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Chapter Disaster Risk Reduction

Big Data in the Disaster Cycle: Overview of use of big data and satellite imaging in monitoring risk and impact of disasters

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Introduction

Although Big Data has been seen and defined along quite divergent lines, perhaps the most comprehensive definition has been provided by Kitchin (2013) as datasets that are: high in *volume*, *velocity*, and *variety;* exhaustive in *scope*; fine-grained in *resolution* (either temporal or spatial) and inherently *relational*. Three common types of Big Data include data produced by individuals (e.g. call records data, Twitter, Flickr), gathered by sensors (e.g satellites, drones, videos), and data repositories made public by institutions such as businesses and governments (E.g. Zillow house prices, subway records in NYC). There are various scales of "big" in Big Data, which can range from gigabytes (call details record (CDR)), to terabytes (satellite data), to petabytes (web traffic), with each magnitude requiring unique algorithms to extract the signal from the noise. When the right analytics are applied to data sets, however, important information can be gleaned from these "digital bread crumbs" to inform the disaster risk and management cycle. Importantly, then, Big Data entails more than *just* data; it also needs new practices, analysis methods, and approaches to problems (Burns 2014). In the case of user-generated data, there are stark variegations in who produces data and what places are represented, with more data produced by, and representing, the global North (Graham *et al* 2014). In the case of satellite data, coverage is typically global in scope, leaving no country "data poor." However, the socio-economic, infrastructural, and educational barriers to using the data in many developing countries remain obstacles for Big Data to truly transform disaster monitoring. Big Data has been used in three phases of the disaster cycle: *preparedness and early warning; response;* and *mitigation, long term planning,* and *risk and vulnerability modeling* (see Table 1). Below examples are provided for each, followed by issues for practitioners to keep in mind while using Big Data, including *scale, granularity, ambiguity, privacy,* and *representation*.

Preparedness and Early Warning

Big Data from people and sensors can contribute to early warning. By using "citizens as sensors" (Arribas-Bel 2014; Aulov & Halem 2012), many crises can be predicted before they occur, allowing for valuable lead-time for evacuation and other crucial preparations. For example, the UN Global Pulse Program was able to analyze tweets by using key words about price and inflation in an algorithm to classify and categorize tweets to predict three separate food crisis in Indonesia in 2012 with Crimson Hexagon's ForSight software (UN Pulse 2014). Using social media data to monitor public sentiment can provide a powerful indicator of crisis like food security, even before official statistics come out and inflation rises. In some cases, automated social media monitoring can provide near real time information of a crisis even faster than the advanced scientific monitoring. The USGS has begun monitoring tweets for mentions of an earthquake on a platform called Twitter Earthquake Detector (Earle, Bowden & Guy 2012). This platform filters place, time, and keywords to gather geo-located tweets about shaking. While seismographs detect earthquakes in 2-20 minutes, sometimes it can be detected faster by looking at social media, as was the case in the 2011 9.0 earthquake near Japan (ibid.). Public health professionals have also used human sentiment analysis as an early warning to flu outbreaks, as web traffic algorithms can correlate geolocated web queries of disease for early detection (Ginsberg et al 2009). This has been made into a public application called Google Trends.

The second major source of Big Data for early warning prediction is the use of satellite imagery and radar sensors. Using sensors to detect weather patterns has a well-established history, and remains an important source of Big Data. For instance, it has been useful in predicting floods (Borga et al 2011), droughts (Kumar et al 2014), fires (Verbesselt et al 2006), and ENSO (El Nino Southern Oscillation) driven drought (McPhaden et al 1998). Rainfall and temperature data can also be used to predict weather patterns such as El Niño and La Niña events (Verdin et al 2005). Satellite estimates of precipitation, evapotranspiration, soil moisture, temperature, vegetation density and water content, and most recently, groundwater levels (Sun et al 2013) can be combined with other models to make early warning predictions at the appropriate spatial and temporal scale. Satellite imagery can also be used as an early warning for epidemics, but using spatial modeling to correlate disease cases with land use characteristics, as has been done with Malaria, Rift Valley Fever (Anyamba et al 2009), and Schistosomiasis (see Beck et al 2000 for a list of satellite types, and diseases detectable). These risk prediction maps can alert health agencies of imminent outbreaks and potential spread.

