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Cell Phones as an Anticipatory Technology: Behind the Hype of Big Data for Ebola Detection and Containment

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Content

Abstract

This paper analyzes ethnographic and cartographic evidence from Sierra Leone that show the limitations of big data relative to the containment of Ebola. In this paper, big data is both a technology itself and also a foundation and catalyst for other technologies. Early in 2014, big data's technologies of data collection as well as its algorithmic functions were heralded by US media for detecting the West African Ebola outbreak. Later in the epidemic, big data—specifically, data from millions of cell phones—was further hyped as able to help stop the infectious and often fatal disease by tracking the mobility and migrations of contagious people. Big data's failures in this case are directly linked to what big data epidemiologists did not understand about the social life and thing-self issues of cell phones in Sierra Leone. In addition to identifying ethical concerns about human contagion tracking, the paper shows that cell phones did not serve well as beacons of contagion because they do not operate as inalienable indicators of individual property and identity in Sierra Leone.

Cell Phones as an Anticipatory Technology: Behind the Hype of Big Data for Ebola Detection and Containment

Anthropologists have long noted how conceptions of the self vary from place to place (e.g., Hallowell 1955; Rosaldo 1980; Stoller 1999; Piot 1999). I raise this disciplinary expertise as a backdrop to analysis of the hype and push at the beginning of the 2014–2016 West African Ebola Virus Disease epidemic to use big data to detect and contain the often-fatal disease. The problem of self in the phone-big data-Ebola conjunction was in the way Ivy League computational epidemiologists assumed that, like North Americans, West Africans and their cell phones would be synonymous. Ask a North American what a cell phone is and the answer may well be, “My life!” In Sierra Leone, there is a far looser link between cell phone ownership and the self. It is more accurate to say that most Sierra Leoneans possess cell phones, often temporarily, sometimes only fleetingly. Cell phones are loaned, traded, and passed around among family and friends, like clothes, bicycles, and books. Cell phones are fluid, exchangeable, relational objects. A 17-year-old high school student living in a neighborhood in Freetown, Sierra Leone’s capital city, told me he’d had six cell phones in five years: one had been sent from the UK by his aunt; two had been “stolen,” but he knew who had them; and one he gave to a friend who “needed it more.” At the time of our interview, he had three cell phones and numerous SIM cards. He was not unusual for a teenage secondary school student living in Freetown. Thus, as beacons of individual identity and precise whereabouts, cell phones do not work well in Sierra Leone; people cannot be easily tracked by them because a cell phone and a person are not as one.

In 2014, there were people in the global public health community who were theorizing that big data from international newsfeeds (e.g., Figure 1) could first detect the spread of disease, and that algorithms using data from cell phones could also stop its spread (e.g., Figure 2). For the latter, they counted on the ‘pings’ cell phones send and receive from cellular towers to leave a trail (footprint), and thus create digital visuals for tracking people contagious with Ebola. Cell phones would serve, according to this logic, as beacons of contagion, signalling the mobility

Figure 1
Associated Press (2014a) August 10

Figure 2
Richards (2014) October 1

patterns of people with the disease. As this paper shows, the two claims are flawed; the first because an algorithm cannot detect a disease outbreak without humans initially reporting it, and the second because Harvard-based computer scientists did not know that cell phones do not operate 'as people' the world over.

Many Sierra Leoneans have more than one cell phone, often on several different phone networks, because "out-of-network calls cost too much." "You don't have to be rich to have lots of phones," I heard. Cheap cell phones are sold in the central downtown Freetown market. Usman, one of about 10 young men in Freetown's Aberdeen neighborhood who regularly traded information and expertise about the latest apps and cheap downloads, was a discerning consumer when it came to buying cell phones from the market. He showed me how to check a phone's serial number (*#06#) to tell if it was a genuine product. Start with the phone's weight, he said. "When you hold it […] well, the light ones we call 'duplicates' and they have nothing inside […] you want to see when you open it, [that] it is made in Korea or Finland." Be sure to write down your serial number, Usman coached. That way, even if I lost my phone, he said, "you can still lock it so the thief cannot use it." He had an app for that.

