GROUNDING BIG DATA ON CLIMATE-INDUCED HUMAN MOBILITY*

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ABSTRACT. How can site-based fieldwork support big-data research? We reflect on this question by sharing our experiences in combining on-site fieldwork with an existing big-data analysis using call-detail records (CDR), which detected anomalous population flows in Bangladesh during cyclone Mahasen. In the original study of the CDR, this mobility was hypothesized to reflect late evacuations from homes. We discuss how site-based fieldwork enabled us to discover that the detected patterns in our area of study reflected something different: the movement of fishers seeking to protect their trawlers located at harbor areas. Moreover, the fieldwork, in conjunction with remote sensing shoreline evolution data, allowed us to identify and study high-risk behaviors of immobility that the CDR analysis was not able to detect. In sharing our findings, we are reflective of our own endeavor to optimally combine qualitative and big-data methods. While mistakes were made and challenges had to be overcome, insights were gained on how a combined methodology makes research well-grounded, reflective, and more interactive. Keywords: Bangladesh, big data, environmental change, fieldwork, human mobility.

How can qualitative fieldwork support big-data research? This question has been a focal point for geographers for some time (for example, Dobson 2001; Delyser and Sui 2013; Graham and Shelton 2013; Kitchin 2013; 2014; Shelton and others 2014; Palen and Anderson 2016; Ash and others 2018). Questions have been raised as to how qualitative social science–based methods still matter in an era that some are calling the “fourth paradigm of science” based on the “ease of collecting, storing, and processing” large volumes of high-resolution spatiotemporal data (Miller and Goodchild 2015: 499). This inquiry has been supported by a range of arguments stressing the essential role of social theory and qualitative methodologies to better ensure the interpretation and contextualization of using big data to understand the meaning of what we see (for example, Dobson 2001; Delyser and Sui 2013; Kitchin 2013; 2014; Graham and Shelton 2013; Shelton and others 2014; Palen and Anderson 2016; Ash and others 2018). As emphasized by Kitchin (2014: 8):

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Big data can reveal patterns of geographic concentration of certain groups of people, mobility flows, disaster-affected areas, etc., but the important questions are who constitutes such concentrations, why do they exist, what were the processes of formation and reproduction, and what are their social and economic consequences? It is one thing to identify patterns; it is another to explain them. This requires social theory and deep contextual knowledge.

Dismissing contextual analyses can result in overgeneralization or an overemphasis on patterns that later turn out insignificant (Boyd and Crawford 2012; Palen and Anderson 2016). Spatiotemporal big data produces “data shadows of people, machines, commodities, and even nature” that do not provide a complete picture of what is on the ground (Shelton and others 2014: 168). Big data only includes “what is typed, swiped, scanned, sensed” (Kitchin 2013: 265), and often concentrates on outliers as opposed to representative samples of the population (Shelton and others 2014); therefore, “groups who are considered valuable are increasingly data mined, while other populations are excluded from analysis” (Ash and others 2018: 34). Big data is thus in need of interpretation and verification, which makes the use of qualitative methods essential.

This article aims to contribute to the continued investigation of the role of qualitative methods to support and position big data research. We do so in two ways. First of all, our focus is how site-based fieldwork can intersect with big-data research. Much of the literature combining qualitative and big-data methods focus the qualitative research on digital content, usually social media (Crutzer and Zook 2009; Shelton and others 2014; Palen and Anderson 2014). Such digital analysis is, however, not always feasible. Big data that are extremely large-scale and highly resolved often contain a very narrow slice of information. For example, in this article we will work with deidentified mobile phone call-records data that provides high-resolution information on individual users’ locations over time within a very large-scale mobile network (Lu and others 2016a, b). Such data does not provide information on users or the messages they conveyed when calling, and thus cannot easily be assessed qualitatively through digital means. A vigorous interplay between big-data analytics and on-site ethnographic case-study contributions is then needed to evaluate whether large-scale big-data patterns meaningfully reflect the key processes and mechanisms on the ground.

Second, our aim is to be transparent about, and reflective on, our own experiences in doing site-based fieldwork with big-data analysis. We emphasize how combining qualitative and quantitative data helps researchers to become more aware of assumptions about the research subject and on methods used in the process, resulting in better scientific research.

