR. For instance, Senior & Fazel (2019) extracted the rank of scientists, countries and institutions related with mental health (psychiatry, psychology and related fields) and concluded that the c-score improves on simple publication or citation metrics. Other SR comparisons using different methods are available in research fields such as refractive surgery (Randleman et al., 2023) or cheminformatics (Banerjee et al., 2025).

No similar analyses have been found in the fields of Earth Sciences and Biology, where the subfield of Paleoecology is classified in the SR. It would be interesting to expand the database—or make it publicly available, if possible—to include all known paleontologists beyond the 500 featured in the SR, in order to allow a full appraisal of this specialty with respect to the h-index, the c-score and their related variables. Such an expansion would benefit not only the authors themselves but also the institutions responsible for their evaluation. In its current form, although the c-score appears to be the best tool available for this purpose (Rull, 2025), comparisons are possible only among the 500 paleontologists listed in the SR. The combination with other complementary descriptors, such as the author position ratio (APR) to account for authorship patterns (Rull, 2026), is highly recommended.

Acknowledgments

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Tables

Table 1. Variables considered in this study and their corresponding abbreviations. Variables calculated from the raw data in the Supplementary Material are marked with an asterisk, and the specific calculations from the variables of the original database are displayed in the "calculation" column.

Variable	Abbreviation	Calculation
Career duration in years*	CD	lastyr – firstyr
Total papers published	TP	np6024
Total citations received	TC	nc9624
Average citations per paper*	TC/TP	nc9624 / np6024
Total citations excluding self-citations	TCns	nc9624 (ns)
Average citations per paper excluding self-citations*	TCns/TP	nc9624 (ns) / np6024
Total self-citations*	SC	nc9624 – nc9624 (ns)
Papers published as first/single author or author papers	AP	cpsf
Citations to AP	AC	ncsf
Citations to AP excluding self-citations	ACns	ncsf (ns)
Papers published as intermediate author or collaborator papers*	CP	np6024 – npsfl
Citations to CP*	CC	nc9624 – ncsfl
Citations to CP papers excluding self-citations*	CCns	nc9624 (ns) – ncsfl (ns)
Papers published as last author or manager papers*	MP	npsfl – cpsf
Citations to MP*	MC	ncsfl – ncsf
Citations to MP excluding self-citations*	MCns	ncsfl (ns) – ncsf (ns)

Table 2. Variables relevant to the *h*-index and *c*-score. See Table 1 for abbreviations. St dev, standard deviation; Var coeff, variation coefficient; Conf int, confidence interval.

Variable	Range	Mean	Std dev	Var coeff (%)	Conf int (95%)	Skewness (G_1)	Outliers	Threshold
CD	18-89	40.53	9.48	23.39	±0.83	0.275	1	73
TP	37-761	165.09	91.28	55.29	±8.00	2.226	12	399
TC	2230-76,063	9402.27	7863.58	83.63	±689.26	3.883	18	23,849
TC/TP	7-305	60.75	36.29	59.74	±3.18	2.541	14	150
TCns	1670-63,593	7745.91	6934.62	89.53	±607.84	3.838	21	19,308
TCns/TP	3-298	51.03	35.10	68.78	±3.08	2.725	16	131
SC	77-12,470	1656.36	1249.75	75.45	±109.54	3.327	7	5195
AP	7-395	51.29	40.36	78.68	±3.54	3.710	21	125
AC	309-28464	2733.82	2328.87	85.19	±204.07	5.950	17	6667
ACns	245-28,225	2337.72	2249.78	96.24	±197.20	6.363	15	5962
CP	2-504	68.77	53.29	77.49	±4.67	2.697	7	210
CC	52-65,222	4720.15	6110.28	129.45	±535.60	5.076	15	15,314
CC-ns	42-55,118	3820.34	5530.18	139.52	±467.20	5.034	18	12,033
MP	1-348	45.03	34.57	76.76	±3.03	3.293	8	127
MC	30-14,909	1948.30	1707.96	87.067	±149.65	3.149	10	6375
MCns	28-13,962	1587.85	1476.81	93.01	±129.45	3.543	11	5145
h-index	20-110	46.70	12.64	27.06	±1.11	1.097	3	90
c-score	3.1991-4.5637	3.6500	0.2042	5.60	±0.02	1.019	2	4.3832

Table 3. Correlations between the h-index and the variables considered in this study (log_{10}-transformed for high G_1 values; see Table 2). Linear correlations significant at $p < 0.01$ are marked with an asterisk. The best-fit models, their determination coefficients (R^2), and the variance explained by each model are also indicated. r, linear correlation coefficient; r^2, linear determination coefficient; Var exp, percentage of variance explained; Exp pow, explanation power; Var dif, difference between the variance explained by the best-fit and linear models; NS, non-significant. The explanation power of significant correlations is classified into weak (< 25% of variance explained), moderate (25-50%) and strong (> 50%), as defined in the methods section.

