AN ABSTRACT OF THE MPP THESIS ESSAY OF

Jeremiah Osborne-Gowey for the degree of Master of Public Policy in Public Policy presented on Wednesday, June 8th, 2016.

Title: Electrified : what Twitter data can tell us about public energy discussions

Abstract approved:

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Dr. David Bernell

Researchers and policy-makers interested in assessing public communication to better inform the decision-making process are increasingly utilizing data harvested from social media. Twitter is one of the largest online sources of near-instantaneous information about a myriad of topics socially relevant in the public sphere. Renewable energy (RE) is a socially relevant topic that has emerged in recent years as a critical and contentious public policy issue. Yet little is known about whether RE discussions are happening on Twitter and if so whether any of that information would be valuable to decision-makers or for the policy-making process. This research – as a proof of concept – indicates there are a multitude of substantive, public discussions about renewable- and other forms of energy occurring on Twitter. These discussions vary by energy-related topic (e.g., solar, wind, etc.) and through time. We conclude the energy-related Twitter discussions provide both challenges and opportunities for researchers and policy-makers, yet may be important for understanding the public discourse and how it shapes or is shaped by the agenda-setting process.

Electrified : what Twitter data can tell us about public energy discussions

by
Jeremiah D. Osborne-Gowey

A THESIS ESSAY

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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Jeremiah D. Osborne-Gowey, Author

ACKNOWLEDGEMENTS

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"Technology is neither good nor bad; nor is it neutral."

First "law of technology", Melvin Kranzberg, 1986[1].

Even those who don't believe in climate change believe we should develop renewable energy. Americans get it: it's time. This is not controversial. It's actually right in the wheelhouse of American business.

~Marshall Herskovitz (unknown date, link here)

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[1] Kranzberg, M. (1986). Technology and History:" Kranzberg's Laws". *Technology and culture*, *27*(3), 544-560.

Introduction

Researchers and policy-makers interested in assessing public communication to better inform the decision-making process are increasingly utilizing data harvested from social media (Driscoll & Walker, 2014; Murphy et al., 2014; Schober, Pasek, Guggenheim, Lampe, & Conrad, 2016). Twitter is one of the largest online sources of near-instantaneous information about a myriad of topics socially relevant in the public sphere. Renewable energy (RE) is a socially relevant topic that has emerged in recent years as a critical and contentious public policy issue. Yet little is known about whether RE discussions are happening on Twitter and if so whether any of that information would be valuable to decision-makers or for the policy-making process. This research considers the RE discussions occurring on Twitter and addresses the challenges and opportunities researchers and policy-makers face when utilizing 'big data' from social media. To that end, this project asks the following research questions:

1) Are RE discussions occurring on Twitter?
2) If so, what are the discussions about (e.g., what type of RE is being discussed)?
3) Are there temporal patterns in the RE discussions?
4) Can the RE discussions provide value (if any) to decision- and policy-makers?
5) What sorts of challenges and opportunities do the RE discussions provide?

To answer these questions, we a) summarized a rich literature dealing with public opinion and popular media's influence in the decision- and policy-making spheres as well as the cause and consequence of these discussions, b) examined Twitter mentions over time (2008-2013) about a number of energy-related keywords, c) discuss how these findings illustrate theoretical points about the cause and consequence of public discussions, and d) discuss challenges and opportunities for understanding and finding meaning in this sort of "big data" from social media. Research questions 1-3 are addressed in the Results section of this paper while questions 4-5 are addressed primarily in the Discussion section.

In summary, results from this study indicate there is a sizeable body of energy-relevant and potentially valuable data on Twitter. Over the six 20-day time frames examined in this study – one in each year from 2008-2013 – there were 1,060,143 tweets related to the energy terms of interest in this study. While the number of energy-related mentions increased during every period of this study, some categories of energy-related terms experienced varying levels of discussions (e.g., increased or decreased) from period to period. Twitter mentions of solar, bio-energy/-fuel and wind were the most frequently mentioned energy-related terms discussed on Twitter during this study while 'fracking' was the most-frequently mentioned energy-related term in the final period. Similar to other research findings, the use of hashtags – a word or phrase preceded by a hash or pound sign and used to identify messages on a specific topic – was low, typically representing 25% or less of the tweets for each energy-related keyword category. Overall, there was substantial growth in the frequency of energy-related mentions on Twitter but the percent change in number of mentions from beginning to end of the study – with the exception of mentions about 'fracking' – declined dramatically from 2010-2011 and plateaued from that point onward, perhaps indicating saturation in use of Twitter.

There is an apparent wealth of energy-related data on Twitter, yet this data is currently under-utilized by decision-makers and energy planners, perhaps because the link between human behavior and use of social media is not as obvious as in other disciplines (George, 2004; Martin, Chizinski, Eskridge, & Pope, 2014). Planners, researchers and policy- and decision-makers, however, would benefit from exploring these data as a means of assessing things such as public awareness, understanding, perception, opinion and discourse about energy. At the very least, the richness of these data suggest they could be explored as way of making sense of the flood of information from new forms of readily-available media as a means of supplementing data from other more traditional sources like surveys and polling.

Background and Literature Review

Growing public and political demand for RE has resulted in an increase in legislative and policy approaches such as Renewable Portfolio Standards (RPSs), tax incentives, feed-in tariffs and others (Loiter & Norberg-Bohm, 1999; Sawin, 2001; Wiser, Porter, & Grace, 2005a, 2005b). As a result, development of RE sites in the United States has dramatically increased in the last decade (Chow, Kopp, & Portney, 2003; DSIRE, National Renewable Energy Laboratory, & Lawrence Berkeley National Laboratory, 2014; Loiter & Norberg-Bohm, 1999) with RE power plants – active, under construction and proposed – now widely dispersed nationwide (see Figure 1). Additionally, as of January 2016, twenty nine (29) states, Washington DC and two (2) U.S. territories have adopted renewable portfolio *standards*, while another eight (8) states and two (2) territories have adopted voluntary renewable portfolio *goals/targets* (see Figure 2) in part illustrating the potential for and rapid growth of the RE sector.
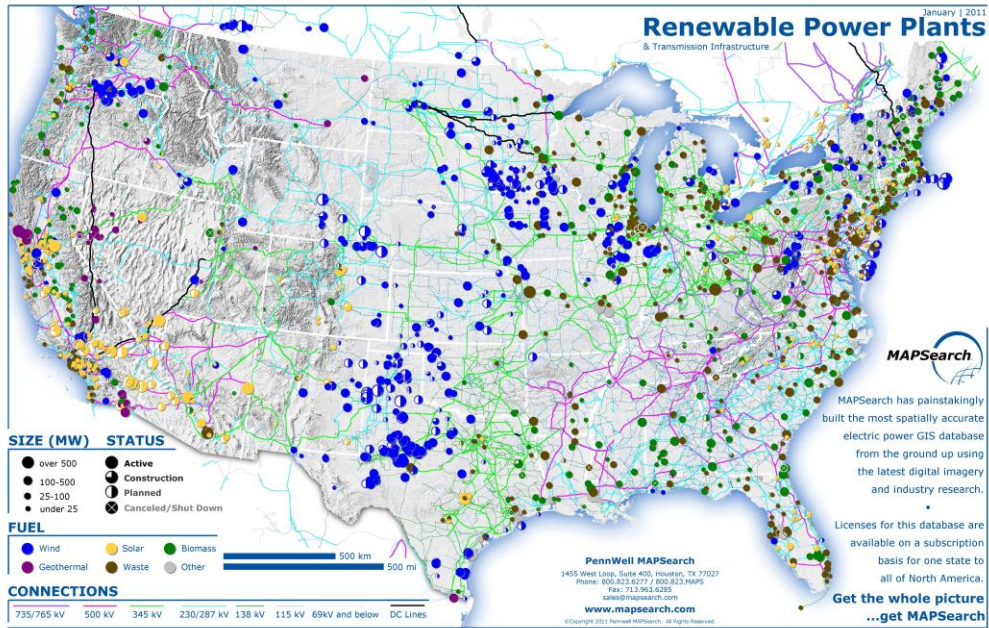
Figure 1. Renewable energy power plants (active, under construction and planned) by energy sector in the United States as of January 2011. Map courtesy of PennWell MAPSearch (http://www.mapsearch.com/gis-asset-data/renewable-energy-gis-data.html).
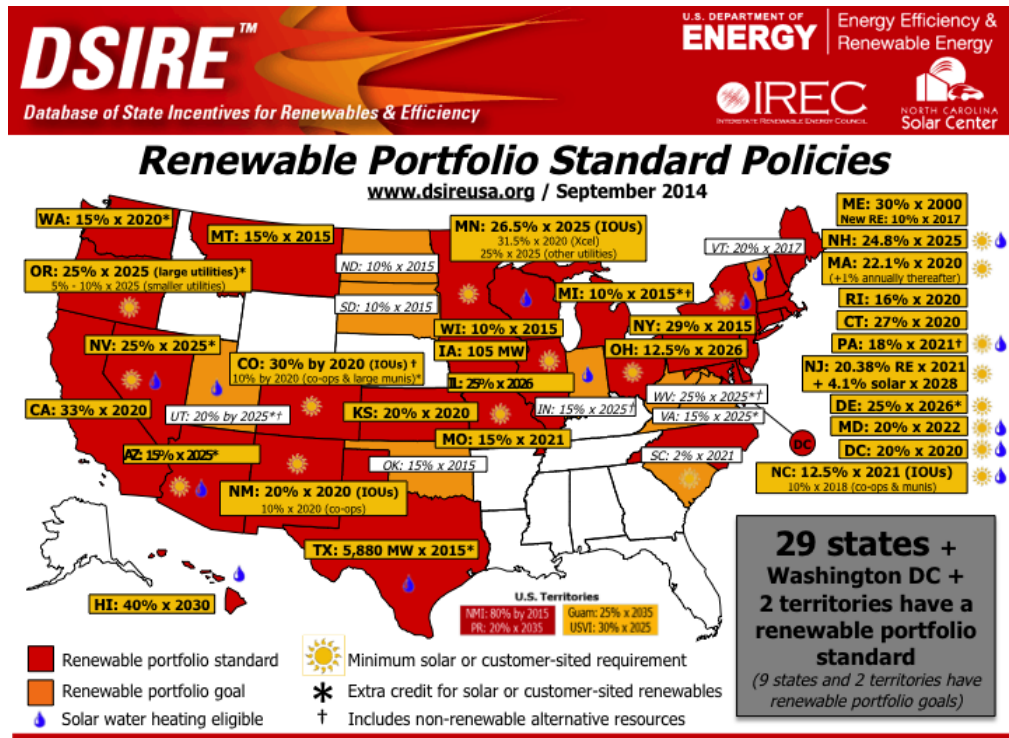
Figure 2. Renewable portfolio standard policies and goals for the United States and territories as of September 2014. Figure reproduced with permission from the Database of State Incentives for Renewables & Efficiency (www.DESIREusa.org).

