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

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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. Scientists are increasing their online media communication, via social media and 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 the Altmetric Attention Score–an indicator of the amount and reach of the attention an article has received–along with other forms of bibliometric performance (year published, journal impact factor, and article type). We found that Attention Score was positively correlated with citation rates. However, in recent years, we detected increasing media exposure did not relate to the equivalent citations as in earlier years; signalling a diminishing return on investment. Citations correlated with journal impact factors up to ~13, 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.

1 **Title:**

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3 **Conservation**

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43 **Abstract**
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45 research products are often used to shape policy and decision making. Scientists are increasing
46 their online media communication, via social media and news. Such media engagement has been
47 thought to influence or predict traditional metrics of scholarship, such as citation rates. Here, we
48 measure the association between citation rates and the Altmetric Attention Score–an indicator of
49 the amount and reach of the attention an article has received–along with other forms of
50 bibliometric performance (year published, journal impact factor, and article type). We found that
51 Attention Score was positively correlated with citation rates. However, in recent years, we
52 detected increasing media exposure did not relate to the equivalent citations as in earlier years;
53 signalling a diminishing return on investment. Citations correlated with journal impact factors up
54 to ~13, but then plateaued, demonstrating that maximizing citations does not require publishing
55 in the highest-impact journals. We conclude that ecology and conservation researchers can
56 increase exposure of their research through social media engagement and, simultaneously,
57 enhance their performance under traditional measures of scholarly activity.
58

59 **Introduction**

60   Communicating science to policymakers, other scientists, and the public is an

61 increasingly important task in an era of "alternative facts" (Galetti & Costa-Pereira, 2017).

62 Scientists are finding new means to communicate science using a wide array of online media

63 (e.g., Twitter, Facebook, blogs; Piwowar 2013; Bornmann 2014; Donner 2017). The shifting

64 nature of modern science communication is particularly relevant to the fields of ecology and

65 conservation (E&C), where science is often used to identify and mitigate pressing environmental

66 problems (Hoffmann et al., 2010), to inform the public about such issues and how they can get

67 involved. However, an outstanding question from the efforts to diversify the channels of science

68 communication is the extent to which traditional and social media exposure are linked: How can

69 scientists most effectively invest in social media to promote their research?

70   Publications that receive more attention on social (eg. Twitter, Facebook and blogs) and

71 traditional (eg. News and radio) media reach a more diverse, non-scientist group than a

72 publication with a lower media profile. For example, on Twitter–a platform scientists often use

73 to discuss science amongst one another–up to 40% of followers from E&C scientists may be

74   non-scientists, media, and environmental groups (Darling et al., 2013). Recent work by (King,

75   Schneer & White, 2017) demonstrated policy decisions could be shaped through the media

76   increasing public discussion of policy by ~62.7% on social media, compared to baseline levels.

77   For example, the recent ban on grizzly bear (*Ursus arctos*) hunting in British Columbia, Canada

78   (http://bit.ly/2GCrk1W) highlights a change in policy due to social momentum (Artelle et al.,

79   2014; Darimont, 2017) generated largely on social-media platforms. Given the importance of

80   social media in communication, there has been a proliferation of research on the value of various

81   alternative metrics of science communication (hereafter "altmetrics") for measuring broader

82   impacts and predicting important bibliometrics such as citation count (e.g., Thelwall et al., 2013;

83   Bornmann, 2014; Haustein, 2016; Finch, O 'hanlon & Dudley, 2017).

84   A key feature of altmetrics is that they accumulate rapidly after article publication and

85   often have effectively stopped accumulating, or accumulate very little, before the paper's first

86   citation (Eysenbach, 2011). This sequence occurs because the content of publications becomes

87   public knowledge at or right after the publication date (especially for journals with a media

88   embargo policy, like *Science* and *Nature*), whereas publications citing this work may not be

89   available for years after the original work was published. As such, media exposure – including

90   social media- may either influence or forecast the citation rates of a paper. For example,

91   Eysenbach (2011) showed that tweets can predict highly cited articles within 3 days of

92   publication, and Finch et al. (2017) showed that tweets about ornithology papers predict citation

93   rates in a subset of avian-ecology journals. Consequently, altmetrics present a convenient way to

94   rapidly quantify communication of E&C research and may allow for identification of high-

95   impact papers considerably faster than traditional citation rates, which are slow to accumulate.

