Does the public discuss other topics on climate change than researchers?

A comparison of networks based on author keywords and hashtags

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Abstract

Twitter accounts have already been used in many scientometrics studies, but the meaningfulness of the data for societal impact measurements in research evaluation has been questioned. Earlier research has compared social media counts with citations. We explore a novel network approach in which we compare author keywords to Twitter hashtags as indicators of topics. We analyze the topics of tweeted publications and compare them with the topics of all publications (tweeted and not tweeted). Our study is based on a comprehensive publication set of climate change research. We are interested in whether Twitter data are able to reveal topics of public discussions which can be separated from research-focused topics. We find that the most tweeted topics regarding climate change research focus on consequences for humans due to climate change. Twitter users are interested in climate change publications which forecast effects of a changing climate on the agricultural sector. This includes food production and conservation of forests. The networks based on the author keywords in both tweeted and not tweeted papers are broader oriented. Overall, our results show that publications using scientific jargon are less likely to be tweeted than publications using more general keywords. Our results do not support the use of Twitter counts for research evaluation purposes. However, publications that are tweeted can clearly be distinguished from publications that are not tweeted. Furthermore, the Twitter networks can be used to visualize public discussions about specific topics.

Key words

bibliometrics, Twitter, altmetrics, networks, hashtags, author keywords, news
1 Introduction

In the context of an increasing accountability of the science sector in the public sphere, the demonstration of societal impact (popularity, attention, visibility etc.) of research has become a new work area of scientometrics. Societal impact means “all types of research impact inside and outside of academia” (Mohammadi, Thelwall, & Kousha, 2016, p. 1198). The case study approach for providing information on societal impact which is used in the Research Excellence Framework (REF, see http://impact.ref.ac.uk/CaseStudies) faces the problem of missing generalizability and comparability. Furthermore, case studies mainly present success stories.

Moed (2017), for example, argued that “measuring societal impact is problematic” (p. 7). In contrast to the accepted approach of measuring impact on science by using citations, there are only a few established approaches currently available of measuring societal impact quantitatively (e.g., the number of papers which are cited in patents or in clinical guidelines) (OPENing UP, 2016).

Since the advent of altmetrics in the scientometrics universe, a new set of metrics “has been advocated as a potential indicator of such impact” (Sugimoto, Work, Larivière, & Haustein, 2017, p. 2046). According to the National Information Standards Organization (2016), “altmetrics may offer insight into impact by calculating an output’s reach, social relevance, and attention from a given community, which may include members of the public sphere” (p. 1). Altmetrics indicators have been introduced in a manifesto (Priem, Taraborelli, Groth, & Neylon, 2010) and are defined as follows: “altmetric indicators estimate research impact by quantifying the dissemination of scholarly output in social media. Examples include mentions in blogs, number of tweets and retweets or inclusion in social bookmarking services” (Pooladian & Borrego, 2016, p. 1136). Moed (2017) distinguishes four types of altmetrics: social media (e.g., Twitter and Facebook), reference managers (e.g., Mendeley),
various forms of scholarly blogs, coverage in mass media (e.g., daily newspapers). Overviews of studies dealing with altmetrics can be found in Bornmann (2014) and Sugimoto, Work, Larivière, and Haustein (2016). González-Valiente, Pacheco-Mendoza, and Arencibia-Jorge (2016) found more than 250 documents published between 2005 and 2015 in this area. Meanwhile, many publishers add social media metrics to their publications, such as Elsevier, Wiley, and Springer (Thelwall & Kousha, 2015).

In most of the studies published hitherto, altmetrics impact has been measured based on counts of mentions (e.g., Haustein & Larivière, 2014) or field-normalized scores (e.g., Bornmann & Haunschild, 2016; Bornmann & Haunschild, in press; Haunschild & Bornmann, 2016), as an indication of attention to the publications. The problem with most altmetrics is currently that it is not clear what the counts of mentions measure (Bornmann & Haunschild, 2018): is it only background noise or something substantial such as the importance of research for the health of many people? Does altmetrics measure actual impact, perfunctory attention, or broad popularity (Thelwall, Kousha, Dinsmore, & Dolby, 2016; Xia et al., 2016)?

