Title:

Tweet success? Scientific communication correlates with increased citations in Ecology and Conservation

Authors: Clayton T. Lamb[1], Sophie L. Gilbert[2], Adam T. Ford[3]

Affiliations:

[1]Department of Biological Sciences, University of Alberta, Edmonton, Alberta, Canada
[2] Department of Fish and Wildlife Sciences, University of Idaho, Moscow, ID, USA, 83843
[3] Department of Biology, University of British Columbia, Kelowna, British Columbia, Canada

Emails:
CTL: ctlamb@ualberta.ca
SLG: sophiegilbert@uidaho.edu
ATF: adam.ford@ubc.ca

Keywords: altmetric, science communication, twitter, social media

Corresponding Author Information: Clayton Lamb, Centennial Center for Interdisciplinary Sciences, University of Alberta, 116 St. and 85 Ave., Edmonton, Alberta, Canada.T6G 2E9. E: ctlamb@ualberta.ca P:778-215-0334

Abstract

Science communication is seen as critical for the disciplines of ecology and conservation, where research products are often used to shape policy and decision making. Engagement is increasingly performed online, on social media, or news. Such media engagement has been thought to influence or predict traditional metrics of scholarship, such as citation rates. Here, we measure the association between citation rates and Altmetric Score, along with other forms of bibliometric performance (year published, journal impact factor, and article type). We found that Altmetric Score was positively correlated with citation rates, but with increasing media exposure required per citation over time to achieve equivalent citations. Citations correlated with journal impact factors up to ~10, but then plateaued, demonstrating that maximizing citations does not require publishing in the highest-impact journals. We conclude that ecology and conservation researchers can increase exposure of their research through social media engagement and, simultaneously, enhance their performance under traditional measures of scholarly activity.

Introduction

Communicating science to policymakers, other scientists, and the public is an increasingly important task in an era of "alternative facts" (Galetti & Costa-Pereira, 2017). Scientists are finding new means to communicate science using a wide array of online media (e.g., Twitter, Facebook, blogs; Piwowar 2013; Bornmann 2014; Donner 2017). The shifting nature of modern science communication is particularly relevant to the fields of ecology and conservation (EC), where science is often used to solve environmental problems and engage the public. The dissemination of research via online media ~~have~~ has been proposed as a complementary measure of scientific impact (i.e., "alternative metrics", or altmetrics; Piwowar 2013; Bornmann 2014), compared to traditional bibliometric approaches such as citations per article. An outstanding question from the efforts to diversify the channels of science communication is the extent to which traditional and social media exposure are linked: should scientists invest in social media to promote their research?

Comment [GMD1]: Also potentially important venue for debate over conservation policy and interpretation of studies involving conservation/management conflicts

Comment [GMD2]: More widely should scientists "promote" their research at all.

Research that receives more attention on social and traditional media are likely to reach a more diverse, non-scientist group than a publication with a lower media profile. For example, on Twitter, a platform scientists often use to discuss science amongst one another (potentially

Comment [GMD3]: is?

leading to an “echo chamber”), up to 40% of followers from EC scientists may be non-scientists, media, and environmental groups (Darling et al., 2013). Similarly, recent work by (King, Schneer & White, 2017) demonstrates that the media can galvanize public opinion —increasing discussion of policy by ~62.7% on social media and potentially influencing decision makers. Consequently, there has been a proliferation of research on the value of various altmetrics for measuring broader impacts and predicting important bibliometrics such as citation counts (e.g., Thelwall et al., 2013; Bornmann, 2014; Haustein, 2016; Finch, O ’hanlon & Dudley, 2017).

A key ~~component~~ feature of altmetrics is that they accumulate rapidly after article publication ~~and often have effectively stopped~~but often stop accumulating, or accumulate very little, before the paper’s first citation (Eysenbach, 2011). This sequence occurs because the content of publications becomes public knowledge at or right after the publication date (especially for journals with a media embargo policy, like *Science* and *Nature*), whereas publications citing this work may not be available for years after the original work was published. As such, media exposure – including social media- may either influence or forecast the citation rates of a paper. For example, Eysenbach (2011) shows Tweets can predict highly cited articles within 3 days of publication, and Finch et al. (2017) showed that tweets about orinthology papers predict citation rates in a subset of avian-ecology journals. Consequently, Altmetrics present a convenient way to rapidly quantify one aspect of science communication, and may allow for identification of high-impact papers considerably faster than traditional citation rates, which are slow to accumulate.

