Environmental Sociology, 2016
http://dx.doi.org/10.1080/23251042.2016.1220849

Environmental justice in the age of big data: challenging toxic blind spots of voice, speed, and expertise

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(*Received 30 November 2015; accepted 2 August 2016*)

In recent years, grassroots environmental justice activists have increasingly used big data techniques for monitoring, recording, and reporting toxic environmental exposures. Despite the promise of big data for environmental justice, there is a need to address structural barriers to making toxic environmental exposures visible, and to avoid over-relying on new digital methods and techniques as a panacea for problems of voice. The emphasis of real-time analysis in crowdsourced and participatory big data is good at tracking the immediate aftermath of environmental disasters, but it misses slower-burning environmental problems that emerge over time. While big data more generally may have implications for understanding toxic exposure landscapes across different temporal and spatial scales, it is complex, difficult to analyze, and faces significant problems of reliability. There are three key blind spots of the ethos and practice of big data in relation to environmental justice: voice, speed, and expertise. In the context of increasing pressure to embrace new tools and technologies, it is also important to slow down and to reflect on the wider implications of the age of big data.

Keywords: environmental justice; big data; citizen science; slow violence; environmental exposures; environmental health; expertise

Introduction

> 'In the future we may well have scientists at work everywhere, producing facts with the speed that new sophisticated instruments make possible, but the way those facts will be interpreted will mostly confirm the landscape of settled interest.' – Isabelle Stengers, *A Plea for Slow Science*, 2011

Across the online world, there is an increasing sense of urgency to report 'facts' as fast as possible, churning out vast quantities of information in real time. News becomes old almost as soon as it is reported, either circulating for a few hours on Twitter or YouTube, going viral for a few days, or suffering a quick death. Universities, corporations, governments, and think tanks are all talking about Big Data,[1] with its unprecedented scale, speed, and scope. Some are taken in by cyber-utopianism, imagining infinite possibilities of knowledge and connectivity. Others are more skeptical, worried about possible intrusions into their private lives. Many remain undecided but are afraid of being left behind.

Big data is complex and difficult to analyze. The term lacks a clear definition, and it is often used as a catchall to describe numerous types of data. In general, most scholars agree that big data refers to data comprising three v's: volume, velocity, and variety (Laney 2001; Monroe 2011; Uprichard 2013), with debates about further descriptors. Much of the literature focuses on a specific type of big data: data, which is automatically generated, in real-time, through search engines, sensing devices, and financial transactions (Boyd and Crawford 2012; Cukier and Mayer-Schoenberger 2013; Kitchin 2013; Lerman 2013; Monroe 2011). However, there are many other forms of big data, spanning diverse fields from astronomy to genomics, health, traffic, and state surveillance, amongst numerous others. Big data has the potential to be an important knowledge resource, but it also has limitations and risks.

This article offers a conceptual contribution to the question of how big data techniques are impacting environmental justice activism. Having excellent scientific data is important, crucial many would argue, for bolstering environmental justice campaigns. The burden of scientific proof of environmental harm falls on affected communities, not polluters. Indeed, from its very beginning, the environmental justice movement has worked with 'citizen–expert alliances' (Allen 2003) to make credible scientific claims about environmental exposures in their communities. In the age of big data, data scientists will likely become important new expert allies within environmental justice struggles. These alliances are already in the process of formation (Kinchy and Perry 2011; Ottinger 2011). However, the actors and institutions that typically generate big data are also implicated in the political–economic arrangements that produce and reproduce environmental degradation and inequality. To what extent would new citizen–expert alliances be feasible in this context? Are there risks in embracing big data within the repertoire of environmental justice citizen science?

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Before jumping on the big data bandwagon, it is important to consider these questions. This article first examines emerging types, techniques, and uses of big data in relation to environmental justice forms of citizen science. It draws a distinction between two types big data in relation to environmental justice: institutionally generated data (by corporations, states, and other institutions); and citizen-generated (crowdsourced or mined) data. Next, the article discusses three toxic blind spots that are embedded within the production, techniques, and uses of big data: voice, speed, and expertise. These blind spots cut across both types of big data, with different manifestations and implications. The article concludes by suggesting ways of engaging with big data, calling for 'slow science' (Mountz et al. 2015; Stengers 2011; Whatmore 2009) to address the 'slow violence' (Nixon 2011) of environmental injustice.

Environmental justice, citizen science, and big data

The concept of environmental justice emerged in the 1980s in the United States, through a convergence of the anti-toxics and civil rights movements. Environmental justice activists argue that the heaviest toxic burdens of industrial pollution are concentrated in disadvantaged communities, particularly in black, minority ethnic, and low-income areas (Bullard 2005; Bullard and Wright 2009; Taylor 2014). The main aim of the environmental justice movement has been firstly to render structural environmental injustices visible, and secondly to challenge and overcome these injustices. In recent years, the environmental justice movement has become increasingly global, highlighting the disproportionate burden of environmental harm on disadvantaged communities around the world (Laurent 2011; Martinez-Alier et al. 2014; Walker 2012).[2]

The problem of quantifying the health risks of toxic exposure has been a key challenge within the environmental justice movement. Although there are established correlations between environmental exposure to particular chemicals and particular diseases, the levels of exposures, in terms of concentrations, length of time, and how to measure these, are disputed and notoriously difficult to isolate from other environmental factors (Tesh 2000; Vrijheid 2000). This parallels the challenges of proving the chronic yet non-acute effects of sick-building syndrome (Murphy 2006). Many corporations have denied the health risks associated with toxic pollutants emphasizing the uncertainty of science as a strategic use of ignorance (Markowitz and Rosner 2002; Michaels 2008; Proctor and Schiebinger 2008).