96   While there are many types of new media covered under the umbrella of "altmetrics,", it

97   is currently unknown which altmetric types best reflect effective scientific outreach to both the

98   public and scientists, which may vary by discipline (Haustein, 2016). Citation count and other

99   related bibliometrics determine professional success at many institutions (Wade, 1975), but the

100   correlation between altmetrics and bibliometrics varies by altmetric type (Thelwall et al., 2013;

101   de Winter, 2014; Haustein, 2016; Peoples et al., 2016), making it difficult for institutions and

102   researchers to prioritize altmetrics generally and for E&C researchers specifically. Further, some

103   altmetrics are vulnerable to manipulation and commercialization, raising concerns regarding

104   their use for evaluation of research impact (Bornmann, 2014; Haustein, 2016). Determining a

105   single best altmetric predictor of bibliometric performance will likely remain elusive as the

106   online media landscape evolves and new altmetric types emerge. One potential solution to these

107   related problems is to use a broad suite of altmetrics to calculate a combined Altmetric Attention

108   Score (hereafter Attention Score, www.altmetric.com; one of most popular 'altmetrics', and on

109   which we focus here). However, the effectiveness of the Attention Score for predicting research

110   impact has not been evaluated across E&C, or over time (but see Finch, O 'hanlon & Dudley,

111   (2017) for a focused look at ornithology), leaving a knowledge gap with implications for the

112   evaluation and dissemination of research.

113   Researchers are under increasing pressure to publish papers that not only have a high

114   level of impact within the scientific community, but also have broader impacts across the public

115   and policy-making spheres (Donner, 2017). This is certainly true in the fields of ecology and

116   conservation biology, in part because of the intensifying biodiversity crisis (Johnson et al.,

117   2017). As a result, researchers must make difficult decisions regarding allocation of their time

118   and effort in terms of which journals to target and what outreach efforts to undertake, the results

119   of which not only impact the individual researchers' careers, but also society at large if their

120   research succeeds or fails in reaching intended audiences or changing policy and management of

121   natural resources. Here, we examine correlations between traditional bibliometrics (citation rate,

122   journal impact factor), time since publication, and altmetric exposure. We focus on E&C

123   publications, where we anticipate that the growing interest by E&C researchers in social media

124   may be changing the relationship between citation rates and altmetrics.

125

126   **Materials & Methods**

127   *Data:* We gathered citation, Attention Score, and other descriptive data (year published, journal

128   impact factor, and article type) on ecology and conservation (E&C) articles published between

129   2005-2015. This period reflects an era of sufficient social media engagement by researchers to

130   investigate the relationship between Attention Score and citation rates, while allowing sufficient

131   time for more recent articles to acquire citations. Attention Score data was obtained from

132   Altmetric (https://www.altmetric.com/) under a free academic license. Altmetric makes its' data

133   available to academics upon request, but the database is not publicly accessible on their website.

134   The Altmetric data consists of the Attention Score for each paper as well as the counts of

135   individual media sources that comprise the score. Attention Scores are a composite, weighted

136   index of many media sources (https://help.altmetric.com/support/solutions/articles/6000060969-

137   how-is-the-altmetric-score-calculated-). We focused on the most popular and top-weighted

138   media sources: news, blogs, Facebook, Twitter, and Wikipedia.

139   Citation data were obtained from Scopus (https://www.scopus.com/) using the search

140   terms "Ecolog*" AND "Conservat*" between 2005-2015. Our focus was on research addressing

141   the conservation of nature and ecosystems. To disambiguate this research from work in physics,

142 art, and other fields using the term "conservation", we used the Boolean operator AND

143 "ecolog*". We recognize that this approach excludes some studies relevant to the conservation of

144 nature and ecosystems , but feel that at n=39442 papers, our search effectively samples the

145 literature of our focal subject. We obtained journal impact factor using Reuter's 2014 impact

146 factor ratings. We merged Scopus and Altmetric data using a unique identifier of the first 30

147 character of the article and journal titles and the year. Finally, to ensure our citation metrics were

148 comparable between articles, we removed any methods-based articles, which are often cited

149 more highly than other articles, and were not the focus of our investigation. We removed these

150 articles using the keywords "method*" or "technique*" to cull articles with these words in their

151 article title or journal title. To control for other factors influencing citation rates of articles, we

152 included in all models the number of years since publication, journal impact factor, and article

153 type (review, research article, or letter).