Two recent studies demonstrate that altmetrics data can be used beyond simple mentions, counts, or scores (which have the described problems in interpreting the meaningfulness of the results) by producing networks based on specific altmetrics data. According to Ràfols, Robinson-García, and van Leeuwen (2017), an analysis of the data “in terms of networks (which can be more or less formal), can facilitate the understanding of the contexts (attributes of nodes), processes (links) and embedding (networks structure) of researchers”. The authors analyzed productive interactions between academics and stakeholders from other sectors based on Twitter data. In a similar study, Hellsten and Leydesdorff (2018) analyzed Twitter data and mapped the co-occurrences of hashtags (as representation of topics) and usernames (as addressed actors). The resulting networks can show the relationships between three different types of nodes, i.e. authors, actors, and topics. The maps demonstrate how actors and topics are co-addressed in science-related
This new method opens new opportunities for using altmetrics data for societal impact measurements.

We used this method to study the usefulness of Twitter data for reflecting public discourses about research beyond the academic sector. Instead of focusing on counts of mentions in social media – as analogical to citations to publications, we focus on comparing the content in social media and in scientific publication. We pursue a new avenue for theory-building in the social sciences that is less focused on social actors and pure counts of altmetrics activity by focusing on topics of scholarly publications in comparison with topics in communications on Twitter. Is the scholarly discourse clearly distinguishable from the public communication or is this difference gradual? We consider hashtags on Twitter and author keywords in publications as different representations of topics and ask whether Twitter data are useful for measuring the societal impact of scientific publications. To this end, we compare five different networks and visualize the differences (and similarities) between discussions in academia and on social media. We focus on Twitter data, because this altmetric source is commonly used in scientometric studies, the data can be retrieved for large sets of publications, and Twitter data can be used for topic-related network analyses using our methodological approach.

2 Research on Twitter – a short overview

Twitter is a well-known social media platform for micro-blogging (i. e., allowing users to post short messages) which was founded in 2006 (Mas-Bleda & Thelwall, 2016). Tweets are short messages with up to 280 characters in length (up to 140 characters until recently); if publications are mentioned, or a link to the publications is shared in tweets, the number of mentions or shared links can be counted for the use as altmetrics (Shema, Bar-Ilan, & Thelwall, 2014). The advantage of using Twitter data for measuring societal impact is that the impact usually happens immediately after appearance of a paper (days rather than years)
(Wouters et al., 2015) and that mostly non-scholarly audiences use Twitter (Moed & Halevi, 2015). Haustein, Larivière, Thelwall, Amyot, and Peters (2014) judge Twitter as a “particularly promising source of evidence of public interest in science” (p. 208). It seems that tweets are dominated by the public more than by scholarly users (Yu, 2017). The coverage of publications on Twitter varies by discipline and publication date, but seems to be around 10 to 20% (Sugimoto, et al., 2016). The results of Andersen and Haustein (2015) based on medical papers reveal that especially papers with a link to the clinical practice are tweeted (and not papers focusing on basic research). Thus, these results suggest that Twitter data can be used for studying public discussions about scientific research.

One important problem with the use of Twitter data for societal impact measurements is the restriction of tweets to only 280 (and previously 140) characters. This restriction results in tweeted texts with little content from which the reasons for tweeting can scarcely be deduced – in most of the cases (Haustein, et al., 2014; Taylor, 2013). “A typical tweet about a scientific article appears to be quite factual in its nature with little or no opinions expressed” (Vainio & Holmberg, 2017, p. 347). Friedrich, Bowman, and Haustein (2015) state similarly – based on their results – that “the majority of the processed tweets do not contain any sentiments and are therefore neither praise nor criticism but merely diffusion of the paper”. Most of the tweets only repeat the title of a paper or a small part of its abstract (Thelwall & Kousha, 2015), or share a link to the publication. Furthermore, the meta-analysis published by Bornmann (2015) reveals that the correlation between Twitter counts and traditional citation counts is negligible. Thus, tweets do not measure scholarly impact in a similar vein as citations. This is due to the fact that citations to publications take place within the scientific communities whereas tweets can be sent by general publics as well as (potentially scientific) experts alike.