There are many types of new media included under the umbrella of “altmetrics,” which altmetric types best reflect effective scientific outreach to both the public and scientists is currently unknown, and may vary by discipline (Haustein, 2016). Citation counts and other

Comment [GMD4]: This is not necessarily evidence that a wider public is engaging with research *per se*. Is engagement with scientists promotion of their research necessarily the same as engagement with or understanding of the research results?

Comment [GMD5]: Here you seem to be equating discussion of research with discussion of policy which I don’t think is equivalent.

Comment [GMD6]: Altmetrics or altmetrics – ensure capitalization is correct and consistent throughout.

related bibliometrics continue to determine professional success at many institutions (Wade, 1975), but the correlation between altmetrics and bibliometrics varies by altmetric type (Thelwall et al., 2013; de Winter, 2014; Haustein, 2016; Peoples et al., 2016), making it difficult for institutions and researchers to prioritize altmetrics. Further, some altmetrics are vulnerable to manipulation and commercialization, raising concerns regarding their use for evaluation of research impact (Bornmann, 2014; Haustein, 2016). Determining a single best altmetric predictor of bibliometric performance will likely remain elusive as the online media landscape evolves and new altmetric types emerge. One potential solution to these related problems is to use a broad suite of altmetrics to calculate a combined Altmetric Score (www.altmetric.com; one of many ‘altmetrics’ ~~but~~ is the one we focus on here). However, the effectiveness of the Altmetric Score for predicting research impact has not been evaluated across EC and over time (but see Finch, O ’hanlon & Dudley, (2017) for a focused look at ornithology), leaving a knowledge gap with implications for the evaluation and dissemination of research.

Here, we examine correlations between traditional bibliometrics (citation rate, journal impact factor), time since publication, and altmetric exposure. We focus on EC publications, where we anticipate that the growing interest ~~by~~ from EC researchers in social media may be changing the relationship between citation rates and altmetrics.

Materials & Methods

Data: We gathered citation, Altmetric Score, and descriptive data on ecology and conservation ~~(EC)~~ articles published between 2005 and ~~-~~2015. This period reflects an era of sufficient social media engagement by researchers to investigate the relationship between Altmetric Score and citation rates, while allowing sufficient time for more recent articles to acquire citations.

Comment [GMD7]: A wider question of course is whether bibliometric performance is actually an indicator of scientific worth or quality.

Comment [GMD8]: I would suggest reserving the word “almetrics” for that specific score and otherwise refer to “alternative metrics”

Comment [GMD9]: Avoid use of abbreviations where not necessary it reduces readability. There is no reason with “ecology and conservation” wouldn’t be fine here.

Comment [GMD10]: Evidence?

Comment [GMD11]: citation counts/rates?

Comment [GMD12]: How does this date relate to variation in social media membership amongst ecologists/conservationists? What date was Altmetric first introduced and how has journal participation changed over time. What proportion of relevant journals provide an Altmetric Score and is there a risk of bias towards particular types or stables of journals?

Altmetric Score data was obtained from Altmetric (https://www.altmetric.com/) under a free academic license. The Altmetric data consists of the Altmetric Score for each paper as well as the counts of individual media sources that comprise the score. Altmetric Scores are a composite, weighted index of many media sources (https://help.altmetric.com/support/solutions/articles/6000060969-how-is-the-altmetric-score-calculated-). We focused on the most popular and top-weighted media sources: news, blogs, Facebook, Twitter, and Wikipedia.