154 *Modeling Approach:* We used boosted logistic regression trees (Elith, Leathwick &

155 Hastie, 2008) to investigate the relationship between Attention Score and citation rates. Boosted

156 regression trees (BRT) are an advanced form of a generalised linear model (GLM; Elith *et al.*

157 2008). BRTs were well suited to our application because they can handle the complex, non-linear

158 relationships we expected to find with these data, provide greater predictive performance and are

159 less plagued by multi-collinearity than GLM's (Elith, Leathwick & Hastie, 2008). Unlike

160 GLM's, BRTs do not test null hypotheses but instead effectively quantify and illustrate complex,

161 non-linear relationships, such as those expected here. We fit BRTs using the 'gbm' package

162 (Ridgeway, 2015) in Program R (R Core Team, 2017). We analyzed the correlation between

163 Attention Score and citation rates in three periods: 1) an early time period of social media uptake

164   (2005-2009); 2) latter period of social media uptake (2010-2015), and 3) and the combined

165   period of our dataset (2005-2015).

166   A BRT is fitted to data using three main parameters. 1) learning rate: the contribution of

167   each tree to the model. Smaller learning rates result in relatively more trees required to fit the

168   model, with each tree contributing a relatively small amount to the predictions providing a better

169   fit of the model to the data. In general, a lower learning rate is preferred, such that at least 1000

170   trees are generated (Elith, Leathwick & Hastie, 2008). 2) tree complexity: the number of nodes

171   or splits allowed in each tree. Trees with more nodes are more complex. 3) bag fraction, which is

172   the percentage of data used to train (those data used to build the model) and test (data used to test

173   predictions that were not involved in model creation) the model for each iteration (new tree).

174   We tested two commonly used learning rates (4 and 8) and tree complexities (0.001,0.01)

175   and selected as our top model the model that minimized predictive deviance (Elith, Leathwick &

176   Hastie, 2008). We calculated the relative influence of each predictor on resulting citation rates

177   and produced response curves. Relative influence is measured by relative number of times

178   variables included in trees weighted by the square root of improvement to the model, averaged

179   over all trees and the influence of each variable scaled so the sum adds to 100 (Elith, Leathwick

180   & Hastie, 2008).

181   *Model Validation:* We partitioned our data into training (bag fraction= 70%, those data

182   used to build the model) and testing data (30%, data used to test predictions that were not

183   involved in model creation) for each iteration (new tree). We used the testing data and model

184   predictions to calculate predictive accuracy using the coefficient of determination (R^2), which we

185   used to assess the generality of the model to predict responses from data not used to generate the

186   model. Overfitting is reduced in the BRT by optimizing the learning rate and number of trees as

187   described above, but also by using randomness in partitioning of data. The degree of overfitting

188   can be assessed using the model predictive capacity on testing data and BRTs are generally

189   robust to overfitting (Elith, Leathwick & Hastie, 2008).

190

191   **Results**

192   We gathered–for the 2005-2015 period–39, 442 records resulting from the Ecolog* AND

193   Conservation* search from Scopus, and 5,249,064 Altmetric records across all disciplines. The

194   Reuter's 2014 impact factor ratings consisted of 11,718 journal ratings. Merging the Scopus,

195   Altmetric, and impact factor datasets, we produced a final dataset consisting of 8,322 EC articles

196   in 687 different journals, each of which met the search criteria, had an Attention Score available,

197   and was in a journal with an impact factor available.. Most articles published during this time

198   received relatively low Attention Scores (<100, Figure 1), but a few scores exceeded 900.

199   Attention Scores per article have been increasing over the last 10 years and the composition of

200   media sources making up the Attention Score has been shifting (Figure 1), primarily towards

201   increased Twitter activity.

202   Not surprisingly, time alone (years since published) increased citation rates, and

203   letters/notes received fewer citations than traditional articles whereas review papers received

204   more citations than both other article types. Models for both time periods produced good

205   predictive accuracy ($R^2 = 0.66$ for 2005-2009 and $R^2 = 0.56$ for 2010-2015). BRT models for

206   both the early (2005-2009) and late periods (2010-2015) reached minimum deviance at 8 trees

207   and a learning rate of 0.01 and 0.001, respectively. The third BRT model assessed the

208   contribution of each of the media sources that comprise the composite Attention Scoreon

209   resulting citation rates. Model predictive accuracy was high ($R^2 = 0.59$). Minimum deviance was

210   reached at 4 trees and a learning rate of 0.001.