Public opinion about and acceptability of development of renewables, however, has been equivocal, characterized by changes through time and place – evidenced by West Virginia repealing their RPS in 2015 – and with varying levels of awareness. Indeed, public awareness and acceptability are widely recognized as a key factors in realizing RE development (van der Horst, 2007; Walker, 1995; Wüstenhagen, Wolsink, & Bürer, 2007). Further complicating matters, the public may support a concept (e.g. RE) but not support a particular project (e.g., a proposed wind farm) for a number of reasons including, among others, environmental, economic or market factors, lack of awareness, not in my backyard (NIMBY-ism) attitudes, Locally Unwanted Land Uses (LULUs), or low perceived benefit or high perceived risk (e.g., Gardner & Stern, 1996; Schively, 2007; Songsore & Buzzelli, 2014). Thus, understanding public awareness of and perception about RE may be key to overcoming obstacles to RE development and standards.

Concurrent with the growth of RE development is the proliferation and rise in popularity of microblogging and social networking sites like Twitter, Tumblr, Google+, and Facebook, which are becoming widely popular communication tools among internet users. With millions of messages appearing daily on microblogging sites – messages that include information about public awareness, opinions and sentiment about a variety of topics and current issues – these data are increasingly being leveraged by businesses, politicians, marketers, economists and biologists to inform marketing, political, economic, and biological decisions and assess public opinion trends (Fan & Bifet, 2013; Gura, 2013; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2013; Mayer-Schönberger & Cukier, 2013; Shirky, 2011; Weber, Garimella, & Borra, 2012).

Twitter, one of the largest online social networking and microblogging services, allows users to post public text-based messages (called *tweets*) to its online platform. Twitter has roughly 650 million registered users with close to 300 million active users that post roughly 60 million messages a day (approximately 9,100 tweets/second) and perform 2.1 billion search engine queries each day (Statistics Brain, 2015). Twitter provides free real-time access to these public users' posts

(colloquially referred to as the 'fire hose') or users can purchase historic tweets from the company. These 'big data' streams, however, are currently under-utilized by decision-makers and energy planners, perhaps because the link between human behavior and use of social media is not as obvious as in other disciplines (George, 2004; Martin, Chizinski, Eskridge, & Pope, 2014).

The role of Twitter and social media in public debate can be understood as part of larger question about the way media – both traditional mass media and newer "micro-mass media" (e.g., Twitter) – reflect and impact public opinion. These are also connected to the question of how public information and perceptions impact the public acceptance of renewable energy projects in communities throughout the United States. The following sections address the role of media in issue salience and public awareness, perceptions, opinion, and acceptance, and the role of social -networks and social -media (e.g., "micro-mass media") in public opinion.

Mass media, public opinion and issue salience

There is a sizeable, decades-long literature on the substantial and sometimes controversial role of mass media in structuring public discussions (e.g., agenda-setting) and shaping (or being shaped by) public opinion (M. McCombs, 2013; see M. E. McCombs, Shaw, & Weaver, 2014 for an excellent, comprehensive review). In summary, mass media is a dominant presence in U.S. culture that is sometimes 1) reflective of worldviews but 2) also shapes – and may even set – campaign agendas (i.e., agenda-setting; McCOMBS & Shaw, 1972; Jasanoff, 2005; Takeshita, 2006; M. E. McCombs et al., 2014) while 3) also creating/shaping public opinion in powerful ways (Anastasio, Rose, & Chapman, 1999; Baum & Potter, 2008; M. McCombs, 2013; Schramm & Roberts, 1971). The mass media's agenda-setting function was well-stated by Bernard Cohen (1963): the press " may not be successful much of the time in telling people what to think, but it is stunningly successful in telling its readers what to think about."

McCombs and Shaw (1972) studied the agenda-setting capacity of the mass media during the 1968 U.S. presidential campaign and – based in part on their work

and referencing Cohen (1963) – assert mass media influences "the salience of attitudes toward the political issues," thus setting the agenda. In his comprehensive and insightful book "Setting the Agenda: the mass media and public opinion", Maxwell McCombs (2013) – one of the founding fathers of agenda-setting research – summarizes hundreds of studies on the role of media in shaping public opinion. McCombs finds the mass media not only strongly influences the picture of public affairs (see Domhoff, 1998 for a counter-argument) but also strongly influences the details of those pictures, thus shaping both *what* and, to a lesser degree, *how* we think about issues of public salience. Yet, aside from mention in the epilogue, McCombs' (2013) timely text misses the opportunity to include a broader discussion about the role of new media in shaping (or sharing) public opinion.

Despite the relative dearth of empirical studies examining issue salience in policy-making with respect to the role media may play in shaping issue prominence, the theoretical focus on salience in shaping public policy is warranted – and sound. In a critical review of the impact of public opinion on public policy, Burstein (2003) noted the key role of issue salience in democratic responsiveness of governance observing a few studies that indicated voters were "especially likely to take elected officials' action on that issue into account on election day" (e.g., issues of gun control, reproductive rights, etc.). In Burstein's (2003) meta-analysis, public opinion that did not take issue salience into account had no impact on policy a third of the time whereas when salience was taken into account, public opinion always had an effect and that effect was substantive over three-fifths of the time. Given the relatively few studies examining issue salience, however, a more in-depth and critical analysis of how influential a role issue salience plays in shaping public policy is still necessary.

Renewable energy is an issue of current relevance and public salience (see above) that has enjoyed widespread play in mass media in recent decades. Environmental regulation, in general, is quite responsive to public opinion (Erikson, Wright, & McIver, 1993). Understanding whether RE discussions are occurring on *new* forms of mass media (e.g., Twitter) – as well as understanding the nature of those

conversations – may be an important factor in shaping the environmental and RE policy and development landscape (e.g., citizen support, government funding, etc.; Kaplowitz, Lupi, Yeboah, & Thorp, 2013; O'Brien, 2013; Sanz-Menéndez, Ryzin, & Pino, 2014).

Public Perceptions, Awareness, and Acceptance

Results from decades of research on siting of renewable energy projects indicates the largest challenges to RE siting (i.e., development) are societal in nature, not technical (Boholm & Lofstedt, 2004). Furthermore, context – e.g., political history, familiarity with previous RE development and industry, proximity to development, etc. – plays a substantive role in the public's awareness and perceptions of and opinion about environmental issues and decisions (e.g., energy development), although in varied ways (Rosa & Short, 2004; Guidotti & Abercrombie, 2008; Boudet & Ortolano, 2010; Warren, Lumsden, O'Dowd, & Birnie, 2005; Devine-Wright, 2005a)[2].

In their examination of high-level nuclear waste disposal in the U.S., Rosa and Short (2004) find that intersecting contexts play a pivotal role in siting decisions at three different levels: how the waste disposal issue(s) are shaped and framed, the different social and institutional actors engage the issue, and the identity and actions of stakeholders. They indicate an urgent need to better understand the contexts, especially in a rapidly changing and intransigent society. In an examination of the political and NIMBY factors responsible for a failed landfill in Edmonton, Alberta (Canada), Guidotti and Abercrombie (2008) found that "unspoken resentment among county residents against an attempt by the city to annex it decades before" along with other instances of government and political interventions (i.e., the political history the community had faced) played "a major role in conditioning their response to 'locally undesirable land use' (LULUs) and the NIMBY phenomenon." In a paper discussing public perceptions of wind power in Scotland and Ireland, Warren and colleagues

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[2] For a review of the public's attitudes toward and acceptance of RE technologies, see Patrick Devine-Wright's (2007) excellent, critical review.

(2005) found a) proximity of the public to windfarms positively influenced the public's acceptance of them, b) local people became more favorable to the windfarms after they were constructed, and c) NIMBY-ism could "not adequately explain variations in public attitudes." Interestingly, in a similar study by Graham and others of public perceptions of wind energy developments in New Zealand, they found no apparent relationship between negative perceptions (about the proposals) and proximity to proposed wind farms. In a study examining siting of two liquefied natural gas (LNG) facilities in California (USA), Boudet and Ortolano (2010) found public attitudes about the risks associated with the facilities and trust of the process and in decision-makers were key motivators behind the communities' decisions whether to mobilize against development of the LNG terminals. Thus, understanding public perceptions about renewable energy appear to be key factors to whether development occurs in some locations.

Public awareness and acceptability is widely recognized as a potential key barrier to development of RE resources (van der Horst, 2007; Walker, 1995; Wüstenhagen et al., 2007). Nearly two decades ago as alternatives to traditional forms of energy generation were taking root, local Hawaiian peoples voiced their opposition to the development of geothermal energy on the "Big Island", in part because of long-held cultural beliefs that nature is sacred and not to be harnessed or managed as the western view of natural resources held (Edelstein & Kleese, 1995). In the indigenous Hawaiian view, drilling into the ground to harness the heat coming from volcanic activity threatened the Hawaiians' most sacred place in all Hawaii – the fire god Pele's home and body. The lengthy administrative proceedings that resulted from local opposition were a testament to the need to include local knowledge and values in the RE decision-making process.

Almost a decade prior but in a setting where a wind power farm was already developed and on the ground, survey results of residents living near the completed Altamont Pass Wind Energy Development in California indicated nearly all subjects regarded the landscape as man-made and highly conspicuous yet there was a wide range of attitudinal responses about complexity of biological and political processes,

visual palatability, and desirability of the wind farm as an alternative to pollution (Thayer & Freeman, 1987). Interestingly, one of the significant findings from the survey was that subjects with *familiarity* with the specific environment in and around the Altamont development – most often those that lived in closer proximity to the turbines – also responded more negatively to it. This was likely owing to their visual assessments that when the wind was blowing, some turbines were spinning but large numbers of turbines seemed to be non-operational, thus their public perception of the RE facility was of technological or managerial incompetence or tax fraud (Thayer & Freeman, 1987). This runs counter to findings from another study that found that those living closest to a nuclear power plant tended to underestimate the risks of doing so and looked more favorably upon nuclear energy than those living further away (Ester, Mindell, Van der Linden, & Van der Pligt, 1983). Thus, consideration also needs to be given to the distinctions between familiarity with and awareness of RE development – context matters.

Issue unfamiliarity among the public can also lead to slowdowns or outright failure of RE development. Despite the recent rise in popularity of biomass fuels as potential alternative energy sources, the proposed development of a biomass energy plant in the UK failed in 2000 after considerable public opposition (Upreti & van der Horst, 2004). Twice, the governing body responsible for approving or denying all development in the area – the North Wiltshire District Council – rejected the application, once during its original hearing and a second time nearly a year later during the appeal process. In rejecting the application and appeal, councilors cited considerable public opposition and general public perception of risk (Upreti & van der Horst, 2004). These findings underscore the need to involve the public during the development process to a) build trust and b) assess potential incongruences between awareness about the various public risks and benefits.

