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Scientists on Twitter: Preaching to the choir or singing from the rooftops?

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Abstract

There have been strong calls for scientists to share their discoveries with society. Some scientists have heeded these calls through social media platforms such as Twitter. Here, we ask whether Twitter allows scientists to promote their findings primarily to other scientists ("inreach"), or whether it can help them reach broader, non-scientific audiences ("outreach"). We analyzed the Twitter followers of more than 100 faculty members in ecology and evolutionary biology and found that their followers are, on average, predominantly (~55%) other scientists. However, beyond a threshold of ~1000 followers, the range of follower types became more diverse and included research and educational organizations, media, members of the public with no stated association with science, and a small number of decision-makers. This varied audience was, in turn, followed by more people, resulting in an exponential increase in the social media reach of tweeting academic scientists. Tweeting, therefore, has the potential to disseminate scientific information widely after initial efforts to gain followers. These results should encourage scientists to invest in building a social media presence for scientific outreach.

Key words: science communication, social networks, public understanding of science

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Introduction

Communication has always been an integral part of the scientific endeavour. In Victorian times, for example, prominent scientists such as Thomas H. Huxley and Louis Agassiz delivered public lectures that were printed, often verbatim, in newspapers and magazines (Weigold 2001), and Charles Darwin wrote his seminal book "On the origin of species" for a popular, non-specialist audience (Desmond and Moore 1991). In modern times, the pace of science communication has become immensely faster, information is conveyed in smaller units, and the modes of delivery are far more numerous. These three trends have culminated in the use of social media by scientists to share their research in accessible and relevant ways to potential audiences beyond their peers. The emphasis on accessibility and relevance aligns with calls for scientists to abandon jargon and to frame and share their science, especially in a "post-truth" world that can emphasize emotion over factual information (Nisbet and Mooney 2007; Bubela et al. 2009; Wilcox 2012; Lubchenco 2017).

The microblogging platform Twitter is emerging as a medium of choice for scientists (Collins et al. 2016), although it is still used by a minority (<40%) of academic faculty (Bart 2009; Noorden 2014). Twitter allows users to post short messages (originally up to 140 characters, increased to 280 characters since November 2017) that can be read by any other user. Users can elect to follow other users whose posts they are interested in, in which case they automatically see their followees' tweets; conversely, users can be followed by other users, in which case their tweets can be seen by their followers. No permission is needed to follow a user, and reciprocation of following is not mandatory. Tweets can be categorized (with hashtags), repeated (retweeted), and shared via other social media platforms, which can exponentially amplify their spread and can offer links to websites, blogs, or scientific papers (Shiffman 2012).

There are scientific advantages to using digital communication technologies such as Twitter. Scientific users describe it as a means to stay abreast of new scientific literature, grant opportunities, and science policy, to promote their own published papers and exchange ideas, and to participate in conferences they cannot attend in person as "virtual delegates" (Bonetta 2009; Bik and Goldstein 2013; Parsons et al. 2014; Bombaci et al. 2016). Twitter can play a role in most parts of the life cycle of a scientific publication, from making connections with potential collaborators, to collecting data or finding data sources, to dissemination of the finished product (Darling et al. 2013; Choo et al. 2015). There are also some quantifiable benefits for scientists using social media. For example, papers that are tweeted about more often also accumulate more citations (Eysenbach 2011; Thelwall et al. 2013; Peoples et al. 2016), and the volume of tweets in the first week following publication correlates with the likelihood of a paper becoming highly cited (Eysenbach 2011), although such relationships are not always present (e.g., Haustein et al. 2014).

In addition to any academic benefits, scientists might adopt social media, and Twitter in particular, because of the potential to increase the reach of scientific messages and direct engagement with non-scientific audiences (Choo et al. 2015). This potential comes from the fact that Twitter leverages the power of weak ties, defined as low-investment social interactions that are not based on personal relationships (Granovetter 1973). On Twitter, follower–followee relationships are weak: users generally do not personally know the people they follow or the people who follow them, as their interactions are based mainly on message content. Nevertheless, by retweeting and sharing messages, weak ties can act as bridges across social, geographic, or cultural groups and contribute to a wide and rapid spread of information (Zhao et al. 2010; Ugander et al. 2012). The extent to which the messages of tweeting scientists benefit from the power of weak ties is unknown. Does Twitter provide a platform that allows scientists to simply promote their findings to other scientists within the ivory tower (i.e., "inreach"), or are tweeting scientists truly exploiting social media to potentially reach new audiences ("outreach") (Bik et al. 2015; McClain and Neeley 2015; **Fig. 1**)?