**STUDY FOCUS: CLIMATE-INDUCED HUMAN MOBILITY IN BANGLADESH**

We explore the interaction between site-based fieldwork and big data through a case study examining the intersection between human mobility, climate vulnerability, and environmental change. The nexus between human mobility and
the environment has been an emerging field of research in human geography since the 1990s. This research examines whether, when, and how people move in response to environmental changes, such as drought, extreme weather events, or sea-level rise (Warner 2010; Black and others 2011).

Recently, this field of study has interested big-data researchers seeking to fill research gaps about large-scale patterns and future trends of climate-induced human mobility (Lu and others 2016a, b). The relation between environmental change and human mobility has, thus far, remained subject to various uncertainties, given the multi-causal nature of migration, the diversity in adaptive responses to environmental change, and the high uncertainty about future trends (Black and others 2011). Studies have, for instance, demonstrated how forced human mobility in the context of environmental change can be both sudden and gradual (Warner 2010; Black and others 2011), and emphasized that many of those most vulnerable are not able to move to safer places during extreme events (Black and others 2013). Such variances have made it nearly impossible to provide a rigorously tested estimate of how many people may be uprooted in the decades to come (Gemenne 2011). Herein lies the dichotomy of big-data’s role in the research: on the one hand, these uncertainties and complexities about the human mobility-environment-climate change nexus signal the need for more big-data research to gain better insight into long-term trends and to reduce uncertainties about numbers, migration routes, hotspots, and the like. On the other hand, this complexity underscores the need to avoid relying solely on big-data findings to ensure that we know how and whether detected patterns are relevant, avoid misinterpretations of the data, and prevent overlooking important patterns not flagged by big data analysis.

To further scrutinize the use and interaction of qualitative and big-data methods within this field of study, we share our own experiences in conducting a mixed-method analysis of human mobility patterns in Bangladesh. Bangladesh is a country heavily impacted by cyclones, sea-level rise, floods, and shoreline erosion, and thus a useful case to examine climate-induced mobility patterns. We executed a field research design to interpret a big data analysis conducted by Xin Lu and colleagues (2016a, b), detecting anomalous human mobility in the Barisal district (South Bangladesh) following cyclone Mahasen, which hit the area on May 16, 2013 at approximately 3:00 AM. Lu and others (2016a, b) used anonymized call-detail records (CDR) from the mobile network provider Grameenphone to examine human mobility patterns around the time the cyclone made landfall. The “[d] e-identified data entries include information on the time of the call, the mobile phone tower used and the duration of the call, and can thus be used to indicate the geographical position and movements of users” (Lu and others 2016a: 508). In their analysis, anomalous patterns appear as the unusual movements of Grameenphone users between mobile towers on May 16, 2013 between midnight and 6:00 AM, when compared to a normal night. Cyclone Mahasen was a relatively weak cyclone, allowing the Grameenphone mobile network to largely remain undisturbed, making it well analyzable (Lu and others 2016a).
Cell phone data based on mobile phone calls, as opposed to text messages or social media data, is, in principle, appropriate to use to examine these mobility patterns. In many areas of rural Bangladesh, people only have access to a mobile phone without internet functions and thus do not often utilize social media (Boas 2017). Even when access to smart phones is available, many people in rural Barisal forgo texting as they cannot read the Latin letters that are displayed on basic mobile phones, and because short and frequent calls have become a normal way to communicate (Boas 2019).

The fieldwork was conducted in 2.5 months’ time between August and December, 2017. The research concentrated on the region of Char Fasson. Char Fasson is an upazila (an administrative area) in the south of Bhola district, which is part of the state district Barisal located in the central-south of Bangladesh. It consists of a central town and many agricultural and fisheries villages. Char Fasson was one the areas hit by cyclone Mahasen and an area where high levels of anomalous movement were detected in the analysis of Lu and others (2016a, b). Our fieldwork aimed to reconstruct why high numbers of people were moving during cyclone Mahasen. The information gained on-site helped identify who to interview and what explanatory narrative to follow. The possible explanations of the anomalous population flows were constantly compared with the big-data analysis published by Lu and others (2016a, b, and Fig. 1), and on that basis either refuted or verified. It thus required a flexible research strategy with a constant interaction between different types of data. In total, we conducted thirty-six individual interviews and ten group-based interviews. This included interviews with affected fishers, farmers, local businessmen, Red Crescent volunteers, council members, local chairmen, and men and women who lost their homes or took shelter during the storm.

