



Unveiling hidden migration and mobility patterns in climate stressed regions: A longitudinal study of six million anonymous mobile phone users in Bangladesh



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ABSTRACT

Climate change is likely to drive migration from environmentally stressed areas. However quantifying short and long-term movements across large areas is challenging due to difficulties in the collection of highly spatially and temporally resolved human mobility data. In this study we use two datasets of individual mobility trajectories from six million de-identified mobile phone users in Bangladesh over three months and two years respectively. Using data collected during Cyclone Mahasen, which struck Bangladesh in May 2013, we show first how analyses based on mobile network data can describe important short-term features (hours–weeks) of human mobility during and after extreme weather events, which are extremely hard to quantify using standard survey based research. We then demonstrate how mobile data for the first time allow us to study the relationship between fundamental parameters of migration patterns on a national scale. We concurrently quantify incidence, direction, duration and seasonality of migration episodes in Bangladesh. While we show that changes in the incidence of migration episodes are highly correlated with changes in the duration of migration episodes, the correlation between in- and out-migration between areas is unexpectedly weak. The methodological framework described here provides an important addition to current methods in studies of human migration and climate change.

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1. Introduction

Where climate change renders places less habitable and productive, vulnerable populations often migrate (Black et al., 2011; McLeman and Smit, 2006). It is critical to develop methods for quantifying and modeling migration as a behavioral response to climate-related weather extremes (Palmer and Smith, 2014). However, this research is hampered by methodological difficulties

in data collection, difficulties in attributing individual migration events to climate change, and by the large number of contextual factors found to influence migration (Feng et al., 2010; Henry et al., 2004; Mueller et al., 2014). Currently, representative household surveys form the basis of the knowledge on climate-induced migration (Black et al., 2013; Bohra-Mishra et al., 2014; Gemenne, 2011; Gray and Mueller, 2012). While household surveys are likely to remain the methodological cornerstone of efforts to quantify the sizes and causal mechanism behind climate-induced migration patterns, they carry several limitations.

First, migration trajectories resulting from climate-related impacts are highly complex and dynamic (Castles et al., 2005;

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Kniveton et al., 2012) and frequently include repeated movements across short distances (Tacoli, 2009). Analysis of such trajectories therefore requires detailed mobility data over a range of temporal and spatial scales, which is often not collected, analysed or reported in traditional survey based research studies (Bohra-Mishra et al., 2014; Findley, 1994). Secondly, household surveys are vulnerable to recall and interviewer bias, especially when multiple trips by several family members are to be recorded (Wesolowski et al., 2013; Wesolowski et al., 2012). Third, logistical difficulties of data collection mean that longitudinal household surveys are not always performed at the same time at each follow-up round, which may bias results when significant seasonality exists in migration patterns (Adger et al., 2002; Gray and Mueller, 2012; Henry et al., 2004; Raleigh and Kniveton, 2012; Saldaña-Zorrilla and Sandberg, 2009; Smith and McCarty, 1996). Fourth, due to the sudden and unanticipated nature of most climatic events, high-quality survey data on resulting migration patterns is extremely difficult to collect, especially when migrating households are spread across large areas (Fussell et al., 2014).

To adequately understand and quantify the interplay between extreme weather events, changing habitability and migration, it would be ideal to supplement traditional survey-based methodologies with analysis of longitudinal, high-resolution, individual-level mobility data, covering both local and national scales (Palmer and Smith, 2014). One data source that potentially can fulfill these requirements, while circumventing the above limitations, is mobile network operator call detail records (CDRs). CDR data comes in an industry standard format, which contains for each of the mobile network operator's subscribers, the location of the closest mobile phone tower at the time of each call, text message or data download. The data is routinely collected and stored by mobile network operators (see Section 2, S1). Previous studies have used CDR data for quantifying population mobility patterns to understand the spread of infectious disease (Bengtsson et al., 2015; Tatem and Smith, 2010; Wesolowski et al., 2012), infer regular internal migration patterns (Blumenstock, 2012), and to predict population movements (Deville et al., 2014; Lu et al., 2012, 2013).