Here, we ask whether scientists are, in fact, engaging broader audiences through social media by examining who follows tweeting scientists and how audience composition changes as followers accumulate over time. We define broader audiences as members of the public who are not scientists, which can include members of the media, decision-makers, and people in other non-scientific sectors and interest groups (Burns et al. 2003). If tweeting is mainly a form of inreach, we expect that the majority of followers of tweeting scientists to consist of other scientists, with perhaps some spillover across scientific disciplines (Ke et al. 2017), but with fewer non-scientific followers (**Fig. 1**). Such a limited reach by scientists could arise through an "echo chamber" effect, where individuals preferentially seek and consume information from like-minded individuals (i.e., homophily; Sears and Freedman 1967; McPherson et al. 2001; Sunstein 2001), or through a "bubble filter" effect, where algorithms that generate recommendations about whom to follow are based on a user's existing followees (Pariser 2011). In contrast, if tweeting functions as an outreach tool, we hypothesize that tweeting scientists might initially gain mainly other scientists in their own discipline as followers, but that over time the range of follower types might increase, from scientists in other disciplines to non-scientific members of the public, the media, and ultimately decision-makers (e.g., politicians; **Fig. 1**). Although reaching decision-makers might not be a sought-after goal for all tweeting scientists, it does represent a potentially powerful conduit for the practical application and communication of scientific discoveries.

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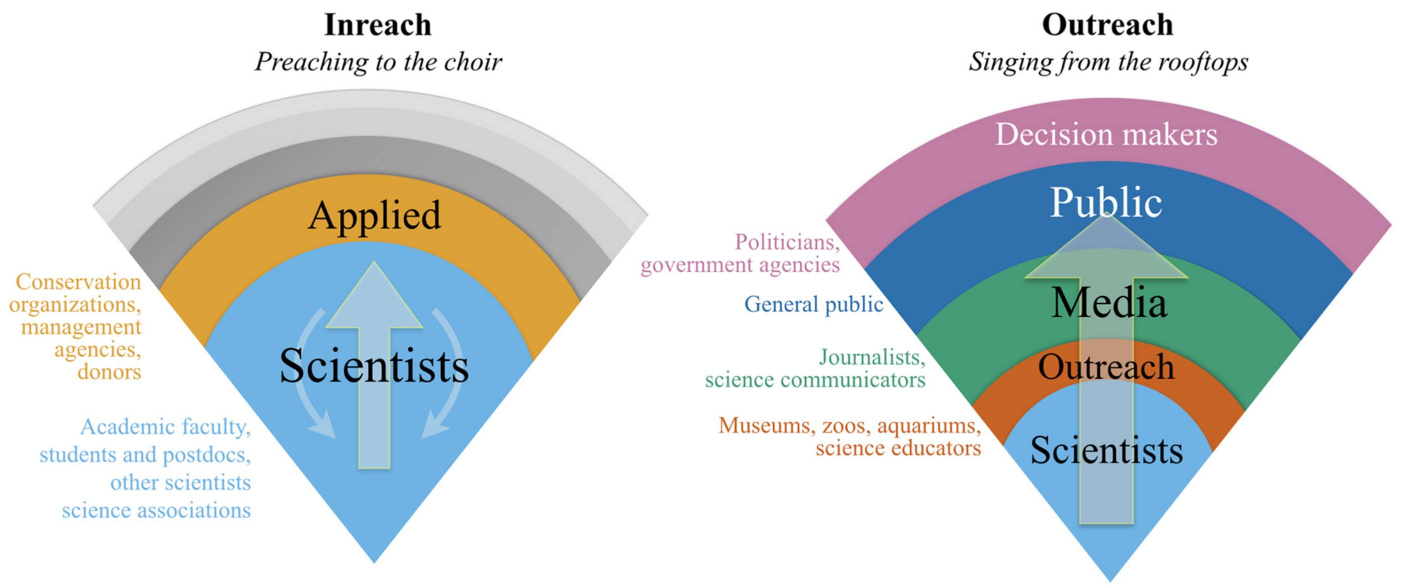

Fig. 1. Conceptual depiction of inreach and outreach for Twitter communication by academic faculty. Left: If Twitter functions as an inreach tool, tweeting scientists might primarily reach only other scientists and perhaps, over time (arrow), some applied conservation and management science organizations. Right: If Twitter functions as an outreach tool, tweeting scientists might first reach other scientists, but over time (arrow) they will eventually attract members of the media, members of the public who are not scientists, and decision-makers (not necessarily in that order) as followers.