Comment [GMD13]: Provide a citation rather than an in-line URL

Comment [GMD14]: Not sure what you mean here, are you suggesting you calculated your own Altmetric score based on a subset of the

Citation data was obtained from Scopus (https://www.scopus.com/) using the search terms “Ecolog*” AND “Conservat*” between 2005 and ~~-~~2015. We obtained journal impact factor using Reuter’s 2014 impact factor ratings. We merged Scopus and Altmetric data using a unique identifier of the first 15 character of the article and journal titles and the year. Finally, to ensure our citation metrics were comparable between articles, we removed any methods-based articles, which are often cited more highly than other articles, and were not the focus of our investigation. We removed these articles using the keywords “method*” or “technique*” to cull articles with these words in their article title or journal title. To control for other factors influencing citation rates of articles, we included in all models the number of years since publication, journal impact factor, and article type (review, article, or letter).

Comment [GMD15]: I wonder if there are other relevant controls to consider such as journal stable, publication mode (OA v. subscription) and whether a journal is associated with a society and/or association

Modeling Approach: We used boosted logistic regression trees (Elith, Leathwick & Hastie, 2008) to investigate the relationship between Altmetric Score and citation rates. Boosted regression trees (BRT) are an advanced form of a generalized linear model (GLM; Elith *et al.* 2008). BRT’s were well suited to our application because they can handle the complex, non-linear relationships we expected to find with these data, provide greater predictive performance and are less plagued by multi-collinearity than GLM’s (Elith, Leathwick & Hastie, 2008). Unlike

GLM's, BRT's do not test null hypotheses but instead effectively quantify and illustrate complex, non-linear relationships, such as those expected here. We fit BRT's using the 'gbm' package (Ridgeway, 2015) in Program R (R Core Team, 2017). We analyzed the correlation between Altmetric Score and citation rates in three periods: 1) an early time period of social media uptake (2005-2009); 2) latter period of social media uptake (2010-2015), and 3) and the combined period of our dataset (2005-2015).

A BRT is fitted to data using three main parameters. First, learning rate, which is the contribution of each tree to the model. Smaller learning rates result in relatively more trees required to fit the model, with each tree contributing a relatively small amount to the predictions providing a better fit of the model to the data. In general, a lower learning rate is preferred, such that at least 1000 trees are generated (Elith, Leathwick & Hastie, 2008). Second, tree complexity, which is the number of nodes or splits allowed in each tree, where trees with more nodes are more complex. Third, bag fraction, which is the percent of data used to train (those data used to build the model) and test (data used to test predictions that were not involved in model creation) the model for each iteration (new tree).

We tested two commonly used learning rates (4 and 8) and tree complexities (0.001,0.01) and selected as our top model the model that minimized predictive deviance (Elith, Leathwick & Hastie, 2008). We calculated the relative influence of each predictor on resulting citation rates and produced response curves. Relative influence is measured by relative number of times variables included in trees weighted by the square root of improvement to the model, averaged over all trees and the influence of each variable scaled so the sum adds to 100 (Elith, Leathwick & Hastie, 2008).

Comment [GMD16]: This is not a complete sentence, please rephrase.

Comment [GMD17]: Check phrasing here particularly "relative number of times variables included in trees" Seems a little unclear

Model Validation: We partitioned our data into training (bag fraction= 70%, those data used to build the model) and test~~ing~~ data (30%, data used to test predictions that were not involved in model creation) for each iteration (new tree). We used the test~~ing~~ data and model predictions to calculate predictive accuracy using the coefficient of determination (R^2~~), which we used to assess the generality of the model to predict responses from data not used to generate the model~~. Overfitting is reduced in the BRT by optimizing the learning rate and number of trees as described above, but also by using randomness in partitioning of data. The degree of overfitting can be assessed using the model predictive capacity on test~~ing~~ data and BRT's are generally robust to overfitting (Elith, Leathwick & Hastie, 2008).

Results

We found bibliometric and altmetric data on 10,048 EC articles. Most articles published during this time received relatively low Altmetric Scores (<100, Figure 1), but a few scores exceeded 900. Altmetric Scores per article have been increasing over the last 10 years and the composition of media sources making up the Altmetric has been shifting (Figure 1), primarily towards increased Twitter activity.