Difficulties in quantification and prediction of migration as an adaptive response to climate change are especially pertinent in

countries like Bangladesh, where climate resilience is a major concern due to cyclone vulnerability combined with sea-level rise that is occurring faster than global averages, exposing roughly 11 thousand km² of land and 20.5 million people to inundation risk by 2050, based on the IPCC AR4 medium scenario (Karim and Mimura, 2008). Usage of mobile phones in Bangladesh is increasing rapidly. Between 2011 and 2014, the proportion of households with at least one mobile phone rose from 78% to 89%, with much of that growth concentrated among rural households (S1) (National Institute of Population Research and Training (NIPORT), 2015).

To assess how mobile network data can augment our understanding of migration during and after extreme weather events across a wide range of temporal and spatial scales, we analysed two de-identified datasets from the largest mobile network operator in Bangladesh, Grameenphone (GP). Analyses were done both on the environmentally stressed areas in the Southern delta region of Bangladesh before and after Cyclone Mahasen, as well as on long-term national level migration patterns. The first dataset (D1) covers 1 April–30 June 2013, the period before and after Cyclone Mahasen, which struck Bangladesh on 16 May 2013 (see Section 2 and S1). The data includes, for each call, the position of the mobile phone tower closest to the caller for all 5.1 million GP phones in Barisal division and Chittagong district, the primary impact zones of Cyclone Mahasen (Fig. S2b). The second dataset (D2) covers a simple random sample of 1 million mobile phones drawn from the entire national set of mobile phones in the GP network. This dataset spans almost two years (1 January 2012–30 November 2013) and includes, for each calendar month, the location of each mobile phone's most frequently used tower that month (S1).

2. Data and methods

Each time a subscriber makes a phone call with his or her mobile phone, a call detail record (CDR) is generated in the system of the telecom operator. A CDR includes a timestamp of the call, the mobile phone number and the mobile tower used to route the call. This data can be used to analyse how phones move between towers