211   Within E&C, we found discipline-specific differences in research impact. Articles with

212   "conservat*" in the article or journal title received slightly larger Attention Scores (9.4 ± 0.7 [$\bar{x}$

213   ± SEM]). compared to "ecology*" in the article or journal title(7.6 ± 0.4). However, articles with

214   "conservat*" in the article or journal title received fewer citations (31.4 ± 1.3) than those with

215   "ecology*" in the article or journal title (36.0 ± 1.5).

216   Citation rates were positively correlated with Attention Scores during the 2005-2009

217   period, and to a lesser extent during the 2010-2015 period. Journal impact factor and time since

218   published were more important during the later period (Figure 2). Higher Attention Scores

219   generally correlated with increased citations, but an asymptote was present in both time periods

220   (Figure 3). The association between Attention Scores and citation rates has attenuated over time

221   (Figure 3), and maximal gains in citation rates were attained at Attention Scores of 68 during the

222   early period, and 530 in the late period, after which the relationship plateaued in both time

223   periods. In both periods citation rates were maximized in journals having impact factors between

224   11-14. Finally, across the entire 2005-2015 time period, Attention Scores derived from coverage

225   on Blogs, Wikipedia and Tweets had the largest influence on citation rates, while Facebook posts

226   and news articles had the least influence (Figure 2).

227

228   **Discussion**

229   The fields of ecology and conservation (E&C) have traditionally been linked to applied research,

230   policy, and public engagement (Lubchenco, 1998). As such, E&C researchers increasingly rely

231   on social media platforms to promote science to their peers, decision makers, and to the public

232   (Bickford et al., 2012; Darling et al., 2013; Priem, 2013; Parsons et al., 2014). Our analyses show

233   that: 1) most published E&C research garners very little attention on social media (e.g., over

234   80% of articles tracked by Altmertics were tweeted < 5 times); 2) social media exposure is

235   positively correlated with citation rates for E&C papers; 3) both journal impact factor and social

236   media exposure on citation show diminishing returns in recent years. Below, we discuss the

237   implications of these findings and highlight how E&C researchers can use social media to

238   measure research impact.

239   The distribution of Altmteric Scores was highly right-skewed, indicating that a few

240   papers can have very wide-reaching attention but most do not. However, average Attention

241   Scores have increased rapidly since 2011 – a trend explained, in part, by broader engagement of

242   the public with all forms of online content. In addition to this broader societal trend, many

243   researchers are heeding calls to engage in outreach through social media (Milkman & Berger,

244   2014; Parsons et al., 2014; Cooke et al., 2017). Postdoctoral fellowship programs in E&C, such

245   as the Liber Ero Fellowship (Canada: www.liberero.ca), the Smith Fellows (USA:

246   http://conbio.org/mini-sites/smith-fellows), Wilburforce Fellows (USA/Canada:

247   http://www.wilburforce.org/grants/fellowship/), and others provide specialized training in social

248   media engagement for E&C researchers. In the future, graduate and undergraduate E&C students

249   may routinely receive training in social media as part of their studies.

250   The association between Attention Scores and citation rates varies by type of media

251   within the Attention Score: tweets contributed most to Attention Score for E&C papers, but

252   blogs had the greatest influence on citation rates. This may signal that researchers turn to blogs

253   as a form of information curation, or that other forms of media (e.g., facebook, twitter, radio,

254   news) create the initial article "hype" which then signals bloggers to cover the article. We cannot

255   discern the causes of these patterns from our analyses, but indeed we observed the latter pattern

256   in a recently published article (Lamb et al., 2018) where twitter and news "hype" rapidly

257   accumulated after publication, followed by blogs once the Attention Score had surpassed 200.

258   Finally, the degree and type of social media attention an article receives is also dictated by the

259   articles content, with articles featuring charismatic animals, climate change, or sharing positive

260   news draw more attention (Papworth et al., 2015), but we were unable to include these factors in

261   our analysis.

262   Twitter is a rapidly growing science-communication tool in E&C and likely contributes

263   to the increasing Attention Scores received by articles (Fig 1B & C). Previous work by Peoples

264   *et al.* (2016) found a weak and highly variable relationship between tweet volume and citation

265   rates, whereas we find a stronger, more positive relationship (Figure S1), likely due to our

266   application of BRT models to address interactive and non-linear effects (Elith, Leathwick &

267   Hastie, 2008). Finally, we detected asymptotic relationships between citation rate and each of the

268   media sources comprising the Attention Score. Similar to our study, Finch et al (2017) also

269   found asymptotic relationships between citation rates, impact factor and Almetric Scores for

270   research focused on the E&C subdiscipline of ornithology. Thus, investigators will likely realize

271   the greatest citation return on investment by diversifying their media outreach channels among

272   blogs, traditional media, twitter, and other outlets for E&C-related subdisciplines.