In this study, we take up the critique of using Twitter counts for measuring broad impact and follow the approaches by Ràfols, et al. (2017) and Hellsten and Leydesdorff
(2018) to use Twitter data for reflecting public discourses on scientific publications.

According to Holmberg, Bowman, Haustein, and Peters (2014): “In addition to retweets and mentions, users also make use of the hashtag affordance to categorize, organize, and retrieve tweets. [...] As such, hashtags may resemble the traditional function of metadata by enhancing the description and retrievability of documents” (p. 3). In our opinion, these results suggest that hashtags on Twitter provide similarly useful information regarding publications as author keywords in scientific publications.

In the following, we compare (i) networks of author keywords in scientific publications that were tweeted with those that were not tweeted and (ii) author keyword networks versus networks of hashtags. We discuss whether these comparisons reveal public discussions about (climate change) research which can be analytically distinguished from research-focused discussions. Is the borderline between scholarly discourse and the public communication sharp or fuzzy?

3 Methods

3.1 Dataset used

We used the Web of Science (WoS, Clarivate Analytics) custom data of our in-house database derived from the Science Citation Index Expanded (SCI-E), Social Sciences Citation Index (SSCI), and Arts and Humanities Citation Index (AHCI) produced by Clarivate Analytics (Philadelphia, USA). A publication set containing most of the relevant literature regarding climate change research was compiled by Haunschild, Bornmann, and Marx (2016) using a sophisticated method known as “interactive query formulation” (Wacholder, 2011). In the first step, a set of key papers was retrieved. In the second step, the search query was reformulated according to the keyword analysis of the key papers. This procedure is repeated until most of the relevant publications are included in the results set. A detailed description of the search process for retrieving the relevant publications on climate change research can be
found in Haunschild, et al. (2016). The search was restricted to the publication years 1980-2014 and to the document types “article” and “review”.

In total, the set of climate change publications consists of 222,060 papers of which 149,657 (67.4%) possess a digital object identifier (DOI) in the WoS database. Using the Perl module Bib::CrossRef\(^1\), Bornmann, Haunschild, and Marx (2016) obtained 30,784 additional DOIs from CrossRef. We use the combined set of 180,441 papers (81.3%) to match them via the DOIs with our locally maintained database with data shared with us by the company Altmetric (see https://www.altmetric.com) on October 02, 2017.

The following information was thereafter appended to the DOIs: (1) links to the tweets which mentioned the corresponding paper, (2) the numbers of tweets in which the respective paper was mentioned, and (3) the numbers of mentions in news outlets of this same paper. Among the climate change papers with DOIs, 17.8% \((n=32,056)\) climate change papers were mentioned in 241,996 tweets; 10.6% \((n=19,145)\) of these papers were mentioned in at least two tweets and 2.4% \((n=4,279)\) of them were also mentioned in news outlets.

### 3.2 Methods

#### 3.2.1 Data

We downloaded the 241,996 tweets which mentioned a climate change paper using a dedicated routine written in Visual Basic ([http://leydesdorff.github.io/haunschild/index.html](http://leydesdorff.github.io/haunschild/index.html) for the dedicated routines with instruction). Tweets1.exe downloads the webpages corresponding to the tweets in html format. A routine Tweets1a.exe in the xBase language, but compiled with Harbour under Linux (see [https://github.com/harbour/core](https://github.com/harbour/core)) parses the downloaded webpages to extract the tweets, authors, time, and year. This information is stored in a database file (tweets.dbf). Another routine (Year.exe) was used to extract the

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\(^1\) See: [http://search.cpan.org/dist/Bib-CrossRef/lib/Bib/CrossRef.pm](http://search.cpan.org/dist/Bib-CrossRef/lib/Bib/CrossRef.pm)
tweets from specific years. The tweets from the years 2011-2014 were stored for further analysis.

We chose the time period of 2011 to 2014, because no climate change papers were mentioned in tweets before 2011 and our publication set does not contain papers published after 2014. Further routines (frqtwt.exe) and (tweet.exe) were used for producing a ranked frequency distribution of terms and a Pajek file corresponding to a word/document matrix. The routines are available from http://leydesdorff.github.io/haunschild/index.html (source codes on request).

