Global Environmental Change 38 (2016) 1–7

Contents lists available at ScienceDirect

Global Environmental Change

journal homepage: www.elsevier.com/locate/gloenvcha

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

Xin Lu[a,b,c], David J. Wrathall[d], Pål Roe Sundsøy[e], Md. Nadiruzzaman[f,g], Erik Wetter[a,h], Asif Iqbal[e], Taimur Qureshi[e], Andrew Tatem[a,b,i], Geoffrey Canright[e], Kenth Engø-Monsen[e], Linus Bengtsson[a,b,*]

[a] Flowminder Foundation, Stockholm, Sweden
[b] Department of Public Health Sciences, Karolinska Institutet, Stockholm, Sweden
[c] College of Information System and Management, National University of Defense Technology, Changsha, China
[d] United Nations University-Institute for Environment and Human Security, Bonn, Germany
[e] Telenor Research, Oslo, Norway
[f] Department of Geography, University of Exeter, Exeter, UK
[g] International Centre for Climate Change and Development, Dhaka, Bangladesh
[h] Stockholm School of Economics, Stockholm, Sweden
[i] Department of Geography, University of Southampton, Southampton, UK

ARTICLE INFO

Article history:
Received 25 October 2015
Received in revised form 2 February 2016
Accepted 8 February 2016
Available online xxx

Keywords:
Climate change
Adaptation
Disaster
Mobile data
Migration
Bangladesh

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.

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;

* Corresponding author at: Flowminder Foundation, Roslagsgatan 17, 113 55 Stockholm, Sweden.
E-mail address: linus.bengtsson@flowminder.org (L. Bengtsson).

http://dx.doi.org/10.1016/j.gloenvcha.2016.02.002
0959-3780/

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 km^2 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

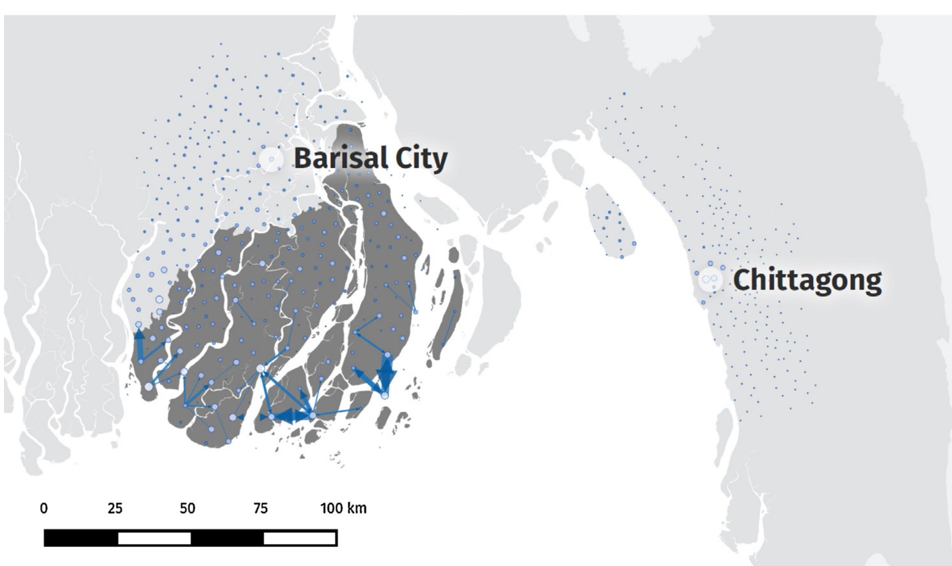


Fig. 1. High-risk mobility of mobile phone users during cyclone landfall and passing (00:00–06:00 a.m., 16 May). The dark grey area indicates the most affected areas (REACH Initiative, 2013). The thickness of each link represents the number of moving SIM cards, and the size of each node is proportional 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