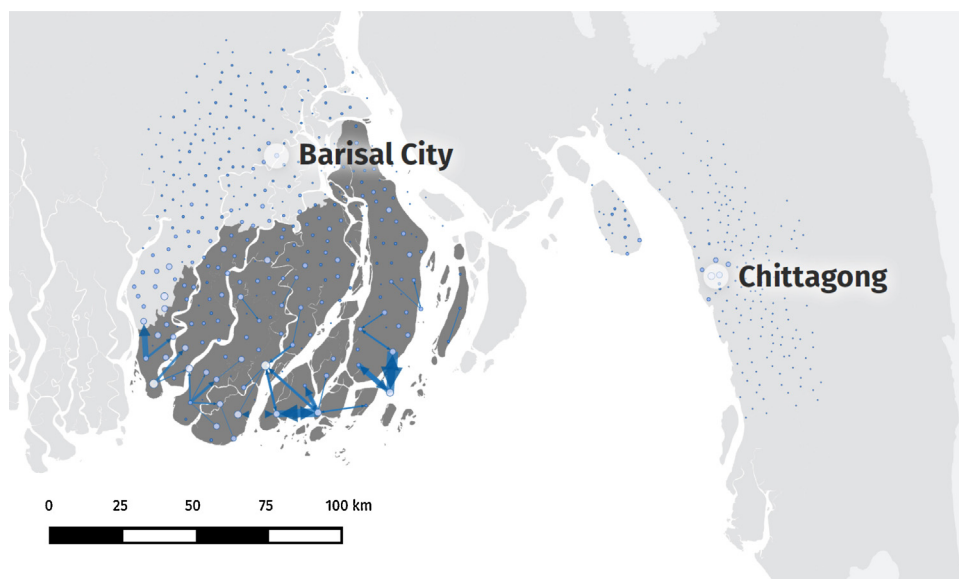


Fig. 1. High-risk mobility of mobile phone users during cyclone landfall and passing (00:00–06:00 a.m., 16 May). The dark grey area indicates the most affected areas (REACH Initiative, 2013). The thickness of each link represents the number of moving SIM cards, and the size of each node is proportional to the number of incoming subscribers to the node (max/min flow: 510/59 moves). Links encode movement that is greater than 10 km and by 50 or more subscribers (see Section 2 and S3). The map shows movements of phone users over distances of more than 20 km, from the Southwestern coast of Barisal toward the interior, as well as a pronounced southward flow within the island of Bhola in Southeastern Barisal. At this time, all people in the area should have taken shelter.

between calls (Gonzalez et al., 2008). Two de-identified CDR datasets (D1 and D2) were extracted by the largest mobile network operator in Bangladesh, Grameenphone (GP). The work was founded in a larger collaboration between five organizations (ICCCAD, Flowminder, Grameenphone, Telenor Research and United Nations University) with the aim of better understanding climate induced migration and displacement in Bangladesh, and supported by the Bangladesh Ministry of Disaster Management and Relief. Tower locations were moved in random directions up to 200 m to increase spatial uncertainty in urban areas, where tower density is high. The operator removed all personal identifiers from the data before analysis started.

For mobility analyses on dataset D1, we filtered away subscribers who were not active in the study area before the cyclone and those who were not active in the last ten days of the data collection period (20–30 June, 2013). This filtering excludes phones which were destroyed due to the cyclone or which belonged to incoming relief workers. The final dataset included 2.95 million users. We performed similar filtering for analyses on D2 and included the 64% of the subscribers who were active

throughout the 23-month period. This filtering rule out the effect of recycling of phone numbers (subscriber churn) and avoid biases due to changes in the size of the study population size during the period.

The spatial distribution of users in D2 was compared to the spatial distribution of the population from the Bangladesh 2011 census, resulting in a correlation of $r = 0.948$ ($p < 0.001$, see Fig. S1a).

In analyses of mobility during cyclone landfall, movements are calculated for users who called at least two times between 00:00 and 06:00 a.m., 16 May. A move is only counted if it was longer than 10 km to account for potential disturbances in the network during landfall. Given these criteria the number of registered moves is an underestimate. Additional methodological details are presented in S1.

3. Human mobility around Cyclone Mahasen

Cyclone forecasting, early warning and cyclone shelters providing refuge for affected populations have significantly