~~Not surprisingly, t~~Time alone (years since published) increased citation rates, and letters/notes received fewer citations than traditional articles whereas review papers received more citations than both other article types. Models for both time periods produced good predictive accuracy ($R^2 = 0.60$ for 2005-2009 and $R^2 = 0.65$ for 2010-2015). BRT models for both the early (2005-2009) and late periods (2010-2015) reached minimum deviance at 8 trees and a learning rate of 0.001. The third BRT model assessed the contribution of each of the media sources that comprise the composite Altmetric score on resulting citation rates. Model predictive

Comment [GMD18]: What constitutes low in your mind. I would imagine that an Altmertric score of 100 is in the top few centile.

Comment [GMD19]: Uncertain what this is referring to the contribution of the different "media sources" are not explained or quantified. I don't recall this element of the analysis being explained in the methods.

accuracy was high ($R^2 = 0.61$). Minimum deviance was reached at 4 trees and a learning rate of 0.01.

Within EC, we found discipline-specific differences in research impact. Conservation articles (8.8 ± 0.6 [$\bar{x}$ ± SEM]) received slightly larger Altmertric Scores compared to ecology articles (7.6 ± 0.3). However, conservation articles (29.5 ± 1.3) received fewer citations than ecology articles (34.1 ± 1.4).

Citation rates were positively correlated with Altmetric Scores during the 2005-2009 period~~,~~ and to a lesser extent during the 2010-2015 period. Journal impact factor was more important during the later period (Figure 2). Higher Altmetric Scores generally correlated with increased citations, but an asymptote was present in both time periods (Figure 3). The association between Altmetric Scores and citation rates has attenuated over time (Figure 3), and maximal gains in citation rates were attained at Altmetric Score of 68 during the early period, and 538 in the later period, after which the relationship plateaued in both time periods. In both periods citation rates were maximized in journals having impact factors between 11 and~~-~~14. Finally, across the entire 2005-2015 time period, Altmetric Scores derived from coverage on Blogs, Wikipedia and Tweets had the largest influence on citation rates, while Facebook posts and news articles had the least influence (Figure 2).

Discussion

The fields of ecology and conservation ~~(EC)~~ have traditionally been linked to applied research, policy, and public engagement (Lubchenco, 1998). As such~~, EC~~ researchers are increasingly relying on social media platforms to promote science to their peers, decision makers, and to the public (Bickford et al., 2012; Darling et al., 2013; Priem, 2013; Parsons et al., 2014). Our

Comment [GMD20]: Your methods did not explain how or why you proposed to compare impact between disciplines

Comment [GMD21]: Are these differences significant? Should this factor be included in your BRT if you believe it's an important factor?

Comment [GMD22]: Can you also show the uncertainty/error around your estimates of mean number of citations?

Comment [GMD23]: Might be helpful to either clearly define the years corresponding to early and late in your methods or to consistently refer to the time period when describing your results

Comment [GMD24]: I think there might be a lot of ecologists who would disagree with this statement, perhaps a little sweeping.

Comment [GMD25]: Alternative explanation is that we'll do anything to drive up citation rates and metrics of the "worth" of our research as we increasingly compete for ever more limited funding and in a more crowded job market. Promotion and tenure policies based on publication and citation rates probably also help.

analyses show that: 1) most published research garners very little attention on social media (e.g., over 80% of articles tracked by Altmertics were tweeted < 5 times); 2) social media exposure is positively correlated with citation rates; 3) both journal impact factor and social media exposure effects on citations have shown diminishing returns in recent years. ~~Below, we discuss the implications of these findings and highlight how researchers can use social media to measure research impact.~~

The distribution of Altmteric Scores was highly right-skewed, indicating that a few papers can have very wide-reaching attention but most do not. However, average Altmetric Scores have increased rapidly since 2011 – a trend explained, in part, by broader engagement of the public with all forms of online content. In addition to this broader societal trend, many researchers are heeding calls to engage in outreach through social media (Milkman & Berger, 2014; Parsons et al., 2014; Cooke et al., 2017). Postdoctoral fellowship programs in EC, such as the Liber Ero Fellowship (Canada: www.liberero.ca), the Smith Fellows (USA: http://conbio.org/mini-sites/smith-fellows), Wilburforce Fellows (USA/Canada: http://www.wilburforce.org/grants/fellowship/), and others provide specialized training in social media engagement for EC researchers. In the future, graduate and undergraduate EC students may routinely receive training in social media as part of their studies.