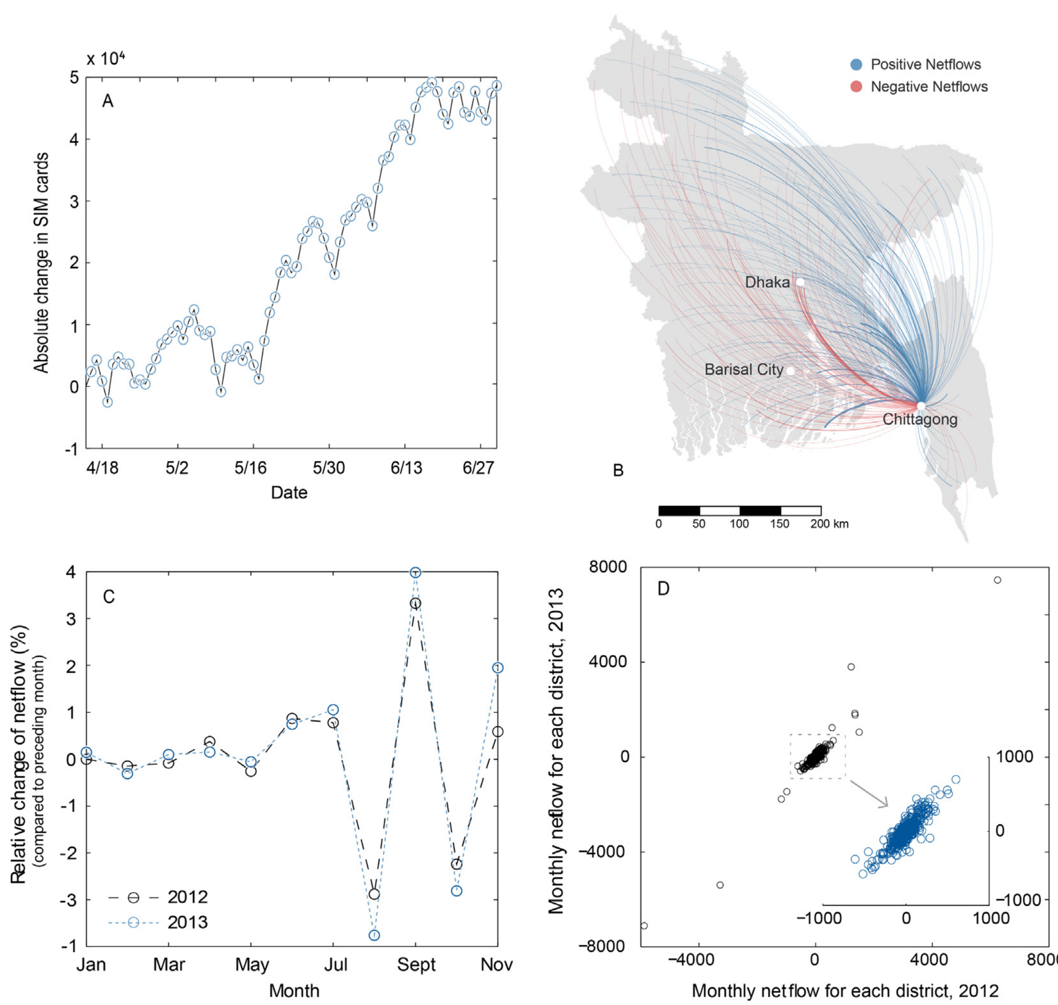


Fig. 2. (a) Weekly number of unique subscribers in Chittagong City. There is a clear increase in the number of unique subscribers (SIM cards) in Chittagong City after the cyclone (16th May). The increase amounts to approximately 50,000 unique subscribers (see Section 2 and S1). (b) Visualisation of the 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 Przyluski, 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 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.

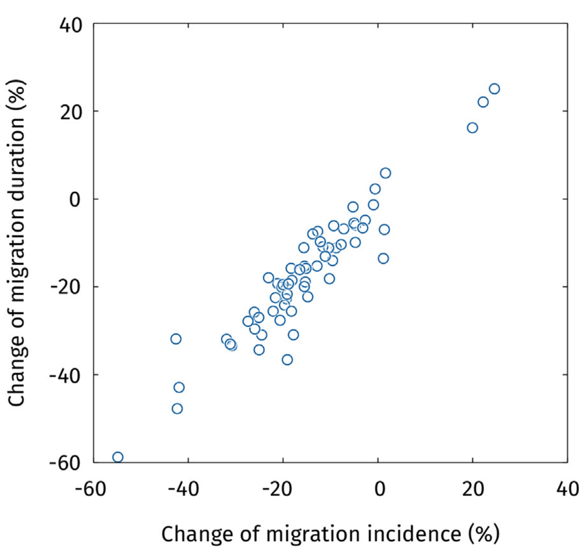


Fig. 3. Change in migration incidence and migration duration, comparing 2013 with 2012. Migration events are included if they lasted during at least two consecutive months.

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).

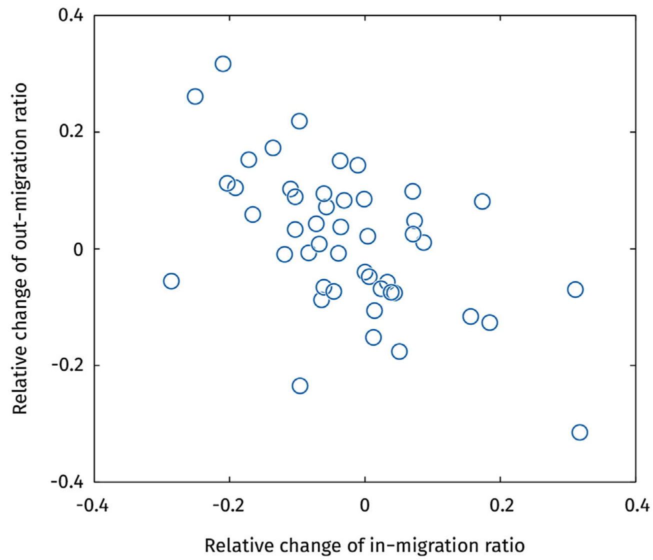


Fig. 4. Scatter plot of changes in out- and in-migration rates per district (comparing 2013 with 2012). Changes in out-migration rates are negatively correlated with changes in in-migration rates ($r = 0.561$, $p < 0.001$). Considerable heterogeneity exists. Districts with less than 200 migrants in any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

Acknowledgements

Grameenphone provided data and dedicated support to the project. Rockefeller Foundation and Munich Re Foundation financed the work. Stephen Roddick helped to assemble the project team. X.L. acknowledges the Natural Science Foundation of China under Grant Nos. 71301165 and 71522014. Dr. Jeffrey Bury provided valuable support and feedback. Additional support was provided by the UK's Economic and Social Research Council under grant number 4030005790. Linus Bengtsson was funded by the Swedish Research Council.

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.

References

Adger, W.N., Kelly, P.M., Winkels, A., Huy, L.Q., Locke, C., 2002. Migration, remittances, livelihood trajectories, and social resilience. AMBIO: J. Hum. Environ. 31, 358–366.

Barrios, S., Bertinelli, L., Strobl, E., 2006. Climatic change and rural–urban migration: the case of sub-Saharan Africa. J. Urban Econ. 60, 357–371.