In the context of scientific uncertainty and vested corporate interests, many people suffering from acute health problems in toxic polluted areas have taken science into their own hands. For example, residents living in contaminated areas have conducted 'popular epidemiology' (Brown 1997) by doing their own health surveys, monitoring, and research, and by recruiting support from professional epidemiologists. 'Citizen–expert alliances' (Allen 2003) have emerged in many environmental justice campaigns, including alliances between community activists and epidemiologists, as well as toxicologists, geologists, economists, and legal experts. Over the decades, environmental justice activists have managed to succeed in holding some corporations accountable for the costs of clean-up or relocation by demonstrating the links between toxic pollution and human health through a combination of civil rights-based social mobilization and grassroots citizen–expert research (Bullard 2005; Lerner 2010; Ottinger and Cohen 2011; Taylor 2014). However, most environmental justice success stories have only been in worst-case examples of corporate negligence because of the significant scientific and political barriers to proving the health risks of toxic pollution.

Popular epidemiology and citizen–expert alliances within environmental justice campaigns have been described as forms of 'citizen science' (Brown 1997; Kinchy and Perry 2011; Ottinger and Cohen 2011). Citizen science is a broad term that has been used to describe publicly engaged science, across a continuum of science-led and citizen-led science (Bonney et al. 2009; Hampton et al. 2013; Irwin 1995; Newman et al. 2012). One of the most common forms of science-led citizen science, for example, uses citizens as data nodes to report observations of birds, wildlife, astronomy, plants, and weather. This is a very different vision of citizen science than the citizen–expert alliances found within the environment justice movement. Wylie (2015) proposes that 'civic science' could help to distinguish between grassroots-led and professional science-led kinds of citizen science, and also to get away from the language of 'citizens'. Following Wylie (2015), I recognize the limitations of citizen science as a concept, but I nonetheless use this term as a shorthand description for a wide range of citizen–expert alliances, techniques, and strategies in relation to the environmental justice movement.

Environmental justice activists have already adopted many citizen science techniques that could be classified, broadly speaking, as part of the big data phenomenon (Breen et al. 2015; Goodchild 2007; Freifeld et al. 2010; Hastaoglu et al. 2015; Plantin 2015; Ranard et al. 2014). These techniques have primarily included voluntary forms of big data, including citizen sensing (data nodes for monitoring pollution) and crowdsourced data (pollution and health reporting). Other relevant forms of big data analysis for environmental justice include the mining of data (twitter posts about pollution and health) and secondary analysis of existing large data sets, which might be classified as a form of 'small' big data (Gray et al. 2015). These different forms of data have been used for mapping and visualization, to raise public awareness of injustices, and to gather evidence of pollution and exposure, building on longer traditions of citizen science within environmental justice activism.

Despite these developments, environmental justice activists and researchers have yet to widely embrace the language of 'big data'. Thus far, they have tended to frame their use of big data techniques with more specific terms, such as 'crowdsourcing', 'participatory epidemiology', 'mapping mashups', 'Geodata', or 'pollution sensing', depending on the focus of the study. One possible explanation for this lack of explicit engagement with big data terminology is that the big data trend is largely associated with automated data collection by corporations, states, and other institutions. There have been a number of criticisms of big data, including concerns about infringements on privacy, unreliability, lack of representativeness, and elitism and exclusivity in terms of access to the data as well as the production of the data itself (Bollier 2010; boyd and Crawford 2012; Johnson 2014; Lerman 2013). The big data movement is anchored in a growing fascination with the 'quantified self' (Swan 2012), with multiple ways of monitoring, measuring, mapping, and recording the self, the environment, and mobility, through mobile phone applications (health, sleep, diet, etc.), social media, bio-monitoring equipment, scanned objects, digital transactions, and other mediated engagements of the self with technology. Swan (2012) has dubbed this phenomenon 'sensor mania' in her research on the implications of the 'quantified self'. Much of this focus is on real-time information, continual streaming updates, and an obsessive attention to sensing devices, collectively known as the 'Internet of Things'. Thus, the ethos of big data is entangled with the consumerism and individualism that underpins neoliberal capitalism, and sits uncomfortably alongside the concerns of environmental justice activists, rooted in disadvantaged areas without access to the latest sensing devices. For environment justice activists and scholars, the usefulness of big data depends not only on its promises of new techniques and forms of data collection; it also depends on the use of the concept itself. It the language of big data is laden with market-driven, privacy-intruding connotations, perhaps another vocabulary would be more apposite.

One of the biggest problems with the concept of big data is its wide-ranging definition, which represents an unwieldy collective phenomenon that is difficult to break down. There are big differences between state-led, corporate-led, and citizen-led production and uses of big data. There are also key differences in the purposes for which data is produced. Kitchin (2013) usefully distinguishes between three types of big data: directed (through surveillance), automated (through smart phones, transactions, other mobile sensors), and volunteered (through crowdsourcing and other participatory sensing). Ethical objections to the exclusions and injustices of big data tend to focus on particular types of big data: directed and automated, produced by elites, rather than volunteered, by civil society. It is often assumed that volunteered, participatory research is inherently good. However, this assumption is worth questioning. All types of big data, however they are produced, pose their own analytical challenges. The difficulty of analyzing big data is one of the most significant limitations for effective use within environmental justice campaigns.