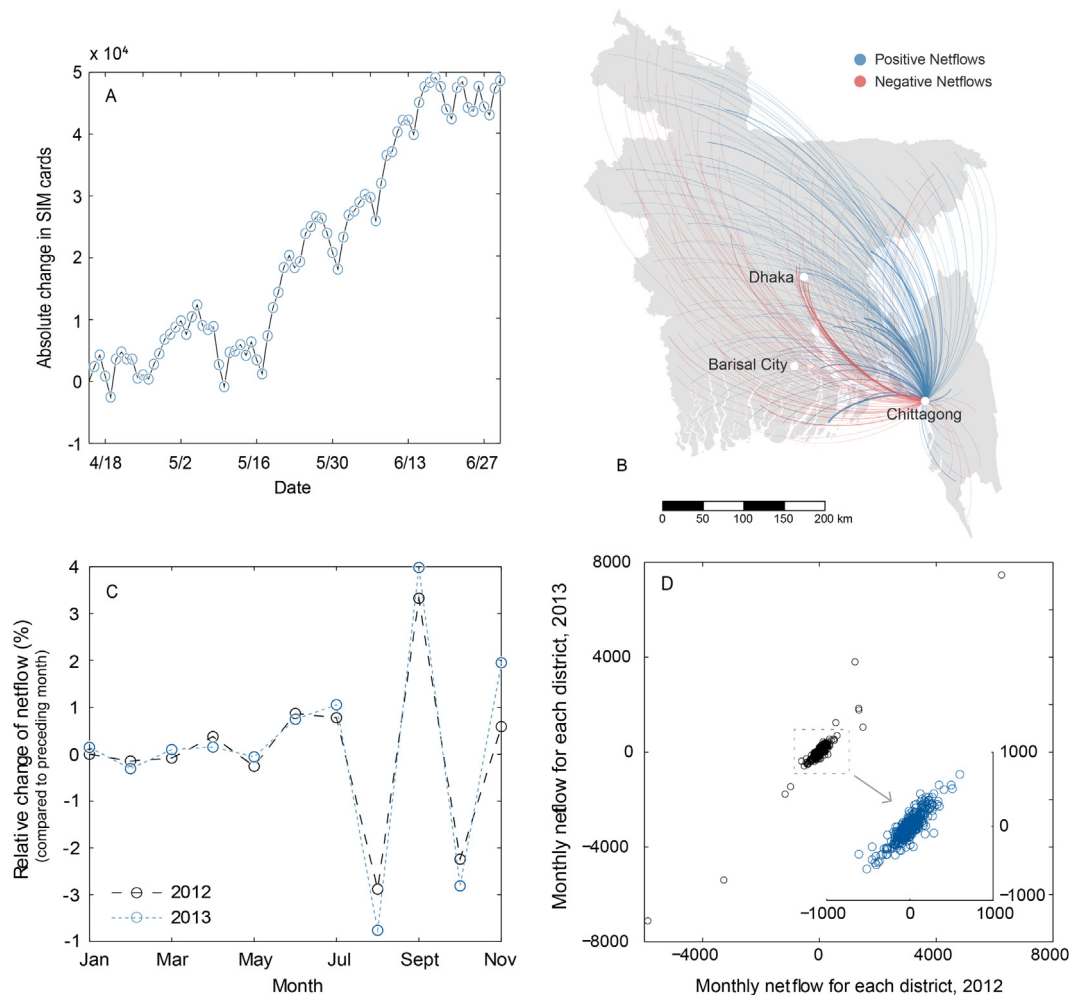


Fig. 2. (a) Weekly number of unique subscribers in Chittagong City. There is a clear increase in the number of unique subscribers (SIM cards) in Chittagong City after the cyclone (16th May). The increase amounts to approximately 50,000 unique subscribers (see Section 2 and S1). (b) Visualisation of the netflow (inflow minus outflow) between Chittagong City and all Bangladeshi districts two months after the cyclone (May–July 2013). Positive netflow: blue; negative netflow: red. (c) Chittagong City's monthly relative change in subscriber numbers during 2012 (grey) and 2013 (blue). The changes from May (cyclone landfall 16 May, 2013) to July are virtually identical during the two years, rendering a relationship to Cyclone Mahasen highly unlikely. Correlation between data points: $r = 0.977$, $p < 0.001$. (d) Seasonality of migration patterns for all districts. Each circle represents a particular district in a particular type of month ("February", "March", "April" etc). Y-axis shows the netflow in each month (inflow minus outflow) for 2013 and x-axis for 2012. For example, the bottom left circle represents district Dhaka in August (having a negative netflow of -7111 in August 2013 and a negative netflow of -5881 in August 2012). Seasonality in population changes are extremely strong ($r = 0.967$, $p < 0.001$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

lowered mortalities in recent cyclones in Bangladesh (Hallegatte and Przulski, 2010; Paul, 2009). However evacuees may leave for cyclone shelters late or not at all, in order to safeguard their homes and assets (Chowdhury et al., 1993). On 16 May 2013, Cyclone Mahasen struck the Southern coast of Bangladesh (S2). The mobile network held up well during the cyclone landfall and we were thus able to observe the mobility patterns during landfall. Consistent with earlier research we saw, especially in the Southeast part of Barisal, how considerable mobility took place during cyclone passing, at a time when all people should have moved to cyclone shelters (Fig. 1). While our data cannot provide detailed explanations of these movements, the findings exemplify how mobile network data can enable identification of areas where high-risk behaviors are observed. Local inquiry into the reasons for delayed evacuations can then be performed, ultimately enabling local, context-specific interventions. Additionally, analysis of CDR data allowed us to assess mobility as a response to evacuation messages across this large area (S3). Given the large sample size and high spatiotemporal resolution the data lends itself well to investigate locally and contextually determined mobility patterns following disasters.