Much has been made of the gap between public support for RE as a *concept* and the LULU and NIMBY attitudes toward RE development (Schively, 2007; van der Horst, 2007; Wolsink, 1994) wherein individuals and the public at large may support RE (and policies pertaining to development) but support breaks down or turns

to opposition when development projects are proposed in locations that carry significant place attachments for locals (Devine-Wright, 2011; James F. Short & Rosa, 2004; Vorkinn & Riese, 2001) or on other self-interested grounds (Schively, 2007). Additional discussions in the literature indicate the need to distinguish between gaps in attitude-behavior and gaps between public opinions of RE and opinions about *particular* RE projects. This 'social' and/or 'individual' gap in support for a concept but low success rate in planning applications (Bell, Gray, & Haggett, 2005; Bell, Gray, Haggett, & Swaffield, 2013; Devine-Wright, 2005a, 2007, 2014) –

Public attitudes and perception can and do change, however, with changing knowledge and familiarity of technology, proximity to local RE development, exposure to media and opinions of trusted sources (e.g., friends and relatives), and when making distinctions between RE innovation and the actual development of RE infrastructure (Bell et al., 2005; Bolsen & Cook, 2008; Devine-Wright, 2005b; Eltham, Harrison, & Allen, 2008; Haggett, 2008; Wüstenhagen et al., 2007). Two studies of public opinions about RE development of wind farms – one in the Netherlands and the other in England, both before and after the RE projects were commissioned – found that more people living in proximity to the wind farms supported the farms *after* they were built than before (Krohn & Damborg, 1999; Wolsink, 1989), though support varied based on local people's previous experience with wind power. A later study about the aforementioned project in England, performed both before and well after the RE project was developed, found little difference between support before and after with the overwhelming majority of residents in favor of wind development in their area (Eltham et al., 2008) though recall bias may have been present as respondents in that study were asked to *recall* whether they supported the development before it was commissioned. Nevertheless, opposition groups organize for a variety of reasons and can be an effective voice in the decision-making process (Haggett & Toke, 2006; Walker, 1995) underscoring the importance of understanding public awareness, perception and involvement and the role *context* plays in shaping public perception and support (or opposition) for RE development *throughout* the RE planning process (Rosa & Short, 2004).

Social Networks, Social Media and Public Opinion

Social media services are increasingly playing a role as news sources (Barthel, Shearer, Gottfried, & Mitchell, 2015; Lenhart, Purcell, Smith, & Zickuhr, 2010; Mitchell, Kiley, Gottfried, & Guskin, 2013). Given the substantive role mass media plays in the agenda-setting process, social media may be important for setting – or at least *shaping* – the public agenda (M. McCombs, 2013; M. E. McCombs et al., 2014; also see discussions, above). Recent work from focus groups and interviews indicate people's networks on social media function in a micro-agenda setting role (Wohn & Bowe, 2016) and are "positive and significant predictors of people's social capital and civic and political participatory behaviors" (Gil de Zúñiga, Jung, & Valenzuela, 2012) as well as political engagement (Hargittai & Shaw, 2013; Holt, Shehata, Strömbäck, & Ljungberg, 2013). Further, despite being in a relatively nascent stage of research investigating the role of online news on public opinion, initial studies indicate a positive relationship between reading news online and the public's factual political knowledge (Beam, Hutchens, & Hmielowski, 2016). While traditional media producers are adopting online platforms for sharing news (Macnamara, 2014) and news consumers are now getting a majority of their news from online, social media sources (Barthel et al., 2015; Media Insight Project, 2015), it seems to matter less to them which platform they got the news from (traditional print, online, etc.) but rather whether they find the source to be credible (Barthel et al., 2015; Brenner & Smith, 2013, 2013; Lenhart et al., 2010; Mitchell et al., 2013). While some users may find their online friends to be reliable sources of news of relevance in the public sphere, others may view news from traditional new organizations to hold more credibility. Thus, social networks and traditional news organizations both may help shape the public opinion and agenda (see agenda discussions, above).

The relationship between media and public awareness about and opinions of public issues has long been studied with research endeavors largely focused on developing theories about the media's influence on social constructions of reality (Adoni & Mane, 1984; Anastasio et al., 1999; Hansen, 1991) or the accuracy, validity and reliability of public opinion measurements originating from the media (Murphy et

al., 2014; Schober et al., 2016; Trilling, 2015). One of the more pressing issues facing researchers has been whether public opinions or sentiment expressed through various *new* media avenues (e.g., blogs, social networking sites, online discussion forums,) accurately portray the public's beliefs or if the public's stated and revealed preferences (i.e., their actual behaviors) align. Indeed, results from public opinion and social media research from recent political debates have been equivocal. For example, Metaxas and others (2011) found that Twitter was no better than random chance at predicting the outcome of US Senate races from two recent congressional elections. Although careful consideration must be given when defining and measuring public opinion (Anstead & O'Loughlin, 2015), Twitter may have coarse-scale predictive power about the political alignment of individuals and the general public (Conover, Gonçalves, Ratkiewicz, Flammini, & Menczer, 2011), and provide value when assessing large-scale patterns of public opinion via polling (O'Connor, Balasubramanyan, Routledge, & Smith, 2010).

Additionally, while deployment of issues to social media by political campaigns can be problematic (Trilling, 2015), media can alter perceptions about reality (Anastasio et al., 1999) and public responses on Twitter have been shown to be important in representing (Elson, Yeung, Roshan, Bohandy, & Nader, 2012; Yeung, Elson, Roshan, Bohandy, & Nader, 2012) and shaping the broader public opinion (Ampofo, Anstead, & O'Loughlin, 2011). Furthermore, there are no lack of people expressing opinions and attitudes online via social networks (Jansen, Zhang, Sobel, & Chowdury, 2009; Pak & Paroubek, 2010a; Stieglitz & Dang-Xuan, 2012), further illustrating the potential importance of social media (Twitter) for gauging public opinion and in shaping a) issues of public salience and b) the public agenda.

Data and Methods

To assess the type and temporal patterns of energy-related discussions occurring on Twitter, we collected historical tweets from 20-day periods, one period in each of the years 2008-2013 for a total of six 20-day periods (Table 1). Start dates for each 20-day periods (six in total) were randomly generated. Collected tweets met

at least three conditions of a set of filtering rules passed to Twitter – that is to say, Tweets contained at least one energy-related keyword of interest, originated from the United States of America and were original tweets/messages, not retweets (reposts or forwards of messages from another Twitter user). Acquisition of the Twitter data occurred on May 7, 2014.

Table 1. Twenty-day date ranges from which historical Tweets were collected for this project.

Year	Start date	End date
2008	May 04	May 23
2009	March 18	April 07
2010	August 18	September 07
2011	July 13	August 02
2012	March 01	March 21
2013	June 30	July 20

While the focus of this research was on renewable energy, we added several additional energy-related search terms (e.g., coal, nuclear, etc.) since the current energy discussions in the broader sphere include more than just discussions of renewables, and knowing something about the breadth and proportion of discussions on various energy-related topics may provide value for understanding public emphasis. Search terms for the historical Twitter data query for this project included keywords from three broad categories: renewables, quasi-renewables, and non-renewables (Table 2). Keywords in the renewable category corresponded to biomass, geothermal, hydropower, solar, wind and general renewable energy-related (e.g., #renewableenergy). Keywords in the quasi-renewables category corresponded to ethanol while keywords in the non-renewable category corresponded to coal, hydraulic fracturing (i.e., 'fracking'), natural gas and nuclear (Table 2). Since the primary focus was on renewable-energy related discussions on Twitter, 'oil' was not included as a search term. Additionally, after adding in a number of other non-

renewable energy keywords (including 'oil') to the search, initial results indicated the inclusion of 'oil' would cause rate cap limitation problems. That is to say, a Twitter query that reaches the maximum number of search results allowed causes the search to terminate and ignore results for additional keywords. Thus, we elected to exclude 'oil' from our list of keywords of interest.

Table 2. Keywords, by category, used to collect tweets related to various energy terms.

Category	Group	Keywords
Renewables	Biomass	bioenergy power, bioenergy farm, bioenergy turbine, bioenergy plant, biofuel energy, biofuel power, biofuel farm, biofuel turbine, biofuel plant, #biofuel, #bioenergy
	General	renewable energy, #renewableenergy
	Geothermal	geothermal energy, geothermal power, geothermal farm, geothermal turbine, geothermal plant, #geothermal
	Hydropower	hydropower energy, hydropower power, hydropower farm, hydropower turbine, hydropower plant, hydroelectric energy, hydroelectric power, hydroelectric farm, hydroelectric turbine, hydroelectric plant, #hydropower, #hydroelectric
	Solar	solar energy, solar power, solar farm, solar turbine, solar plant, #solarenergy, #solarfarm
	Wind	wind energy, wind power, wind farm, wind turbine, wind plant, #windenergy, #windpower, #windfarm, #windturbine
Quasi-renewables	Ethanol	ethanol energy, ethanol power, ethanol farm, ethanol turbine, ethanol plant, #ethanol
Non-renewables	Coal	coal energy, coal power, coal farm, coal turbine, coal plant, coal mine, coal ash, #coal, #coalenergy, #coalpower, #coalplant, #coalash, #coalmine
	Hydraulic Fracturing	fracking, #fracking
	Natural Gas	natural gas energy, natural gas power, natural gas farm, natural gas turbine, natural gas plant, #naturalgas
	Nuclear	nuclear energy, nuclear power, nuclear farm, nuclear turbine, nuclear plant, #nuclear, #nuclearenergy, #nuclearpower

We selected relevant energy-related keywords based on 1) common search terms from the ProQuest[3] and Newsbank[4] databases used for finding newspaper articles related to energy, 2) manual searches of the most frequent mentions of energy-related search terms on Twitter[5], Google Trends[6], and Google Correlate[7] and 3) our experience with energy-related research. The final rule-set used to query Twitter was:

(wind OR solar OR nuclear OR bioenergy OR biofuel OR coal OR natural gas OR geothermal OR hydropower OR hydroelectric OR ethanol OR fracking)(energy OR power OR farm OR turbine OR plant OR mine OR ash) OR #geothermal OR #windenergy OR #windpower OR #windfarm OR #windturbine OR #renewableenergy OR #solarenergy OR #solarfarm OR #nuclear OR #nuclearenergy OR #nuclearpower OR #biofuel OR #bioenergy OR #naturalgas OR #coal OR #coalenergy OR #coalpower OR #coalplant OR #coalash OR #coalmine OR #hydropower OR #hydroelectric OR #ethanol OR #fracking

The parentheses represent an implicit "AND" so only Tweets that have a combination of one of the first words and one of the second words were returned. The hashtag (the '#' sign) precedes a word or phrase (without any spaces) and is used in social media to identify messages on a specific topic. Thus, users who search for a hashtagged topic are able to find all messages posted about the hashtagged topic of interest.

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[3] ProQuest for researchers: http://www.proquest.com/researchers/
[4] Newsbank for Colleges and University researchers: http://www.newsbank.com/libraries/colleges-universities
[5] Twitter search for renewable energy: https://twitter.com/search?src=typd&q=renewable%20energy
[6] Google Trends: https://www.google.com/trends/
[7] Google Correlate finds search patterns which correspond with real-world trends. https://www.google.com/trends/correlate.