In the Freetown neighborhood where I lived in 2014 for several months, every man, most women, and many teenagers I met had cell phones. Most professionals had more than one. An HIV / AIDS counselor, Fatmata, had four cell phones, one for each of the primary phone networks operating in Freetown, because calling outside of network was more expensive than having four separate cell phones. Network access could be accomplished by having multiple SIM cards rather than so many cell phones. But the counselor told me she liked separating the networks by cell phone to help her manage her various roles — as a health care worker, as a mother and friend, and as a small business owner. The networks did not fall neatly along these groupings, she admitted, but "*aw foh du*" ("It doesn't matter.") Another reason to have many cell phones, Fatmata pointed out, is how much time it takes to charge a battery. Electricity in Freetown is irregular, so one or two cell phones charge while she uses the other ones. Few people had cell phone plans; buying *topup* (credit) from a general store kiosk was preferred, but that can be a hit or miss proposition, especially when travelling. There are many reasons to have more than one cell phone. And this easily observable fact is only the beginning of explaining why cell phones do not serve as personalized beacons of an individual, and why using cell phones to contain Ebola could not work. As I show below, the model used for Ebola containment — the public health model that links cell phones with human mobility and malaria — was a flawed exemplar, and an example of a travelling model (see also Behrends, Park and Rottenburg 2014) that did not work.

Big data was championed by computational epidemiologists and others as able to track people contagious with Ebola via Call Detail Record (CDR). These are the automated call and text messaging data passively collected at cell towers; they are the big data resource for tracking any single cell phone. CDR data is stored on the thumbnail-sized plastic and heavy metal chip card inside a cell phone, what is called the subscriber identification module (SIM) card. The CDR data collected by cell phone servers is stored in SIM cards. Big data epidemiologists presume that CDR can show where people go by following a cell phone through space and time, from cell tower to cell tower, ping to ping. In theory at least, CDR enables disease ecology and cell phone triangulation information to be all rolled into one new public health "disease disaster management" strategy (e.g., Cinnamon, Jones and Adger 2016).

At this intersection of global public health and big data, I take up the tacit assumptions of big data potentiality to explore how big data in the world *works* as an anticipatory technology. In this paper, big data is both a technology itself and a foundation and catalyst for other technologies.

At its base, it is a counting and measuring technology. The larger field of big data goes further still: Big data analysis, as a field of activity, focuses on the computational ability to analyze extremely large data sets, such as those collected from newsfeeds or millions of people making cell phone calls. It involves the work of multidisciplinary teams, including people trained in computer science, mathematics, and, as in this case, for example, computational epidemiologists. This paper is about that particular zone of multidisciplinary and multisectoral engagement in Sierra Leone in 2014 where, in a race against time, big data, global public health, the social lives of cell phones, and the geographies of Ebola confounded big data disease detection and containment advocates who were harping an advantage that did not exist.

This paper is based on research from a 2013–2014 ethnographic research project on Sierra Leonean global health[1] data use and applications, which was funded by the Social Sciences and Humanities Research Council of Canada. In 2014, I worked with a team of three graduate students, one of whom is Sierra Leonean. Team members conducted participant observation fieldwork for three months or more, living in the capital city of Sierra Leone, Freetown, with several trips to smaller cities and towns; all team members spoke Krio, the local lingua franca. Over 70 one-on-one interviews were conducted, and have been transcribed and coded. Data for this particular paper emerged while conducting research in Sierra Leone, and was secondary to the primary purpose of the study, which was to examine how health data travel across humanitarian and commercial sectors. The study was approved by the Simon Fraser University Research Ethics Board, study number 2012s0643.

The paper begins with an introduction to the 2014–2016 Ebola Virus Disease epidemic and to the way that big data is emblematic—as a collected, compiled and analyzed thing—of anticipatory technologies of our time. I then turn to a big data prototype that modeled malaria parasite migration using cell phone data, and point out the ways the model did not translate well to Ebola. I follow-up with an explanation of how cell phones 'track' people. This background informs the sections on how early Ebola detection and containment via big data did not deliver as promised. The paper concludes with a call to use anthropological insights for prudent and appropriate epidemic response, and broaden public recognition of our cultural domain expertise to include our insights and analysis about technology use.

Ebola Hits Post-Conflict Sierra Leone

The first West African case of Ebola occurred in Guéckédou district, Guinea, in December 2013 (Baize et al. 2014), an area bordering Liberia and known as the Parrot's Beak, for its shape and the way it dips into the far eastern part of Sierra Leone near Kailahun (see Figure 3). By July 2016, when Ebola was finally contained in the three countries most impacted by the disease—Guinea, Liberia, and Sierra Leone—a total of 28,616 people had had Ebola, 11,310 of whom had died. Sierra Leone, a country of 6 million people, had almost half the cases in the region, 14,122, and about a third of the deaths, 3,955 (World Health Organization 2016a).