A common adaptation strategy for rural households affected by disasters or other economic hardship is temporary migration to urban areas for short-term employment (Hugo, 1996; Tacoli, 2009). In discussions with NGOs in the cyclone-affected area we found anecdotal evidence of increased arrivals of migrants in urban areas following the cyclone (Nadiruzzaman, 2013). However, as migrants frequently disappear into large informal urban settlements (Barrios et al., 2006), implementation of traditional household surveys to capture such temporary migration events in recipient areas requires prohibitively large sample sizes.

Using our D1 dataset covering 5.1 million subscribers in Barisal Division and Chittagong district, we were able to readily quantify the changes in subscriber numbers in Chittagong City the second largest city in Bangladesh (Fig. 2a; high resolution data for Dhaka City was not available). We saw a clear increase of users arriving in Chittagong beginning approximately two days after the cyclone and continuing throughout the remaining one and a half months, during which highly temporally resolved data were available. The increase in absolute terms amounted to approximately 50,000 additional subscribers moving into the city within the six weeks of the cyclone. In addition to estimating changes in overall number of people coming to cities after climatic events, specific neighborhoods receiving migrants could be identified in order to steer intervention resources and can provide sampling frames for needs assessment surveys. Fig. S3c shows the night-time distribution (approximating individuals' sleeping area) of phones coming into Chittagong City after the cyclone. Additional results are presented in S3.

4. Year-to-year regularity of long-term migration patterns

In order to quantify the migration effects of climatic events, it is critical to not only understand to where people go, but also from where they originate. For the purposes of this study, the term “migration” is used to denote a change in residence lasting between one and twenty-three months. Currently, the approach to investigate migration is to perform cross-sectional or longitudinal migration surveys in migrants' home areas, before and after climatic shocks (Henry et al., 2004). However, even if population flows are very large they become extremely difficult to quantify if changes in migration rates result from a sufficiently small proportion of the population in each departure area.

To understand areas across Bangladesh where people departed to Chittagong city following Mahasen, we used the national dataset D2 (S1). We calculated the netflow (inflow minus outflow)

between Chittagong City and all Bangladeshi districts two months after the cyclone (July 2013) and visualised the mobility pathways (Fig. 2b). Note that the increase in Chittagong after the cyclone is generated by a large number of small, highly distributed mobility streams from across the whole of Bangladesh, which added together produces the large increase of subscribers seen in Chittagong City (Fig. 2a). Such small movements across vast areas are extremely difficult or impossible to measure using traditional survey-based approaches, highlighting the benefit of temporally resolved individual-level data that can be collected on a national level.

Observing the detailed patterns of population exchange between Chittagong City and the rest of the country during the first two months after Cyclone Mahasen (Fig. 2b), contrary to expectations, we found that the inflow to Chittagong City largely originated from outside the cyclone affected area. North and Central Bangladesh, which experienced no or very limited impact from Cyclone Mahasen, were large contributors. This begs the question whether the increase of subscribers in Chittagong City, albeit starting only two days after the cyclone (Fig. 2a), could actually be attributed to the cyclone, or if the increase was due to other causes, for example, regular seasonal migration patterns (Bryan et al., 2014).

Unexpectedly, analyses on D2, from the year preceding the cyclone (2012) showed that the population increase taking place from May 2013 in Chittagong City is matched by an equally large increase in May 2012 (Fig. 2c) out of which the composition departure areas were extremely similar (S4). Together, these results render a causal relationship to Cyclone Mahasen highly unlikely. Similarly, movements to and from the three cyclone affected southernmost districts are virtually identical comparing 2012 and 2013. The only notable change is a minute drop in flow from the cyclone affected districts to Chittagong and Dhaka comparing 2012–2013, which runs counter to the hypothesis that the cyclone would increase migration to the cities. Overall these results indicate a limited impact of Cyclone Mahasen on overall changes in population distributions (S4). Additionally, while the operator data allows for following mobility patterns of users with unprecedented detail, the analyses also highlight the importance of only cautiously attributing causality to any short-term change in population mobility.