In the development of early warning systems that rely on both “citizen sensor” and “machine sensor” data, it is important to test the ability of this data to accurately model past events in order to account for uncertainty when making warning predictions. For example, defining appropriate thresholds for the amount of change in sea surface temperature (measured from satellites) likely to produce ENSO driven drought should be based on our observations of the range of sea surface temperatures that have been linked to drought in the past. Using big data for early warning should be based on science to insure false alarms are not being issued.

Table 1.

Phase	**Data Type**	**Example Data Sets**	**Notes**
Preparedness and Early Warning	User-generated	Twitter (food crisis, earthquake), web traffic (Flu)	Requires machine learning, classification algorithms
	Sensor	Precipitation (PERSIAN, TRMM), evapotranspiration, soil moisture, temperature, vegetation density and water content (MODIS, LANDSAT), groundwater levels (GRACE)	Should be paired with validated and calibrated biophysical models. Used for droughts, floods, fires, epidemics.
Impact and Response	User-generated	CDR, Flickr, Twitter	Requires verification, algorithms to separate signal from noise. CDR data requires agreement with cell provider
	Sensor	Imagery(LANDSAT, MODIS, Geoeye) thermal (LANDSAT, MODIS), radar (RADARSAT-1, CARTOSAT), spatial video	Crowdsourcing aids damage detection. Crisis map mash ups by volunteer cartographers help publicize and visualize data.
Mitigation, Risk and Vulnerability Modeling	User-generated	CDR, emergency call content, facebook	Data may not be representative of population.
	sensor	Nighttime Lights (NTL), Imagery, thermal, Radar, spatial video, Temporal Flood Inundation Mapping (GIEMS)	Populations without electricity not identified by NTL. Must be paired with socioecological vulnerability models. Uncertainty and scale issues.
	institutional, public	GCM (Global Climate Model), Transportation data (subway, bikeshare), census, Worldpop, Open Cities	Issues in uncertainty- GCMs are most uncertain at predicting extremes, Worldpop combines data scales for modeling and has associated uncertainties

Impact and Response

Big Data, both individual data and sensor data, can be useful in measuring disaster impacts in its immediate aftermath and in the response phase. This can be crucial to support humanitarian aid allocation, and to monitor reconstruction over the long term. New individual datasets that help understand disaster impacts include call detail records (CDR) and airtime expense records. The former are anonymized records of caller and receiver phone IDs and cell towers, and call date and time. Airtime expense records detail the amount and nearest tower location of cell minute purchases. This data has been used by researchers to understand broad demographic changes across many contexts (Taylor & Schroeder 2014). These contexts include measurements in post-earthquake Haiti in 2010 (Lu et al 2012), post-Cyclone Mahasen in Bangladesh in 2013 (see the MDEEP project at UN University), and in 2009 Floods in Tabasco, Mexico (Pastor-Escuredo 2014).

Recent innovations have increased the utility of spatially-referenced video. Such spatial videos involve attaching a camera to a vehicle or small aircraft and recording a damage-affected area, possibly later isolating individual frames to use as static images. Spatial video can be much quicker for damage assessments than deploying staff to the field (Lue et al 2015). It has been used to track damage after tornadoes in Tuscaloosa, Oklahoma (Curtis and Mills 2012), and to track recovery of New Orleans neighborhoods after Hurricane Katrina (Curtis et al 2010).

Traditional satellite imagery data can be used for disaster impact assessment by extracting the spatial extent of impact for floods (Schumann et al 2007), fires (Verbesselt et al 2006), landslides (Metternicht et al 2005), drought (Tucker and Choudury 1987), and more, when the right data and techniques are employed. Joyce et al (2009) provides a review of satellite types and the spatial and temporal resolution required to assess disaster damage. In order for satellite data to be useful in the disaster aftermath, Hodgeson et al (2010) recommend that processes must be in place *prior* to a disaster in order to collect imagery of the event within 1-3 days, have access to ancillary spatial information (census, elevation etc.), and have trained GIS and remote sensing staff to process results.