Methods

We focused on scientists who tweet mostly about science and science-related issues (including political opinions that pertain to science) and little about personal affairs. We also limited our analysis to scientists who are university faculty members, i.e., individuals who produce science and for whom science communication in any form (e.g., tweeting, blogging, etc.) is an addition to their "day job". We used a space-for-time substitution by analyzing a cross-section of actively tweeting scientists and their followers, as monitoring the accumulation of followers over time for individual scientists would be difficult. Space-for-time substitutions are widely used in ecological studies when longitudinal studies are not possible, and are useful to establish general trends (Pickett 1989), which was our purpose here.

To our knowledge, there is currently no publicly available global list of scientists on Twitter. Compilations of "science superstars" on Twitter were not useful for our purpose, as we required tweeting scientists with a broad range of numbers of followers. We therefore turned to curated groups of Twitter accounts (i.e., Twitter "lists") to generate a sample of tweeting academics. We used the online list of ecology and evolutionary biology (EEMB) researchers compiled by J. Byrnes (twitter.com/jebyrnes/lists/eemb) because it was large enough, with ~450 members when accessed in 2015, to generate a suitable sample of tweeting academics. This Twitter list is curated by the list owner adding Twitter users who tweet about ecology, evolution, and marine biology (J. Byrnes, personal communication, 2018). However, there is the potential for bias in how users are added to Twitter lists, and the extent to which this, or any, Twitter list might be an unbiased representation of the group it purports to reflect remains unknown. For this analysis, the EEMB list included representation by professors of all ranks, as well as professors with a large range of times since joining Twitter and numbers of followers. In particular, it included many relatively new Twitter users, who were critical to allow us to build patterns of follower accumulation over time.

We identified 200 researchers on the EEMB list as faculty members (e.g., assistant, associate and full professors, or their equivalent) from the information contained in their Twitter profiles, which we confirmed using web searches. For each researcher, we recorded their Twitter handle (i.e., Twitter username), full name, current university, number of tweets and followers, the month and year they joined Twitter, and the date of their last tweet. To limit our analysis to active Twitter users, we removed 33 researchers who had not tweeted within the two weeks previous to data collection, and from the remaining list of 167 faculty members, we randomly selected 110 profiles for further analysis (Table S1).

For each faculty member, we obtained the online profiles of each Twitter follower and their Twitter "reach", defined as the number of followers of each follower, using a professional social media marketing company (nuvi.com). We assume that Twitter users with a larger reach can share tweets to a wider audience than users with a smaller reach (see Table S2). We then classified each follower, based on their 160-word Twitter profile, into one of 10 types, using a series of pre-defined keywords and regular expression search strings (Table S3) with the package "stringr" (Wickham 2017) in R (R Core Team 2017). The 10 types were as follows: science faculty, science graduate students and postdocs, science educators, professional science associations, other scientists, outreach organizations (e.g., museums, zoos, and aquariums), applied science organizations (e.g., conservation or management organizations), media, decision-makers, and "general public" (Table 1). Followers were classified as "general public" when their profile words did not trigger categorization into one of the other nine categories. It is, therefore, possible that some followers in the "general public" group might have

Table 1. Classification of Twitter followers of academic faculty.