Bengtsson, L., Gaudart, J., Lu, X., Moore, S., Wetter, E., Sallah, K., Rebaudet, S., Piarroux, R., 2015. Using mobile phone data to predict the spatial spread of cholera. Sci. Rep. 5.

Black, R., Bennett, S.R., Thomas, S.M., Beddington, J.R., 2011. Climate change: migration as adaptation. Nature 478, 447–449.

Black, R., Kniveton, D., Schmidt-Verkerk, K., 2013. Migration and Climate Change: Toward an Integrated Assessment of Sensitivity Disentangling Migration and Climate Change. Springer, pp. 29–53.

Blumenstock, J.E., 2012. Inferring patterns of internal migration from mobile phone call records: evidence from Rwanda. Inf. Technol. Dev. 18, 107–125.

Bohra-Mishra, P., Oppenheimer, M., Hsiang, S.M., 2014. Nonlinear permanent migration response to climatic variations but minimal response to disasters. Proc. Natl. Acad. Sci. 111 (27), 9780–9785.

Bryan, G., Chowdhury, S., Mobarak, A.M., 2014. Underinvestment in a profitable technology: the case of seasonal migration in Bangladesh. Econometrica 82, 1671–1748.
Castles, S., Miller, M.J., Ammendola, G., 2005. The Age of Migration: International Population Movements in the Modern World. The Guilford Press, New York.
Chowdhury, A.M.R., Bhuyia, A.U., Choudhury, A.Y., Sen, R., 1993. The Bangladesh cyclone of 1991: why so many people died. Disasters 17, 291–304.
Deshingkar, P., 2012. Environmental risk, resilience and migration: implications for natural resource management and agriculture. Environ. Res. Lett. 7, 015603.
Deville, P., Linard, C., Martin, S., Gilbert, M., Stevens, F.R., Gaughan, A.E., Blondel, V.D., Tatem, A.J., 2014. Dynamic population mapping using mobile phone data. Proc. Natl. Acad. Sci. 111, 15888–15893.
Dillon, A., Mueller, V., Salau, S., 2011. Migratory responses to agricultural risk in northern Nigeria. Am. J. Agric. Econ. 93, 1048–1061.
Feng, S., Krueger, A.B., Oppenheimer, M., 2010. Linkages among climate change, crop yields and Mexico–US cross-border migration. Proc. Nat. Acad. Sci. 107 (32), 14257–14262.
Findley, S.E., 1994. Does drought increase migration? A study of migration from rural Mali during the 1983–1985 drought. Int. Migration Rev. 539–553.
Fussell, E., 2009. Post-Katrina New Orleans as a new migrant destination. Organ. Environ. 22, 458–469.
Fussell, E., Curtis, K.J., DeWaard, J., 2014. Recovery migration to the City of New Orleans after Hurricane Katrina: a migration systems approach. Popul. Environ. 35, 305–322.
Gemenne, F., 2011. Why the numbers don't add up: A review of estimates and predictions of people displaced by environmental changes. Global Environ. Change 21, S41–S49.
Gonzalez, M.C., Hidalgo, C.A., Barabasi, A.-L., 2008. Understanding individual human mobility patterns. Nature 453, 779–782.
Gray, C., Frankenberg, E., Gillespie, T., Sumantri, C., Thomas, D., 2014. Studying displacement after a disaster using large-scale survey methods: Sumatra after the 2004 Tsunami. Ann. Assoc. Am. Geographers 104, 594–612.
Gray, C.L., Mueller, V., 2012. Natural disasters and population mobility in Bangladesh. Proc. Natl. Acad. Sci. 109, 6000–6005.
Hallegatte S., Przyluski V. (2010). The economics of natural disasters: concepts and methods. World Bank Policy Research Working Paper Series, Vol.
Henry, S., Schoumaker, B., Beauchemin, C., 2004. The impact of rainfall on the first out-migration: a multi-level event-history analysis in Burkina Faso. Popul. Environ. 25, 423–460.
Hugo, G.1, 1996. Environmental concerns and international migration. Int. Migration Rei. 105–131.
Karim, M.F., Mimura, N., 2008. Impacts of climate change and sea-level rise on cyclonic storm surge floods in Bangladesh. Global Environ. Change 18, 490–500.
Kniveton, D.R., Smith, C.D., Black, R., 2012. Emerging migration flows in a changing climate in dryland Africa. Nat. Clim. Change 2, 444–447.
Lu, X., Bengtsson, L., Holme, P., 2012. Predictability of population displacement after the 2010 Haiti earthquake. Proc. Natl. Acad. Sci. 109, 11576–11581.
Lu, X., Wetter, E., Bharti, N., Tatem, A.J., Bengtsson, L., 2013. Approaching the limit of predictability in human mobility. Sci. Rep. 3.
Massey, D.S., Arango, J., Hugo, G., Kouaouci, A., Pellegrino, A., 1999. Worlds in Motion: Understanding International Migration at the End of the Millennium: Understanding International Migration at the End of the Millennium. University Press, Oxford.
McLeman, R., Smit, B., 2006. Migration as an adaptation to climate change. Clim. Change 76, 31–53.
Mueller, V., Gray, C., Kosec, K., 2014. Heat stress increases long-term human migration in rural Pakistan. Nat. Clim. Change 4, 182–185.
Nadiruzzaman M. (2013). Personal Communication with Rafiqul Islam, Oxfam Bangladesh on 15 November, Personal Communication ed.
National Institute of Population Research and Training (NIPORT), M.a.A., and ICF International (2015). Bangladesh Demographic and Health Survey 2014: Key Indicators. National Institute of Population Research and Training (NIPORT), Mitra and Associates, and ICF International, Dhaka, Bangladesh and Rockville, Maryland.
Palmer, P.I., Smith, M.J., 2014. Earth systems: model human adaptation to climate change. Nature 512, 365–366.
Paul, B.K., 2009. Why relatively fewer people died? The case of Bangladesh's Cyclone Sidr. Nat. Hazard. 50, 289–304.
Raleigh, C., Kniveton, D., 2012. Come rain or shine: an analysis of conflict and climate variability in East Africa. J. Peace Res. 49, 51–64.
REACH Initiative. (2013). Tropical storm Mahasen final assessment report (Phase 3 Shelter, WASH, Early Recovery Detailed Assessment) Bangladesh 2013, Dhaka, Bangladesh.
Saldaña-Zorrilla, S.O., Sandberg, K., 2009. Impact of climate-related disasters on human migration in Mexico: a spatial model. Clim. change 96, 97–118.
Smith, S.K., McCarty, C., 1996. Demographic effects of natural disasters: a case study of hurricane andrew*. Demography 33, 265–275.
Tacoli, C., 2009. Crisis or adaptation? Migration and climate change in a context of high mobility. Environ. Urbanization 21, 513–525.
Tatem, A.J., Smith, D.L., 2010. International population movements and regional *Plasmodium falciparum* malaria elimination strategies. Proc. Natl. Acad. Sci. 107, 12222–12227.
Wesolowski, A., Eagle, N., Noor, A.M., Snow, R.W., Buckee, C.O., 2013. The impact of biases in mobile phone ownership on estimates of human mobility. J. R. Soc. Interfac. 10, 20120986.
Wesolowski, A., Eagle, N., Tatem, A.J., Smith, D.L., Noor, A.M., Snow, R.W., Buckee, C. O., 2012. Quantifying the impact of human mobility on malaria. Science 338, 267–270.
Zaninetti, J.-M., Colten, C.E., 2012. Shrinking New Orleans: Post-Katrina population adjustments. Urban Geogr. 33, 675–699.
Zimmerer, K.S., 2013. The compatibility of agricultural intensification in a global hotspot of smallholder agrobiodiversity (Bolivia). Proc. Natl. Acad. Sci. 110, 2769–2774.
Zimmerer, K.S., 2014. Conserving agrobiodiversity amid global change, migration, and nontraditional livelihood networks: the dynamic uses of cultural landscape knowledge. Ecol. Societ. 19, 1.