Data were collected using Gnip's Historical PowerTrack (HPT) service. Although real-time data collection from Twitter's streaming API stream is free and publically available, Gnip is one of the few Twitter-licensed options for purchasing historical data and allows users access (for a fee) to full search results of the Twitter engine. Twitter data typically includes a number of data fields, not all of which were of interest for this project.[8] In addition to access to historical Twitter data, Gnip's HPT service provides three additional benefits over accessing Twitter's public application programming (or API) interface: data enrichments, a finer-grained system for keyword matching and absence of a data cap (for an additional fee). Gnip's HPT service can also provide supplementary metadata with the data delivery. Data for this project were delivered with Gnip's proprietary metadata enrichments that included expanded versions of shortened URLs, geocoding and normalization of users' profile locations (if possible), Klout scores[9], language detection, language and matching rules for metadata. Tweet data fields preserved for this project are listed in Table 3.

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[8] For a complete list of Twitter data fields, see https://dev.twitter.com/overview/api/tweets.

[9] Klout is a company that provides an analytical metric of users' online social media influence – the ability to drive action. Scores range from 1-100, with higher scores indicating higher levels of online influence. https://klout.com/corp/score

Table 3. Twitter data fields maintained for this study.

Field	Data Type	Description	Example*
id	integer	unique Twitter identifier for this user	"id":114749583439036416
preferredUsername	character string	user-defined name on the account	"preferredUsername" : "EconDevelopment"
created_at	date-time string	UTC time and date of Tweet	"created_at":"Wed Aug 27 13:08:45 +0000 2008"
from_user	character string	Twitter user name	
from_user_id	integer	Twitter unique ID	
in_reply_to_status_id	integer	if tweet is a reply to user, contains original tweet ID	"in_reply_to_status_id":114749583439036416
in_reply_to_user_id	integer	if tweet is a reply to status, contains original tweet ID	"in_reply_to_user_id":819797
text	character string	actual UTF-8 text of the tweet	"text":"Tweet Button, Follow Button, and Web Intents ja
source	character string	client (web/phone/etc) user used to post the tweet	"source":"\u003Ca href=\"http:\/\/itunes.apple.com\/us\/a rel=\"nofollow\"\u003ETwitter for Mac\u003C\/a\u003E
link	character string	URL for the user's status post	"link" : "http://twitter.com/EconDevelopment/statuses/80
hashtags	character string	list of hashtags parsed from user's tweet text	"hashtags":[{"indices":[32,36],"text":"lol"}]

coordinates	character string	geographic location, if available	"coordinates":
			{
			  "coordinates":
			  [
			    -75.14310264,
			    40.05701649
			  ],
			  "type":"Point"
			}

place**	multiple		"place":
			{
			  "attributes":{},
			  "bounding_box":
			  {
			    "coordinates":
			    [[
			      [-77.119759,38.791645],
			      [-76.909393,38.791645],

Field	Data Type	Description	Example*

			[-76.909393,38.995548],
			[-77.119759,38.995548]
			  ]],
			  "type":"Polygon"
			},
			  "country":"United States",
			  "country_code":"US",
			  "full_name":"Washington, DC",
			  "id":"01fbe706f872cb32",
			  "name":"Washington",
			  "place_type":"city",
			  "url":"http://api.twitter.com/1/geo/id/01fbe706f872cb
			}

location	character string	User-defined location for the account profile	"location":"San Francisco, CA"
lang	character string	language of the tweet	"lang": "en"
profile_image_url	character string	user profile image/avatar URL	
to_user_id	integer	tweet is replying to which Twitter unique ID	
friends_count	integer	number of users this account is following	"friends_count": 32
geo_enabled	boolean	user enabled possibility of geotagging tweets	"geo_enabled": true
retweet_count	integer	Number of times tweet was retweeted	"retweet_count":1585
gnip	character string	matching rule set for relevant tweets	"gnip" : { "matching_rules" : [{ "value" : "(wind OR sol \"natural gas\" OR geothermal OR hydropower OR hydr turbine OR plant OR mine OR ash)", "tag" : null }] } }

* Examples come from Twitter's data field page: https://dev.twitter.com/overview/api/tweets.

** May contain multiple data types. For a complete description, see https://dev.twitter.com/overview/api/places.

Gnip's HPT Twitter data comes as machine-readable, gzip-compressed[10] JSON-formatted data files based on the UTF-8 character set and timestamped in UTC, the Unix Epoch time tracking standard listed as a running total of seconds from January 1st, 1970. These HPT Twitter data were delivered in bundles of files each representing 10-minute time-series containing the relevant tweets. Thus, each hour's worth of relevant tweets from Gnip can come in six (6) files (or fewer if there are no relevant tweets for a specific 10-minute time period). Compressed files were delivered via Amazon's Simple Storage Service (S3[11]), a scalable cloud service. Files were downloaded from Amazon's S3 using cURL[12], an open-source command-line utility for making HTTP requests and transferring data. Downloaded data totaled 15,383 gzipped files of approximately 2.64Gb in total unzipped disk space. Downloaded data were concatenated into a single file for import into a database program (MongoDB; more, below). Downloaded data were stored on a local machine and backed up using cloud file storage services.

Data were organized, manipulated, and analyzed using a combination of MongoDB codes and scripts and Python scripting in iPython and iPython Notebooks using methods, codes and scripts described in Chodorow (2013), Russell (2013), and Kumar and colleagues (2013). MongoDB is a scalable, open-source, document-oriented database software program designed to store and manipulate JSON-formatted data. Python is a widely used, general purpose, object-oriented, dynamic programming language that runs well in the iPython interactive command shell and in iPython Notebook, a web-based, interactive computer environment designed to work with JSON-formatted data.

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[10] GZip is a format used for file compression and decompression. For a description, see
https://en.wikipedia.org/wiki/Gzip.
[11] Amazon's Simple Storage Service (S3) - http://aws.amazon.com/s3/.
[12] cURL - https://curl.haxx.se/.

Results

Are Renewable Energy Discussions Occurring On Twitter? (research question 1)

A total of 1,060,143 tweets from the six, twenty-day periods from 2008-2013 matched our rule-set for origin of location (USA), contained at least one energy-related keyword from our list, and were original Tweets (not retweets; Table 4). The number of Tweets matching our rule-set increased substantively during each consecutive time period with the greatest percent change occurring during the two earliest time periods (i.e., between 2008-2009 and 2009-2010) and decreasing with each successive time period. The number of energy-related Twitter mentions increased eight and one-half fold between 2009-2010, more than doubling from 2010 to the final period in 2013 when there were more than 350,000 energy-related tweets.

Table 4. Total number of energy-related Tweets collected, by time frame. Numbers in parentheses indicated the percent change in number of tweets from the previous time period.

Year	Date Range (20d./ea.)	Num. Tweets (%ch)
2008	May 04-23	1,472 (na)
2009	Mar 18 – Apr 07	17,790 (1,109)
2010	Aug 18 – Sept 07	152,676 (758)
2011	Jul 13 – Aug 02	219,188 (44)
2012	May 10-30	315,032 (44)
2013	Jun 30 – Jul 20	353,985 (12)
TOTALS: 6 yr. span	**120 days**	**1,060,143 Tweets**

What Are the Renewable Energy Discussions About? (research question 2)

Over the course of this study, the "Renewable Energy"-related keyword categories had the most mentions (960,043), accounting for nearly twice as many mentions as the next closest category – "Non-renewables" (589,282; Figure 3). Of the "Renewable" category, Tweets about solar, bio-fuels/energy and wind had the highest

number of mentions, accounting for 91.8% of all renewable-related occurrences (Figure 3 and Table 4). Of the "Non-renewable" category, discussions about hydraulic fracturing (i.e., "fracking") and nuclear had the highest number of mentions, accounting for 75.3% of all non-renewable-related occurrences. During the period of this study, there were relatively few Twitter discussions about quasi-renewables (e.g., ethanol) accounting for <1% of the total energy-related Twitter discussions tracked in this study.

Except for #ethanol (53%), #fracking (31%) and #naturalgas (31%, hashtagged keywords typically accounted for less than 25% of the overall Tweets related to any particular energy-related group (Table 5). The most heavily used energy-related hashtags in this study were from the non-renewable category, with the #coal (22,025) and #nuclear (17,138) hashtags accounting for more than double the number of any other hashtag category used in this study. Despite the seemingly high use of some hashtags, the highest occurrence of any hashtag in this dataset (#coal) accounted for no more than 2% of all energy-related mentions in this study.
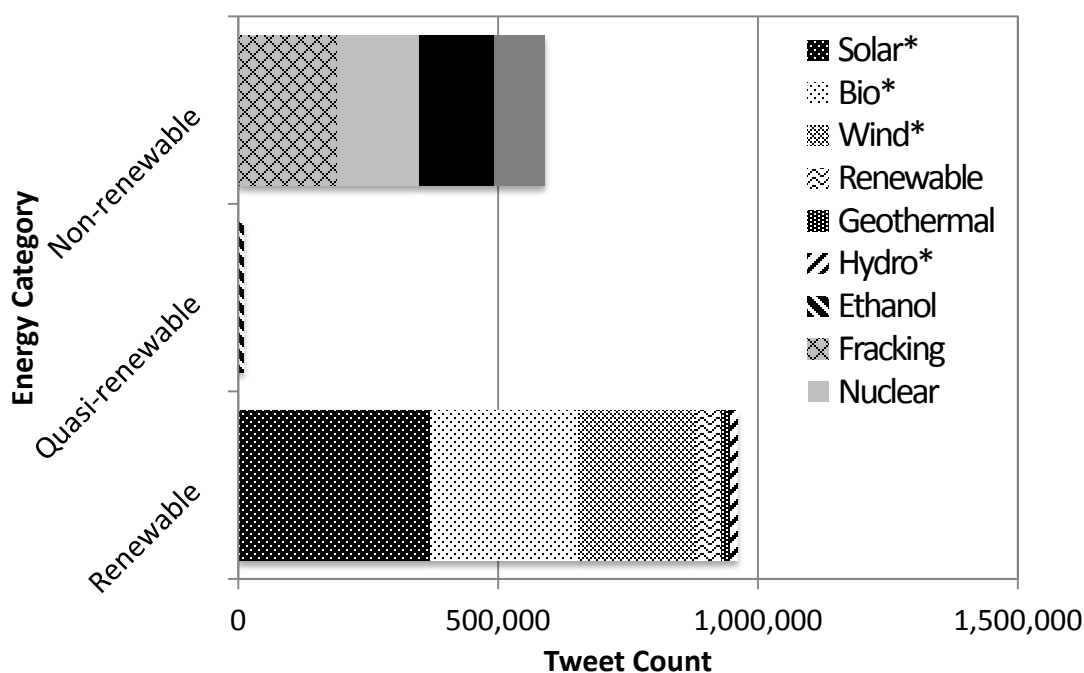
Figure 3. Tweet count, by category, for energy-related keywords used in this study.
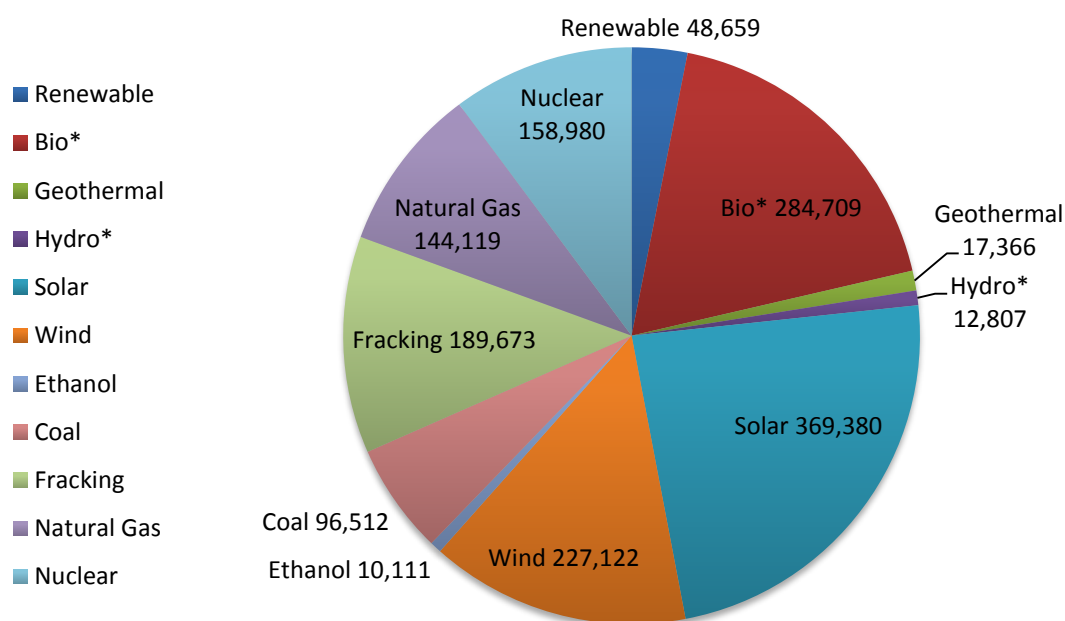
Figure 4. Proportion of Tweets by energy-related keyword category. Tweets originate from a search during six (6), twenty (20) day time-periods from 2008 – 2013. See Table 1 for the list of start and end dates for each time period.