273   In spite of the growth in social media activity by researchers, there are asymptotic

274   benefits for traditional measures of scholarly impact (i.e., citation rates). If we assume that social

275   media exposure predicts or contributes towards citation rates (see Eysenbach, 2011; Finch, O

276   'hanlon & Dudley, 2017), then our results suggest a diminishing return on investment: it now

277   takes four to six times the Attention Score to achieve an equivalent citation rate as it did 5-10

278   years ago. This weakening return on investment is consistent with the idea that media

279   consumption is finite (Rodriguez, Gummadi & Schölkopf, 2014), and that increasing the number

280   of communicators in a social media network may not increase the amount of media consumed

281   (Kaplan & Haenlein, 2010; Milkman & Berger, 2014; Ferrara & Yang, 2015). This asymptotic

282   relationship between social media and citation rates has important implications for how

283   researchers and institutions should devise media outreach plans, and if/how social media impact

284   can be used to measure research impact. Next steps will be for science communication

285   professionals to work with their research and outreach personnel to optimize strategies.

286   While our results suggest that an increasing amount of social media attention is needed to

287   generate maximal gains in E&C article citation rates, our results also show that minor increases

288   in social media attention are associated with a steep rise in citation rates for articles with few

289   citations – social media can transform the highly obscure to the notable. This transformation is

290   important, because research impact at many institutions is evaluated both by publication in high

291   impact journals (i.e., impact factors > 10) and citation rates – which are positively correlated

292   (Figure 3, Wade, 1975; Judge et al., 2007). Since space in high impact journals is highly

293   competitive, social media can help level the playing field between the few papers accepted into

294   such high-profile outlets and the many more that are rejected. Indeed, we were surprised to

295   discover that the influence of social media exposure on E&C article citation rates was actually

296   far greater than journal impact factor between 2005-2009, and comparable more recently (see

297   Figure 2). We also found that journal impact factor also has diminishing returns on E&C article

298   citation rates, peaking around 13 before levelling off. Combined, these results suggest that,

299   generally, evaluation of research impact should consider discipline-specific asymptotes in media

300   attention and impact factor (i.e., "twimpact factor"; *sensu* Eysenbach G. 2011). Finally, our

301   results also suggest that conservationists concerned about reaching a broad audience can do so as

302   effectively with high impact and moderate-impact journals, as has been suggested elsewhere

303   (Peoples et al., 2016).

304   For many E&C researchers, the benefits of social media outreach extend well beyond

305   boosting citation rates. Social media is also a tool to engage with peers, the public, and policy

306   makers from around the world (Kaplan & Haenlein, 2010; Parsons et al., 2014; Bombaci et al.,

307   2016; Cooke et al., 2017). Quantifying causal links between research innovation, Attention

308   Scores, citations rates, and policy changes is challenging (e.g., Danaher 2017); yet such linkages

309   are likely why many in E&C fields use social media (Bombaci et al., 2016; Peoples et al., 2016).

310   Our analysis provides guidance on the potential benefits of social media engagement for research

311   impact. However, we have not identified a specific mechanism linking citations to Attention

312   Scores. A number of factors constrain the effectiveness of science communication in general,

313   including via social media (e.g., the appearance and race of the scientist; Milkman and Berger

314   2014; Gheorghiu *et al.* 2017). Moreover, linkages between social media, policy/management

315   change, and public engagement were beyond the scope of our work, but are important avenues of

316   continued inquiry in contemporary scientific communication (King, Schneer & White, 2017).

317   Researchers need to weigh the benefits of social media – potentially enhanced citation

318   rates and public engagement - against the costs of time and risk of exposure (Cooke et al., 2017).

319   Understanding how to better harness the power of social media will be a growth area for applied

320   disciplines like E&C, and for evaluation of research impact in the modern era of science

321   communication.