Emerging examples

Environmental justice activists have demonstrated remarkable skill, resourcefulness, and creativity in adapting to changing contexts. There have been a number of grassroots citizen science initiatives that make use of volunteered, participatory techniques associated with big data (Ottinger and Cohen 2011; Bullard and Wright 2009). For example, the Citizen Science project (www.citizensense.net), a European Research Council-funded project led by Dr Jennifer Gabrys, engaged in a pioneering participatory citizen data science project in 2014 with residents in rural Pennsylvania, developing low-cost digital monitoring technologies to collect air quality data as evidence of pollution from natural gas exploration (Gabrys and Pritchard 2016). The data generated through this project used big data techniques of collection and dissemination, including the development of an online visualization tool using open source software. This initiative drew inspiration and input from citizen science initiatives for volunteer watershed monitoring around fracking areas in Pennsylvania, which have been conducted as a supplement to struggling government agencies since 2008 (Kinchy and Perry 2011).

While there are clear differences between institutionally generated and citizen-generated data, many citizen-led data projects aim to complement and shape existing institutional data. In California and Louisiana, grassroots environmental justice campaigns have designed and used a US Environmental Protection Agency (EPA)-approved 'bucket' for residents to sample air quality to use as evidence of toxic pollution at particular times and locations (Bullard and Wright 2009; Ottinger and Cohen 2011). Similarly, the crowdsourced online IWitness Pollution Map (http://map.labucketbrigade.org) was created by the Louisiana Bucket Brigade and the Gulf Monitoring Consortium as an alternative tool for residents to report what they see, smell, hear, and feel, including the time and their location. These reports are then forwarded to the Louisiana Department of Environmental Quality (LDEQ). The IWitness Pollution Map aims to fill in gaps in the EPA's 'Toxic Release Inventory' (http://www2.epa.gov/toxics-release-inventory-tri-program), an official government agency initiative based on the grassroots work of citizen' scientists, which aggregates data on industrial emissions that have been reported through official channels to the EPA, and is searchable at ZIP code level. However, there are many anomalies in what emissions industries report to the EPA (Sadd et al. 2013). This gap highlights limitations in the degree of complementarity between institutionally generated data and citizen-generated data.

Another potential use of crowdsourced data is to raise the visibility of environmental justice issues through participatory mapping and data visualization techniques. There are several examples around the world of initiatives for mapping, monitoring, and understanding toxic pollution, some using relatively simple visualization tools and others using participatory mapping techniques associated with big data.[3] For example, the crowdsourced Japan Radiation Map by 'SAFECAST', which mapped radiation in post-Fukushima Japan, was an innovative environmental grassroots initiative. This participatory mapping involved amateur 'mapping mashups', in which citizens mapped radiation through drawing on both official and crowdsourced data (Plantin 2015). These maps addressed a lack of official information about levels of radiation across Japan, particularly in the immediate aftermath of the disaster. Another example, Grassroots Mapping, is a project of the Public Laboratory for Open Technology and Science, which was founded in 2010 in New Orleans in the aftermath of the Deepwater Horizon Oil Spill. The Grassroots Mapping project uses 'Do-It-Yourself' remote sensors, located in cameras in balloons and kites, for activists around the world to map local environmental issues (Breen et al. 2015). A pioneering visualization example is the work of Lee Liu (2010), who did a systematic study of 'cancer villages' (where cancer death rates related to pollution are well above the national average) in China in 2010 and identified media and Internet reports of 459 cancer villages. In the same year, journalist Deng Fei published a map of cancer villages and the *China Digital Times* produced an interactive online map of cancer villages.[4]

Other potential uses of big data for understanding environmental exposures are not voluntary: they mine data that was not originally produced for this analytical purpose. In fact, the majority of big data falls into this category (Kitchin 2013). Mei et al. (2014) 'sniffed' social media (Twitter) data about air pollution in China and found correlations between high air pollution readings and high social media activity with key words related to pollution. This technique is particularly useful in areas that do not have official reports about air pollution levels, even though these areas may be less likely to have high or reliable levels of social media activity. Similar methods have been used to track disease epidemics, such as H5N1 influenza outbreaks (Brownstein, Freifeld, and Madoff 2009) and the 2014 outbreak of Ebola in West Africa (Anema et al. 2014; Vayena et al. 2015). However, these methods also have limitations and have been known to fail in their predictions, for example in 2013 when Google vastly overestimated a flu outbreak in the United States (Butler 2013). The method of sniffing or mining data, in real time or retrospectively, has the potential for tracking changes in pollution levels, although it is not very fine-grained and has the capacity for error.