Category	Description	Sample representative keywords
Science faculty	University professors, lecturers, teaching faculty	Lecturer, professor, chair
Science students	Undergraduates, graduate students, and postdocs	Graduate student, postdoctoral fellow, BS/MA/MSc/PhD/DPhil candidate
Science organizations	Universities, conferences, academic journals, professional organizations, and online science associations. Includes formal and informal groups of scientists such as synthesis or interdisciplinary centres	Scientific associations, conferences, journal, chapters, societies, synthesis centres, university institutes
Other scientists or science-associated groups	People or groups associated with some kind of science, but unspecified positions or types, and could not be classified into a more specific category.	*ologist or *ology, researchers, scientists (leftover after other faculty, student categories)
Outreach	Museums, zoos, aquariums, science teachers, and educators	Museum, "zoo", aquarium, "botanical garden*" (or museum, zoo, aquarium in username), teachers, educators
Applied	Conservation organizations and scientists, management agencies and scientists, restoration or recovery groups, foundations, philanthropy	Trust, organization, group, NGO, non-profit, society, fund, foundation, program officers
Media	Journalists, media and communications professionals and organizations	Writer, journalist, video*, blog*, publisher, corresponden*, com* or comm*, scicomm*, author, producer, news*, audio, radio, podcast, documentar*, film*, photograph*, director
Decision-makers	Government agencies, parliamentarians	MP, congress*, senator, mayor
General public	General public (or no information provided to be included in any of the above accounts)	Not included in any of the above categories, foreign language accounts removed and accounts with no information removed as "unknown" classification

Note: Regular expression searches used in the analysis of profiles are described in Table S1.

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actually belonged to a different category, but we have no means to estimate the magnitude of this error. Followers that we could not assign to one of these 10 types, mainly because profiles were not provided, were classified as "unknown". For analyses, we further condensed faculty, graduate students, postdocs, and other scientists into a "scientists" category. Classifications were not mutually exclusive, and it was possible for a follower to be classified into one or more types, but this was rare (<3% of followers; see Results). We considered as many non-English Twitter profiles as possible by including common translations of languages we were familiar with (i.e., French and Spanish: biologista, professeur, profesora, etc.) in our search strings; we removed profiles that were not classified by these search words and identified as other languages using the package "cldr", an R wrapper of the Compact Language Detection library (github.com/aykutfirat/cldr).

We estimated misclassification rates of our categorization algorithm by randomly selecting ~5% of the total follower profiles ($n = 3161$) and manually checking the assigned type against the profile description. We either confirmed the classification or reclassified to another type to derive a correction factor for each pair of types, estimated as the number of corrected classifications divided by the number of original classifications (**Table S4**). The misclassification rates were from 4% to 6% for scientists and applied scientists, from 14% to 16% for outreach, media and general public categories, and 40% for decision-makers (**Table S4**). The very small number of decision-makers among followers (0.16%) means that the larger error rate for this category will have a minimal effect on overall patterns. To examine the effect of the ~15% error rate in classifying outreach, media, and general public followers, we conducted subsequent analyses on both the original data and on data corrected using each category's specific error rate. Given that the two are qualitatively similar (**Figs. S1** and **S2**), we present only the former here.

We used one-way analyses of variance (ANOVAs) assuming unequal variances to compare the mean proportion of total followers and mean Twitter reach across follower types. To visualize how different types of followers accumulated with each faculty member's total number of Twitter followers, we fit locally weighted smoothing (LOESS) curves to the data. Given the non-linearity of the trends (see Results), we estimated the location of inflection points, i.e., at which number of total followers the slope of the regression changed significantly, for each follower type using the R package "strucchange" (Zeileis et al. 2002). This calculated the mean inflection value and confidence intervals from Bayes information criteria (BIC) based on the location of the optimal piecewise regression models and their breakpoints.

Results

The 110 faculty scientists included in our survey hailed from 85 institutions in 11 countries (**Table S5**). They occupied a range of positions (30% assistant professors, 24.5% associate professors, and 45.5% full professors) and had joined Twitter 4–74 months prior to our study. The selected scientists varied widely in numbers of followers, from 10 to 8776 (median $\pm$ 1 SD = 663 $\pm$ 1330.6 followers), in types of followers (**Table 1**), and in their total reach (0–56 030 924 users; median $\pm$ 1 SD = 1 653 792 $\pm$ 6 444 287 users; **Table S1**). There were 34 women and 76 men in our sample. We found no evidence that gender affected tweeting activity or the number of Twitter followers after controlling for the number of months active on Twitter (**Table S6**).