In the remainder of this article, we describe and reflect on our efforts to add further depth to the big data analysis by Lu and others (2016a, b) through the method of on-site fieldwork. In the next two sections, we describe our journey and discuss the challenges we had to overcome to make the interaction of methods work. We conclude with a discussion of lessons learned on how and why a qualitative methodology is a vital component of big-data research.

**Explaining the Anomalous Flows: Who Was on the Move and Why?**

We started the research by delving into some of the core findings by Lu and others (2016a, b) to understand how and why people were moving during cyclone Mahasen. Of interest to us were especially findings that had puzzled Lu and others (2016a, b). This led us to concentrate our fieldwork on the southeast of Char Fasson where Lu and others (2016a, b) detected large anomalous population flows in the hours around the time that cyclone Mahasen made landfall (see Fig. 1, large bounding box). The cyclone made
landfall in the middle of the night, around 3:00 AM, whilst between Midnight and 6:00 AM, much anomalous mobility had been detected. Lu and others (2016a) understandably assumed this to represent late evacuation. Char Fasson had suffered from delayed cyclone warnings, prompting people to seek shelter when they should have already been evacuated (Lu and others 2016a). Doubts about this hypothesis, however, remained as much of the detected human mobility was towards the coast—the Meghna River and Bay of Bengal, both being extremely dangerous sites during heavy storms. The coast did not seem the most logical place to go to for safety.

Whilst choosing to examine Char Fasson specifically because of the doubts we had around the meaning of the patterns, we began our research with the main hypothesis by Lu and others (2016a, b), assuming the anomalous mobility was connected to the evacuation or displacement within the area. A commonsense assumption is to think
that if there is a heavy storm, and people move, it must mean that people are heading for safety or are running for their lives. We initially also thought it would reflect this in some way, and aimed to find out why this search for safety led towards the coast. We had even hypothesized that people may have taken boats to get to safety, and for that reason were moving towards the coast as opposed to moving away from it.

When in Char Fasson, we started the fieldwork through explorative interviews. Most interviewees told us they did not move to a shelter or other safe havens during that storm; they, instead, stayed at home to protect their belongings—which was possible as the water had not crested the embankment—or they stayed on top of the embankment or on the high roads in front of their houses. People, mainly women, only went to a shelter if these were located close by. It was also the women who were least likely to have access to a mobile phone. All such movements took place in close distances of a single mobile tower. As the analysis by Lu and others (2016a, b) focused on movement between towers, it did not examine or include the behavior within the area.

Our initial hypothesis of people leaving by boat was also immediately refuted, with interviewees saying that it was the strangest idea they had ever heard. Going on to the water during a cyclone would quite likely equal death, or at least be extremely dangerous. Many fishers told us tales of the dangers at sea during a cyclone. They explained how they may not survive unless they are able to secure their fishing boat somewhere (for instance, at a nearby uninhabited island). Also far from a safe place to be is on the Meghna River. Once during the fieldwork, we ourselves were on the Meghna River with a small boat to get to another small char (island) of Char Fasson. At first, our informants at the harbor did not allow us to go as the wind was too strong. The next day, winds were less fierce, so we were allowed to travel. On the way back, however, we had to dock elsewhere as the waves were too strong for our boat to reach the harbor—and this was just a minor wind. We have seen much higher waves from shore during days of heavy winds and rain, with boats going up and down, and the water reaching very high levels. It is not difficult to imagine this scene to be even more extreme during a cyclone.

The information gathered from our fieldwork, observations, and conversations with locals showed us that evacuation or forced displacement could not explain the movement detected by the big-data analysis of Lu and others (2016a, b). The area in the southeast of Char Fasson was also much less vulnerable and impacted by the cyclone than we had anticipated based on the detected large-scale mobility patterns. The embankments were, in most parts, secure enough to withstand the rising water.