One of the most successful uses of big data for understanding environmental exposures involves the analysis of very 'big' but conventional datasets. Gray et al. (2015) make a useful distinction about types of big data that are also 'small', or more conventional, and how these could be used longitudinally to analyze social and economic change. The works of Conley (2011) and Egeghy et al. (2012) use sophisticated data analysis methods with big yet traditional sets of data to examine toxic exposure landscapes. Conley (2011) uses spatial interaction modeling to provide a more nuanced, 'realistic' estimate of a community's exposure to pollution, combining analysis of four sets of data: lung cancer age-adjusted mortality rates from the years 1990 through 2006 inclusive from the National Cancer Institute's Surveillance Epidemiology and End Results database, the Environmental Protection Agency's (EPA) Toxic Release Inventory releases of carcinogens from 1987 to 1996, covariates associated with lung cancer, and the EPA's Risk-Screening Environmental Indicators model. Egeghy et al. (2012) catalogue available information on chemical toxicity and exposure from widely dispersed public sources extracted into Aggregated Computational Toxicology Resource (ACToR), which combines information for hundreds of thousands of chemicals from >600 public sources. Similarly, Elliott and Frickel (2013) use what might be called 'small' big data to combine: (1) unique longitudinal data containing geospatial and organizational information on more than 2800 hazardous manufacturing sites over 60 years in Portland, Oregon, and (2) historical census and environmental data. Taken together, these forms of data provide interesting urban ecological insights on the accumulation of toxic hazards over time.

The above examples are only some of the possible uses of big data for deepening understandings of toxic exposure and for advancing causes of environmental justice. Notably, all of the above-cited examples stand apart from the main types of big data that are the subject of so much interest and debate: real time, automated, transactional data, primarily produced by corporations and governments. Moreover, many of the more participatory models, such as citizen mapping, nonetheless rely on Google maps and other corporate IT infrastructure to facilitate online participation. For example, Plantin (2015) shows how the release of the Google Maps API in 2005 spurred the growth of participatory mapping mashups, providing technological platforms that enabled users to collect and disseminate information about levels of radiation in Japan, beyond the limitations official national data sources. The Japan Radiation Map example shows that it is not easy to draw a clear line between citizen-produced data and corporate-produced data. The key challenge is about asking the right questions of the data. Who produces data and with what intended purposes? Who benefits from the data? What are potential uses and misuses of data, beyond its intended purposes? Who is included and excluded from the data? What can big data can tell us, empirically, that other forms of data cannot? How scientifically reliable is the data? What are the relative political risks and advantages of using the data? Finally, how could we analyze big data, which is often unstructured, in new ways, for example through triangulation or mining?

Table 1 summarizes some of the key producers, techniques, uses, and structural barriers of big data for environmental justice.[5] The table distinguishes between two kinds of producers: (1) corporations, governments, scientists, and other institutions, and (2) citizen-led scientists and civil society. While the techniques for analysis are largely the same regardless of who produced the data, the key difference between these two kinds of producers are in terms of the main uses of data for environmental justice (real-time

Table 1. Big data and environmental justice (EJ).

Produced by	Types of data	Techniques for analysis by EJ	Uses for EJ	Structural barriers for EJ
States Corporations Scientists Institutions	Transactions Clickstream data (from web and application use) Sensed data (from a variety of sensors in the environment: apps, humans, cameras, equipment); scanned objects (passports, barcodes) Machine-to-machine interactions Surveillance Surveys Official records	*Primarily* Mining Retrospective analysis Longitudinal analysis *With access* Real-time monitoring and measuring Mapping and visualization	Evidence rcorporate activities, pollution levels, epidemiology, health, relating to and site-specific and population-specific reports, including longitudinal analysis of existing historical data	Access (voice) Representativeness (voice) Focus on extreme vs. subtle cases (voice and speed) Limitations of real-time analysis (*premised on access*: speed) Reliance on experts for *access* as well as *analysis* (expertise) Reliability of data (speed; expertise)
Civil society and citizen science	Sensed data (data nodes: balloons, humans, phones) Crowdsourced data (e.g. pollution and health) Social media interactions (twitter posts)	*Primarily* Real-time monitoring and measuring Mapping and visualization Mining *In the future* Retrospective analysis Longitudinal analysis	Real-time data about environmental issues as they unfold Wider-ranging data that can be quickly gathered Alternative modes of mapping and monitoring (beyond conventional tools)	Access (voice) Representativeness (voice) Focus on extreme vs. subtle cases (voice and speed) Limitations of real-time analysis (speed) Reliance on experts for *implementation* and analysis (expertise) Reliability of data (speed; expertise) *Capacity (voice; expertise)*

versus retrospective). Much of the big data produced by corporations, governments, and scientists that would be useful and accessible for environmental justice activists would be secondary data that could be used for retrospective or longitudinal analysis. By contrast, the citizen-produced data would be real-time or close-to-real time data (sensed and crowdsourced data), with relatively good access but limited possibilities for retrospective and longitudinal analysis in the short and medium term. Furthermore, most of the structural barriers for environmental justice are similar regardless of who produced the data, with particular issues around access for using data produced by corporations, states, and scientists, and issues around capacity and implementation for data produced within citizen-led science. Overall, with variations according to different data contexts, the structural barriers can be grouped into three common themes: voice, speed, and expertise. At this critical juncture, with the advancing ethos of big data and the associated 'Internet of Things', there are some key blind spots to consider when thinking about the uses of big data for environmental justice. These blind spots represent some of the key structural barriers to effective use of big data within environmental justice, but they also represent opportunities for future intervention.

Big data and toxic blind spots

Voice

The first blind spot is voice. As Lerman (2013) has persuasively argued, many people are excluded from the kinds of data that we commonly associate with big data: sensed data captured automatically by corporations and states. Reliance on big data as a key technique within environmental citizen science activism emphasizes the global digital divide, as discussed above. Even in an era of increasing mass access to the Internet and mobile telephone technologies, vast populations around the globe have limited effective access. The populations captured through crowdsourced big data are not representative and exclude many people, particularly marginalized and vulnerable groups who are most likely to suffer from environmental risks and exposures.