We identified 64 666 unique Twitter followers of the 110 faculty members. Of these, 1708 followers (or 2.6%) were identified as having a non-English profile that was not characterized to a follower type and were excluded from further analysis. Of the remaining 62 958 profiles, ~82% ($n = 51\ 625$) were classified to one of the 10 follower types (**Table 1**), and 1564 followers (3.0%) were classified to more than one type.

Different follower types contributed in variable proportions to the total following of tweeting scientists (one-way ANOVA assuming unequal variances, $F_{5,\ 266.8} = 922.1$, $p < 0.0001$; **Fig. 2a**).

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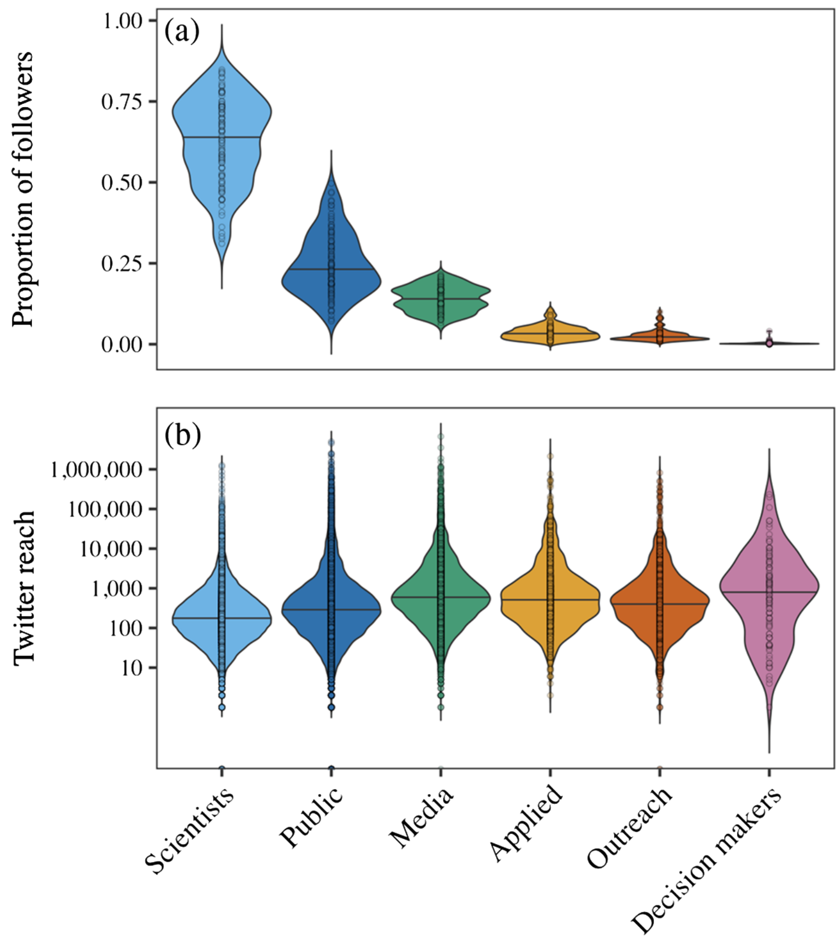

Fig. 2. Summary of followers of academic faculty by type and their Twitter reach. (a) The different types of followers of tweeting academic scientists, expressed as proportions of total followers ($n = 110$ faculty scientists) and (b) the average Twitter reach of each type, quantified as the number of follower's followers ($n = 51\ 625$ followers). Violin plots show the probability density, median, and interquartile range, and dots indicate the raw data.

As expected, scientists formed the majority of followers of tweeting scientists (Fig. 2a), and these followers had the lowest Twitter reach, on average (Fig. 2b; Table S7). However, on average, more than 40% of followers were not academic scientists but consisted of members of the public, media, applied organizations, outreach groups and, in very low numbers, decision-makers (Fig. 2a). These non-academic followers had variable Twitter reaches, and members of the public, media, and applied scientific organizations had the highest reaches (Tukey's post hoc tests; Fig. 2b; Table S7).

The patterns of accumulation of all follower types were non-linear (Fig. 3). Academic scientists initially gained followers that were mainly other scientists, and beyond ~450 total followers, the rate of accumulation of scientists increased significantly (Table 2; Fig. 3). Similar inflection points in follower accumulation trends also existed for non-scientist followers associated with the general public, the media, applied organizations, and outreach groups, but they occurred at larger numbers of total followers (~870–960 followers; Table 2). Decision-makers were the most uncommon follower type (Fig. 2a), and they started increasing in numbers when tweeting academic scientists had beyond ~2200 followers (Table 2; Fig. 3). On average, academic scientists with more than ~1000 followers had more non-scientist than scientist followers (Fig. 3).