This left us quite puzzled. Even though we knew in advance the detected mobility patterns were somewhat unexpected in terms of their direction, we had no other hypothesis to work with. We needed to change strategies, to abandon all preassumptions, and focus on what was there.
We started to more actively compare Figure 1 (large bounding box) with topographical information available via Google Maps. We explored the area whilst marking key sites (such as markets, villages, and harbor areas), including the mobile phone towers, on Google Maps. We used motor cycles as transportation for flexibility and to cover large distances. On this basis, we could determine that the anomalous mobility could only have taken place via a few roads directed towards coastal areas in the southeast direction; these roads are mostly used for walking, motor cycles, or bikes. In addition, we tracked the GPS-locations of where our cell phones switched between mobile phone towers when moving around on those roads by motor cycles. This gave us a clear indication of the area and direction in which people had been moving. We asked people living close to those locations whether they had seen people moving towards the coastal areas during cyclone Mahasen. For instance, we asked such questions to people alongside some of these roads that we had previously identified. We did so without putting a label on the movement, like asking whether people went to a shelter at night.

After taking this step, all pieces of information began to fall into place. People told us they had seen many heading towards the coast, or going back and forth. When we asked why, they replied that fishers went to the harbor areas to secure their trawlers—big wooden fishing boats on which many people in the area work.

To verify this possible explanation of the anomalous movements, we conducted most of our fieldwork at the respective harbor areas, called Char Fakira, Patchkapat, and Aatkapat. At these harbor sites, we spoke with many fishers, but also investors of trawlers, head of the dockyard, and Red Crescent officers, who all spoke about their strategies of securing the trawlers during storms. We often visited with fishers during their work; for instance, when they were mending fishing nets, we were able to conduct group-based interviews per trawler.

Each harbor contains thirty to fifty trawlers, with eight to eighteen employees per trawler, meaning potentially hundreds of fishers may have moved to the coast during cyclone Mahasen to secure the trawlers (if not out on sea). Many told us how vital it is to protect the trawlers when a storm comes. The trawler is their livelihood and lifeline: they depend on it for their daily income, and have often even coinvested in a loan to obtain the trawler. Losing it would have severe repercussions. We learned that during cyclone Mahasen, some even spent the whole night in the trawler, which shows how important the trawler was to them.

Captains and employees of the fishing boats reported to communicate with each other about this livelihood strategy via mobile phones, to ask more people to come, to warn others about their trawlers, or to ask others whether they were safe and to keep in touch with their families. Almost all the men we spoke to at the harbor areas (there were usually no women there) had a mobile phone (usually without internet). Mobile phone technology is thus the central
communication strategy of the fishers around coordinating efforts to protect themselves and their trawlers (Boas 2019). In this way, the fishers also communicated about who could stay with their families versus those who had to come to the harbor, or who had to come later to replace another fisher, and on. Communication with their families went via their sons who had phones, or via brothers or neighbors. Occasionally, a husband would leave his phone behind with his wife, and borrowed a phone from someone at the harbor to reach her.

The evacuation or livelihood strategies that people reported are not limited to cyclone Mahasen, but are part of their standard response procedure to extreme storms. During the interviews and conversations, we noticed that many people did not catalogue experiences by year or by individual storm, given how they are frequently affected by inclement weather. As such, we tried to ask about their general responses to cyclones or extreme storms, and on that basis discovered that the movement of fishers towards the harbor areas during heavy storms was a common strategy, and not exceptional to cyclone Mahasen. Moreover, it was not just the fishers taking part in this act. For instance, it also included investors who provide fishers with loans to purchase a trawler. During storms, investors usually keep in frequent phone contact with the fishers, saying that they need to collect the crew and to go to the harbor area to secure the trawler. Sometimes they, themselves, even went to help as damages to trawlers could put their business in financial peril.

**Interpreting Cases of Immobiley**

In addition to the southeast of Char Fasson, we examined a village area called Mohammadpur located in the northeast of Char Fasson. The first time we arrived here was with our local host from the NGO Coast Trust showing us some of the sites worst affected by cyclone Mahasen. Mohammadpur, a village area in the local union Madras, was amongst those sites. Interestingly, however, little-to-no anomalous population flows during the night of cyclone Mahasen had been detected for this area in the CDR analysis from Lu and others (2016a, b) (see small bounding box, Fig. 1). From the perspective of researching mobility, this makes it perhaps seem like an area of little interest. But, as other human geographers have highlighted (Black and others 2013; Torres and Carte 2016), a lack of mobility may just as well reflect vulnerability.