1 In this paper, 'global health' is taken up as a global social field, inclusive of nation-states at all levels of income. For additional considerations of what constitutes the social field of global health, see Fassin (2012) and Pigg (2013).

The same region had been pummeled during decade-long wars in Liberia and Sierra Leone. “We don’t have a ‘wild west’, we have a ‘wild east,’” a primary school teacher told me, alluding to that area. I had lived in eastern province for two years prior to the war, and when I had visited this area again in 2008, the region was drastically changed, war-torn. It retained the highest number of weapons remaining after the war, despite a nation-wide United Nations disarmament project. Just before Ebola hit, the region was not actively inundated by violence, but there were more isolated events annually involving firearms there than in other parts of the country. People talked about the region as loosely organized politically and beyond Freetown governance. In this region where Sierra Leone, Liberia, and Guinea border each other, an area that had been divvied up by colonial powers without regard for extant family, village, and city life, there is a long history of cross-border traffic, family ties, and market exchange.[2]

The topography of the far eastern province is a mix of savanna and tropical rainforest, including primary forest. The Golo Forests run along the border between Sierra Leone and Liberia. There are many people living in this area; the corridor from Koidu to Kailahun is home to over 100,000 people. In terms of infrastructure, this area was the most devastated by the wars in Sierra Leone and Liberia. Economically, important strides have been made in Sierra Leone in the decade and a half after the war ended; nevertheless, in 2014 the far eastern region was the least recovered area.

Promises, Promises: Anticipating Health with Big Data

Big data for health has come with big promises: stopping Ebola (Talbot 2014; CNBC 2014; Caulderwood 2014); predicting diabetes (Cichosz et al. 2016); revolutionizing healthcare (Groves et al. 2013); even making the scientific method obsolete (Anderson 2008). But human health is a particularly precarious social sector for big data promises because people are so vulnerable. Big data problem-solving capacities can appear infinite, evoking a pleasing sense of what Taussig, Hoeyer and Helmreich (2013: 3) have called the affective potentiality “to imagine particular human futures, and to warn against undesirable outcomes.” Big data has proved advantageous and certainly profitable in some societal sectors (Mayer-Schönberger and Cukier 2013), but questions remain about the degree to which health is one of those sectors. Some public health professionals (Anema et al. 2014; Salathé et al. 2012) laud the potential of big data; others are more circumspect (e. g., McDonald 2016; Letouzé and Vinck 2015). By big data, I mean those overly large data sets from multiple sources that require computational software to make some kind of meaning. For the purposes of this paper, I distinguish between big data in global public health, which tends to process large heterogeneous data sets, and big data in genomic science, which processes volumes of more homogenous genomic sequencing data. This paper is about the former.

Data consists of ‘digital footprints’ (also known as pings, cookies, pixel tags, and Web beacons). Generally speaking, people’s digital footprints leave a time-coded trail from their cell phone via pings from cell phone towers they pass on foot or public transportation, when driving

2 See Silberfein and Conteh 2006 for an overview of boundary issues in this region.

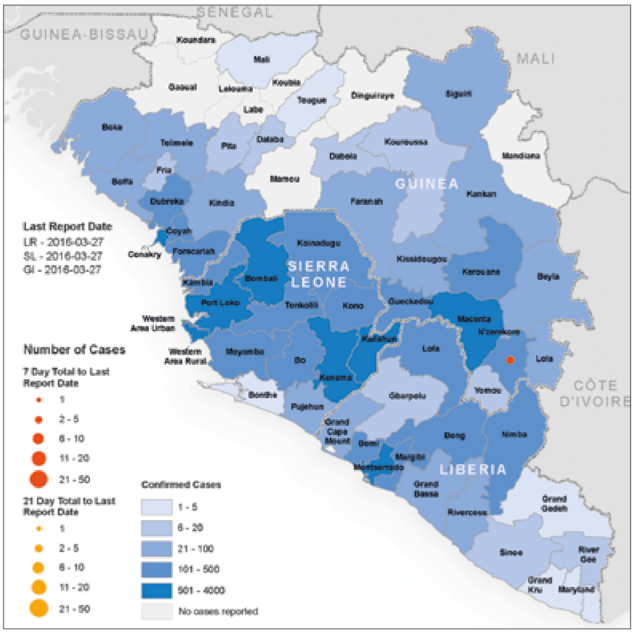

Figure 3

Total confirmed cases in Guinea, Liberia, and Sierra Leone, as of March 27, 2016 (World Health Organization 2016b). Ebola first emerged in Gueckedou, Guinea, at about the center of the map.