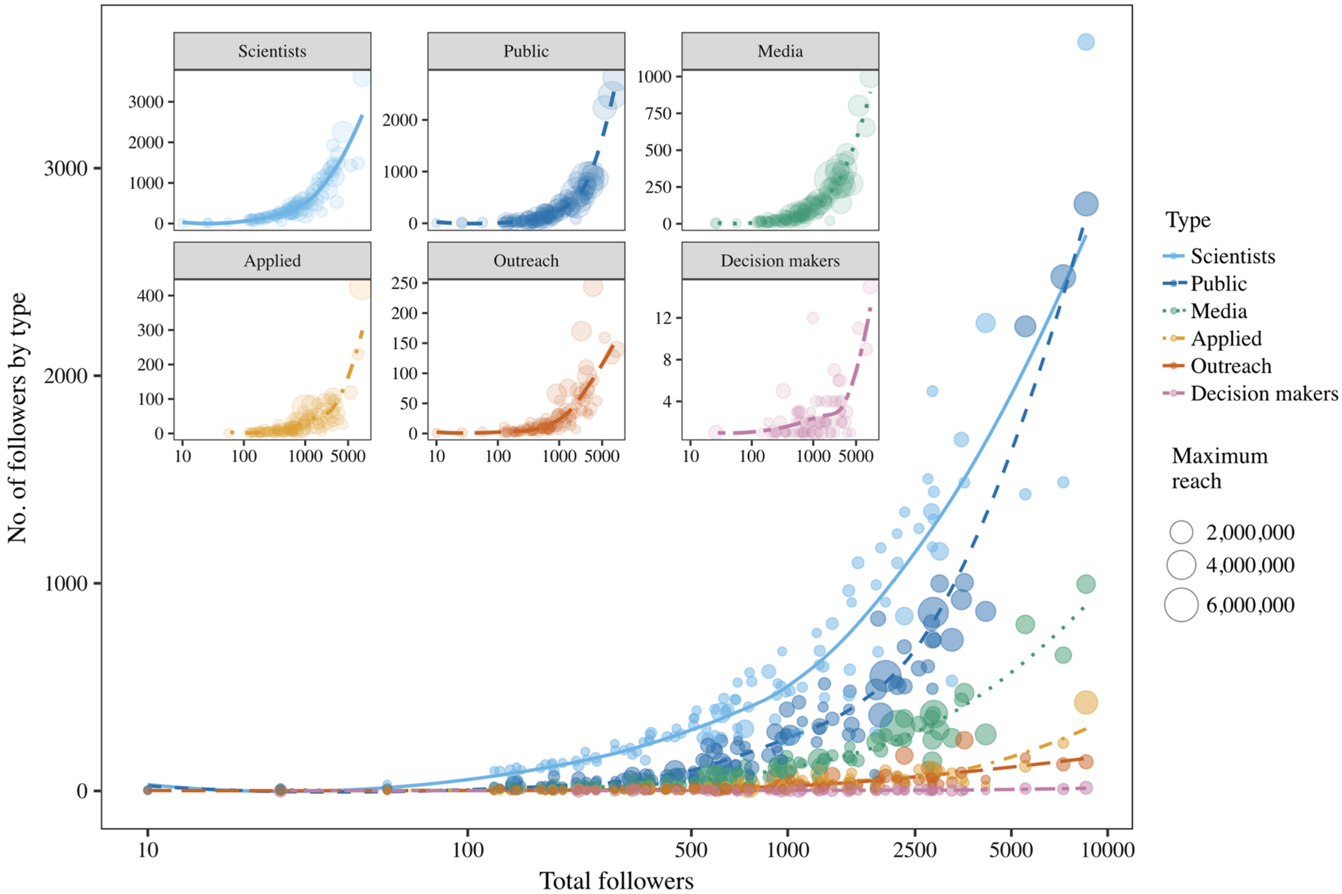

Fig. 3. Follower accumulation for academic faculty on Twitter. Relationship between the numbers of different types of followers and the total number of followers of tweeting academic scientists ($N = 110$ academic faculty). Locally weighted smoothed (LOESS) curves are shown for each follower type by colour and line type. For clarity, relationships for each follower type are also shown as insets, with varying y-axis scales. Note that x-axes are presented on a log scale. The size of the data points reflect the maximum Twitter reach of each type, defined as the maximum number of follower's followers.