In contrast to the above discussed southeast of Char Fasson, which was a reasonably well-protected area, Mohammadpur has been poorly protected by embankments. It basically has had no proper embankment since the early 2000s, other than some temporary sand-based embankments that constantly get damaged or even completely break down. It was not until 2017 that the construction of a stronger concrete-based embankment was finally being prepared. When doing fieldwork in the area, concrete blocks had been delivered, planning to be put into place in 2018. Vulnerability in this area is thus likely to decrease in the coming years, if the embankments are well-maintained.
Given this state of vulnerability back in 2013, Mohammadpur was weakly protected when cyclone Mahasen hit the area. Mohammadpur quickly flooded, making it difficult to move around. People were left to climb on rooftops or to stay in nearby shelters (such as school buildings). Some even reported to climb trees as they had no other option to escape the rising water. When we asked about their trawlers and whether they did not want to protect those like those in Char Fasson, people looked at us in disbelief. Securing trawlers would probably have cost their lives, and more importantly, their families at home were at serious risk. As such, whilst having similar livelihoods to those in the southeast, the situation in Mohammadpur was so life-threatening that saving one’s life became more vital than saving one’s livelihood. Yet, despite their high vulnerability, these behaviors were not detected by the CDR analysis, which prioritized large anomalous flows of people, and, consequently, overlooked potential higher forms of vulnerability associated with immobility.

**Adding Shoreline Evolution Data to the Fieldwork**

Given that the analysis from Lu and others (2016a, b) was focused on detecting mobility, as opposed to immobility, we considered other methods that could better help us understand the case of Mohammadpur. We started using the Deltares Aqua Monitor (Donchyts and others 2016). The Aqua Monitor uses satellite images from the NASA Landsat catalogue and Google Earth Engine, an open platform for the analysis of planetary-scale geospatial datasets. The analysis is carried out at thirty-meter resolution, and it highlights land changes over the last thirty years and shows both land-areas that are now lost to the water and where new land has emerged. This monitor is openly accessible via [http://aqua-monitor.appspot.com](http://aqua-monitor.appspot.com). For Mohammadpur, it detects extreme land loss in the last twenty years (Donchyts and others 2016) that used to be inhabited areas (Rose 2017).

It is important to note that this land loss has only in-part been caused by cyclones. The main and largest threat that people reported was shoreline erosion. Char Fasson is situated in Bangladesh’s dynamic river delta. Natural to this delta is shoreline erosion and the appearance of new areas of land. For example, Char Fasson itself is a relatively new part of Bhola (which explains why it is called char, meaning island). According to interviewees, the southeastern part has only existed for several decades and was only recently populated (from around 1970 onward). By means of coastal protection efforts, such as sluicegates and embankments, the Bangladesh’s government tries to keep the erosion at bay. But due to a lack of funds, ongoing corruption around the selection of protected sites, and corruption during the construction of the embankments themselves, many parts have remained weakly protected from the delta dynamics, exacerbated by climatic changes such as sea-level rise and more extreme cyclones.

Given that erosion and land loss were key issues in this area, we decided to concentrate on that. To obtain a better and more detailed understanding of the erosion impacting the area, the second author (who was in the Netherlands) provided
a shoreline evolution analysis using the GPS coordinates of Mohammadpur provided by the first author. The shoreline algorithm needs a bounding box (area of interest) and transects within this box at which the satellite images are analyzed. We produced an overview figure of the shoreline evolution showing all coastline images between 1988 and 2017, and a video of the satellite images used, which visualizes the coastal erosion and accretion near Mohammadpur.

This produced imaginary was helpful to get a better understanding of how and when Mohammadpur was affected, and to structure group-based and individual interviews accordingly. The video showing erosion in the area was most useful for this effort, also to examine the impact of cyclone Mahasen. The video shows how, in 2013 (the year Mahasen hit), there was a sudden jump in the shoreline evolution, with many more parts inland being under water (see left figure in Fig. 2). According to the interviewees, cyclone Mahasen had completely broken the sand-based embankment (already weakened because of the erosion), which was not repaired until several months later, leaving the area flooded. The video supports this account and shows how the situation goes back to a slightly more normal state in 2014 (see right figure in Fig. 2). Working with such images helps to stimulate interviewees to collectively discuss and reflect on what happened—on how far the water came inland, what was destroyed, and how it changed their village.