http://apps.who.int/ebola/current-situation/ebola-situation-report-30-march-2016

a car with a Global Positioning System (GPS), when paying with a credit card, and from internet searches. Digital footprints are left when people use the internet, most landline and cell phones, computers, digital televisions. In the health sector, big data collection is from a grab-bag of sites; data is collected from electronic health records, physicians' clinical notes, digital diagnostic images, lab tests, insurance claims, reimbursement regimes, credit systems, and customer relations calls. Unstructured big data is of little practical use; it must be analyzed in relation to a question or need. The aim is to have a humungous cache of data ready at hand to test any future hypothesis. In practical terms, the data collected is raw, that is, not yet aggregated, organized, or analyzed. This is the opposite of the scientific method which establishes a research question first and collects data second. "[D]imensionally agnostic statistics…forces us to view data mathematically first and establish a context for it later," Anderson (2008: 1) has argued. Big data analysts assume that "n = all" (Mayer-Schönberger and Cukier 2013) and that having so much data will cancel out problematic contextual and situational variabilities.

In the case of big data applications to Ebola, there was a similar exposition: collect CDR cell phone data first; decide what questions to ask of the data; ask the questions and see what newly organized data patterns come back after computer computation; and assume that N (the subject size) equals everyone. "N = all", though, is shorthand for the conceit that everyone is taken into account, or so Mayer-Schönberger and Cukier (2013) assert. Similarly, in Sierra Leone, I heard expatriate international development workers working with large data sets talking about how "the big numbers take care of the independent variables," including language and literacy differences. Sampling biases in big data are presumed non-existent because the sample is assumed to be representative since it includes entire populations; there can be no bias if everyone is counted, the logic goes. This makes the Sierra Leone case ironic since the number of phones and SIM cards relative to the population of Sierra Leone could be well over 100% but not because each member of the population has a cell phone. Rather, many people have more than one cell phone. CDR data for the same person could be counted far more often than once. Not only were there 'phone-as-self' problems in Ebola mobility tracking and counting models, as I have already described, but there were the more basic pedestrian cell phone coverage problems as well as I describe below.

Traveling Models of Disease Management

Before Ebola, cell phone data was championed for finding links between human migration and malaria parasite travel. In this section, I put aside the faulty first principle that 'cell phones are people' to explore how computational epidemiologists have processed cell phone data for malaria. The application of that mobility model had flaws particular to its unsuitability for Ebola detection, breathing life into Behrends, Park and Rottenburg's observation that embodied knowledge does not travel *with* models (my emphasis), "but needs to be re-invented at the new sites through experimental practice and experience" (2014: 2).

The mobility model itself looks like this: In a 2012 Harvard study, cell phone data from nearly 15 million Kenyans were analyzed to show that human travel patterns contribute to the spread of malaria (Wesolowski et al. 2012). In the 2012 study, Carolyn Buckee and her colleagues found that labor migration contributed to malaria disease concentration; humans living in East Africa carry malarial parasites in their blood when they travel. This is not a new finding; that the finding has been confirmed with cell phone data, however, is new, and the research methodology was distinguished as a "breakthrough technology of 2013" (Talbot 2013).

Relative to Ebola, though, applications of this Harvard study are fundamentally flawed in three significant ways: one, the researchers *estimated* the daily locations in 2008 and 2009 of 14,816,521 Kenyan cell phone subscribers, those traveling from home to their worksite (Wesolowski et al. 2012: 268). Two, the study was based on 2009 malaria prevalence[3] *estimates* for those subscribers (Wesolowski et al. 2012: 268), not actual cases of malaria. Estimated location and prevalence—rather than specific people and incidence—inform the Harvard malaria mobility study. But estimations are not good enough to contain Ebola. The approximate-able ecologies of the malaria findings in the Harvard study model do not translate to Ebola containment. With Ebola, the contact tracing that brought an end to Ebola relies on the *exact* person in an *exact* location with the disease. Contact tracing is the door-to-door public health process to identify and then diagnose people who potentially came in contact with someone already sick with a contagious disease. In Sierra Leone during the Ebola epidemic, it was called ´Operation Os-to-Os´ (Operation House-to-House).