We are interested in all hashtags (terms starting with the # sign), including name variants, so that no stop word list was needed. The most frequent hashtags were chosen for further analysis (see below). Among other things tweet.exe produces a cosine-normalized (McGill, 1983) term co-occurrence matrix (see https://www.leydesdorff.net/software/twitter).

3.2.2. Author keywords

For a comparison of the hashtags with keywords, we exported the author keywords of the climate change papers published between 2011 and 2014. Whitespaces within keywords were replaced with underscores so that they can all be treated as word occurrence. All author keywords which belong to a single paper were grouped in a line of the file text.txt to analyze the keywords analogously to the hashtags with the routines frqtwt.exe and tweet.exe.

We exported four different sets of author keywords: (1) author keywords of papers tweeted at least twice and mentioned in news outlets at least once, (2) author keywords of papers tweeted at least twice, (3) author keywords of not tweeted papers, and (4) author keywords of all climate change publications. We used the top-1% (n=60) author keywords of the first set and the top-60 author keywords of the other two sets each in order to compare networks of the same size.
3.2.3 Limitations

Twitter data are affected by manifold “background noise” (Didegah & Thelwall, 2018; Robinson-Garcia, Costas, Isett, Melkers, & Hicks, 2017). For example, many journals tweet at the occasion of a newly published paper or encourage the authors to do so. To reduce the “background noise” in the Twitter data used in this study, we consider only papers as tweeted if they were tweeted more than once. Since this strategy provided meaningful results, we advise to use this cleanup in studies based on Twitter data.

3.3 Visualization

The resulting files (containing cosine-normalized distributions of terms in the Pajek format, see http://mrvar.fdv.uni-lj.si/pajek) were laid-out using the algorithm of Kamada and Kawai (1989) in Pajek and then exported to VOSviewer 1.6.7 (see http://www.vosviewer.com) for visualizations. The clustering algorithm in VOSviewer was employed with a resolution parameter of 1.0, a minimum cluster size of 1, 10 random starts, 10 iterations, a random seed of 0, and the option “merge small clusters” enabled.

4 Results

4.1 Author keywords

Figure 1 shows the semantic map of the top-60 author keywords of climate change publications during the time period 2011-2014. Four different clusters can be identified in Figure 1. The red cluster contains various important author keywords of climate change publications. The green cluster is focused on effects of climate change on agriculture. The blue cluster contains mostly keywords related to greenhouse gases. The yellow cluster contains terms of policy-related topics. Mainly, the expected keywords for the overall climate change literature in this period are visible. Besides the search terms and their synonyms (climate, climate change, global warming) the following keywords appear: “greenhouse_gas“
and “greenhouse_gases“ (as generic terms and the specific keywords: “Carbon_dioxide“, “Methane“, and “Nitrous_oxide“), the most affected countries and ecosystem-related terms (“Australia“, “China“, “Agriculture“, “Biogeography“, and “Vegetation“), the specific impacts (“Drought“, “Rainfall“, and “Soil_moisture“), the most important keywords with regard to the past climate (“Pal(a)eoclimate“, “Stable_isotopes“, and “Pollen“), and to the future climate (“Model(l)ing“ and “Uncertainty“); also, the expected policy-relevant terms appear (“Climate_policy“, “Adaptation“, “Mitigation“, “Renewable_energy“, “Energy_efficiency“, and “Sustainable_development“).

Figure 1: Top-60 author keywords of climate change research papers published between 2011 and 2014. An interactive version of this network can be viewed at https://tinyurl.com/yd6tt95w.
Figure 2 shows the semantic map of the top-60 keywords of not tweeted papers for comparison. Five different clusters can be found in Figure 2. Overall, the corpus of author keywords is very similar in Figure 1 and Figure 2, although cluster assignments have changed in some cases. This is due to the sensitivity of the clustering algorithm to minor changes of the text corpus.