The video also shows satellite imagery of the shoreline situation in the 1990s. This enabled people to share the history of the area, including how far the land was before, how often the local bazaar had been moved farther inland, how often they had moved houses, and where others no longer in Mohammadpur had moved. It triggered discussions about politics and governmental efforts to support them or the lack thereof, such as the numerous sand-based embankments Mohammadpur has had, the corruption delaying the work, the political complexity about getting a new place on some of the newly emerging chars.

![Fig. 2—Shoreline evolution of north-east Char Fasson (Madras union) during the period 1988–2017 with emphasis on the years 2013 and 2014. The light grey lines indicate the shoreline in the late 1980s whereas the dark grey lines show the shoreline in recent years. The blue line in the left figure shows the 2013 shoreline, whereas the blue line in the right figure represents the 2014 shoreline.](image)
To an extent, we were able to collect this information via field observations and interviews alone, without using such imagery. Yet, the use of satellite-based information helped to check conflicting timelines and to verify what was said, especially as people had difficulty in remembering exact years and dates. At the same time, the face-to-face interviews were essential to interpret the satellite-based images. Without the interviews, we would not obtain a good understanding of the dynamics causing the land loss: in this case, being a mix of delta dynamics, climatic changes, poor governmental protection, and corruption. Nor would we have known about the people’s responses to this loss, as to where they relocated, and how it altered livelihood practices.

CONCLUDING DISCUSSION

We discuss what lessons can be drawn from this case study and from our own experiences in using site-based fieldwork to support big-data research. First, we reflect on the role of site-based fieldwork in uncovering and rectifying uneven or imperfect “data shadows” (Graham and Shelton 2013). Second, we discuss how the usage of different methods has made us, as researchers, more aware and reflective of our own hypotheses, assumptions, and methods used. Third, we discuss how big data visualizations can make the fieldwork, and the research, more tangible and engaging to the people whom we study.

GROUNDING BIG-DATA SHADOWS

Numbers do not speak for themselves and neither do flow maps or other images visualizing big-data analyses (Boyd and Crawford 2012). As noted in the introduction, big-data analyses produce “big data shadows” that are “the imperfect representations of the world derived from the digital mediation of everyday life” (Shelton and others 2014: 167). The challenge for qualitative research is to uncover who or what these big-data shadows represent, and what or who they fail to represent (Crutzer and Zook 2009; Shelton and others 2014; Kitchin 2014; Ash and others 2018).

Digital ethnography of big data, such as a close-content analysis of social media or twitter data, can be beneficial when it is possible to assess the content of the big data. Our case, however—examining a big-data analysis of deidentified CDR providing no social content on its users—required us to visit the actual places of where the anomalies had been detected. As opposed to examining the data in real time or uncovering what exactly had been said by Grameenphone users (which would have been possible by twitter data for instance), we had to carefully reconstruct what happened by the use of more traditional fieldwork methods: face-to-face interviews, site-visits, explorative conversations, and so forth. The data shadows gave us a starting point of where and what to look for, but nothing more (for example, Fig. 1 shows the area and that it concerns large-scale movement of phone users).
As such, site-based fieldwork was essential to obtain a meaningful understanding of what the big-data analysis by Lu and others (2016a, b) represents. As opposed to evacuation or displacement and thus something extraordinary and extreme, our research demonstrated that the detected mobility patterns reflected local preparedness (fishers protecting their trawlers in reasonably well-protected areas). In the meantime, those not able to move, and not detected in the CDR analysis as they remained in the vicinity of the same mobile tower, turned out to be most at risk. As such, exactly by combining big data methods with on-site field research, we obtained a better understanding of the diversity in which people use their mobility, or fail to do so, in the context of sudden events or gradual environmental changes.

COMBINING METHODS MAKES A REFLECTIVE RESEARCHER

Examining a big-data analysis without being reflective of initial assumptions and hypotheses can result in the search for something that is not there: in this case, late evacuation or forced displacement. The societal debate on climate-induced human mobility is subject to a type of confirmation bias, which often frames it as sudden, unidirectional, mass migration (Bettini 2013). Big-data analytics and visualizations risk to uncritically feed into commonly held views (Methmann 2014). For example, if people see an image of large flows of people during a storm, a commonsense conclusion is to think it represents evacuation, displacement, or migration. Whilst conducting the fieldwork, we realized we had made the mistake of interpreting the big-data analysis in such a manner. As opposed to starting the research open-minded, we were guided by the assumption that the big data represented some form of evacuation or displacement, making us initially closed of seeing alternative explanations.