A striking finding is the regularity of the changes in user numbers in the city, over the two years. Generalising the above findings to understand the level of seasonality in changes in population numbers across all districts in Bangladesh over our two year period, we found for each calendar month and district, an extremely strong correlation ($r=0.967$, $p<0.001$) between its monthly net change in subscriber numbers in 2012 and in 2013 (Fig. 2d, S5a, b).

These analyses on post-Mahasen mobility taken together highlight first the spatio-temporal detail and scale with which migration as an adaptive response to climate change can be studied across a country. Second, the findings illustrate the profound significance of seasonality in migration patterns in general and the importance of taking these into account in the planning, executing and interpretation of migration surveys in particular.

5. Correlation between incidence and duration of migration episodes

We now proceed to analyse how mobile network data can be used to better characterize national level migration patterns and in particular how this data source can shed light on indicators commonly reported in survey-based research on migration around weather extremes. First, we focus on the relationship between the

incidence of migration events and their temporal and directional characteristics. Secondly, we focus on the correlations between in-, out- and net migration for districts in Bangladesh.

Migration studies based on data from longitudinal and retrospective cross-sectional household surveys often analyse the correlation between the occurrence of migration events and climatic factors preceding the event (Dillon et al., 2011; Gray and Mueller, 2012; Henry et al., 2004). However due to the absence of highly resolved spatio-temporal data on individual trajectories, studies of migration around extreme weather events often unable to control for concurrent changes in the volume and duration of migration episodes. As an example, a longitudinal survey of an area may find that the out-migration increased after a climatic event. If this pattern is statistically significant across areas, it naturally leads to the conclusion that migration increased during the study period (possibly as a behavioral response to the climatic event). However, if the average duration of migration episodes concurrently decreased, there may *at any given time* have been fewer people located outside the area compared to before, leading to a set of very different conclusions. A relevant question is thus whether changes in the proportion of the population moving out of an area are also representative of changes in the total time migrants spend outside their area.

As these relationships between migration incidence and duration have not previously been evaluated at a national scale, we calculated, for each district, the proportion of subscribers in a district (defined as subscribers being located in the district each month during January–April), which subsequently left the district at least once and for at least two consecutive months after Cyclone Mahasen (May–November 2013). We term this “migration incidence.” For this group of subscribers we also calculated the average duration of their stay outside the district (May–November 2013, including those who did not return). We term this “migration duration.” Based on these numbers we then calculated, for each district, the change in migration incidence and the change in migration duration, comparing 2013 with 2012. We plotted the two measures against each other for all districts with least 500 subscribers leaving the district during both 2012 and 2013 (Fig. 3). Migration events are included if they lasted at least two consecutive months.

The result is a strong linear correlation ($r=0.945$, $p<0.001$) between change in migration incidence and change in migration

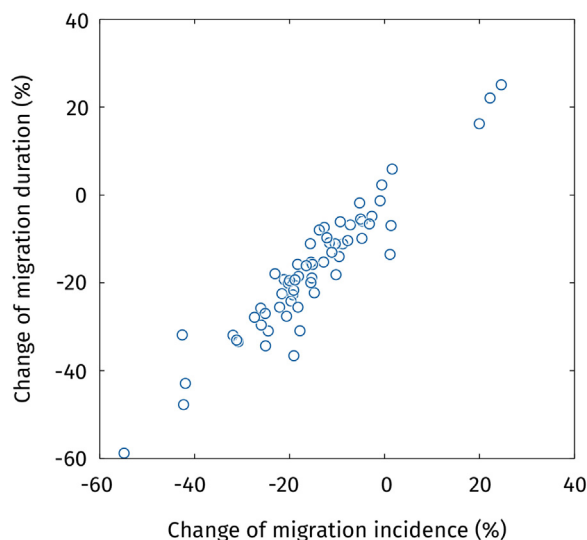


Fig. 3. Change in migration incidence and migration duration, comparing 2013 with 2012. Migration events are included if they lasted during at least two consecutive months.