Lastly, three, the Harvard malaria model study is flawed because Ebola and malaria are fundamentally different diseases with regard to disease vectors (human to human rather than mosquito to human, respectively) and pathogens (virus in human body versus parasite in humans and insects, respectively). Most people who get malaria do not die, but more than half who contract Ebola do die. Nevertheless, this approximating malaria model became the basis for Harvard computational epidemiologists asserting that "human mobility models for West Africa … support ongoing efforts to control the ebola [sic] outbreak" (Wesolowski et al. 2014b).

3 In public health parlance, prevalence is the proportion of a population that has a disease over a given period. Prevalence and incidence are two widely used global public health metrics that aim to enumerate the concentration of a disease within human populations. Incidence refers to the number of new cases of a disease occurring during a given period.

Location, Location, Location

How does big data estimate cell phone subscriber location? Broadly speaking, there are two ways, global navigation satalite systems (GNSS), of which global positioning systems (GPS) is one[4] and cell phone tower 'pinging', both involving triangulation. A GPS chip in cell phones sends and receives intermittent signals from a constellation of about 30 satellites orbiting earth, owned and operated by the US Department of Defense (USDOD). Cell phone companies buy or rent software to operate their cell phone services using USDOD satellites. Three to four GPS satellites are typically involved in finding a cell phone, calculating location based on the length of time cell phone signals (pings) take to travel to the satellites. A second way to detect cell phone locations are via cell phone towers. Cell phones send and receive pings indicating where their users go. Pings are the time-coded signals sent, received, and registered each time a cell phone passes a telecommunications tower, making it possible to track a cell phone's movement and travel. See Figures 4 and 5.

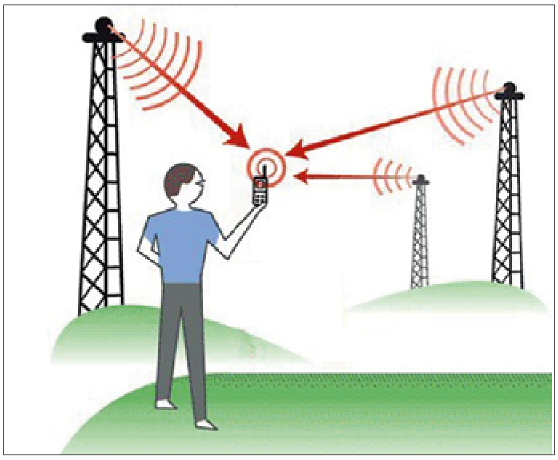

Figure 4
www.quora.com/Can-my-mobile-carrier-track-the-last-location-of-my-phone, accessed April 1, 2017.

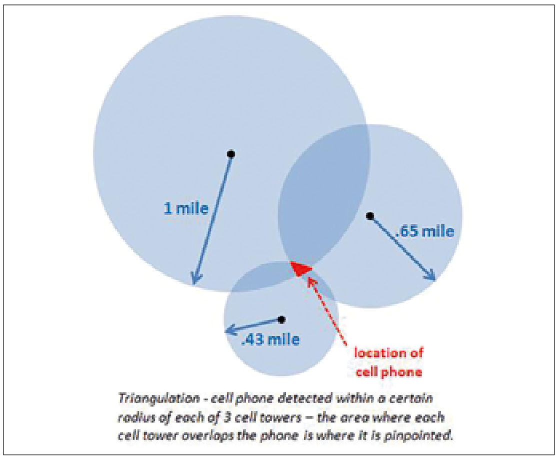

Figure 5
Smith (2008) http://searchengineland.com/cell-phone-triangulation-accuracy-is-all-over-the-map-14790, accessed April 1, 2017.

Using Call Detail Record logs from cell phone providers, computational epidemiologists estimate the caller's longitude and latitude coordinates. Once the location is estimated, the next step is to use or create an algorithm that captures how far people travel from their base, starting with, for example, an equation called "the radius of gyration" (Wesolowski et al. 2013: 5) (in this case assumed to be the distance from home). Crunching big data sets requires that, for example, the radius of gyration equation and several others need to be written as computer code. The trick is to match up the instructional computer code they make up with a desired result. Bad code results in useless correlations. Good code results in a close expression of the idea. In the case of Ebola, code was scaffolded onto the false first principle that cell phones are people.

4 There are alternatives to GPS, which is a US government controlled system initiated by the US military but made available to civilian users. For the explanatory purposes of this paper, I will use the GPS satellite system as the default reference. Russia has its own system, GLONASS, and there are systems for smaller regional coverage like that of Japan's QZSS and China's Beidou. The European Union is currently developing a system called Galileo, and China is developing a global system called Compass (Bhatta 2011).