While many early warning tools rely on automated modeling and algorithmic approaches, crowdsourcing can augment efforts to filter the signal from noise in Big Data. Networks of volunteers often dubbed "digital humanitarians" (Meier 2015) have been solicited to geotag and categorize images of damaged buildings in post disaster assessments for earthquakes in Haiti, China, and Christchurch, as well as for Typhoon Haiyan in the Philippines (Barrington et al 2011). Groups such as TomNod and the Humanitarian OpenStreetMap Team have also aided disaster relief logistics by digitizing features like roads and buildings from satellite imagery (Zook et al 2010). Other organizations such as Ushahidi and Mission 4636 have started short message service (SMS) platforms for victims to text information and requests to relief organizations. Finally, the public, in various cases, has generated "crisis map mashups," combining and curating datasets of diverse information such as Flickr and Twitter photos, rainfall data, and gas stations' operational status to increase situational awareness (Liu and Palen 2010). Digital humanitarians can be especially important in countries where local data, computing power, and expertise are limited, or where governments fail to share critical information.

Risk and Vulnerability Modeling

Finally, Big Data can aid efforts toward long-term risk and vulnerability analysis, in the mitigation phase. "Hotspot" maps and hexagonal cells are examples of simple and intuitive visualization techniques that can combine the value of biophysical and social data to assist with prioritizing areas at particular risk (Poorthuis *et al* forthcoming; Sherbinin 2014). Many analyses are now include reframing future risk in terms of climate change from GCM (global circulation model) and reanalysis or downscaling of this data made available through products such as Climate Wizard, where users can choose a variety of emissions scenarios to download maps on predicted changes in temperature and precipitation. Combining climate model outputs and disaster risk models with satellite imagery such as nighttime lights (NTL), to estimate human settlement and economic exposure to risk is common (Christensen et al 2014, Ceola et al 2014). A major advantage of satellite data is due to its collection in the same place over time (in days, weeks, or months depending on the source), allowing for automated validation and updating of risk models with each new satellite pass. This allows for analysis of change over time or summary of long-term trends, resulting in data sets such as GIEMS (Fluet-Chouinard et al 2014), that maps average annual and historic flooding for each month at a global scale.

In addition to using climate model outputs and satellite imagery as an input into scientific risk modeling, new Big Data sets are being tested to increase the breadth of potential variables in risk mapping. New sensor data includes unmanned aerial vehicles (commonly: "drones") and spatial video. Spatial video has been used to quickly identify sites of standing sewage and water to aid in cholera risk mapping in Haiti (Blackburn et al 2014) and vulnerability of homes in LA to wildfire (Burkett and Curtis 2011). Drones can provide very high-resolution 2-d and 3-d imagery, which can be useful in mapping complex urban riverine topography, which has been used in Haiti for flood modeling assessments. High-resolution satellite imagery has also been paired with crowdsourcing to produce detailed maps of building locations, types, and conditions to assist earthquake risk assessments in Dhaka, Bangladesh (Opencitiesproject.org).

Advances have been made in understanding vulnerability and mobility through analyzing individual data for risk modeling through location based analysis of calls, tweets, and transportation data. In New Orleans, content analysis of 911 call data revealed that the callers who mentioned medical conditions where the same people who were unable to evacuate in Katrina (Curtis 2010). Monitoring 911 calls in the future could provide real-time household scale indicators of who might need physical assistance in their evacuation. Other data to estimate mobility patterns can be gleaned from geolocated tweets. Wang et al (2014) found that by analyzing New York City tweeters before, during, and after Hurricane Sandy that pre-disaster mobility patterns can indicate the potential range of mobility during a disaster. Other indicators of mobility include transit by bikes (Zaltz Austwick et al 2013), buses and subways being made available by hundreds of municipalities (see https://code.google.com/p/googletransitdatafeed/wiki/PublicFeeds for a list) (Arribas-Bel 2014). Transit data can monitor population flux at different times of day, and is just one example of open Big Data cities are releasing that could be valuable for risk assessment.

New demographic datasets combining satellite, census, and call record data are available via WorldPop (www.worldpop.org.uk) based on methods by Linard *et al* (2012), Gaugan *et al* (2013), and Tatem *et al* (2007). Age structure, population, and poverty are available for download for most country in the global south. This spatially explicit social data can aid in disaster vulnerability analysis.

Important issues in Big Data

While there is a variety of Big Data available for each phase of the disaster cycle, understanding issues of scale, granularity, ambiguity, accessibility, representation, and privacy are all key in using Big Data information correctly and ethically. Understanding how to combine data from different resolutions and temporal scales with different kinds of disasters is key. For example, in monitoring drought, analyzing satellite data with a high return period, such as MODIS, which covers the same area daily, is important in measuring inter annual changes, even though the resolution is relatively low (500m pixels). However, when analyzing urban flood risk, high resolution (1-5 meter, e.g. from Digital Globe) and 3-d imagery is key to estimate elevation and urban cover to understand where water will flow and pool. Combining data of different scales and quality, especially when considering biophysical and social data, takes special consideration (See Preston et al 2011, National Academy of Sciences reports *People and Pixels* 1998, and *Tools and methods for estimating populations at risk from natural disasters and complex humanitarian crises,* 2007).