duration. The slope of the curve is close to one (Fig. 3). Thus, in this context and on this temporal scale, an increase in the proportion of persons migrating from a district seems to generally represent well also the increased time these migrants spend away from the district (S6). Although the linear correlation is high, we do not see a perfectly straight line. A number of districts experienced differences of 20 percentage points in the change in migration incidence and the change in migration duration. Changes to the extent new migration episodes are permanent, cyclical or short-lived “failed” migrations will affect this correlation, and different environmental changes are likely to produce different outcomes along these two axes (Henry et al., 2004). CDR data from longer study periods and diverse contexts will be able to better characterise these relationships.

While the above problem centers on the difficulties in quantifying the length of temporary migration episodes, similar difficulties arise in the quantification of migration into areas in relation to climate change. Resource limitations mean that standard longitudinal household surveys are constructed as closed or semi-closed cohort studies. They follow selected households over time but generally do not study or quantify the number of new households appearing in the study area (Bohra-Mishra et al., 2014; Dillon et al., 2011; Gray and Mueller, 2012; Henry et al., 2004; Mueller et al., 2014).

6. Correlation between in- and out-migration per district

When changes in climatic conditions, such as decreased rainfall and increased temperatures, are correlated with increased incidence of out-migration, it is natural to assume that the area under study is undergoing declining local habitability and increased livelihood stress (Bohra-Mishra et al., 2014; Mueller et al., 2014). While this is likely often the case, solely focusing on pre-existing households and their out-migration (excluding households coming into the area) may conceal important information on overall livelihood conditions in the area. Hypothetically, increased out-migration may occur concurrently with increased in-migration and could potentially be correlated with an overall improved capacity of the area to sustain a population. Increased out-migration taking place concurrently with stable or increasing in-migration, may for example occur in areas with increasing land prices and gentrification (Zaninetti and Colten, 2012), in areas where in-migrants are assisting family members to adapt *in situ* (Adger et al., 2002; Deshingkar, 2012; Zimmerer, 2013, 2014), when migrants seek employment opportunities during post-disaster reconstruction efforts (Fussell, 2009; Gray et al., 2014), or when people move into an area to take advantage of new production niches, while others decide to leave (Massey et al., 1999).

To evaluate the extent to which increases and decreases in out-migration are associated with changes in in-migration over our 23-month time frame we measured, among subscribers who were located in the same district each month during January–April (before Cyclone Mahasen), the number of subscribers who had moved out by November. We then determined the change in this measure between 2012 and 2013 and plotted this change against the corresponding change in inflow (among users not present in the district during January–April, but who had moved in by November). In total 574,138 and 601,159 subscribers were located in their respective districts during January–April in 2012 and 2013 respectively. Out of these, 29,818 and 29,588 subscribers in 2012 and 2013 respectively had moved to a new district by November. The overall correlation between changes in districts’ in- and out-migration rates comparing the two years is negative (Fig. 4), meaning that when out-migration from a district increases, the general tendency for that district is to experience fewer incoming migrants and vice versa (S7).