Table 2. Inflection points in the non-linear trends of accumulation of different types of Twitter followers of 110 academic faculty members in ecology and evolution.

	No. of Twitter followers at inflection point		
		Confidence	
	Mean	2.5%	97.5%
Scientists	444	374	449
Outreach	872	697	913
Media	872	754	913
Applied	913	700	924
Public	961	913	987
Decision-makers	2197	872	2320

Note: The trends are shown in Fig. 3. The inflection points denote the total number of Twitter followers at which there was a significant change in the slope of the trends, and were identified from Bayes information criteria of piecewise linear models.

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Discussion

Academic scientists on Twitter start by preaching to the choir but can eventually sing from the rooftops. Twitter is partly an echo chamber for academic scientists where, on average, tweeting academic scientists have more followers who are scientists than who are non-scientists. This pattern is particularly marked for academic scientists who have fewer than 1000 followers: these academics are primarily followed by other scientists. However, beyond this threshold, the tweets of academic scientists can reach a more varied audience, composed primarily of non-scientists. Twitter then has the potential to function as an outreach tool.

The extent to which Twitter allows academic scientists to reach broad audiences has, until now, been unclear. Indeed, the intended audience of many tweeting scientists is often limited to fellow researchers (Priem and Costello 2010; Collins et al. 2016), and disciplinary silos exist in social media, with little mixing across subject-specific networks of scientists (Ke et al. 2017). However, the audiences of academics can be much more varied. Darling et al. (2013), for example, found that the followers of that paper's four co-authors included academic, government, and non-governmental organization (NGO) scientists, students, and journalists. A survey of live tweeting from an international conservation congress similarly found that tweets from that conference reached a non-attending audience that was far more diverse than the conference participants (Bombaci et al. 2016). Our results support these findings and show that audience heterogeneity rises over time, as the number of followers increases. Having more followers does not only mean a more diverse audience, but a vastly expanded reach. Academic scientists generally have limited reaches, i.e., they are followed by people (usually other academics) who have few followers. The broadening of diversity associated with a larger following also brings follower types that are more popular, drastically increasing the overall reach of scientific messages.

Of course, high numbers, diversity, and reach of followers offer no guarantee that messages will be read or understood. There is evidence that people selectively read what fits with their perception of the world (e.g., Sears and Freedman 1967; McPherson et al. 2001; Sunstein 2001; Himelboim et al. 2013). Thus, non-scientists who follow scientists on Twitter might already be positively inclined to consume scientific information. If this is true, then one could argue that Twitter therefore remains an echo chamber, but it is a much larger one than the usual readership of scientific publications. Moreover, it is difficult to gauge the level of understanding of scientific tweets. The brevity and fragmented nature of science tweets can lead to shallow processing and comprehension of the message (Jiang et al. 2016). One metric of the influence of tweets is the extent to which they are shared (i.e., retweeted). Twitter users retweet posts when they find them interesting (hence the posts were at least read, if not understood) and when they deem the source credible (Metaxas et al. 2015). To our knowledge, there are no data on how often tweets by scientists are reposted by different types of followers. Such information would provide further evidence for an outreach function of Twitter in science communication.