Nonetheless, some forms of institutionally generated big data, for example on corporate activities, population health, and toxic hazards, would be of great potential interest for environmental justice concerns. Political voice is another key issue for institutionally generated data: who has de facto access to the information, what gets included and excluded from official accounts, and what rights people have with regard to access to information about environmental exposures and health risks. In order to address issue of access, rights, and inclusion, one would first need to know what to look for, and where, which is no simple task given the complexity, scale, and opacity of big data. Thus, issues of voice in relation to institutionally generated data are deeply interconnected with issues of expertise, which will be discussed further in the following.

Voice is also an important blind spot to consider within citizen-generated big data. Cases of environmental exposure are typically only made visible if they are active sites of mobilization, aligned with grassroots movements with some degree of political voice. Crowdsourced data has the capacity to capture problems of pollution, for example in citizen movements against fracking in Pennsylvania (Gabrys and Pritchard 2016). However, the degree of mobilization in cases of environmental injustice does not necessarily correspond with the degree of harm, and in fact there are numerous cases of communities facing extreme harm from environmental exposure yet with little resistance. This is evident in communities with strong ties to industry and jobs, and in communities with high levels of poverty and marginalization (Taylor 2014; Boudia and Jas 2014). In a richly detailed ethnography of Flammable, a contaminated shantytown in Argentina, Auyero and Swistun (2009, 4) describe the community's predicament as 'a story of silent habituation to contamination and of almost complete absence of mass protest against toxic onslaught'.

Beyond questions of effective access, there are issues of representativeness: how well do big data techniques including crowdsourced, participatory mapping, represent different voices within affected communities? What gets left out through these techniques? How long can an environmental justice campaign sustain capacity and momentum to continually self-monitor and report pollution and exposure information? How reliable is this kind of data, and how effectively can it be used as evidence, given the strong burden of scientific proof that falls on communities rather than polluters? Of course, similar questions can be raised in relation to more 'traditional' environmental justice campaigns, such as the analogue health event logs that the Louisiana-based chemist and environmental justice scientist Wilma Subra developed during the 1980s, or the related popular epidemiology efforts that Brown (1997) identified in the case of a leukemia cluster caused by toxic contamination in Woburn, Massachusetts. The use of new technologies, including sensing devices, crowdsourcing applications, and monitoring equipment, could potentially scale up these local grassroots campaigns, relatively cheaply and efficiently. At the same time, new technologies can alienate people who are not able or keen to embrace them. They also introduce further problems of reliability, with the anonymity of online activity.

Finally, the uses of big data depend on the politics of data and evidence, for example the question of whether online visibility (of crowdsourced or mined data) would add to or detract from longer-term environmental justice issues of legal traction and scientific reliability. As previous environmental justice research has shown in numerous cases, this question would depend not so much on the quality of the data itself, but on the mobilizing power of the community (Boudia and Jas 2014; Taylor 2014).

Tackling the question of voice, and the related question of visibility, is central to the environmental justice movement, which aims to render injustices visible. But to render injustices visible is not only a matter of identifying the voices of *who* gets less behind, in terms of political participation and access to technology. It is also about examining the mechanisms of exclusion, focusing on structural questions of how invisibility, and lack of voice, is produced. As boyd and Crawford (2012, 673) argue, there are 'significant questions of truth, control, and power in Big Data studies: researchers have the tools and the access, while social media users as a whole do not'.

Speed

Long before the advent of big data, the environmental exposure cases that have received the greatest attention have been large-scale disasters, such as Bhopal and Chernobyl. Smaller scale exposure cases have gained media attention through fierce political action, such as Love Canal and Woburn in the United States. Disasters erupt, are obsessively mapped and dissected for a brief period, then all but disappear as others emerge on the media horizon. Yet most toxic exposure cases are slow-burning and unspectacular, beyond the scales and frames of analysis of fast-moving media or science. In *Slow Violence and the Environmentalism of the Poor*, Nixon (2011, 2) calls attention to the 'slow violence' of environmental injustice: 'a violence that occurs gradually and out of sight, a violence of delayed destruction that is dispersed across time and space, an attritional violence that is typically not viewed as violence at all'. This idea echoes Sarah Whatmore's (2009, 595–596) call for 'slowing down' collective reasoning in order to make a difference to the framing of environmental problems, and Isabelle Stengers' provocative 'plea for slow science' (2011): that we should reclaim the practice of slow science, taking the time to ask questions and mull over interpretations, rather than churning out fast results.

Much of the hype around big data focuses on its velocity (one of the three v's) and in particular, its capability of generating data in real time. It privileges the speeding up of time and space in the global era, what Harvey (1989) calls 'time-space compression'. Many proponents of big data emphasize the importance of the capacity to act on the present. Having access to fast, low-cost, 'big' citizen-generated data could be very useful for environmental justice campaigns. We have seen emerging examples of this in crowdsourced air quality data monitoring initiatives in the United States around fracking and toxic pollution (Gabrys and Pritchard 2016). The use of big data within environmental justice could potentially expose a greater number of cases of environmental harm around the world, and foster dialogue between different national and regional case studies. Indeed, real time big data has helped with tracking toxic exposures following disasters, such as Deepwater Horizon and Fukushima (Plantin 2015), and disease epidemics such as Ebola in West Africa (Anema et al. 2014; Vayena et al. 2015). But the fallout of disasters and conflicts, while important, is only one part of the picture.