The Promise of Early Detection

Early on in the West African Ebola Virus Disease outbreak, about five months into what would be a two-and-a-half-year event, big data analysis was touted as capable of early warning and prediction. In late summer to early fall of 2014, blog, news aggregating, and investment spheres were prolific with hope, promise, and overstatement about the problem-solving uses to which big data could be put in the Ebola crisis. In newsweeklies like Newsweek (Schlanger 2014), on blogs (Public Health Watch 2014), and by e-news giants like US News and World Report (Ngowi 2014), the promises and potentialities of HealthMap were anticipatory prophesies of the first order: Big data could predict pandemics! (e. g., Figure 1) HealthMap, a digital surveillance system of infectious disease (Freifeld et al. 2008), was widely credited as the "online tool [that] nailed Ebola" (Associated Press 2014b).

HealthMap's value to the global public health community lies in its reported ability to predict the next pandemic. On its website, HealthMap claims that disease threats are categorized from tens of thousands of sources, with over 90% accuracy (HealthMap 2017). It uses open source products like Google Maps and Google Translate, but its own algorithm—the step-by-step equation that produces its disease database—is not online and HealthMap is not open source. Below is what it stated in the "About Us" website section in 2014 during the Ebola Virus Disease epidemic:

> *"HealthMap brings together disparate data sources, including online news aggregators, eyewitness reports, expert-curated discussions and validated official reports, to achieve a unified and comprehensive view of the current global state of infectious diseases and their effect on human and animal health. Through an automated process, updating 24/7/365, the system monitors, organizes, integrates, filters, visualizes and disseminates online information about emerging diseases in nine languages, facilitating early detection of global public health threats...HealthMap's content is aggregated from freely available information from the following sources: ProMED Mail, World Health Organization, GeoSentinel, World Organisation for Animal Health, Food and Agriculture Organization, EuroSurveillance, Google News, Moreover, Wildlife Data Integration Network, Baidu News, SOSO Info... HealthMap is a Linux/Apache/MySQL/PHP application and relies on the following open products: Google Maps, GoogleMapAPI for PHP, Google Translate API, xajax PHP AJAX library, Fisher-Robinson Bayesian filtering" (Healthmap 2014).*

Decisions about data selection, weightedness, and sequence (choosing which numbers count, in what order, and by how much) as well as the translations to computer code (which code is matched with what problem) are not open source. If it were, its code would be available to the public, freely distributed and other coders would be able to modify and possibly improve it. Although the 'secret sauce' of the algorithm obscures the undisclosed subjectivities of HealthMap's algorithm-making, this is not reason alone to dismiss its claims to predictive powers. HealthMap is an interesting exercise in visualizing disease. Meaningful links, however, between the algorithm, its results, and improved health outcomes are simply not evident. Claims made in August 2014 about HealthMap as an effective early warning system during the Ebola outbreak were clearly overstated; our research team observed Sierra Leonean Ministry of Health and Sanitation officials advocating quarantine and contact tracing in March 2014.

Ebola Containment

Phones equal people—that is the primary assumption of the computational epidemiologists championing the benefits of big data interventions. If we continue to take this assumption seriously enough to critique it, the promise of Ebola containment by big data is easily undone by another simple fact: using cell phones to detect human mobility requires network coverage. Network coverage outside of Freetown is spotty, even though cell phone towers have sprung up across Sierra Leone over the last 15 years in quite remote locations, as I have seen for myself.

In the Parrot's Beak area of Sierra Leone bordering Guinea and Liberia, as well as north and south of it, thousands of people were unserved by cell phone coverage. This is the site of the first outbreak and an area severely affected by deaths from Ebola. Figure 6 shows the lack of reception in October 2014, mid-epidemic. The big data human mobility model being championed for Ebola containment would not work because the basic elements of triangulation location technologies require cell phone reception. Further, the locating by GPS option assumes new cell phone models with factory-installed GPS chips, as well as cell phone companies activating GPS satellite connections. The young man mentioned earlier, Abu, was quick to point out that cell phone sellers in Freetown markets regularly "modify" cell phones to sell them cheaply, often meant swapping out a component to put in a different phone. Stopping the spread of a fatal disease with these cell phones, presuming GPS, gives new meaning to faith-based intervention.