**Figure 2**: Top-60 author keywords of not tweeted climate change research papers published between 2011 and 2014. An interactive version of this network can be viewed at https://tinyurl.com/yd9rn9gq.
Figure 3 shows the network of the top-60 keywords of climate change papers which were tweeted at least twice. Four clusters are distinguished in the semantic map of Figure 3. The green cluster contains keywords related to modelling (“Cmip5”, “Climate_models”). The keyword “Cmip5” stands for “Coupled Model Intercomparison Project Phase 5”. The yellow cluster is related to agriculture and food (in-) security. The blue cluster is about greenhouse gases and carbon-related compounds. The red cluster deals with mitigation of effects of climate change.

**Figure 3**: Top-60 author keywords of climate change research papers published between 2011 and 2014 and mentioned at least twice on Twitter. An interactive version of this network can be viewed at https://tinyurl.com/y8dooqws.
Figure 4 shows the network of the top 1% (n=60) author keywords of climate change research papers published between 2011 and 2014 which were mentioned at least twice on Twitter and at least once in a news outlet. We used mentions in news outlets as a second criterion (in addition to multiple mentions of papers on Twitter), as we expected more focused networks of public discussions on climate change. In most of the cases, only those papers are selected for news reports which are of interest for a broader audience. As is to be expected, the scope of the keywords in Figure 3 is broader than in Figure 4.

The semantic map in Figure 4 shows two larger clusters in red and green as well as four smaller clusters in yellow, blue, light blue, and purple. The red cluster contains the keyword “Climate_models” and other keywords connected to modeling, e. g.: “Trends”, “Climate variability”, “Temperature”, and “Drought”. The green cluster has a strong focus on agriculture and ecosystem preservation (e.g., “Deforestation”, “Agriculture”, “Biodiversity”, and “Conservation”) and food (in-)security. The keyword “Redd” is short for “Reducing Emissions from Deforestation and Forest Degradation”. Both blue clusters are about greenhouse gases and carbon-related compounds. The yellow cluster contains vulnerability-related issues.
Figure 4: Top 1% (n=60) author keywords of climate change research papers published between 2011 and 2014, mentioned at least twice on Twitter, and mentioned in a news outlet. An interactive version of this network can be viewed at https://tinyurl.com/y8bktogf.

Overall, the topics covered by Figure 3 and Figure 4 are again similar but the topics are more focused in Figure 4 due to the restriction of papers which also were mentioned in news outlets. The author keyword networks in Figure 1 and Figure 2 (semantic maps of all and not tweeted papers) do not show a special focus within climate change research as the author keyword networks in Figure 3 and Figure 4 (semantic maps of tweeted papers) do. Some more professional keywords (scientific jargon) appear only in the semantic maps of Figure 1 and Figure 2 or remain below the threshold of the top-60 lists in the semantic maps of Figure 3 and Figure 4; for example, “Microclimate” (red cluster), “Carbon_footprint”
In total 23 out of 60 keywords appear only in the semantic map of not twittered papers (Figure 2) and not in the semantic maps of twittered papers (Figure 3 and Figure 4). However, sometimes synonymous keywords occur in the semantic maps of tweeted and not tweeted papers, e. g., “Modeling” in Figure 2 and “Climate_models” in Figure 3 and Figure 4. In sum, our results show that publications using scientific jargon are less likely to be tweeted than publications using more general keywords. The general public seems to be more interested in climate forecast and consequences of climate change to agriculture and beyond than in the methodology of climate change research and causes of climate change.

4.2 Hashtags and twitter handles

Figure 5 shows the network of the top-60 hashtags from tweets between 2011 and 2014 which mentioned a climate change research paper. In total, we identified nine different clusters in the semantic map of Figure 5. The network of hashtags features a blue cluster about food security, a green cluster connected to agriculture, energy, and environment, a red cluster related to preservation of biodiversity, and a yellow cluster about ocean and fish. Furthermore, the semantic map of hashtags shows some journal or publisher names as hashtags: for example, #PLOS, #NATURE, and #SCIENCE. However, manual checks revealed that most of the times #NATURE and #SCIENCE refer to nature and science (not the journals). When Twitter users wish to refer to the journals Nature and Science they typically use the twitter handles @Nature and @Science. This is obviously different in the use of #PLOS, #PLOSBIOLOGY, and #PLOSONE.