The association between Altmetric Scores and citation rates varies by type of media within the Altmetric Score: tweets contributed most to Altmetric Score~~ for EC papers~~, but blogs had the greatest influence on citation rates. This may signal that researchers turn to blogs as a form of information curation, or that other forms of media (e.g., facebook, twitter, radio) are highly responsive to blogs. We cannot discern the causes of these patterns from our analyses, but suspect that either the more in-depth coverage afforded by blogs (as opposed to the shorter format of media like Facebook or Twitter), or the ease with which blog content is located by web search engines creates a more lasting impression on authors when they are developing their literature reviews. Previous work by Peoples *et al.* (2016) found a weak and highly variable relationship between tweets and citation rates, whereas we find a stronger, more positive relationship (Figure S1), likely due to our application of BRT models to address interactive effects (Elith, Leathwick & Hastie, 2008). Finally, we detected asymptotic relationships between citation rate and each of the media sources comprising the Altmetric Score. Similar to our study, Finch et al (2017) also found asymptotic relationships between citation rates, impact factor and Almetric Scores for research focused on ~~the EC subdiscipline of~~ ornithology. Thus, investigators will likely realize the greatest citation return on investment by diversifying their media outreach channels among blogs, traditional media, twitter, and other outlets for EC-related subdisciplines.

In spite of the growth in social media activity by researchers, there are asymptotic benefits for traditional measures of scholarly impact (i.e., citation rates). If we assume that social media exposure predicts or contributes towards citation rates (see(Eysenbach, 2011; Finch, O 'hanlon & Dudley, 2017), then our results suggest a diminishing return on investment: it now takes four to six times the Altmetric Score to achieve an equivalent citation rate as it did 5-10 years ago. This weakening return on investment is consistent with the idea that media consumption is finite (Rodriguez, Gummadi & Schölkopf, 2014), and that increasing the number of communicators in a social media network may not increase the amount of media consumed (Kaplan & Haenlein, 2010; Milkman & Berger, 2014; Ferrara & Yang, 2015). This asymptotic relationship between social media and citation rates has important implications for how researchers and institutions should devise media outreach plans, and if/how social media impact can be used to measure research impact.

Comment [GMD26]: Can you suggest what these implications might be, you're leaving us hanging here a little.

While our results suggest that an increasingly larger amount of social media attention is needed to generate maximal gains in citation rates, our results also show that minor increases in social media attention are associated with a steep rise in citation rates for papers with few citations – social media transforms the highly obscure to the notable. This transformation is important, because research impact at many institutions is evaluated both by publication in high impact journals (i.e., impact factors > 10) and citation rates – which are positively correlated (Figure 3, Wade, 1975; Judge et al., 2007). Since space in high impact journals is highly competitive, social media can help level the playing field between the few papers accepted into such high-profile outlets and the many more that are rejected. Indeed, we were surprised to discover that the influence of social media exposure on citation rates was actually far greater than journal impact factor between 2005-2010, and comparable more recently (see Figure 2). We also found that journal impact factor also has diminishing returns on citation rates, peaking at around 10 before levelling off. Combined, these results suggest that, generally, evaluation of research impact should consider discipline-specific asymptotes in media attention and impact factor (i.e., "twimpact factor"; *sensu* Eysenbach G. 2011). Finally, our results also suggest that conservationists concerned about reaching a broad audience can do so as effectively with high impact and moderate-impact journals, as has been suggested elsewhere (Peoples et al., 2016).

For many EC researchers, the benefits of social media outreach extend well beyond boosting citation rates. Social media is also a tool to engage with peers, the public, and policy makers from around the world (Kaplan & Haenlein, 2010; Parsons et al., 2014; Bombaci et al., 2016; Cooke et al., 2017). Quantifying causal links between research innovation, Altmetric Scores, citations rates, and policy changes is challenging (e.g., Danaher 2017); yet such linkages are likely why many in EC fields use social media (Bombaci et al., 2016; Peoples et al., 2016).