322

323   **Conclusions**

324  Our correlative analysis shows a strong association between science communication

325 (measured by the Altmetric Attention Score) and citation rates. Most online science

326 communication happens within weeks of publication while traditional citations generally begin

327 accumulating months and years later. Pairing the chronology of metric accumulation and an

328 assumption that not all researchers are able to stay up to date with all publications, we believe it

329 is reasonable to suggest that science communication and increasing the profile of one's work

330 may increase citation rates. Of course, to verify this an experimental approach or additional data

331 to what we had here would be required. We encourage E&C researchers to engage in science

332 communication due to potential benefits such as increased citation rates, networking and public

333 engagement.

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498   **Figures and Tables**

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501   **Figure 1**. A: Histogram of Attention Scores for 8,322 ecology and conservation research papers
502   published between 2005-2010. Attention Scores were truncated at 300, however, the maximum
503   score for this period was 1,219. 28 articles had Attention Scores exceeding 300.
504   B: Average Attention Score for ecology and conservation between 2005-2015. 95% confidence
505   interval shown in grey. C: Composition of media sources in Attention Scores between 2005-
506   2015. Starting in 2010, Attention Scores were increasingly composed of tweets from Twitter. By
507   2015, 70% of the total Attention Score was composed of Tweets.

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512   **Figure 2.** A: Relative influence of predictive variables, shown for articles published from 2005-
513   2009, and between 2010-2015. Relative influence is measured by relative # of times variables
514   included in trees weighted by the square root of improvement to the model, averaged over all
515   trees (Elith, Leathwick & Hastie, 2008). B: Relative influence of individual media sources on
516   citation rates for the entire period of interest (2005-2015). Policy documents omitted.

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521   **Figure 3.** Response plots showing direction, shape, and magnitude of effects on citation rates.
522   A= 2005-2009, B=2010-2015. We varied each variable from max to min, while fixing the
523   remaining variables at their mean. We quantified the estimated gain in citations per unit increase
524   in Attention Scores during the 2010-2015 period. Assuming 5 years since publication, we
525   estimate the effect of increasing Attention Score on citation rates for three ranges: low (0-50);
526   moderate (50-540); high (540). For low Attention Score ranges, every per-unit increase in
527   Attention produces 0.47 citations, requiring about 21 Attention points for each 10-unit increase
528   in citations. For moderate Attention Score ranges, every per-unit increase in Attention Score
529   produces 0.07 citations, such that it takes about 143 Attention points for each 10-unit increase in
530   citations. For high Attention Score ranges, there was no change in citation rates with increasing
531   Attention Score.