Table 5. Counts of energy-related keywords from a search of Twitter for six, 20-day periods (1/yr) from 2008-2013.

Category	Group	Keywords
Renewables	Bio-energy/fuel	bio* 284,709 #biofuel 4,800 #bioenergy 1,305
	General	renewable* 48,659 #renewableenergy 7,167
	Geothermal	geothermal* 17,366 #geothermal 3,877
	Hydropower	hydro* 12,807 #hydropower 1,202 #hydroelectric 362
	Solar	solar* 369,380 #solarenergy 4,295 #solarpower 1,526 #solarfarm 157
	Wind	wind* 227,122 #windenergy 3,802 #windpower 5,581

Category	Group	Keywords
		#windfarm 1,514
		#windturbine 791
Quasi-renewables	Ethanol	ethanol* 10,111
		#ethanol 5,336
Non-renewables	Coal	coal* 96,512
		#coal 22,025
		#coalenergy 1
		#coalpower 31
		#coalplant 21
		#coalash 383
		#coalmine 101
	Hydraulic Fracturing	fracking* 189,673
		#fracking 58,673
	Natural Gas	natural gas 17,950
		#naturalgas 5,583
	Nuclear	nuclear* 158,980
		#nuclear 17,138
		#nuclearenergy 451
		#nuclearpower 678

Are There Temporal Patterns to the Discussions? (research question 3)

With the exception of "biomass", "solar" and "ethanol", all categories of energy-related discussions on Twitter experienced increases in mentions over every period in this study (Table 6). Twitter mentions about "biomass" increased dramatically from the 2008 through 2011 period, reaching a peak of 97,018 mentions during this study with discussions halving in the following two time periods. Twitter mentions about "solar" also increased substantially during the 2008-2012 period, reaching a peak of 127,408 mentions, then decreasing 40% the following time period to 76,856 mentions in 2013. Twitter mentions of "ethanol" also increased through the 2011 period followed by a 4% decline during the 2012 period, reaching a peak in 2013 with 3,359 mentions. At their peak (2013), Twitter mentions of "ethanol" represented 0.3% of all Tweets during that time period and 1% of all Tweets in all time periods examined.

Six energy-related groups ranked in the top five Tweet counts for each of the six periods analyzed in this study – solar, fracking, wind, biomass, natural gas and nuclear. Over the course of this study, discussions about "solar" ranked as the first or

second most-discussed energy topic in each of the six years being mentioned in 34.8% of all tweets in the dataset, followed by biomass (26.9%), wind (21.4%), fracking (17.9%), nuclear (15%) and natural gas (13.6%). Mentions of fracking, natural gas and coal increased over every period in this study with mentions of fracking the most commonly mentioned energy-related term during the final period of this study. All mentions of keywords in this study totaled 1,559,336 in 1,060,143 Tweets, with an average of 1.5 keywords mentioned per Tweet.

Table 6. Tweet counts (and percent growth), by time frame, of energy-related keyword groups. Each year represents Tweets collected from a randomly generated, 20-day time period, one in each year from 2008-2013. See Table 1 for the list of start and end dates in each year.

	Renewables						Quasi-renewables	Non-renewables			
Year	Bio*	Renewable	Geo-thermal	Hydro	Solar	Wind	Ethanol	Coal	Fracking	Natural Gas	Nuclear
2008	275 (-)	24 (-)	18 (-)	22 (-)	366 (-)	487 (-)	43 (-)	129 (-)	200 (-)	129 (-)	263 (-)
2009	3,780 (1,275)	744 (3,000)	193 (972)	257 (1,068)	7,569 (1,968)	6,101 (1,153)	295 (586)	1,683 (1,205)	875 (338)	1,956 (1,416)	2,129 (710)
2010	92,005 (2,334)	8,115 (991)	3,462 (1,694)	1,452 (465)	67,511 (792)	50,902 (734)	1,397 (374)	11,271 (570)	3,204 (266)	12,263 (527)	23,737 (1,015)
2011	97,018 (5)	10,918 (35)	3,734 (8)	2,378 (64)	89,670 (33)	53,701 (5)	2,556 (83)	17,317 (54)	18,487 (477)	23,161 (89)	41,056 (73)
2012	43,729 (-55)	12,741 (17)	4,072 (9)	4,063 (71)	127,408 (42)	56,380 (5)	2,461 (-4)	24,895 (44)	49,865 (170)	37,651 (63)	45,641 (11)
2013	47,902 (10)	16,117 (26)	5,887 (45)	4,635 (14)	76,856 (-40)	59,551 (6)	3,359 (36)	41,217 (66)	117,041 (135)	68,958 (83)	46,154 (1)
TOTALS*	**284,709**	**48,659**	**17,366**	**12,807**	**369,380**	**227,122**	**10,111**	**96,512**	**189,673**	**144,119**	**158,980**

* Total count of all tweets matching the rule-set = 1,060,143. Total counts of keywords exceeds total number of tweets as multiple keywords may occur in a single tweet.

Figure 5. Tweet volume by year for various energy-related keywords. The Renewable category represents Tweets that contained the word "renewable". Each year represents Tweets collected from a randomly generated, 20-day time period. See Table 1 for the list of start and end dates in each year.