Supplementary Information:

Title: *Unveiling Hidden Migration and Mobility Patterns in Climate Stressed Regions: A Longitudinal Study of Six Million Anonymous Mobile Phone Users in Bangladesh*

Xin Lu [a,b,c], David J. Wrathall[d], Pål Roe Sundsøy[e], Md. Nadiruzzaman[f, g], Erik Wetter[b,h], Asif Iqbal[e], Taimur Qureshi[e], Andrew Tatem[b,i], Geoffrey Canright[e], Kenth Engø-Monsen[e], Linus Bengtsson[a,b]*

[a]Department of Public Health Sciences, Karolinska Institutet, Stockholm, Sweden; [b]Flowminder Foundation, Stockholm, Sweden; [c]College of Information System and Management, National University of Defense Technology, Changsha, China; [d]United Nations University-Institute for Environment and Human Security, Bonn, Germany; [e]Telenor Research, Oslo, Norway; [f]Department of Geography, University of Exeter, Exeter, UK; [g]International Centre for Climate Change and Development, Dhaka, Bangladesh; [h]Stockholm School of Economics, Stockholm, Sweden; [i]Department of Geography, University of Southampton, Southampton, UK.

Keywords: Global environmental change; Adaptation; Disaster; Cyclone; Mobile data; Population displacement; Bangladesh; Migration

Corresponding Author:
Linus Bengtsson, Roslagsgatan 17, 113 55 Stockholm, Sweden
Tel: +41 789 648 828
Email: linus.bengtsson@flowminder.org

S1. Methods, Data and Mobile Network

Compared to other countries of comparable income levels, Bangladesh has a high mobile phone penetration. This also includes rural areas. Fifty percent of the population above the age of 15 has a mobile subscription (Lucini and Hatt, 2014). The proportion of households with at least one mobile phone is increasing rapidly; between 2011 and 2014, household ownership across the whole of Bangladesh rose from 78% to 89%, with much of that growth concentrated among rural households (NIPORT, 2015).

Research in Haiti has previously showed mobile phone movements patterns to match closely with data on retrospectively reported mobility patterns from a large-scale representative household survey (Bengtsson et al., 2011). Similar results were reported from Kenya, where a comprehensive evaluation showed mobile phone-based estimates of mobility to contain only minor bias from economic differences between users (Wesolowski et al., 2013). As mobile penetration increases within and across households, estimates of population flows are likely improve but additional research in multiple contexts is needed (Bengtsson et al., 2011; Wesolowski et al., 2012).

We use two separate datasets extracted from call detail records (CDRs) from the Grameenphone (GP) mobile network in Bangladesh. GP is the largest mobile operator in Bangladesh with 42 million customers at the time of the cyclone, with a network covering 99% of the population and 90% of the land area (Telenor, 2013). The first dataset (D1) was registered during 1 April to 30 June 2013, the period before and after Cyclone Mahasen, which struck Bangladesh on 16 May 2013 (S2). The data covers 5.1 million de-identified GP users who made at least one call from within Barisal Division or Chittagong District, the primary impact zones of Cyclone Mahasen. For each call placed by the user, the data contains the position of the mobile phone tower, which was used to place the call. In total, D1 includes 4,576,077,029 location updates. The second dataset (D2) covers a sample of one million mobile subscribers drawn randomly with equal probability from the entire national set of mobile subscribers using the GP network. This dataset spans almost two years (1 January 2012 to 30 November2013) and includes, for each calendar month, each subscriber's most frequently used mobile phone tower (together with latitude and longitude coordinates) for that month.