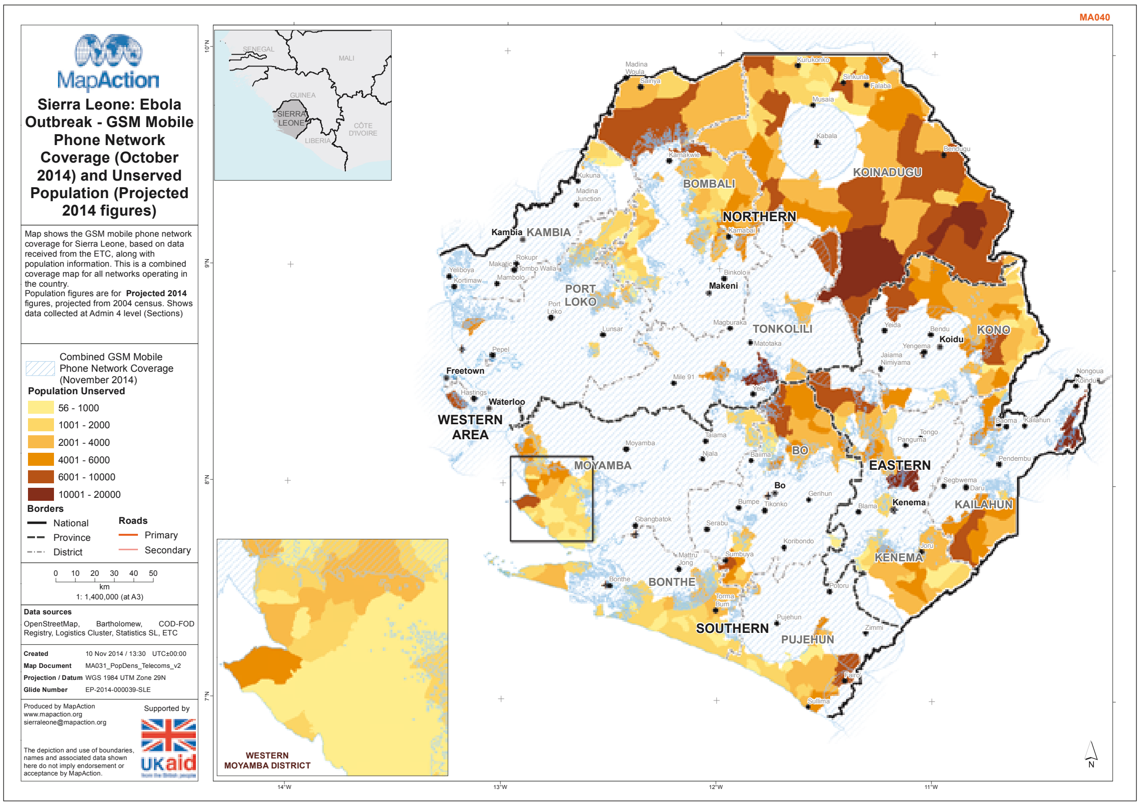

Figure 6

Mobile Phone Network Coverage (MapAction 2014) accessed May 15, 2017. Author added red circle indicating network coverage and non-coverage near the initial Ebola outbreak areas at the borderlands of Sierra Leone, Liberia and Guinea. www.humanitarianresponse.info/system/files/documents/files/MA040_PopUnserved_Telecoms_v1-300dpi.pdf

During the Ebola crisis, the 'gee whiz' of big data distracted people at Ivy League institutions from the urgent need to develop care infrastructures in the short term, and a functioning health care system in the longer term[5]. There is a prevailing belief that technology will provide answers to complex postcolonial postconflict health care challenges hundreds of years in the making. The World Health Organization actively promotes technology because it is deemed "capable of target[ing] almost any disease — from haemorrhagic fevers to the common cold" (World Health Organization 2014). Global health models coming out of academic domains like the Harvard School of Public Health are taken seriously, and they exert disproportionate influence in global public health decision-making.

Technologies like big data, if missteps like those explored in this paper are remedied, though, will always need a primary health care infrastructure to plug in *to* in times of crisis and epidemic. "[E]conomies of fear, hope, salvation, and precariousness" (Adams, Murphy, and Clarke 2009: 260) can fuel the overselling of potential health futures that require massive hardware and software investments, as if basic health services are already in place and operative. After the 2014–2016 Ebola outbreak, the need for improved health systems is more widely recognized than prior. Liberian president Ellen Johnson Sirleaf argued that "the long-term cure for Ebola [is] the investment in health systems" (Sirleaf 2014). Likewise, prioritizing technology is at odds with what many people in Freetown say they want. They want a health *system*, not silver-bullet technologies.