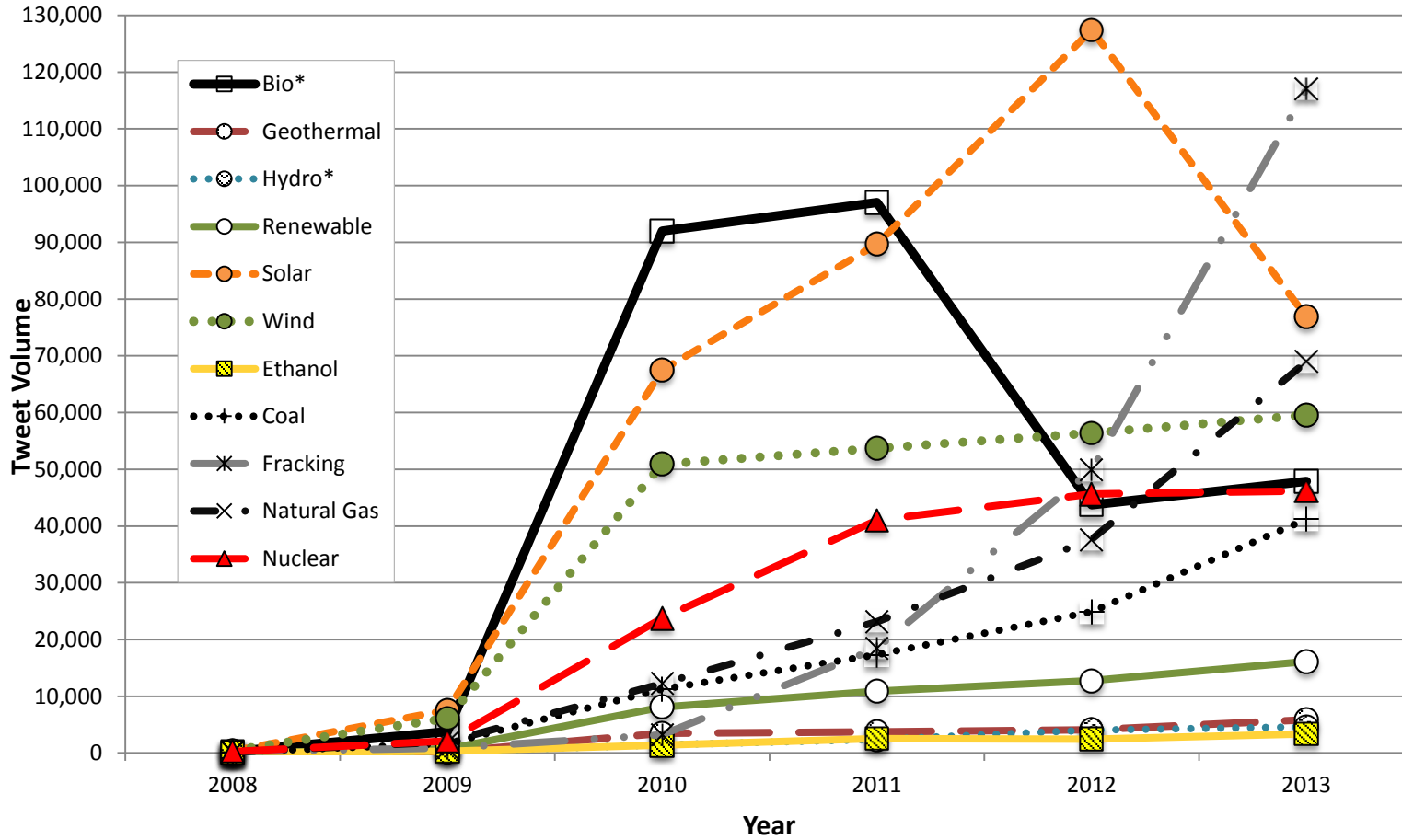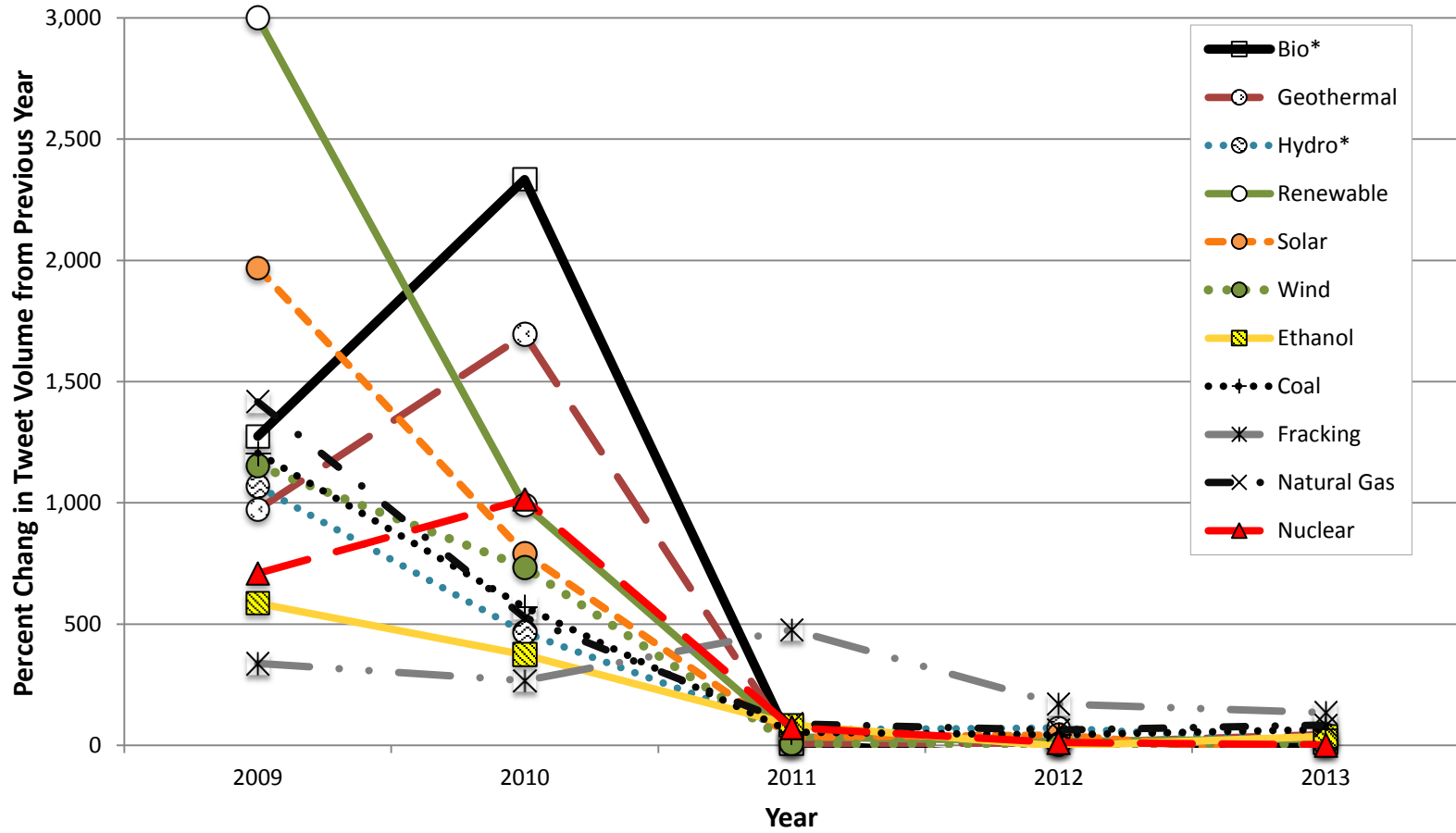**Figure 6. Percent change in Tweet volume from the previous year for various energy-related keywords. The Renewable category represents Tweets that contained the word "renewable". Each year represents Tweets collected from a randomly generated, 20-day time period. See Table 1 for the list of start and end dates in each year.**

Discussion

There were a large and growing number of energy-related discussions occurring on Twitter in the United States (1,060,143 tweets) over the six 20-day periods examined in this study (2008-2013). Over the course of this study, Twitter discussions averaged roughly 8,800 energy-related tweets per day but were increasing throughout the length of the study to a high of nearly 17,700 energy-related tweets per day in the final period of this study (2013). Data for this project did not include retweets – messages originating from one user but passed along unaltered by other users – thus the overall energy-related discussions on Twitter are likely much broader (e.g., geography, impact, number of users reached, etc.) than indicated in this study.

Of the energy-related Twitter discussions that occurred in the United States over the course of this project, the majority were about renewable energy. Of the renewable energy discussions, solar was the most commonly mentioned renewable accounting for nearly 40% (38.5) of all renewable-related discussions and appearing in nearly 35% (34.8) of all tweets in the dataset, followed by bio-energy/fuel (29.7% and 26.9%, respectively) and wind (23.7% and 21.4%, respectively). The predominance of solar and wind discussions was not surprising given the number of RE development projects coming online in recent years. The relative frequency of bio-energy/fuel discussions was surprising given the comparatively light federal research and development funding for it in previous years relative to solar and wind. While the bio-energy/-fuel discussions held 1st and 3rd rankings for the first four periods examined in this study (2008-2011), the bio-energy/fuels mentions in the dataset ranked no higher than 5th during the final two periods (2012-2013). Conversely, there have been a growing number of bioenergy research patent applications in recent years (see McCorkle & Donohue, 2016) which may indicate increasing research and business sector attention on bio-fuels/-energy, yet the Twitter (i.e., public) discussions were flagging compared to other energy-related discussions. There is an opportunity for bio-energy/fuels researchers and industry professionals to expand the bio-energy/fuels discussions on Twitter as a means of raising awareness

about new research developments, patents and advances in the field. It's possible,
however, the challenges to the Renewable Fuel Standards (RFS) leading up to and
during some of the years included in this study, as well as the subsequent change by
EPA to the requirements to blend ethanol into the country's gasoline supply (Ando,
Khanna, & Taheripour, 2010; Gallagher, Shapouri, Price, Schamel, & Brubaker,
2003; Rajagopal, Hochman, & Zilberman, 2011; Schnepf & Yacobucci, 2013), raised
the level of public awareness and interest to a level reflected in discussions in the
public sphere and on Twitter. Twitter discussions about bio-fuels and bio-energy
waned considerably after 2011 with less than half the number of Twitter mentions in
2012 and 2013 compared to the previous years, a decline of 55% from 2011 to 2012.
A Google Trends search for 'Renewable Fuel Standard' indicates high points in
public searches of the Google search engine in 2009 and 2010 with a substantive lull
in searches in 2011 and 2012[13].

Overall, there was substantial growth in the frequency of energy-related
mentions on Twitter but – with the exception of mentions about 'fracking' – the
percent change in number of mentions from beginning to end of the study, including a
dramatic decline from 2010-2011, plateauing from that point onward, perhaps
indicating saturation in use of Twitter. This is relevant to note given the proliferation
of new media communication platforms in recent years. Not all of these platforms
may be of interest or even relevant for decision-making or sense-making purposes.
While it can seem overwhelming deciding which social media platform(s) may
provide the most value to the planning or decision-making process, selecting
platforms that have substantial public use offers the greatest potential benefit given
the amount of information moving through them. Thus, while they may be interesting
to track, researchers and decision-makers likely need take the 'early buy-in' approach
for monitoring public discussions on these platforms unless there's specific and
relevant information originating from them.

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[13] See Google Trends search for Renewable Fuel Standards:
https://www.google.com/trends/explore#q=renewable%20fuel%20standard&geo=US&cmpt=geo&tz=
Etc%2FGMT%2B6

While the majority of energy-related Twitter discussions in the United States over the course of this project were renewable-energy related, discussions about *non-renewables* also made up a sizeable proportion. Of the non-renewable energy discussions, nuclear and natural gas nearly always ranked in the top five of all energy discussions during this study accounting for 26.9% and 24.2% (respectively) of all non-renewable-related discussions and appearing in nearly 15% and 13.6% (respectively) of all tweets in the dataset. Interestingly, discussions about hydraulic fracturing (fracking) appeared very infrequently in the early periods of this study but were the most discussed energy-related topic in the final period, accounting for 42.8% of all non-renewable discussions, 24% of all *energy* related mentions and 33% of all tweets in that time period. Given natural gas and fracking are coupled – natural gas is a primary product from hydraulic fracturing – when those terms were analyzed together, they accounted for 68% of all non-renewable discussions, 38.1% of all energy related mentions and 52.5% of all tweets in that time period, easily ranking 1st among all energy-related discussions. Given the emphasis on the United States' domestic energy policy in recent years and the increasing number of research papers and news items (e.g., the link between fracking and water quality and earthquakes; Vengosh, Jackson, Warner, Darrah, & Kondash, 2014; Vidic, Brantley, Vandenbossche, Yoxtheimer, & Abad, 2013; US Energy Information Administration, 2016; Zeller, Jr., 2015; USGS, 2016; Atkinson et al., 2016), it's not too surprising the number of discussions occurring on Twitter about it have also increased. A Google Trends search for the number of times people searched (using the Google Search engine) for 'fracking' yields similar results with a substantial increase in searches from 2010 through the end of 2013[14]. Similarly, Proulx and colleagues (2014) demonstrated that the timing of people searching for various conservation-related issues (e.g., timing of biological processes, spatial distribution of invasive species, level of public awareness, etc.) on the Google search engine could be used to track

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[14] See Google Trends search for 'fracking': https://www.google.com/trends/explore#date=1/2008+72m&cmpt=q&q=fracking,+natural+gas&geo=US

species invasions, biodiversity, changing climate, disease outbreaks, and other conservation issues. Collectively, these studies illustrate the public's growing awareness about issues, their desire to find out more information about them, and this awareness can be tracked by online activity.

While this project did not track 'oil' and its related keywords in this study – due to issues with accessing Twitter's public API – we did track some keywords that may be used as surrogates or to better understand discussions on social media. Fracking and natural gas are both intricately tied to and part of domestic energy production and consumption. Thus, when examined together, they are able to serve somewhat like a proxy for public discussions about oil. While it may be problematic to rely on opinion, perception, and awareness discussions from natural gas and fracking in place of oil, they are part of the larger public discussions about energy production and therefore serve as window into public viewpoints. Planners, researchers and decision-makers are likely to benefit from understanding what the public is discussing on these large social media platforms and what they are saying in the discussions as these discussions lend real-time insights into 1) what issues are salient to the public, 2) what the public's perceptions and opinions are of those issues, and 3) how those discussions may be driven by or driving issues in the political sphere and in public debate.