By defining each user's most frequent tower location during 2012-2013 as the home division (admin. level 1) in which he or she lives, we compared the spatial distribution of sampled users from D2 with the national population distribution from the Bangladesh 2011 census (Fig. S1a). The phone data matches the census data well, with some overrepresentation of phones in Dhaka division and a corresponding underrepresentation in Chittagong division. The overall linear correlation between the two data sources is 0.948 ($p<0.001$).

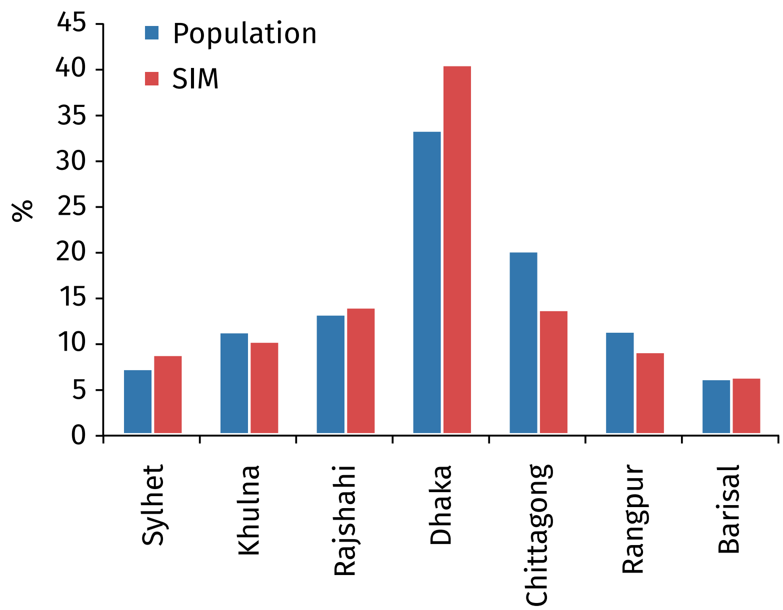


*Figure S1: **a**, Density distribution of SIM cards and population from the 2011 Census. (Bangladesh Bureau of Statistics)*

The study area for D1 (Barisal division and Chittagong district) has near complete coverage of mobile phone towers (Fig. S1b). The distribution of the day when a user is first observed and the day the user is last observed is almost symmetric. On the first day of the study period (April 1, 2013), 49% of users were observed, and between the first day, and cyclone Mahasen (16 May 2013), 83% of all users were observed (Fig. S1c). The average number of active days during the 90-day period for all users in the dataset is 45 (Fig. S1d).

Figure S1: ***b,*** *Map of study area with approximate locations of cell phone towers.*

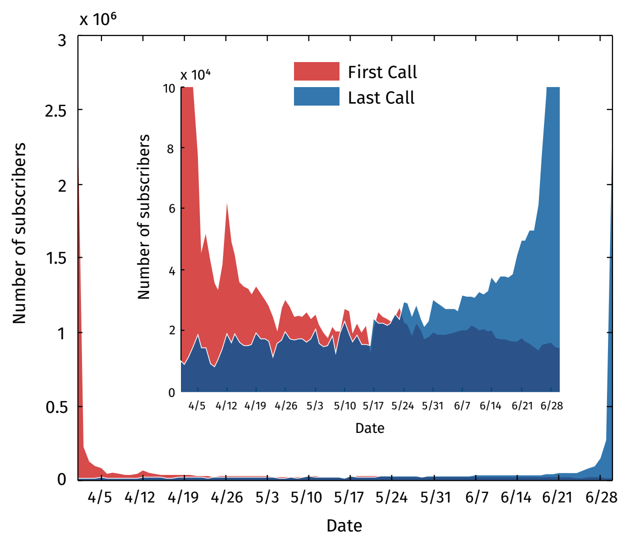


Figure S1: ***c,*** *Distribution of first and last observations, i.e., first call and last call (inset in the middle is zoomed in for the part of the y-axis lower than 100,000 users)*

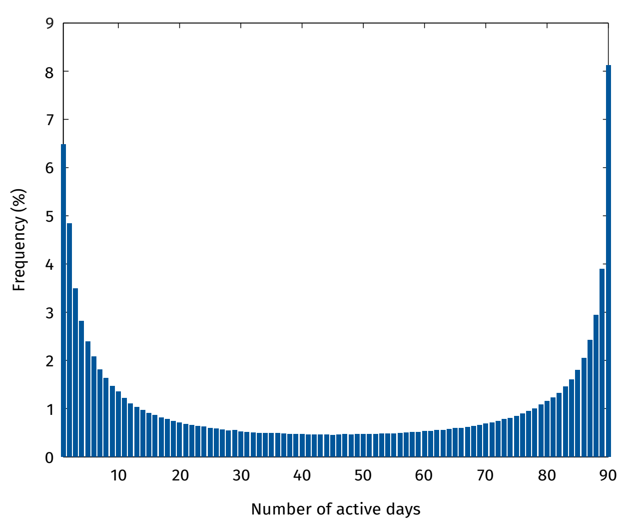


Figure S1: ***d,*** *Histogram of the distribution of users with different numbers of active days during the period.*

S2. Cyclone Mahasen

Cyclone landfalls in Bangladesh have produced the deadliest disasters in human history. Most notably, the Bhola Cyclone of 1970 left an upward estimate of 500,000 fatalities, and in a 1991 Cyclone, 138,000 people perished. In recent years, cyclones such as Sidr (2007) and Aila (2009) have been less deadly, but have resulted in economic devastation, with estimated damages of $1.67 billion and $1.15 billion, respectively (Government of Bangladesh, 2008, 2009).