Variable	**r**	**r^2**	**Var exp (%)**	**Exp pow**	**Best-fit**	**R^2**	**Var exp (%)**	**Exp pow**	**Var dif (%)**
CD	-0.006	0.000	0.00	NS	Quadratic	0.002	0.22	NS	0.22
TP	0.624*	0.390	39.00	Moderate	Power	0.391	39.06	Moderate	0.06
TC	0.864*	0.747	74.73	Strong	Logistic	0.748	74.79	Strong	0.06
TC/TP	0.373*	0.139	13.88	Weak	Quadratic	0.149	14.87	Weak	0.99
TCns	0.824*	0.679	67.93	Strong	Logistic	0.681	68.08	Strong	0.15
TCns/TP	0.324*	0.105	10.52	Weak	Quadratic	0.115	11.49	Weak	0.97
SC	0.772*	0.596	59.61	Strong	Power	0.690	68.99	Strong	9.38
AP	-0.064	0.004	0.42	NS	Logistic	0.010	1.01	NS	0.59
AC	0.320*	0.103	10.25	Weak	Quadratic	0.108	10.78	Weak	0.53
ACns	0.297*	0.088	8.80	Weak	Quadratic	0.091	9.11	Weak	0.31
CP	0.692*	0.479	47.87	Moderate	Power	0.562	56.20	Strong	8.33
CC	0.781*	0.610	61.04	Strong	Quadratic	0.672	67.17	Strong	6.13
CCns	0.771*	0.595	59.46	Strong	Quadratic	0.640	64.04	Strong	4.58
MP	0.542*	0.294	29.43	Moderate	Power	0.303	30.28	Moderate	0.85
MC	0.659*	0.434	43.43	Moderate	Power	0.488	48.79	Moderate	5.36
MCns	0.644*	0.415	41.48	Moderate	Power	0.459	45.91	Moderate	4.43

Table 4. Correlations between the c-score and the variables considered in this study (log_{10}-transformed for high G_1 values; see Table 2). Linear correlations significant at $p < 0.01$ are marked with an asterisk. The best-fit models, their determination coefficients (R^2), and the variance explained by each model are also indicated. r, linear correlation coefficient; r^2, linear determination coefficient; Var exp, percentage of variance explained; Exp pow, explanation power; Var dif, difference between the variance explained by the best-fit and linear models; NS, non-significant. The explanation power of significant correlations is classified into weak (< 25% of variance explained), moderate (25-50%) and strong (> 50%), as defined in the methods section.

Variable	**r**	**r^2**	**Var exp (%)**	**Exp pow**	**Best-fit**	**R^2**	**Var exp (%)**	**Exp pow**	**Var dif (%)**
CD	0.237*	0.056	5.60	Weak	Quadratic	0.057	5.66	Weak	0.06
TP	0.196*	0.039	3.86	Weak	Quadratic	0.048	4.75	Weak	0.89
TC	0.611*	0.373	37.32	Moderate	Logistic	0.374	37.37	Moderate	0.05
TC/TP	0.497*	0.247	24.67	Weak	Power	0.249	24.91	Weak/Mod	0.24
TCns	0.661*	0.437	43.68	Moderate	Quadratic	0.441	44.06	Moderate	0.38
TCns/TP	0.511*	0.261	26.14	Moderate	Exponential	0.263	26.34	Strong	0.20
SC	0.172*	0.030	2.97	Weak	Quadratic	0.089	8.90	Weak	5.93
AP	0.176*	0.031	3.08	Weak	Quadratic	0.033	3.30	Weak	0.22
AC	0.746*	0.556	55.62	Strong	Quadratic	0.566	56.58	Strong	0.96
ACns	0.789*	0.622	62.19	Strong	Power	0.626	62.57	Strong	0.38
CP	0.079	0.006	0.63	NS	Quadratic	0.055	5.51	NS	4.88
CC	0.307*	0.094	9.44	Weak	Quadratic	0.134	13.46	Weak	4.02
CCns	0.340*	0.116	11.58	Weak	Quadratic	0.147	14.67	Weak	3.09
MP	0.133*	0.018	1.78	Weak	Quadratic	0.029	2.95	Weak	1.17
MC	0.395*	0.156	15.62	Weak	Quadratic	0.218	21.81	Weak	6.19
MCns	0.435*	0.189	18.93	Weak	Quadratic	0.250	24.97	Weak/Mod	6.04