Despite the popularity and growing prevalence of hashtag use in social media, hashtag use for energy-related discussions examined in this study indicate mixed popularity in their use accounting for between 2-30% of the overall number of tweets by energy-related category (e.g., renewable, non-renewable, etc.), 9.4% of all energy-related Twitter mentions and 13.8% of all tweets in this study. Hashtags, however, provide value by allowing programs to prioritize anything posted with a particular hashtag, making it similar to a search for related posts. Hashtag use also allows users to follow along with and/or participate in a topical discussion, promote ideas or topics (e.g., #neverTrump, #cleancoal) or target certain areas or people groups (e.g., #BoulderFlood, #energyefficienthome).

From leadership, decision-making, and policy perspectives, one of the more promising features of hashtags is in the tracking of its usage lifecycle (and surrogates – alternative hashtags). One can image hashtag use during particular events, political campaigns or in the legislative process might be of high relevance but have relatively short lifespans (e.g., #SuperBowl50, #neverTrump, #passHR3270, etc.). Additionally, people may be motivated to post messages on social networks for different reasons. In a study of why Twitter users tweeted – in the early stages of Twitter's development – Java and colleagues (2009) found users posted for two primary reasons: to talk about their daily activities or share information. In a study of hashtag use during a major sporting event – the 2012 World Series of Major League Baseball – Blaszka and colleagues (2012) found hashtags were used predominately by laypersons as a way to express "fanship" and to interact with others (i.e., interactivity). In another study of Twitter and hashtag use during a political campaign, Larsson and Moe (2012) found some users used the #val2010 (Swedish for #election2010) to engage in discussions with other users, some used the hashtag primarily to receive and redistribute information, while others used it primarily as a means of identifying with or belonging to an elite, "or at least affiliated with prominent positions in mainstream media or political life in general," bringing up the possibility of whether users falling into this latter category are actually broadening the debate or simply participating in established social circles and norms. Hashtag use can and does deviate from its original/intended use, however, as former Florida Governor Jeb Bush experienced with his #JebCanFixIt campaign (Lapowsky, 2015)[15], a prescient reminder for careful consideration of hashtags during the innovation phase of their development and use.

For items and topics with longer or larger importance in the public sphere (e.g., #solarpower, #dirtycoal, #renewableenergy, etc.), hashtags may offer a way for decision-makers to track the evolution of the public discussions, apply various frameworks and theoretical approaches to test and explain their use (see Chang

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[15] Originally meant to symbolize Jeb Bush's ability to fix problems, the hashtag was hijacked by political satirists and people upset with Jeb and his policies, with references to things like Jeb "fixing" votes and playing political favorites.

[2010] for diffusion of innovation theory and Twitter hashtag use), or track public opinion and sentiment. Tracking public opinion and sentiment has long been regarded as one of the primary ways researchers can leverage data from social networks. Many of the studies tracking public sentiment are related to marketing and brand approval (Chamlertwat, Bhattarakosol, Rungkasiri, & Haruechaiyasak, 2012; Jansen et al., 2009). Yet some studies have indicated the potential uses for decision-makers, political campaigns and the stock market. For example, Bollen and colleagues (2011) found that public mood – as assessed from a large-scale sentiment analysis of the text in tweets – was related to fluctuations in broad social and economic indicators during the same time period and Chamlertwat and colleagues (2012) found tweets to be valuable for assessing customer sentiment toward various aspects of their smartphones (e.g., applications, screen size, camera function, etc.). In a study of public opinion during the 2010 UK election cycle, Anstead and O'Laughlin (2015) found Twitter to be an important, yet underappreciated by traditional opinion pollsters, avenue for expressing public. In another study by Bollen and colleagues (2011), they found consumer confidence and public opinion over a two year study often correlated well with sentiment expressed in contemporaneous Twitter messages. Thus, it is apparent there are a number of potentially valuable uses energy decision- and policy-makers as well as developers may realize when utilizing (and even leveraging) data from Twitter and other social networks.

This study was a *preliminary* dive into energy discussions on Twitter – a proof of concept. As such, this analysis understandably lacks some of the depth researchers looking for a dive deeper may be looking for. What is clear from this study, however, is that there has been a correspondingly rapid increase in public discussions along with the rapid increase in use of social media. Coupled with this rise in popularity of the came a corresponding increase in the number of social media analysis tools available to researchers. Much of the current methodological discourse about analysis of data from social media is in the form of conference papers and proceedings. Yet this 'grey literature' is largely accessible online offering researchers the opportunity for leveraging and expanding the methodological approach in this

paper. Additionally, there is a small body of how-to 'cookbook'-style books that present easy-to-follow 'recipes' for various approaches to analysis of data from social media (Russell, 2011; Kumar et al., 2013; Russell, 2013). Future research looking to use Twitter data (or data from other social media platforms) for policy- or decision-making, would benefit from additional analyses like those outlined in these texts (e.g., assessing sentiment and opinion, geospatial analyses, etc.).

Finally, it is not yet fully clear how public opinion as expressed via social media may differ from opinion expressed in other media or from traditional surveying and polling nor whether opinions expressed on social media translate into actionable behaviors. In results from a series of interviews of traditional pollsters and those engaged in social media (semantic) polling, Anstead and O'Loughlin (2015) found neither method fully captured the nuances nor methodological and theoretical rigor typically associated with sociological or physical science. In an excellent review and report of emerging technologies, Murphy and colleagues (2014) further elucidate issues with linking public opinion from traditional methods and new forms of assessment (e.g., social media). Nonetheless, a growing body of research evidence coupled with acceptance of emerging technologies by professional associations, suggest social communication platforms like Twitter (and other social networking sites) can at the least provide solid supplemental public opinion information that may eventually supplant traditional forms of public opinion polling and surveying (e.g., Anastasio et al., 1999; Anstead & O'Loughlin, 2015; Baum & Potter, 2008; Liu, 2011; Murphy et al., 2014).

Lastly, much has been made about "armchair activism" or "slacktivism" (McCafferty, 2011) – online acts that show support for or against a cause but require minimal personal effort or investment – and whether online opinions and actions translate into actual behaviors *could* translate into meaningful support. Recent studies, however, suggest online advocacy leads to a stronger path and increased likelihood of deeper participant engagement. For example, work from Georgetown University's Center for Social Impact Communication and Ogilvy Public Relations Worldwide group (2011) found that online activities were "supplementing – not replacing –

actions" by online activists. They found online activists were twice as likely to volunteer their time as those who did not post online, four times as likely to contact their political representatives and five times more likely to recruit others to sign petitions suggesting "they (online activists) are more likely to share what they're doing with their networks, and there's real value inherent in these relatively small actions that should not be underestimated." Kristofferson and colleagues (2014) found that initial token displays of support for a cause online subsequently led to "increased and otherwise more meaningful contributions to the cause". The "socially observable nature (public vs. private) of initial token support," however, was a "key moderator that influences when and why token support does or does not lead to meaningful support for the cause" – if the initial token support was private, consumers exhibited greater likelihood of subsequent public, meaningful support or action. More recently, and perhaps most convincingly of the recent slacktivism studies, Barberá and colleagues (2015) found that online engagement via Twitter was key to turning social protests into social movements and the power of slacktivism comes from the large number of users engaged in the online causes. Further, Barberá and colleagues (2015) found that peripheral participants (online) were critical at increasing the impact (reach) of protest messages, illustrating the potentially critical role Twitter may play in activism in the public sphere.

Collectively, these indicate the growing and critical role social media can play in assessing the public's collective pulse and for responding to or helping set the public (and political) agenda.

Limitations

Despite the relative wealth of information on Twitter (and other social media sites), access to this "big data" is not all a panacea. Limitations of this sort of data tend to fall into one (or a combination of) four categories: limitations of the 1) public API, 2) geo-location information, 3) lexicon/language, and 4) context.

While Twitter has made data posted to their site public via their public API, they limit the number of requests and amount of data in any single request within a

certain timeframe. Additionally, users looking for historic data cannot access it via the Twitter API but must purchase it via one of Twitter's official data repositories (we used Gnip). There are several ways to work around the rate limitations, however, to harvest data from Twitter. One solution is to run regularly recurring searches at various intervals and save/store the data to your own database (e.g., MongoDB). For smaller projects (e.g., around 200,000 lines of data), users with little to no programming experience can use Martin Hawkeye's #TAGS[16] utility (2016) that uses Google Sheets as an automated data repository for search results from Twitter. Not only is the program free and relatively easy to set up, it has an excellent graphical user interface with data visualizations and a wealth of how-to documents and videos available online.

One of the original ideas during the initial development phase of project was to ascertain geospatial patterns in the data. After an initial survey of the existing white and grey literature, however, it became apparent there might be substantial problems with acquiring enough data containing place-based information. The number of Twitter users typically posting geolocation information in their tweets is a small proportion of the overall number of tweets being posted. Weidemann and Swift (2013) found that roughly 0.8% of all Twitter users have enabled current physical locations using GPS coordinates or active location monitoring, roughly 2.2% of all tweets contained substantial ambient location information, and on average 3.5% of all tweets were location enable, peaking on a Friday. In this dataset, just 0.3% of tweets (3,337 of 1,060,143) contained the exact location of the tweet (i.e., latitude and longitude). Gnip offers a data location enrichment option with their data services but even with this data enrichment, the geolocation improvement was marginal at 0.4% of tweets (4,054 of 1,060,143). Nonetheless, these numbers fall in line with other studies that have shown proportions of less than 1% up to around 4.5% (e.g., see Crampton et al., 2013, 2013; Fuka et al., 2013; Han, Cook, & Baldwin, 2014; Reips & Garaizar, 2011; Weidemann & Swift, 2013) and demonstrate the need for better locational

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[16] Get a copy of the TAGS utility at https://tags.hawksey.info/

information when using tweets to help inform decision-making, especially when looking to implement localized policies or carry out actions in geographies where there may be a lack of data from social media – often the case in many rural areas. Thus, in cases like this, researchers may need to rely on traditional forms of polling and surveying to assess public opinion.

Regardless of the relatively low percentage of tweets with specific geolocation information embedded in them, the sheer volume of daily messages posted on the service result in a plethora of information potentially useful to decision-makers, even providing insight into geospatial patterns. In a study of "psychological landscapes" in the public sphere, Reips and Garaizar (2011) found it was possible (and repeatable) to "detect differences and changes in voiced (twittered) emotions, cognitions, and behaviors" to events between cities, regions and countries using Twitter. In another study, Li and colleagues (2013) found distinct spatial, temporal and socioeconomic patterns in Twitter and Flickr[17] posts collected nationwide but focused on those originating from California (USA). Yepes and colleagues (2015) found that despite a low occurrence of geotagged tweets, the volume of daily tweets was such that it allowed them to analyze medical information as posted on Twitter, leading them to believe Twitter may be a good locus for surveying public health (also see Sutton, League, Sellnow, & Sellnow, 2015 for an additional study on public health as expressed via Twitter).