On 14 May 2013, when forecasts predicted that Cyclone Mahasen (also known as Viyaru) would make landfall over the Chittagong District, Bangaldesh's Comprehensive Disaster Management Programme concentrated early warnings in the Chittagong City and Cox's Bazaar, and over a million people were evacuated from those areas (Associated Press, 2013). Nevertheless, in its final approach, Mahasen veered westward toward Barisal Division, with gale-force winds arriving in the late hours of 15 May. By 03:00 hours, heavy rains had begun to fall over parts of Southern Barisal, and by 05:00 hours on 16 May 2013, the storm made landfall (Figs. S2a, b). Throughout the morning, Mahasen extended eastward toward Chittagong, and gradually moved north and east into India, where it rapidly dissipated (Fig. S2b). Although Mahasen carried significant wind and rain (with maximum wind speeds of 85 km/h, dropping 544 mm of rainfall in total over Bangladesh it was a relatively weak cyclone) (Gutro and Pierce, 2013). Nevertheless, according to estimates, 1.3 million people were affected; 133,000 homes were damaged or destroyed, and an estimated 128,000 hectares of crops were lost or damaged (REACH Initiative, 2013). Due to successful early warnings, and a landfall that coincided with low tide thus generating only minor storm surge, only 17 persons perished.

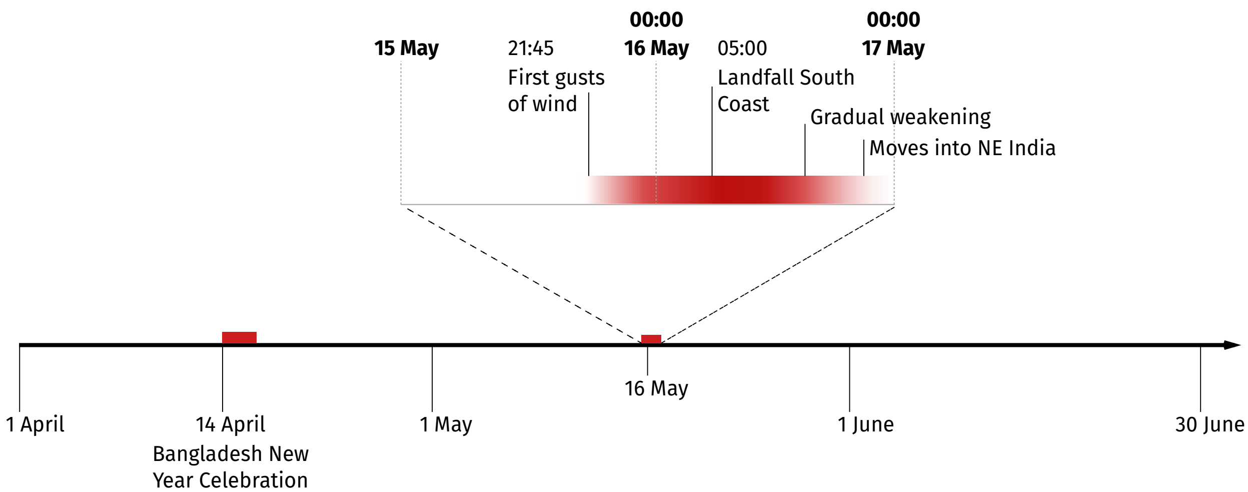


Figure S2: ***a,*** *Timeline of Mahasen, 2013.*

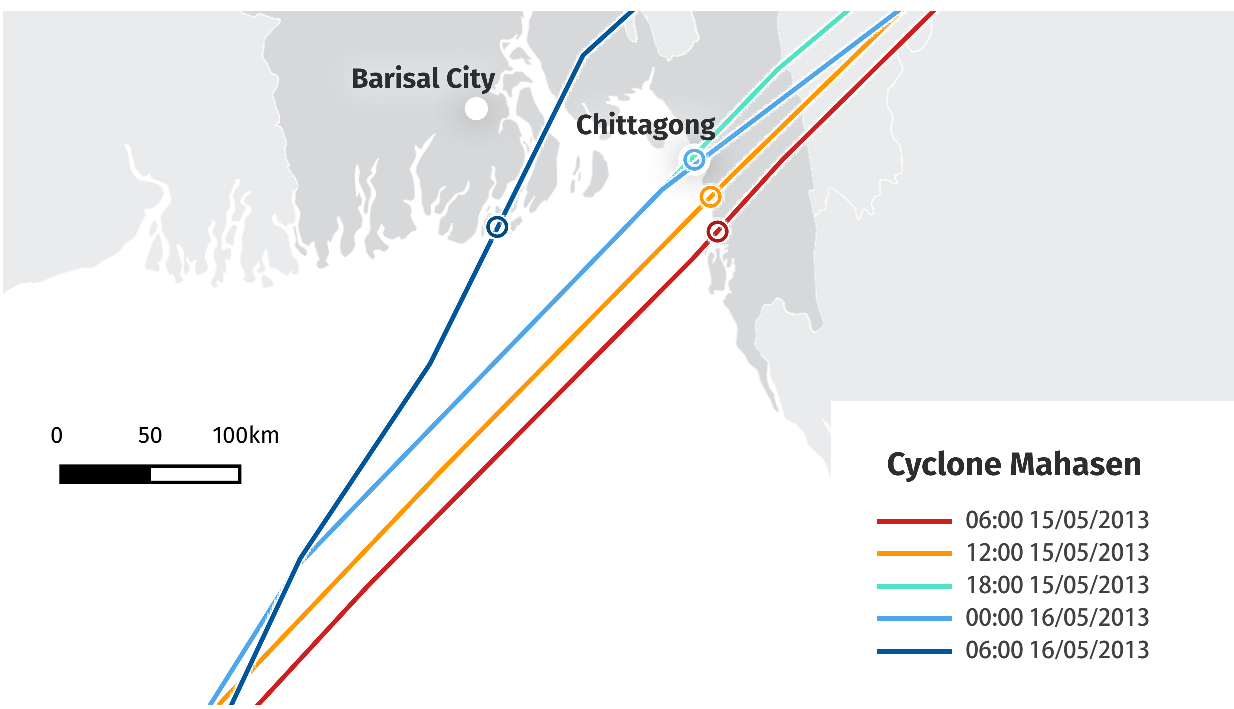


Figure S2: ***b,*** *Cyclone Mahasen's path, projected versus actual. As late as midnight on 16 May 2013, with only 3 hours before landfall, Mahasen was projected to make landfall over Chittagong City leading the government to concentrate early warnings in the Chittagong Division (source: recreated from van Ormondt 2013, available at www.deltares.com)*