Overall the semantic map of hashtags (Figure 5) fits well to the semantic maps of tweeted papers (Figure 3 and Figure 4) and does not represent climate change research as a whole as seen in comparison with the semantic map of all or not tweeted papers in Figure 1 and Figure 2. This result is in line with previous research on Twitter use in the context of climate change.
change, in particular tweets about a 2013 publication of the Intergovernmental Panel on Climate Change (IPCC) where the focus is on food, and agriculture was one of the core topics on Twitter (Pearce, Holmberg, Hellsten, & Nerlich, 2014).

Figure 5: Top-60 hashtags from tweets between 2011 and 2014 which mentioned a climate change research paper. An interactive version of this network can be viewed at https://tinyurl.com/ya4fz38y.

5 Discussion

Hashtags can be considered as meta-information regarding tweets like author keywords are considered as meta-information regarding scientific publications. Our study is
based on a comprehensive publication set of papers about climate change research. We are interested in whether Twitter data are able to reveal topics of public discussions which can be compared to research-focused topics. This provides useful information about which scientific publications enter the public discussion on Twitter, i.e. which publications may have broader societal impact beyond academia.

Twitter counts have already been used in many scientometrics studies, but the meaningfulness of the data for societal impact measurements in research evaluations has been questioned. We proposed to focus on the content of tweets and scientific publications by focusing on the hashtags in tweets and the author keywords in scientific publications. We used a novel network approach in which we analyzed the topics of tweeted publications and compared them with the topics of scientific publications which were not tweeted. We contrasted publications that were tweeted with those that were not tweeted.

Our results show that the most tweeted topics regarding climate change research are consequences for humans due to climate change. Twitter users are interested in climate change publications which forecast effects of a changing climate on the agricultural sector and beyond. This includes food production and conservation of forests. This focus of Twitter users is reflected in both the author keywords of the tweeted papers and the hashtags the Twitter users choose themselves. In contrast to the author keywords of all and the not twittered publications, the hashtags don’t mirror a scientific discourse; neither with regard to the understanding of the climate system (the primary aim of basic research) nor concerning the evolution of climate change from a hypothesis to a widely accepted fact (at least within the scientific community). The comparison of the networks based on tweeted and not tweeted data reveals the public discussion around climate change topics which can be separated from topics being of interest for academia only. Overall, our results show that publications using scientific jargon are less likely to be tweeted than publications using more general keywords.
In this study, we used climate change as an example to demonstrate a new approach of meaningful analysis of Twitter data (beyond analyzing Twitter counts – as comparable to citations). Since the tools for undertaking the necessary analyses steps are publicly available, our approach can be used for other datasets as well.

Some scientometrics studies have pointed to the problem of background noise in Twitter data. In this study, we proposed a two-step method to reduce noise in the analysis of Twitter data: First, we considered only publications tweeted at least twice. Second, we removed even more noise by focusing on papers not only tweeted at least twice but also mentioned in news outlets. We encourage other scientometricians working with Twitter data to use this approach (or similar approaches) to receive more meaningful results based on Twitter data. Another possible approach proposed previously is to reduce noise in Twitter data by removing self-tweets (Sankar, 2015). However, this does not capture semi-automatic tweets from journal accounts. Also, identification of self-tweets is more difficult than identification of self-citations.

The main limitation of this study is the focus on publications with DOI which reduces the number of analyzed publications, their keywords and hashtags of the tweets in which the publications are mentioned (Sugimoto, et al., 2016). However, although only 67.4% of the publications in our data set possess a DOI in the WoS database, we were able to increase the number of publications to be analyzed to 81.3% by adding DOIs found at CrossRef.

Another limitation of this study is that it is focused on climate change research. Similar studies with a focus on other topics should be performed because there are disciplinary differences in Twitter usage: “For instance, conversations in tweets in one small study were more common in Digital Humanities and Cognitive Science (both 38%), Astrophysics (31%) and History of Science than in Biochemistry and Economics (both 16%). In Biochemistry, 42% of tweets are retweets, whereas in nine other fields the proportion varied from 18% in Social Network Analysis to 33% in Sociology” (Thelwall & Kousha,
2015, p. 612). This approach can further be refined to provide guidelines on which kind of publications are more likely to be tweeted about and hence might have the potential for broader social impact also beyond the sciences.
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