Under most theories of change that describe how science ultimately affects evidence-based policies, decision-makers are a crucial group that should be engaged by scientists (Smith et al. 2013). Policy changes can be effected either through direct application of research to policy or, more often, via pressure from public awareness, which can drive or be driven by research (Baron 2010; Phillis et al. 2013). Either pathway requires active engagement by scientists with society (Lubchenco 2017). It is arguably easier than ever for scientists to have access to decision- and policy-makers, as officials at all levels of government are increasingly using social media to connect with the public (e.g., Grant et al. 2010; Kapp et al. 2015). However, we found that decision-makers accounted for only ~0.3% ($n = 191$ out of 64 666) of the followers of academic scientists (see also Bombaci et al. 2016 in relation to the audiences of conference tweeting). Moreover, decision-makers begin to follow scientists in greater numbers only once the latter have reached a certain level of "popularity" (i.e., ~2200 followers; **Table 2**). The general concern about whether scientific tweets are actually read by followers applies even more strongly to decision-makers, as they are known to use Twitter largely as a broadcasting tool rather than for dialogue (Grant et al. 2010). Thus, social media is not likely an effective replacement for more direct science-to-policy outreach that many scientists are now engaging in, such as testifying in front of special governmental committees, directly contacting decision-makers, etc. However, by actively engaging a large Twitter following of non-scientists, scientists increase the odds of being followed by a decision-maker who might see their messages, as well as the odds of being identified as a potential expert for further contributions.

So how can a scientist build and engage with their Twitter following? In general, people who tweet more have more followers (e.g., Huberman et al. 2008; Kwak et al. 2010). Whether causal or simply correlational, the strength of this association is nevertheless variable and generally low (e.g., in this study, $r = 0.48$). Moreover, the size of the following does not reflect how much followers engage with a user's tweets, for example by retweeting (Avnit 2009; Cha et al. 2010). For audience engagement, content matters (Bik et al. 2015). Tweets that contain hyperlinks and hashtags are more likely to be retweeted (e.g., Nagarajan et al. 2010; Suh et al. 2010; Pang and Law 2017), as are tweets that contain images (e.g., Bruni et al. 2012). Even more important for the likelihood of being retweeted is the topical relevance of the tweet to the follower (Shi et al. 2017), which speaks to the need for scientists to make their message matter to their intended audiences (Baron 2010). One final important lesson is that ordinary users that become influential (i.e., that are mentioned and (or) retweeted frequently) tend to limit their tweets to narrow topics (Cha et al. 2010). Thus, although Twitter influence can be gained accidentally because of timing, circumstance, or emotion (e.g., Jackson and Spencer 2017), it is more often the result of concerted and persistent effort.

We assume that the patterns we have uncovered for a sample of ecologists and evolutionary biologists in faculty positions can apply broadly across other academic disciplines. We acknowledge that the initial list from which we chose users at random was likely to be biased in several ways. About 70% of users in the original list, and ~75% in our sample of 110 users (**Table S5**), were from the USA or the UK, although this matches the global distribution of Twitter users (Kulshrestha et al. 2012). Our sample also included predominantly male users (69%), but again, this gender bias reflects accurately the underrepresentation of women in academic positions, particularly across science and technology (e.g., <30% in American public universities, Li and Koedel 2017). Our selection of academics on Twitter also presents some bias through which academics choose to be on Twitter, who actively tweet about science, and who were selected to join the Twitter list we used in our analysis. There are some documented disciplinary differences in use of Twitter. For example, in a comparison of 10 academic fields spanning the sciences and humanities, researchers in digital humanities tweeted the most, economists shared the most links, and biochemists retweeted more than academic users in other fields (Holmberg and Thelwall 2014). However, whether these differences translate into differences in rates of accumulation of followers, and of different follower types, among disciplines is unclear.

The greatest challenge for science communication is reaching the audience (Bubela et al. 2009). Today's audiences are increasingly turning to unconventional media sources of information about specific scientific issues and away from online versions of traditional news outlets (National Science Board 2016). Twitter, therefore, offers a timely means for academics to reach a wide popular audience. Here, we show that reaching a broad audience on Twitter is a non-linear process that requires a sustained online engagement, and may only occur past a certain threshold numbers of followers. Our results provide scientists with clear evidence that social media can be used as a first step to disseminate scientific messages well beyond the ivory tower.

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Author contributions

IMC and ESD conceived and designed the study. IMC and ESD performed the experiments/collected the data. IMC and ESD analyzed and interpreted the data. IMC and ESD contributed resources. IMC and ESD drafted or revised the manuscript.

Competing interests

The authors have declared that no competing interests exist.

Data accessibility statement

All relevant data are within the paper and the Supplementary Material, the R code is available on GitHub (github.com/esdarling/sci-twitter), and additional data are available by request to the authors.

Supplementary material

The following Supplementary Material is available with the article through the journal website at doi:10.1139/facets-2018-0002.

Supplementary Material 1

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