S3. Additional Results: Mobility Before, During, and After Cyclone Landfall

(a) Mobility the day before Mahasen (15 May 2013):

We calculate the mobility network (number of subscribers moving between a pair of mobile base stations) for 15 May for each union, an administrative level smaller than municipalities. We also calculate the mobility network in D1 for the same weekday during 24 April when no holiday or other known social disturbance was taking place. We subtract the baseline mobility from the mobility during 15 April to quantify changes in mobility the day before the cyclone, compared to normal. We plot the positive and negative links (Fig. S3a). Pre-cyclone and evacuation movements are clearly observable. There is in general an increase of flow in Chittagong district and a decrease in most parts of Barisal the day before the cyclone. This likely reflects the early warning information disseminated throughout Chittagong District based on forecasts that the path of the cyclone would cross Chittagong City.

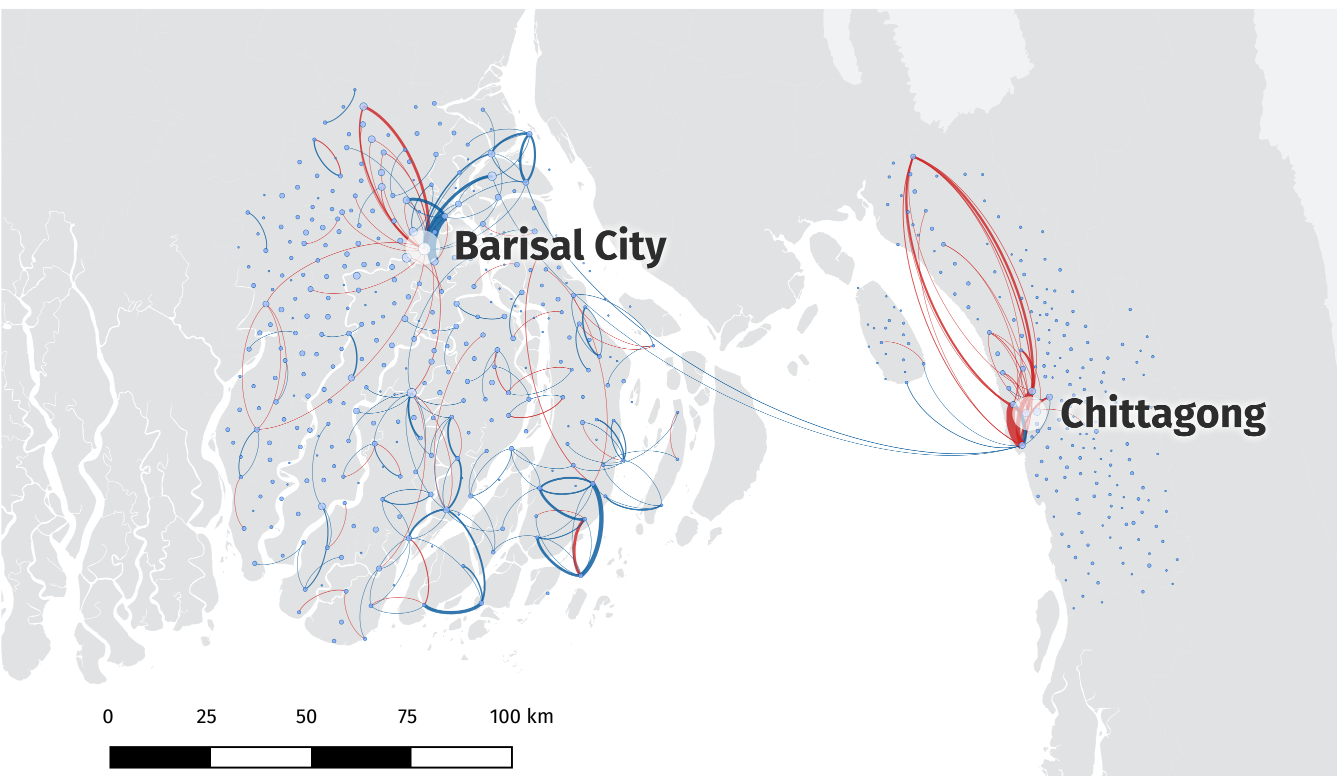


Figure S3: ***a,*** *Pre-cyclone mobility and evacuations: a comparison of 15 May flow network to normal flow network (same weekday, three weeks earlier on April 24). The direction of flow is clockwise. Increases of flow on the link are represented in red and decreases in blue. Change of flows of less than 20, and distance <10km are filtered away. It is notable that compared to the pre-cyclone period, Chittagong district had a significant increase of flow (21% increase), while in the Barisal Division flow decreased by 8%.*