We, however, managed to discover the bias because we actively sought to bring the different types of data in conversation with each other. We, for instance, constantly assessed whether we were in the correct area of where the large flows of anomalous movement had been detected, and whether the reported movement of people aligned with Figure 1. This made us realize that the evacuation hypothesis did not match the actual events, and that we required a more inquiry-based mindset in the fieldwork. Even when we think the research is done inductively, we are often still guided by frames or certain pre-conceived assumptions (Kitchin 2014). When an assumption is well rooted, such as ideas about storm evacuations based on prior research or on images that we see on TV, it is often difficult to be aware that we take it for granted. The combining of methods and data challenges such assumptions; it provides additional checks and balances to ensure that we are open-minded about what we study.

In addition to the reflective attitude about assumptions and hypotheses, an active conversation of methods can make the researcher more critical and aware of the added value that different methods have to best examine the research
questions at hand. In our case, it made us realize during the fieldwork that we
needed to switch our attention to other big-data insights to make better sense of
our findings. As discussed in our case study, the CDR analysis had not focused
on the cases of immobility. Yet, without realizing this in the start of our research,
these cases turned out to be essential to obtain a comprehensive understanding
of cyclone Mahasen’s impact. To make sense of these, we decided to add
satellite-based shoreline evolution data to the fieldwork, which helped us to
explain the high vulnerability of some areas impeding people’s mobility. By
using the satellite-based imagery during interviews and focus groups, we could
narrow down on the main storyline that best explained the vulnerability of the
communities facing immobility during cyclone Mahasen.

This demonstrates how the use of different methods interactively can help to make
the researcher more aware and reflective of assumptions, hypotheses, and methods
used, which in turn can make the research less vulnerable to mistakes. Especially if
accounting for this reflective effect prior to beginning the research, it could help make
the research design more adaptive to new insights gained along the way.

WORKING WITH LOCAL COMMUNITIES

Finally, in using novel methods, it is important to be aware of how it affects the
local communities that the researchers focus on for their analysis. Locals from
the researched areas were excited to see the flow maps of the CDR analysis, and
the tool made them more inclined to help the researchers identify what it
represented. The same usually happened with the shoreline erosion videos,
which allowed villagers to see how their land had changed over time. It triggered
them to discuss how and whether the history of their village matched the
represented images.

Satellite-based imagery of local land changes was, however, not always help-
ful for this purpose. For some participants of focus group sessions, the erosion
imagery was too emotional—seeing how their village was gradually destroyed
(even if seeing this in abstract ways) was too painful. Using the satellite-based
imagery in these instances, rather, had the opposite effect and made people less
keen to participate. Taking such results and feelings into account, and to inform
participants properly on what the imagery shows, is thus crucial to ensure an
ethical application. Furthermore, the effectiveness of big-data visualizations
depends on the simplicity of the imagery. The simplicity of the satellite-based
imagery of shoreline changes increased if the land loss was large and thus took
big jumps over time, showing significant changes. In areas where the erosion was
much more long-term, slow and gradual, taking place in small steps and at times
accreting, the maps become so complex that they are hard to understand,
making them an inadequate tool in this fieldwork setting.

Still, by and large, using visual data in the form of flow maps or videos
during the fieldwork made the research more tangible to local communities
in those research areas. This was perhaps even more relevant due to the language barriers and our reliance on a local translator. Visually showing what the research is about helps to gain community interest (and perhaps support) and for communities to get a better sense of why you are there. To an extent, it even empowered them to engage in the analysis of the research question themselves, as opposed to just being a bystander or component of it, by cobrainstorming what the CDR flow maps could represent.

In sum, using qualitative and big data methods interactively and simultaneously is not without its challenges, but is essential to ensure that novel and high-tech geographic research remains well-rooted in what is seen on the ground. Doing so not only ensures a better understanding of the research topic, but also enables a reflective and open mind-set in finding connections between different data sets. As such, the mixing of methods is an essential ingredient for interdisciplinary geography to become—in addition to more innovative—truly meaningful and effective.