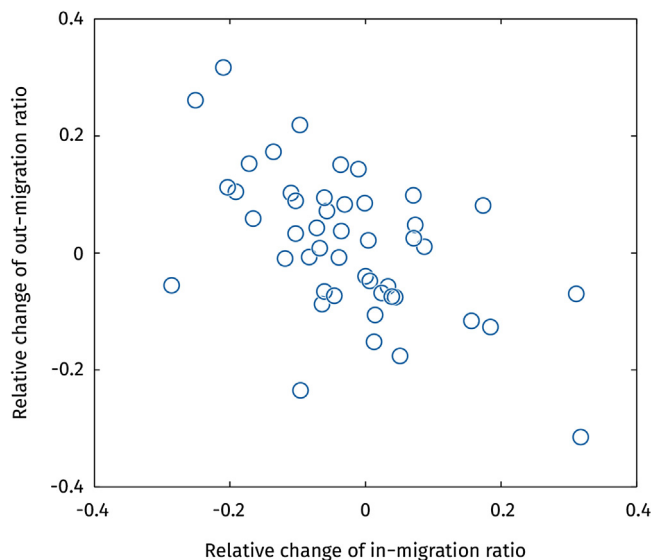


Fig. 4. Scatter plot of changes in out- and in-migration rates per district (comparing 2013 with 2012). Changes in out-migration rates are negatively correlated with changes in in-migration rates ($r=0.561$, $p<0.001$). Considerable heterogeneity exists. Districts with less than 200 migrants in any of the two years are excluded (see S7 for complementary analyses).

This finding is consistent with the “migration as adaptation” hypothesis (Black et al., 2011; McLeman and Smit, 2006), i.e. increasing out-migration may indicate decreasing opportunities in the area, which would negatively affect the probability that people from outside will migrate into the area. The correlation is however relatively weak, and while we find an expected overall negative correlation between increased out- and in-migration, increases in out-migration may, in the case of an individual area, take place concurrently with increasing, decreasing or stable in-migration rates. These results point first to the fact that, when an area experiences increased out-migration, one may only cautiously assume that the area concurrently is experiencing a net loss of population, as the case of Hurricane Katrina illustrates (Fussell et al., 2014). Secondly if changes in out-migration rates are used as a proxy for decreasing habitability of an area, it is advisable to complement analyses with assessments of changes in in-migration rates. In the absence of resources to carry out repeated censuses of large study areas, mobile operator data can play an important role in quantifying these changes.

7. Discussion and conclusion

In this study we demonstrate on a national level in Bangladesh how mobile data allow us to concurrently quantify incidence, direction and duration of migration episodes enabling characterization of previously undocumented features of long-term migration patterns in climate stressed areas. Specifically, mobile network data provide a novel tool to quantify directionality and seasonality of migration patterns on both local and national scales.

The study has several limitations. Cyclone Mahasen caused less damage than feared and arrived at low tide. More powerful cyclones may cause different displacement and migration patterns. Most importantly, mobile operator data will only form one component in a better understanding of migration changes due to climate change. Additional studies using household survey data will be ideally suited to understand the underlying causality of the observed patterns described here and elsewhere. De-identified mobile network data are also limited in only providing mobility information, with insufficient information deducible on

socio-demographic characteristics of the user. Although research so far has shown mobile network data to reflect population mobility characteristics well, the methodology needs further development in varying socioeconomic contexts. The key contribution of mobile data could come from combining the vast spatial, temporal and population coverage of mobile network data with targeted phone-based and household-based panel surveys. This is crucial in order to characterise how especially vulnerable groups such as women, children and the poorest are represented in the mobile data. With further methodological development and continued increases in mobile penetration rates, large stratified samples based on country specific mobile usage patterns will likely provide the most accurate results. With access to operator data covering multiple years, there is also considerable potential in combining operator data with longitudinal climate and remote sensing data to better model human adaptive responses to climate change.

In summary, mobile network data is a highly promising data source to supplement current survey based approaches to monitor, interpret and respond to migration from climate change, both with regard to extreme weather and slow-onset climatic stressors.

Author contributions

XL, DW, PRS, MN, EW, KEM and LB jointly conceived the study, and designed the research; PRS, AI, TQ, KEM oversaw data preparation; XL and PRS wrote codes to perform analysis; LB coordinated writing; XL, DW, KEM and LB led interpretation; all authors contributed to analysis and interpretation.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.gloenvcha.2016.02.002>.

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