Ambiguity, or difficulty separating the signal from the noise, is another challenge. Selecting the appropriate algorithm and quantitative metrics to detect mathematically robust trends is key, as is understanding that Big Data analysis often evidences correlation rather than causation (Boyd and Crawford 2012). The Twitter algorithm used to detect food crises in Indonesia mentioned in this study had one misfire, predicting a food crisis where there was none. In the 2010 Haiti earthquake aftermath, social media data production was only weakly (and inversely) correlated with damage (Currion 2010); also, disaster managers faced challenges making SMS information actionable (Morrow *et al* 2011).

Not all Big Data is free and public. While Facebook has an open API to access its data, access to Twitter's data stream can be prohibitively expensive for many. Accessing CDR data requires an agreement with each provider. Some business data is free to view but not download (Zillow, Trulia), and other data can be purchased (Experian Real Estate data, ESRI business analysis). Some satellite data is free (Landsat, MODIS, SRTM), and others for sale (LiDar data, GeoEye, etc.). Access to the required computing power to analyze data can be an issue, but cloud computing and open source software removes some of those barriers. Products like Google Earth Engine enable new scales spatial and temporal analysis for satellite imagery in a cloud-based API.

Like all new technologies, Big Data is emerging alongside a number of pitfalls and perils that necessitate scrutiny. Both academics and practitioners have raised concerns about the representativeness of Big Data in disaster management (Currion 2010; Haklay 2013). Put simply, this is a question of *who* is producing what kinds of *information* about what kinds of *places* on which *platforms*? Some Big Data sources may be representative of particular segments of society, but may not be generalizable to society as a whole. For instance, social media data in the wake of Superstorm Sandy were more highly concentrated in less-impacted areas of New York City, rather than in neighborhoods in south Queens (Shelton 2012). The platforms on which Big Data proliferate streamline the production and distribution of falsehoods, as well. Much attention was given to the spread of rumors and lies during Superstorm Sandy (Kaczynski 2012; Meier 2012). While methods for combating this are strengthening (Shanley et al. 2013; Cohen 2013), practitioners should continue to be wary of dubious or unverified information, an increasingly difficult task in the context of Big Data.

In addition to representation, privacy issues have been a large concern in Big Data. While data sets that could identify individuals are often anonymized (e.g. call record data) even the best efforts to anonymize and coarsen the data do not preclude individual identification in some cases (Montjoye et al 2014). Practitioners should be aware of the sensitivity of even anonymized Big Data sets.

Lastly, emergency managers should attend to common public expectations of immediate response. Even if responders do not share these expectations, the public often uses social media platforms as they would an emergency dispatch service (Burns and Shanley 2013). Practitioners are encouraged to communicate proper outlets for emergency services and use Big Data analytics in tandem with good disaster governance.

Conclusion

The utility and potential of Big Data for disaster management is growing because the number and access to datasets is expanding rapidly. However, turning the hype into improving disaster risk reduction depends on how Big Data are used in each disaster phase, the sensors involved, and potential practical and ethical concerns. The integration of Big Data into existing workflows and practices is far from seamless, and in fact likely faces serious policy, operational, and even philosophical challenges (Burns 2014; Shanley *et al* 2014). Networks of digital humanitarians are strengthening their ties with the formal emergency management sector, which will likely result in Big Data technology development that more closely suits the needs of responders. It is important to keep in mind that Big Data is more than just data, as it comprises new practices, approaches, and social relations, and the new technologies and resources needed to take advantage of the data are often beyond reach. However, increases in open and public data, cloud computing, and efforts to supporting capacity building for the Global South are important elements of increasing access and participation in the Big Data dialogue. Building partnerships with private companies and municipalities, to increase data access, and with universities, to rigorously test new algorithms, are crucial in advancing Big Data applications. Big Data analytic teams in disaster risk management should involve local participation, advising from computer, social, and biophysical scientists, and be guided by disaster risk professionals.

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