Another potential drawback to using Twitter (as well as data from other social networking sites) for assessing public sentiment and opinion are the difficulties associated with users posting content that does not conform to established lexicons. For example, when assessing consumer sentiment, users often use various abbreviations (e.g., #FTW which stands for "For The Win" or #fail for expressing dissatisfaction with something), emoticons and emojis[18], or slang to express their feeling or opinion about a topic. Unless a researcher is familiar with the lingo various

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[17] flickr is a popular online photo-sharing and hosting service. https://www.flickr.com/about
[18] Emoticons and emojis are small digital images or icons used in electronic communications typically used to express ideas or emotions.

audiences and social groups use to express themselves, accurately assessing the public's mood as expressed via these electronic means may be problematic (Kouloumpis, Wilson, & Moore, 2011). Using established and actively curated lexicons (e.g., Harvard Inquirer[19] or SentiWordNet[20]) and emoticon language models, however, allows researchers to more fully engage the public discussions occurring on social networking sites (e.g., see Go, Bhayani, & Huang, 2009 and Pak & Paroubek, 2010b for some examples) while minimizing the need for researchers to keep as keenly abreast of changes to common language (the lingo).

Some studies of data originating from social networks have also noted the potential problem of representation. While Twitter usage is in the hundreds of millions of active worldwide users monthly, PewInternet reports indicate Twitter represents roughly 20% of overall social networking site usage in the United States with distinct age (generational), socio-economic group and geographic (e.g., urban vs. rural) differences that persist over time (Brenner & Smith, 2013; Lenhart et al., 2010). In an excellent review of electoral prediction research using social media, Gayo-Avello (2013) notes several potential problems with use of social network data, including the neglect of addressing demographics which are oft-ignored when making predicting or forecasting political winners and losers. While Mayer-Schönberger and Cukier (2013) suggest there may be less need for "representative" samples as "big data" becomes even more ubiquitous, Boyd (2010) and Boyd and Crawford (2012) offer critical discussions of the potential drawbacks of using big data – including from social networking sites like Twitter – that includes problems with coverage, objectivity and accuracy. Thus, researchers using big data need to give careful thought to interpreting the relevance of the Twitter data – or any data originating from social media – to the broader public sphere and whether discussions occurring on these social networks are representative of the population of interest, of "micro-

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[19] Harvard Inquirer dictionary and lexicon: http://www.wjh.harvard.edu/~inquirer/homecat.htm
[20] SentiWordNet is a publically available lexical resource for opinion mining: http://sentiwordnet.isti.cnr.it/

ethnographies" (see Crampton et al., 2013) and even geographies (social, cultural, physical).

The presence of irrelevant data in datasets is sometimes a problem for researchers utilizing searches from social media. For example, when searching for observations of coyotes in the wildland-urban interface (WUI), a Twitter search for "coyote" may turn up actual coyote observations but is likely to also include results for users posting about being at a coyote dancing club or attending an Arizona Coyotes National Hockey League (NHL) game. In these cases, researchers have to develop mechanisms to filter out irrelevant data returning results that are highly likely to be observations. This process can be laborious and is usually a combination of manual and machine learning techniques but with resulting datasets of high likelihood of relevance (Fuka et al., 2013). Previous research by Fuka and colleagues (2013) found particular word *combinations* were effective in finding actual species observations from Twitter searches (e.g., "saw a" and "hit a" usually preceded an animal name). For this study, there was little concern of irrelevant results in the dataset as the initial rule-set used to query Twitter included both implicit word combinations (e.g., wind AND farm, solar AND energy, nuclear AND plant) and hashtags (e.g., #windenergy, #hydropower, #coalash) – a highly-conservative approach. After examining a random subset of the data for non-relevant results and finding none, we did not include any additional filtering beyond the initial rule-set. Given the high degree of rule-set specificity in this study, however, it is likely this dataset *under*-represents the energy-related discussions occurring on Twitter. To better understand the breadth of energy-related discussions, future research could take a more inclusive approach with their Twitter search criterion, opting for less-restrictive search criteria, then applying post-acquisition data filtering to find tweets of high probability of relevance.

Lastly, this study was not a comprehensive analysis of the range and breadth of possible uses of Twitter data. Rather, this study was meant to serve as a sort of "proof of concept" of the potential uses policy- and decision-makers stand to gain in leveraging Twitter data. For example, this study did not present any lexical,

sentiment, or spatial analysis of the text of tweets. What this study does do, however, is demonstrate that energy discussions are occurring on Twitter with relatively high frequency, thus there is an abundance of publicly available data that is currently being underutilized by energy planners and policy- and decision-makers.

Future Directions

Sentiment and opinion analyses in future energy-related research using data from Twitter and other social networking sites may provide insights about local support or opposition to the siting and development of energy sites. Assessing differences in public attitudes between localities that have experienced development of renewable energy and those that have not may provide policy-makers and developers insights into which areas may be most open to (or appropriate for) new energy developments.

Future research should leverage additional emerging technologies that, when coupled with traditional social media analyses, would provide additional geolocational information. For social media sites that include imagery, Wood and colleagues (2013) demonstrated that Flickr[21] could be used to track nature-based tourism and recreation rates, with additional layers of information that could be traced, such as the tourists' country or place of origin. Twitter users post millions of images every day, some of which are geotagged by the program capturing the initial image. Regardless of the presence of geolocation information, several new programs, including Google's new deep-learning program dubbed PlaNet, can determine with a relatively high degree of accuracy –twice the accuracy of human recognition and geolocation, in fact – where in the world a particular photo was taken, greatly increasing the ability for researchers to determine locational information (Brokaw, 2016; Weyand, Kostrikov, & Philbin, 2016). While the degree of specificity is improving, this additional information could be combined with societal-based behaviors (e.g., consumer choices, immigration travel records, stated and revealed support or opposition of/to policies or political candidates, etc.) to provide a level of

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[21] flickr is a popular online photo-sharing and hosting service. https://www.flickr.com/about

crowd-sourced information to policy- and decision-makers heretofore unimaginable (Bekmamedova, Shanks, & Carlsson, 2014; Chamlertwat et al., 2012; Loomis & Richardson, 2006).

Future research should also examine the relationship between the expression of opinion on social media and actual behaviors (e.g., voting for or against something, mounting an opposition campaign, etc.; stated vs. revealed preference; see the "slacktivism" discussion, above). Zhao and colleagues (2011) found that Twitter users tended to use the platform to spread news from certain categories (e.g., Sci-Tech, World, Business) rather than express their own opinions about those subjects while Blaszka and colleagues (2012) found Twitter users seemed to be wanting to show fanship or engage in conversations. Furthermore, Anastasio and colleagues (1999) note that media sometimes creates or shapes public opinion in powerful ways while Yang and Dehart (2016) note that social media use can sometimes be a predictor of online political participation. Still others find online activism or support for a cause can lead to actionable and deeper engagement (Barberá et al., 2015; Denise Keyes, 2011; Kristofferson et al., 2014). Nonetheless, theoreticians and practitioners alike would benefit from additional research that elucidates the role social media may play in influencing public attitudes and social identity and reflecting public action.

Lastly, given the high number of Twitter posts that are irrelevant to researchers, being able to find relevant posts amidst all the clatter (signal-to-noise) is of utmost importance. O'Connor and colleagues (2010) developed a seemingly reliable methodological approach that demonstrated high correlations between sentiment word frequencies in Twitter messages and large-scale public trends, indicating the possibility for Twitter and other social text streams as supplements for traditional polling. More recently, Fuka and colleagues (2013) demonstrated a simple, yet reliable method for improving the signal-to-noise ratio for finding relevant tweets. Others have demonstrated more automated, machine-learning, methodological approaches to finding relevant information from Twitter (Go et al., 2009; Khan, Atique, & Thakare, 2015; Pennacchiotti & Popescu, 2011). While sifting the

metaphorical wheat from the chafe may seem a daunting task given the volume of Twitter messages being posted daily, researchers can take advantage of a number of recent methodological advances for finding high signal-to-noise ratios.

Policy Implications

Detailed data on human beings is often invaluable to decision- and policy-makers. Understanding public awareness of or opinion about issues can be a costly and time-consuming undertaking (usually by polls and surveys). While use of big data streams like Twitter presents some challenges (e.g., representation, accuracy, privacy, etc.), it also can provide a number of benefits including the near instantaneous pulse of public attitudes at a greatly reduced cost from traditional surveys. Policy-makers and developers may be better able to manage the potential negative impacts of new energy developments by avoiding siting a new facility where there is broad public resistance or placing one where the public is more accepting, potentially limiting legal opposition costs and expensive advertising and education campaigns. Researchers and policy-makers may also better improve services to the public sector by increasing timeliness and precision of delivery of goods to the areas most in need during natural disasters as during the Fukushima-Daiichi nuclear disaster of 2011[22]. Additionally, researchers and policy-makers now have at their disposal a stream of data with tremendous qualitative and quantitative applications.

Alternatively, policy-makers are faced with tough legal and ethical considerations, particularly with respect to privacy (e.g., "informed consent") even though much of what social media users post is in the public domain. The implications for determining which publics get what resources and when is likely to present some transparency challenges for decision-makers. Imagine moving forward with a new energy development project in an area where there was little public opposition to the development – at least as expressed on the social networks – only to realize the area is home to a group (disadvantaged or otherwise) that is not well reflected in the social media discussions. Additionally, because the amount of

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[22] https://en.wikipedia.org/wiki/Fukushima_Daiichi_nuclear_disaster

information coming from these big data streams is so large, most researchers – let alone policy-makers – are unable to fully grasp what to do with all the data, how to use it, where to store it, and how to analyze it, leading to potential delays in accessing useful information from real-time sources. In short, the implications for policy-makers and developers when adopting big data cannot be trivialized nor ignored, yet data from these sources offers tremendous potential to supplement – and perhaps eventually supplant – more traditional methods of public assessment such as surveying and polling.

Conclusion

The explosion in popularity of social networking sites is awakening researchers and policy-makers to the enormous potential of data coming from them. It is apparent big data streams like Twitter may offer unprecedented insights into numerous aspects about the public and that discussions about energy on Twitter are prevalent. Additionally distinct spatial and temporal patterns in the data provide clues as to which discussions the public views as most important (e.g., solar, #fracking, etc.) and which are least (e.g., ethanol). While geolocational information on Twitter is still lacking and there are substantive concerns about how and which data to use, there are a number of improvements and technological enhancements that allow policy-makers, cost-effective, instantaneous, accurate geographic insights into public opinion, behaviors and agenda-setting opportunities like never before. A new journal dedicated to social media and society (Social Media + Society[23]) underscores the growing emphasis these big data streams play in the public sphere. This "proof of concept" study of energy discussions on Twitter indicates the potential value these discussions may have for informing the policy-making and agenda-setting processes. Energy developers and policy-makers would do well to begin embracing the

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[23] Social Media + Society is an open-access, peer-reviewed scholarly journal seeking to "advance the understanding of social media and its impact on societies past, present and future". http://sms.sagepub.com/

increasingly important role these new data streams play. While there are obvious caveats, the opportunities for understanding meaning and sense-making in the public discussion sphere from these big data streams is clear and present – researchers, planners, and decision- and policy-makers have an abundance of underutilized, publically-available data with which they may now assess public awareness, sentiment, perceptions, and acceptability in real-time.

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