The emphasis on speed and real-time information within crowdsourced and 'sensing' types of big data neglects the wider historical context of toxic pollution and exposure, despite the fact that other forms of big data (analyzed retrospectively, which at the moment only includes institutionally produced data since citizen-produced data is still so new) could potentially address precisely this issue. The emphasis on real-time analysis within the ethos of big data risks entrenching a kind of collective amnesia about the historical legacies of environmental devastation. To miss the slow moving, historical context of environmental pollution is to miss the crux of the problem: Nixon's (2011) provocative concept of 'slow violence' and the 'environmentalism of the poor', which suggests that ordinary, non-spectacular, slow-burning environmental problems of the poor are ignored within the global public view of sensationalism. This echoes Iyengar's (1996) influential analysis of episodic versus thematic framing with media reporting, which found that the majority of news media frames political issues in episodic, individualized, sensationalistic ways, rather than in thematic, contextualized, nuanced ways. This has the effect of shifting dominant attitudes about responsibility for political issues such as poverty and terrorism towards individualized rather than structural accounts.

Another limitation of real-time big data, which links to the next theme, of expertise, is that its credibility rests on the certainty of the phenomenon that it captures. In order to be measurable in real-time, the phenomena must be acute, severe, and traceable in real-time. Otherwise, they would not register. These are most likely to be epidemics, disasters, or other events of seismic proportions. The reality of these events is not in question. However, slow-burning environmental exposures are more uncertain, more controversial, and more difficult to quantify. Real-time data is not sensitized, nor seen to be reliable enough, to offer robust epidemiological data that would hold up in court. For example, in residential areas close to polluting industries or contaminated land, epidemiological claims are very difficult to make, even with more traditional methods of epidemiology.

Despite the emphasis on real-time data collection, institutionally generated big data (and in the longer term, citizen-generated data) can also be useful in longitudinal applications, over time. Big data can be very good (as a source for analysis) at tracking subtle features of a phenomenon. That is one of its key potential benefits and can work well with certain types of data, but the problem is in the complexity and difficulty of such an analysis. One of the potential uses of big data could be to track more subtle changes over time, such as low-level environmental hazards. The longitudinal research examples of toxic exposure landscapes using 'big' yet 'small' data discussed in the previous section (Conley 2011; Egeghy et al. 2012; Elliott and Frickel 2013), suggest possibilities of what kinds of 'big data' could be useful to draw on. The key challenges for engaging with 'big data' would be firstly to identify the right datasets, beyond conventional large datasets, and secondly to develop the expertise for complex analysis, which is no small feat, as a problem at the cutting edge of data science.

Expertise

The third, related blind spot is the problem of expertise. Big data is difficult to analyze and interpret, its validity and credibility are often subject to question, and thus its use could potentially introduce further uncertainty into a field that is already uncertain and contested. Even at the cutting edge of data science, analysts are struggling to figure out how to analyze different forms of big data and to get meaningful results.

Big data has been widely questioned in terms of its reliability. Big data encapsulates a wide range of types of data and techniques of data collection, and thus problems of reliability vary depending on the particular context. For institutionally generated data, there are inherent biases and exclusions in the collection of data, and there are often misalignments or bugs in automatically generated data. Furthermore, experts may know what questions to ask, or what questions could be asked, but they might misinterpret the results if they are not in touch with laypeople about the lived experience of what is happening on the ground. For citizen-generated data, there is the problem of verification of self-reporting for volunteered data, and the problem of achieving credible scientific standards of data collection. Community residents might be able to gather data quickly, but they may not have the equipment or analytical skills to accurately measure and interpret the data.

For decades, the field of science and technology studies has engaged with interrelated science and environmental justice issues, highlighting the inherent politics of science and expertise and offering important resources for critical social science (Frickel et al. 2010; Latour 1993; Ottinger and Cohen 2011). Many scholars have emphasized the importance of lay or local knowledge (Frickel et al. 2010; Corburn 2005; Wynne 1996; Davies and Polese 2015), as either a complement or a challenge to official expert knowledge. The role of experts within environmental justice movements has typically been to lend scientific, legal, and economic legitimacy to residents' claims. Experts have also taken on different roles within social movements, for example in Frickel's (2004) research about chemists whose ethical concerns about the health consequences of genetic mutagens brought about the development of the field of genetic toxicology. New 'citizen–expert alliances' (Allen 2003) involving data scientists could potentially bridge the gap of expertise in big data, but there are some obstacles for realizing this possibility.

The biggest challenge is to find experts who can do big data analysis, which is beyond the technological capacity of most people, including many traditionally schooled computer scientists. Analysis of big data requires the development and application of robust statistical techniques in the context of complex (e.g. high dimensional) or high-volume data. Classical statistical methods often need to be revised or extended in the face of big data questions. This is where machine learning and artificial intelligence become useful techniques and why they are rapidly growing as research areas within computer science. These forms of analysis can begin uncovering features in data that are not evident based on 'standard' analyses, particularly in the context of unstructured data. In other words, the expertise of advanced statistics and mathematics underlying data science is more challenging in the context of big data.