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Figure 1

Summary stats

A: Histogram of Attention Scores for 8,322 ecology and conservation research papers published between 2005-2010. Attention Scores were truncated at 300, however, the maximum score for this period was 1,219. 28 articles had Attention Scores exceeding 300. B: Average Attention Score for ecology and conservation between 2005-2015. 95% confidence interval shown in grey. C: Composition of media sources in Attention Scores between 2005-2015. Starting in 2010, Attention Scores were increasingly composed of tweets from Twitter. By 2015, 70% of the total Attention Score was composed of Tweets.
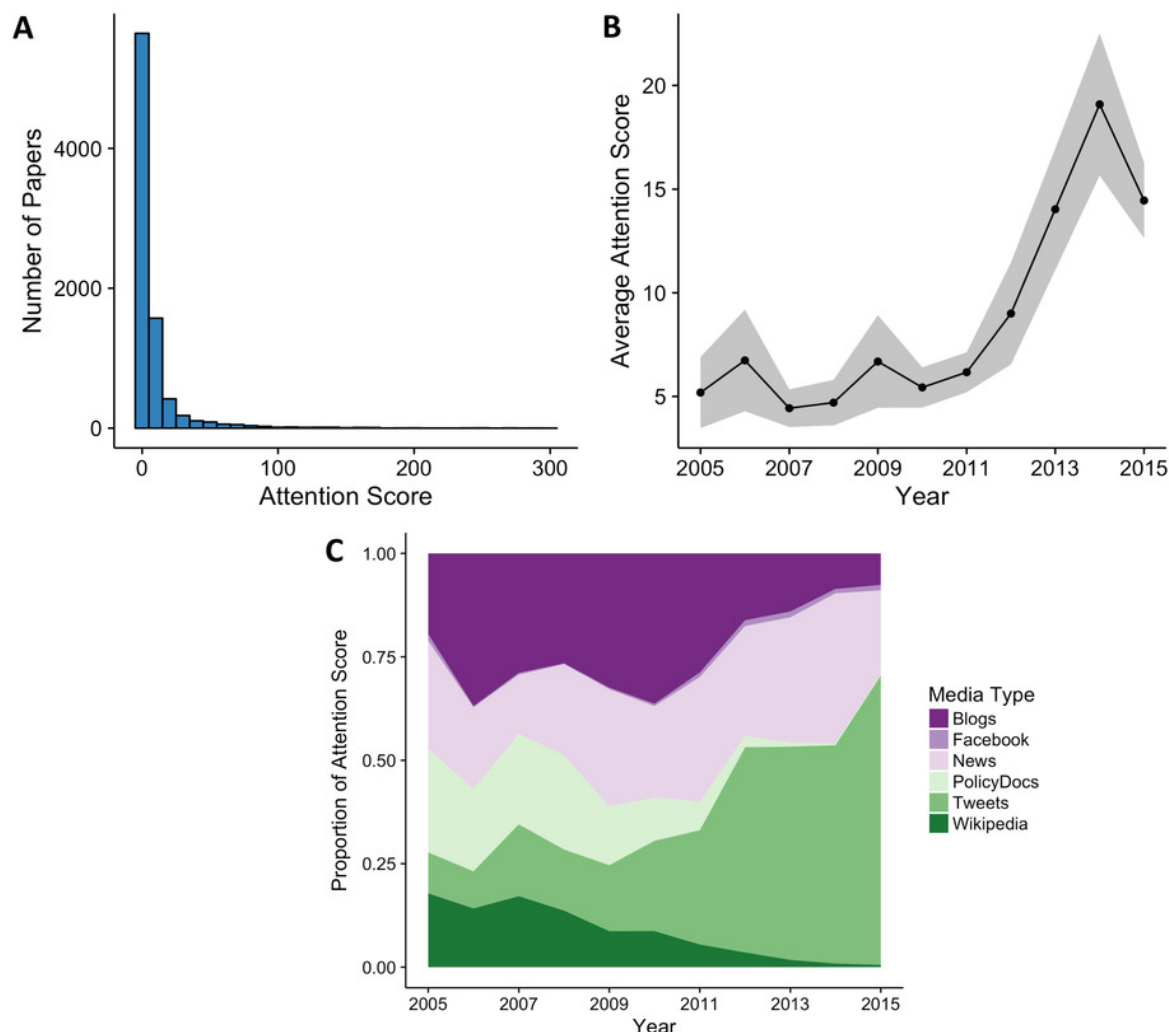
Figure 2