Undeterred by Failure

Big data enthusiasts, including the World Health Organization, appear undeterred by failed applications of big data to Ebola. In November 2016, *The Journal of Infectious Disease* featured a special issue on big data for infectious disease surveillance, the editors of which declared themselves optimistic "that the big-data revolution will vastly improve the granularity and *timeliness* of available epidemiological information" (Bansal et al. 2016, emphasis mine). As I read the issue, I flashed on *Fast Company's* headline "How This Algorithm Detected the Ebola Outbreak before Humans Could" (Titlow 2014), which referred to an article bragging about how HealthMap analytics picked up on Ebola nine days before the World Health Organization announced its presence on March 23, 2014.[6] I was in Freetown at the time, which is about 250 miles from the Guinean site of the first confirmed death from Ebola, that of a little two-year-old

5 I use health care "infrastructure" and "system" interchangeably in this paper, though I see meaningful differences in the words. During the 2014–2016 West African Ebola outbreak, European and North American scholars and others wrote about health systems in ways that connotes a 20th-century Westphalian nation-state using taxes to support health services for all its citizens (i.e., O'Hare 2015; Kieny and Dovlo 2015). Even those who were suggesting different funding mechanisms (i.e., Gostin 2014) used the nation-state-centric ideal as its organizational starting point. Contemporary organizational realities of Sierra Leone — with its ever-shifting mix of government, foreign and domestic non-governmental organizations, multilateral and military organizations, and philanthropy funding schemes — suggests that an infrastructural arrangement that consistently delivered competent health care services would serve Sierra Leoneans well. It is what Sierra Leoneans mean when they say they want a health care system, as I note on page 18.

6 The World Health Organization did not declare Ebola in West Africa as a public health emergency of international concern until August 8, 2014.

boy who died on December 28, 2013. I had read on the Internet about a "strange hemorrhagic fever presenting like Ebola" for the first time on February 27, 2014. It is unlikely I was the first person in Freetown to hear this news; Sierra Leoneans in the Ministry of Health and Sanitation were talking about Ebola in eastern Sierra Leone from the first week of March 2014 onwards. During the first two weeks of March, public health workers were anxious and began planning a response. They were just waiting, they said, for laboratory confirmation of Ebola before they initiated interventions (it did not come until May 2014). But there was so little reaction—an uncommon characteristic to serious outbreaks—on the part of the World Health Organization and the international non-governmental organizations community in Freetown at the time that the panic in the Ministry eased and then quieted almost completely until people started dying in significant numbers during early summer 2014.

We live in a time when reasonable people feel righteous enough during an emergency of Ebola's magnitude to insist that local telecommunications companies devote energies and limited resources to getting customer cell phone data to computer science labs in Boston rather than setting up and facilitating additional communication networks and satellite servers for medical responders in Ebola hot spots. Likewise, global industries of innovation feel justified in using war, natural disaster, and epidemic to actively experiment with new profit-making health technologies. These health technologies are quite distanced from the immediacy of saving lives in epidemic emergency. Experimenting with technologies in times of emergency takes form through scientific and economic enterprise "mold[ing] itself into international norms and politics" (Petryna 2007: 288). These technologies are opportunistic, parasitic to war, natural disaster, and epidemic as they "generate spaces for 'ratcheting up' our technologies, economics, and politics in response to our urgent need to…'grow' economies by expanding anticipation into new domains and registers" (Adams, Murphy, and Clark 2009: 258).

Despite the hype, tracking cell phone data had no demonstrative effect on Ebola containment. The model was flawed from its outset. During the Ebola outbreak, did we understand things better without big data? Yes, there is plenty of evidence that anthropological scholarship was quickly forthcoming at the time, and, with it, essential insights for containing Ebola were shared with global public health response teams (e.g., Wilkenson and Leach 2014; Moran and Hoffman 2014; Spencer 2015; Lipton 2015; Shepler 2014, 2017; American Anthropological Association 2014). Public health acolytes of big data may continue to play with its potential, but in the meantime the world is well served during epidemics when robust qualitative anthropological insights are among the first anticipatory technologies deployed. In the case of big data applications to the 2014–2014 West African Ebola outbreak, simply knowing how Sierra Leoneans use cell phones could have saved time, money, and opportunity costs during an infectious disease emergency.

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