Moreover, the data scientist is a different type of expert than those that environmental justice movement has traditionally been involved with (i.e. epidemiologists, toxicologists, and lawyers). There are vested interests in denying associations (to protect profits, jobs, property markets, or attachment to place or community), which would challenge the science of making such associations. The primary producers of big data are corporate and state organizations that are also responsible for environmental hazards. Thus, there could be significant barriers and risks, both politically and scientifically, to establishing new citizen–expert alliances. Even in citizen-led participatory data science projects, such as post-Fukushima radiation mapping, citizens relied on existing corporate information infrastructures to facilitate their action (Plantin 2015). Most crowdsourced pollution projects aim to complement rather than directly challenge existing institutional data (Gabrys and Pritchard 2016; Breen et al. 2015) In practice, it is difficult to disentangle data, science, and the knowledge politics that are embedded within systems.

Finding data scientists, who would be interested in citizen–expert alliances, and who could ask the right questions, is also a task that would require expertise. Data scientists specialize in a wide range of data science applications, and not all would have interest or expertise in environmental health and exposure data. They are employed in different kinds of institutions and have different kinds of skill sets and job titles. As contrasted with epidemiologists, toxicologists, and environmental lawyers, they are not easily identifiable within or across institutions. Their incentives for participation and alliances might be more difficult to establish, if not aligned explicitly with environmental justice or civil rights concerns. For example, some data scientists might be appealed to more on the basis of ethics of the 'commons', open source communities, and participatory citizen science, as part of hacker culture. Research about the ethical as well as scientific possibilities for alliances would need to be done.

Finally, big data, even if it proved to offer new scientific insights about environmental exposures, could never be a silver bullet. As in most environmental justice campaigns, where the burden of proof rests of communities, it is important for the science to reliable and credible, in order to be useful for citizens to promote change. Kinchy and Perry (2011) argue that volunteer citizen science monitoring, in the context of fracking, can fill knowledge gaps by: providing spatial new information where no data exists; asking different questions and defining problems differently; and deferring future pollution, through scrutiny of industry actions. However, Kinchy and Perry (2011) point to the problem of authority, reliability, and credibility for environmental citizen science, arguing that in the absence of credible evidence, and strong and enforceable penalties, citizen science efforts are unlikely to gain scientific or political traction. Similarly, big data might be useful as a 'context for discovery', as a means to an end, revealing an otherwise unexpected genuine scientific feature that could be further explored using other techniques. However, without strong credibility, or political momentum, it could potentially undermine rather than help environmental justice campaigns. As the American environmental scientist Wilma Subra has argued, some environmental activists get some of their data wrong, and this delegitimizes their cases about environmental exposure in communities:

> If you give out one thing that is wrong, you lose all your credibility, but you have to have that data and it has to be in a form the community can understand and deal with. Then you teach them how to watch the new data as it comes, and then when they see something they call up and say, 'Guess what?' Then we talk about it and we deal with it. But yes, without the data you could have 3,000 people show up at a hearing and say, 'We don't want it,' and it's going to happen. If you have fifteen or twenty people show up at a hearing with substantive comments, you will get a denial and that's just the basis of it. (Interview, 14 December 2013)[6]

Ottinger writes in 'Drowning in Data' (2011) that even if one can achieve pure, pristine, perfect air pollution data humming out of a state-of-the-art air monitoring station, data cannot address the thorny issue of establishing standard benchmarks for a wide range of different chemicals and chemical clusters: where to draw the line at what constitutes a dangerous level of exposure and what is healthy. This example illustrates inequalities in access to good data. As Ottinger explains, the state of the art air monitoring station is not just an ideal, but it exists in real form: in Benecia, California, a middle class community with a strong collective voice, where residents were able to negotiate this monitoring station as a condition for an industrial facility locating near to their community. Indeed, a wide range of scholarship (Taylor 2014; Walker 2012) demonstrates that the places with the strongest oppositional voices do not correspond to the places with the strongest empirical bases for claims of injustice. However, the places with the strongest voices do have greater access to the necessary scientific and legal expertise to bolster their positions. The pursuit of scientific data, for whatever political end, is always limited by structural constraints of inequality. As Boudia and Jas (2014, 16) dishearteningly remind us:

> Providing evidence that meets scientific criteria of damage or potential damage, even serious damage, has often not been enough to obtain the compensation, remediation, or prevention demanded by activist movements or victims' organizations.

Conclusion

The environmental justice movement, with its long tradition of innovative citizen–expert alliances, has started to engage with new big data techniques, tools, and technologies. This is an important task, and it offers possibilities for new citizen–expert alliances to advance new lines of inquiry and research into environmental exposures. However, there are three blind spots of big data in relation to environmental justice – voice, speed, and expertise – that present structural barriers, as well as opportunities, for intervention.

As a counterpoint to the hype about the velocity, volume, and variety of big data, I propose the idea of 'slowing' our approach to the big data. The questions to ask of data, about the reliability, usefulness, advantages, and risks of data, both scientifically and politically, are the most important consideration, and these take time to mull over. This echoes Stengers' (2011) plea for slow science, Whatmore's (2009), call for the 'slowing down' of reasoning, and Mountz et al.'s (2015) call for slow scholarship. It also relates to Nixon's (2011) focus on attending to 'slow violence'. Slowing would entail a shift of analytical focus, emphasizing a greater attentiveness to questions of visibility and voice, looking not only at the loudest voices or the problem of the digital divide, but more structurally at the mechanisms of exclusion. It would also involve looking at slower, and less acute, time scales of environmental hazards, focusing not only on cases of crisis but also on slower-burning issues, that are more difficult to measure, whether with conventional methods of science, or with new techniques of big data. Slowing would involve taking pause before embracing big data, examining its vested interests, loaded associations, and limitations, both politically and scientifically. Slowing would involve slowing down analysis, reasoning, and science, as Whatmore (2009) and Stengers (2011) have suggested, to think more critically and reflexively about the framing of complex environmental challenges. Slowing would not exclude attention to real-time data, to the immediate aftermath of environmental disasters, but it would look at these with more careful consideration of the longer-term implications. This relates to Back's (2007) call in *The Art of Listening* for taking time to mull over sociological reflections and analysis, and to Choy's (2011) similar plea for considered ethnographic analysis in *Ecologies of Comparison*. This does not mean that environmental justice should not engage with techniques that are associated with 'big data'. Indeed, the fact that environmental justice activists have not explicitly adopted this terminology already suggests a cautious and considered approach.