REFERENCES
Ash, J., R. Kitchin, and A. Leszczynski. 2018. Digital Turn, Digital Geographies? Progress in Human Geography 42 (1): 25–43.
Bettini, G. 2013. Climate Barbarians at the Gate? A Critique of Apocalyptic Narratives on ‘Climate Refugees’. Geoforum 45: 63–72.
Black, R., W. N. Adger, N. W. Arnell, S. Dercon, A. Geddes, and D. S. G. Thomas. 2011. The Effect of Environmental Change on Human Migration. Global Environmental Change 21S: S3–S11.
———. 2013. Migration, Immobility and Displacement Outcomes Following Extreme Events. Environmental Science & Policy 27S: S32–S43.
Boas, I. 2017. Environmental Change and Human Mobility in the Digital Age. Geoforum 85: 153–156.
———. 2019. Social Networking in a Digital and Mobile World: The Case of Environmental Migration. Journal of Ethnic and Migration Studies. https://doi.org/10.1080/1369183X.2019.1605891
Boyd, D., and K. Crawford. 2012. Critical Questions for Big Data: Provocations for a Cultural, Technological, and Scholarly Phenomenon. Information, communication & society 15 (5): 662–679.
Crutcher, M., and M. Zook. 2009. Placemarks and Waterlines: Racialized Cyberscapes in Post-Katrina Google Earth. Geoforum 40 (4): 523–534.
DeLyser, D., and D. Sui. 2013. Crossing the Qualitative-quantitative Divide II: Inventive Approaches to Big Data, Mobile Methods, and Rhythmanalysis. Progress in Human Geography 37 (2): 293–305.
Dobson, J. E. 2001. Fieldwork in a Digital World. The Geographical Review 91 (1–2): 430–440.
Donchytys, G., F. Baart, H. Winsemius, N. Gorelick, J. Kwadijik, and N. Van De Giesen. 2016. Earth’s Surface Water Change over the Past 30 Years. Nature Climate Change 6 (9): 810–813.
Gemenne, F. 2011. Why the Numbers Don’t Add Up: A Review of Estimates and Predictions of People Displaced by Environmental Changes. Global Environmental Change 21S: S41–S49.
Graham, M., and T. Shelton. 2013. Geography and the Future of Big Data, Big Data and the Future of Geography. Dialogues in Human Geography 3 (3): 255–261.
Kitchin, R. 2013. Big Data and Human Geography: Opportunities, Challenges and Risks. Dialogues in Human Geography 3 (3): 262–267.
———. 2014. Big Data, New Epistemologies and Paradigm Shifts. Big Data & Society 1 (1): 1–12.
Lu, X., D. J. Wrathall, P. R. Sundsøy, M. Nadiuzzaman, E. Wetter, A. Iqbal, T. Qureshi, A. J. Tatem, G. S. Canright, K. Engø-Monsen, and L. Bengtsson. 2016a. Detecting Climate
Adaptation with Mobile Network Data in Bangladesh: Anomalies in Communication, Mobility and Consumption Patterns during Cyclone Mahasen. Climatic Change 138 (3–4): 505–519.

Methmann, C. 2014. Visualizing Climate-refugees: Race, Vulnerability, and Resilience in Global Liberal Politics. International Political Sociology 8 (4): 416–435.

Miller, H. J., and M. F. Goodchild. 2015. Data-driven Geography. GeoJournal 80 (4): 449–461.

Palen, L., and K. M. Anderson. 2016. Crisis Informatics—New Data for Extraordinary Times. Science 353 (6296): 224–224.

Rose, S. 2017. Habitability at the Frontlines of Sea Level Rise: A Spatiotemporal Analysis of Settlements and Coastal Inundation in Bangladesh between 1990 and 2015. Report for NSF REU Summer Program, Oregon State University.

Shelton, T., A. Poorthuis, M. Graham, and M. Zook. 2014. Mapping the Data Shadows of Hurricane Sandy: Uncovering the Sociospatial Dimensions of 'Big Data'. GeoForum 52: 167–179.

Torres, R. M., and L. Carte. 2016. Migration and Development? The Gendered Costs of Migration on Mexico’s Rural “Left Behind”. The Geographical Review 106 (3): 399–420.

Warner, K. 2010. Global Environmental Change and Migration: Governance Challenges. Global Environmental Change 20 (3): 402–413.