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Figure captions

Figure 1. Geographical distribution (by country) of paleontologists featured in the career-long modality of the Stanford Ranking (SR) released in September 2025. See the Supplementary Material for full data on these authors.

Figure 2. Correlations between the h-index and the c-score. (A) Linear correlation between the actual h-index and c-score values. (B) Spearman rank correlation between authors' ranks based on the *h*-index (*h*-rank) and the *c*-score (*c*-rank).

Figure 3. Variables showing the strongest differences between linear and non-linear models. (A) Linear (orange) versus power (red) regression models, and their corresponding coefficients of determination, for the relationship between the h-index and self-citations (SC). The variance explained is approximately 60% for the linear model and 69% for the power model (see Table 3). (B) Linear (orange) versus quadratic (red) regression models, and their corresponding coefficients of determination, for the relationship between the c-score and manager citations (MC). The variance explained is approximately 16% for the linear model and 6% for the quadratic model (see Table 4).

Figure 4. Summary of correlation analysis results classified by the percentage of variance explained, based on the model explaining the greater variance in each case (see Tables 3 and 4). Weak, < 25%; Moderate, 25-50%, Strong, > 50%.

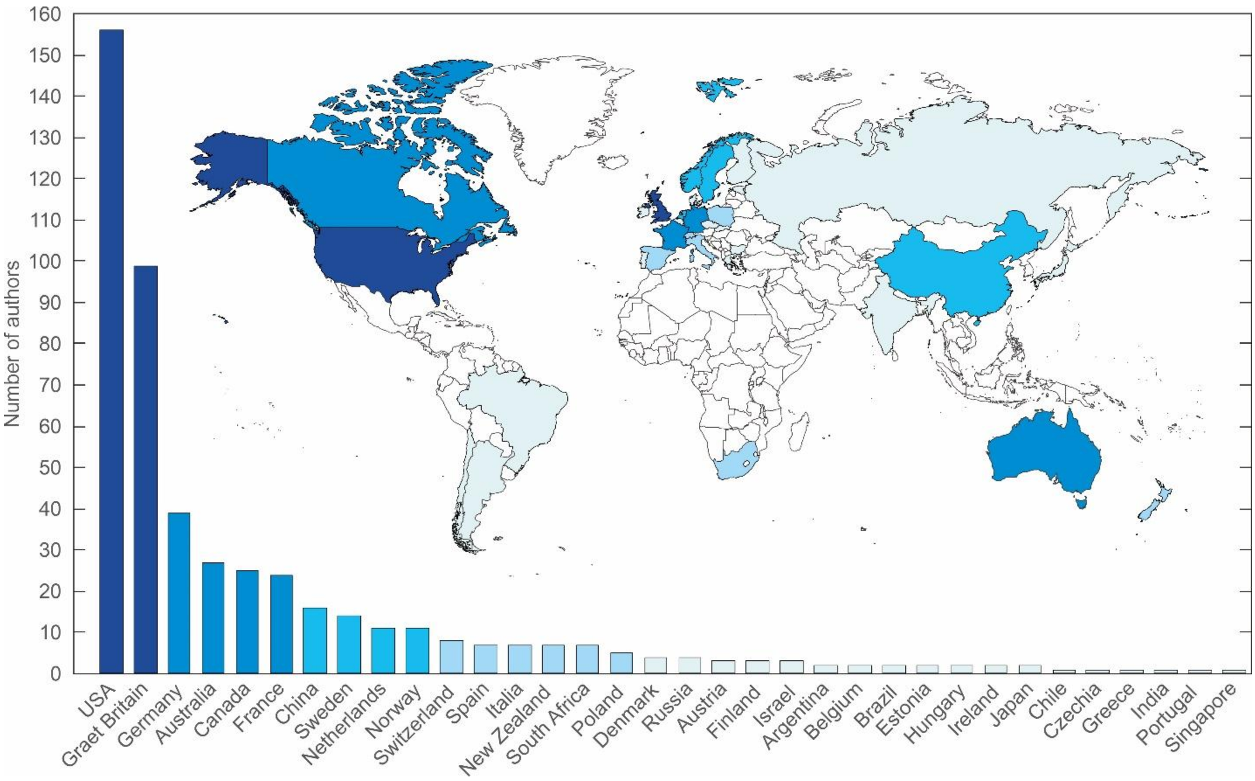

Figure 1

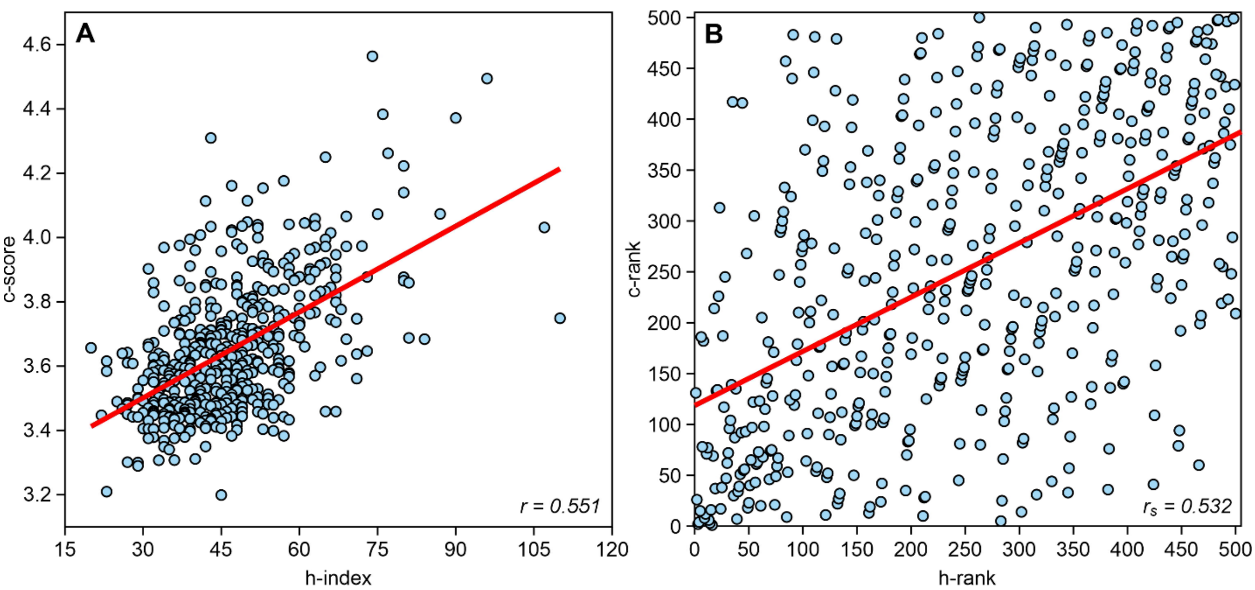

Figure 2

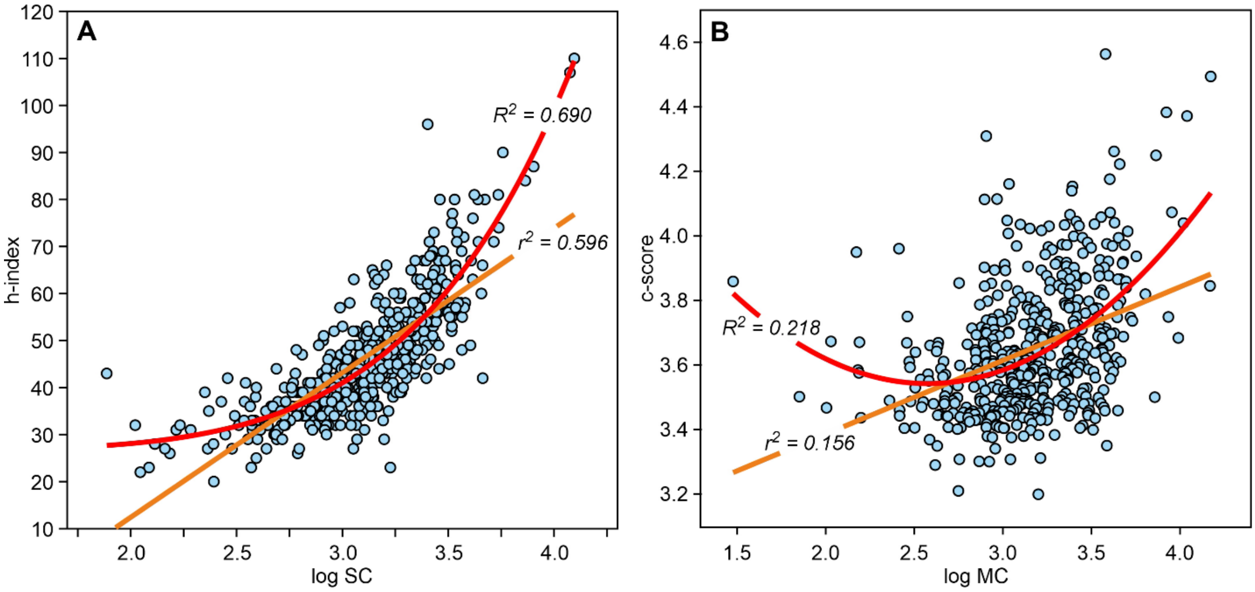

Figure 3

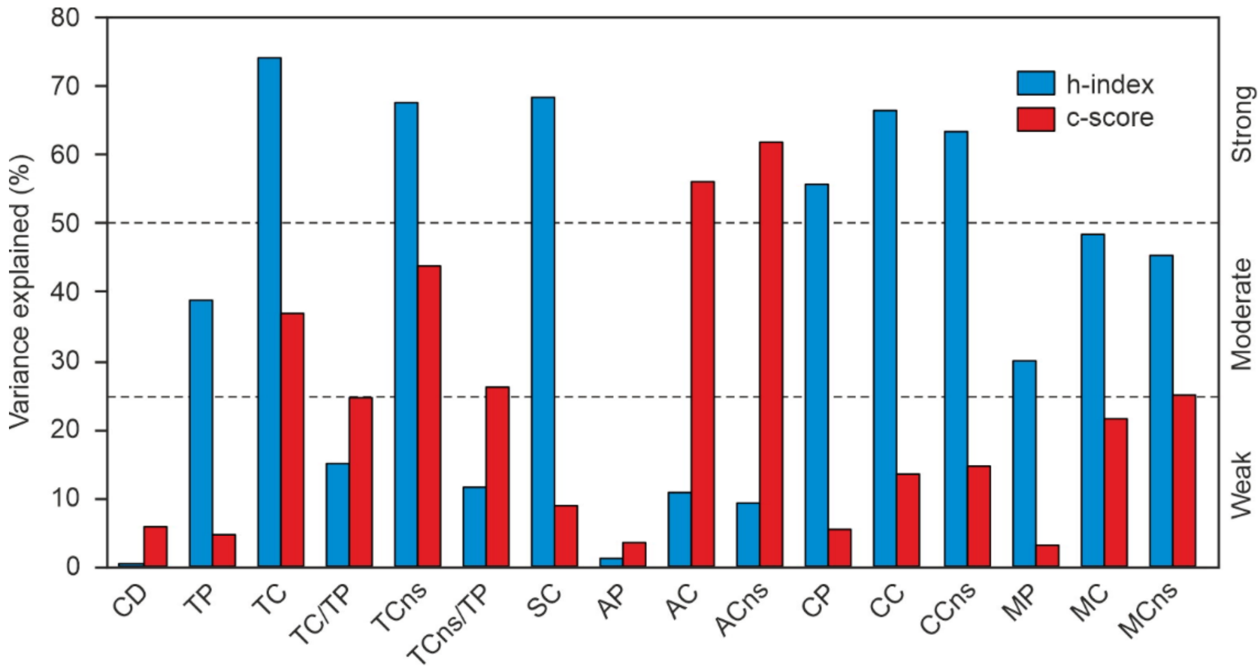

Figure 4