The focus on science with high, almost impossible standards of proof is part of the legal and political–economic landscape of environmental justice. As Morello-Frosch, Brown, and Zavestoski 2011, 4) suggest:

> The insistence of 'better' science in decision making often reinforces dominant political and socioeconomic systems by slowing down policy making, precluding precautionary action, and ensuring regulatory paralysis through (over) analysis.

There could be a risk, the authors argue, of slowing down policy making through insisting on better science. In the age of big data and real-time information, there is constantly a fear of being left behind, of the costs of missing a beat. To be sure, it is important to remain attentive, and to act rather than delay in facing urgent and challenging issues. However, if one acts with haste, in a rush, errors are easily made, and thus it takes even longer to make headway. Importantly, slowing our approach would also involve considering other forms of knowledge and expertise, other than science, to include legal, economic, and lay forms of expertise. Many questions of environmental justice, such as political and moral questions, are not appropriate to frame in scientific terms (Morello-Frosch, Brown, and Zavestoski 2011). Ironically, by slowing our approach, we could potentially give new momentum to policy making, overcoming regulatory paralysis. Although getting better data is important for environmental justice, it is not necessarily what changes social worlds – political action is what changes things.

If the task of new techniques of environmental justice is to render new injustices (and voices) visible, then following a fast-paced approach to big data risks reproducing, or even exacerbating, patterns of invisibility and exclusion. The challenge of making environmental exposures visible is not only about making more voices heard, although clearly this is an important and integral part of the struggle. It is also about questioning patterns of how, why, and what voices can be heard. This analysis cautions against taking on big data as a panacea for problems of environmental expertise. There is a risk of using techniques that have limited claims to reliability or representativeness, and which are embedded in uneven power relations of expertise. Moreover, more data does not necessarily equal social change. Political action is required to bring about change in exposure politics.

Acknowledgements

I would like to thank the editors of this special issue, Kelly Joyce and Laura Senier, and to the anonymous reviewers for their useful comments. I would also like to thank Thom Davies, Cynthia Wang, and Gurminder Bhambra for their feedback on earlier drafts.

Disclosure statement

No potential conflict of interest was reported by the author.

Funding

This work was supported by the European Research Council [grant number 639583].

Notes

1. I follow common usage and treat Big Data as singular, recognizing that the word ‘data’ is actually plural. I only capitalize Big Data on first use.
2. Despite these trends, environmental justice, both as a concept and a practice, remains dominated by American scholars and activists (Reed and George 2011). Furthermore, global grassroots environmental justice organizations do not necessarily use the language environmental justice, framing their struggles around different concepts and strategies, depending on contexts, such as ‘environmentalism of the poor’, ‘popular epidemiology’, ‘ecological debt’, ‘the defense of the commons’, ‘ecofeminism’, and ‘food sovereignty’, amongst others (Martinez-Alier et al. 2014).
3. A pioneering global example is the initiative ejolt.org, a website that draws together scholars and activists from around the world and produces a collective, comparative world atlas of environmental justice issues, across a range of issues including exposures to chemicals, to nuclear radiation, to landfills, industrial facilities, and spills. The atlas maps sites around the world where there have been active environmental justice campaigns. This is an example of how web-based visualization methods can be used to help to map, monitor, and understand global environmental justice issues. Importantly, it draws attention to different case studies across national, regional, and local contexts, and across different types of environmental problem, as a common resource for making comparisons and learning from other examples. For examples of different online pollution maps, see: Ghana http://www.pureearth.org/project/mapping-project-ghana/, India http://cdf.ifmr.ac.in/?project=online-pollution-map-for-india, Russia http://blogs.dickinson.edu/russenviro/tag/pollution/, and globally http://www.pureearth.org/projects/toxic-sites-identification-program-tsip/.
4. See: http://chinadigitaltimes.net/2009/05/a-map-of-chinas-cancer-villages/. For further information about cancer villages in China, see the 2011 documentary film ‘Warriors of Quigang’ co-produced by *Yale Environment 360* by filmmakers Ruby Yang and Thomas Lennon, part of a trilogy of short films set in China, the first of which, ‘The Blood of Yingzhou District,’ won the 2006 Academy Award for Best Documentary Short.
5. This table does not aim to represent a comprehensive taxonomy, but a summary of this review of emerging big data techniques with relevance for environmental justice activism.
6. This interview was conducted as part of some pilot research on environmental justice activism in Louisiana, which has been discussed in Mah, A. 2014. *Port Cities and Global Legacies: Urban Identity, Waterfront Work, and Radicalism*. Basingstoke: Palgrave Macmillan.

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