Comment [GMD27]: It wasn't clear to me how this last part of the sentence fitted here.

Comment [GMD28]: I'm not sure this necessarily helps gain a broad audience but it relates to a larger one. You don't know the background/discipline of those tweeting and/or citing the work.

Our analysis provides guidance on the potential benefits of social media engagement for research impact. However, we have not identified a specific mechanism linking citations to Altmetric Scores. A number of factors constrain the effectiveness of science communication in general, including via social media (e.g., the appearance and race of the scientist; Milkman and Berger 2014; Gheorghiu *et al.* 2017). Moreover, linkages between social media, policy/management change, and public engagement were beyond the scope of our work, but are important avenues of continued inquiry in contemporary scientific communication (King, Schneer & White, 2017).

Comment [GMD29]: gender?

Comment [GMD30]: Suggest restructuring or even removing much of this paragraph. It didn't really seem to flow logically. For instance the first sentence talk about potential benefits but then you switch to the lack of causal mechanisms identified in your study.

Researchers need to weigh the benefits of social media – potentially enhanced citation rates and public engagement - against the costs of time and risk of exposure (Cooke et al., 2017). Understanding how to better harness the power of social media will be a growth area for applied disciplines like EC, and for evaluation of research impact in the modern era of science communication.

Comment [GMD31]: You need to expand on this a little and explain the issue.

Conclusions

Our correlative analysis shows a strong association between science communication (measured by the Altmetric Score) and citation rates. Most online science communication happens within weeks of publication while traditional citations generally begin accumulating months and years later. Pairing the chronology of metric accumulation and an assumption that not all researchers are able to stay up to date with all publications, we believe it is reasonable to suggest that science communication and increasing the profile of one's work may have the ability to increase citation rates. Of course, to verify this one would need to manipulate or collect additional data to ~~what~~ that we had here. We encourage EC researchers to engage in science communication due to potential benefits such as increased citation rates, networking and public engagement.

Comment [GMD32]: Presumably an implication of your work though is that the more people do science communication by twitter the lower the rate of return would be? To play Devil's advocate perhaps your advice should be that we only ruthlessly promote our papers when we feel they're genuine game-changers!

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Figures and Tables

Figure 1. A: Histogram of Altmetric Scores for 10,048 ecology and conservation research papers published between 2005-2010. Altmetric Scores were truncated at 300, however, the maximum score for this period was 1,219. 28 articles had Altmetric Scores exceeding 300.
B: Average Altmetric Score for ecology and conservation between 2005-2015. 95% confidence interval shown in grey. C: Composition of media sources in Altmetric Scores between 2005-2015. Starting in 2010, Altmetric Scores were increasingly composed of tweets from Twitter. By 2015, >70% of the total Altmetric Score was composed of Tweets.

Figure 2. TOP: Relative influence of predictive variables, shown for a) articles published from 2005-2009, and b) articles published from 2010-2015. Relative influence is measured by relative # of times variables included in trees weighted by the square root of improvement to the model, averaged over all trees (Elith, Leathwick & Hastie, 2008). BOTTOM: Relative influence of individual media sources on citation rates for the entire period of interest (2005-2015). Policy documents omitted.

Figure 3. Response plots showing direction, shape, and magnitude of effects on citation rates. A= 2005-2009, B=2010-2015. We varied each variable from max to min, while fixing the remaining variables at their mean. We quantified the estimated gain in citations per unit increase in Altmetric Scores during the 2010-2015 period. Assuming 5 years since publication, we estimate the effect of increasing Altmetric on citation rates for three Altmetric ranges: low (0-50); moderate (50-540); high (540). For low Altmetric ranges, every per-unit increase in Altmetric produces 0.44 citations, requiring about 23 Altmetric points for each 10-unit increase in citations. For moderate Altmetric ranges, every per-unit increase in Altmetric Score produces 0.07 citations, such that it takes about 143 Altmetric points for each 10-unit increase in citations. For high Altmetric ranges, there was no change in citation rates with increasing Altmetric points.