Relative influence

A: Relative influence of predictive variables, shown for articles published from 2005-2009, and between 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). B: Relative influence of individual media sources on citation rates for the entire period of interest (2005-2015). Policy documents omitted.
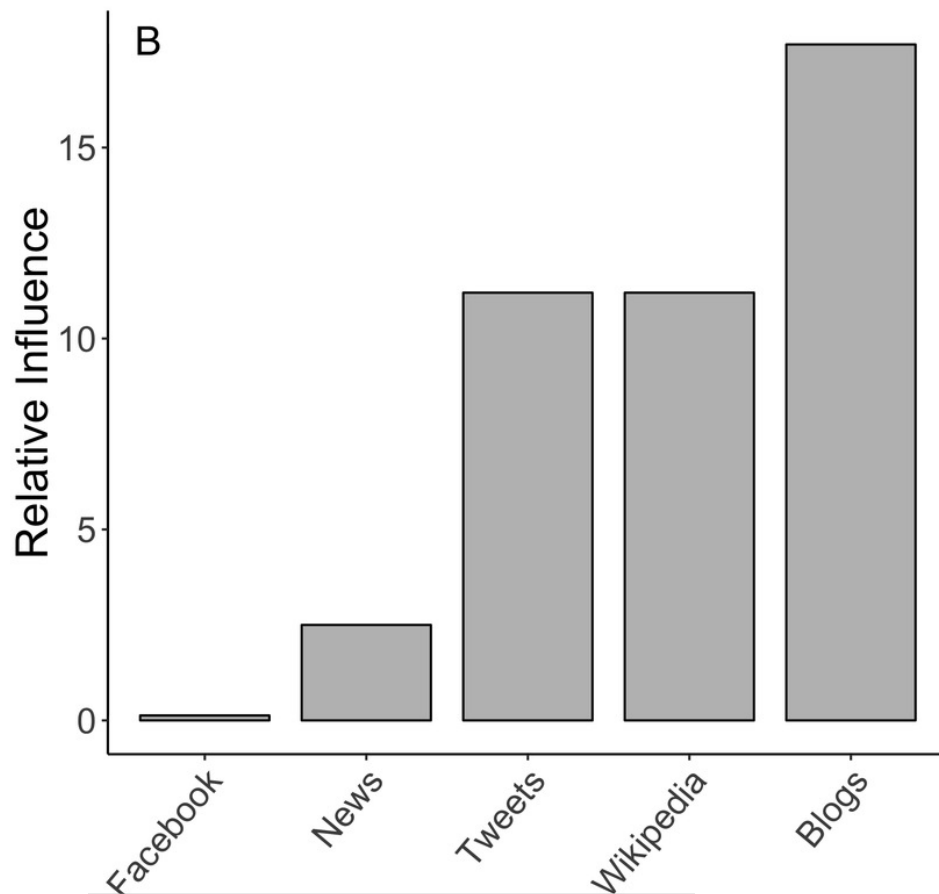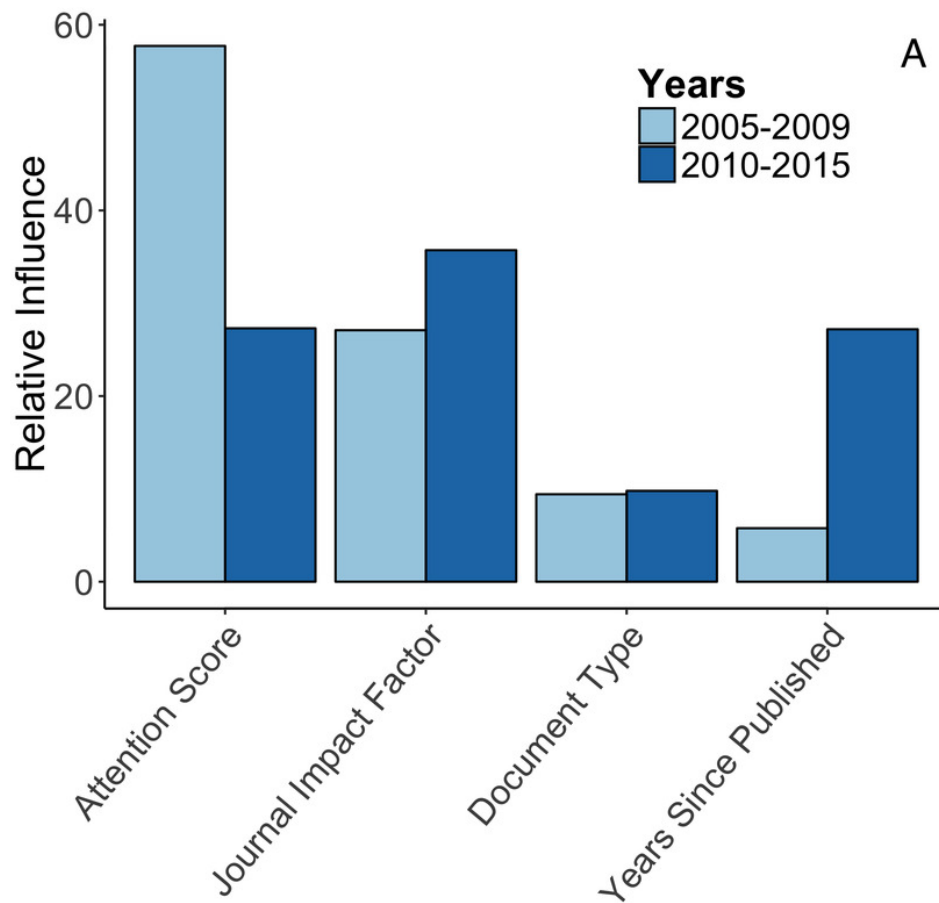
Figure 3

Response plots

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 Attention Scores during the 2010-2015 period. Assuming 5 years since publication, we estimate the effect of increasing Attention Score on citation rates for three ranges: low (0-50); moderate (50-540); high (540). For low Attention Score ranges, every per-unit increase in Attention produces 0.47 citations, requiring about 21 Attention points for each 10-unit increase in citations . For moderate Attention Score ranges, every per-unit increase in Attention Score produces 0.07 citations, such that it takes about 143 Attention points for each 10-unit increase in citations. For high Attention Score ranges, there was no change in citation rates with increasing Attention Score.