(b) Mobility during landfalll

Using the same method described above, we compare mobility during the storm (00:00hrs to 06:00hrs on 16 May 2013) with normal mobility (00:00hrs to 06:00hrs on 25 April). This is complementary to Figure 1 in the main manuscript where total flow (not above-normal flow) is shown. There is a large increase of flow in coast of Barisal, where the cyclone actually hit. Meanwhile there is no major absolute change in mobility in other regions of Barisal and Chittagong (Fig. S3b). This suggests that people were moving in the affected area during landfall.

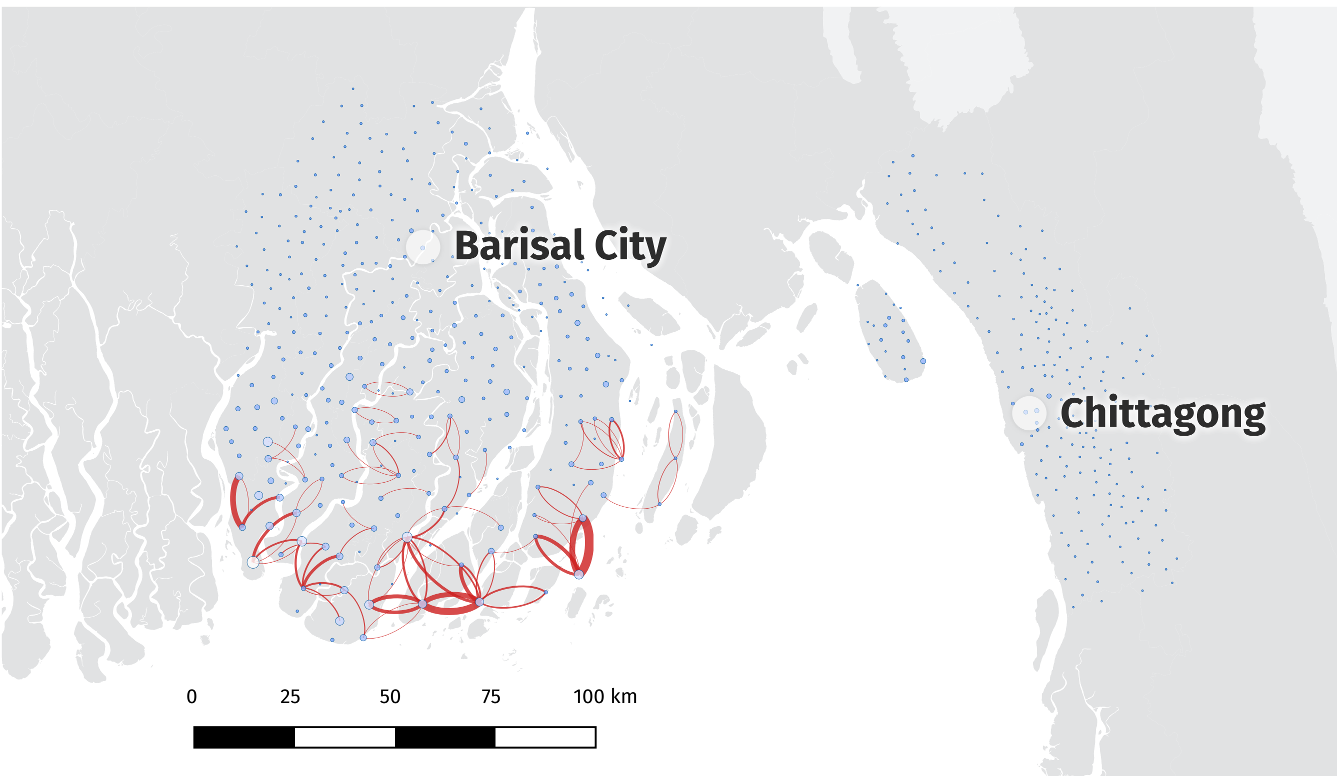


*Figure S3: **b,** During the cyclone's landfall: a comparison of flow networks between 00:00 and 06:00 hrs on 16 May, compared to a normal day (the same weekday, April 25 00:00hrs - 06:00hrs). The difference (increase or decrease of flow for each pair of upazilas was calculated). The direction of flow is clockwise. An increase of flow on the link is represented in red, and a decrease in blue. Absolute change of flow less than 20, and distance <10km are filtered away. S3(b) indicates that despite the cyclone forecasting for Chittagong City, where the cyclone was predicted to strike, there was no major change of travel patterns during the night (0:00-6:00am 16 May). However in the south coastal region of Barisal Division, all pair of unions experienced an increased flow, for travels exceeding 10 km. This mobility was 232% of the normal rate.*

(c) Night-time distribution of people arriving in Chittagong City

The population of SIMs in Chittagong City increased immediately after Cyclone Mahasen's landfall on 16 May, and so we plotted the night time distribution of new SIM cards arriving between 17 May and 30 June. We assume that the night time position of the SIM is where the owner resides (Fig. S3c).

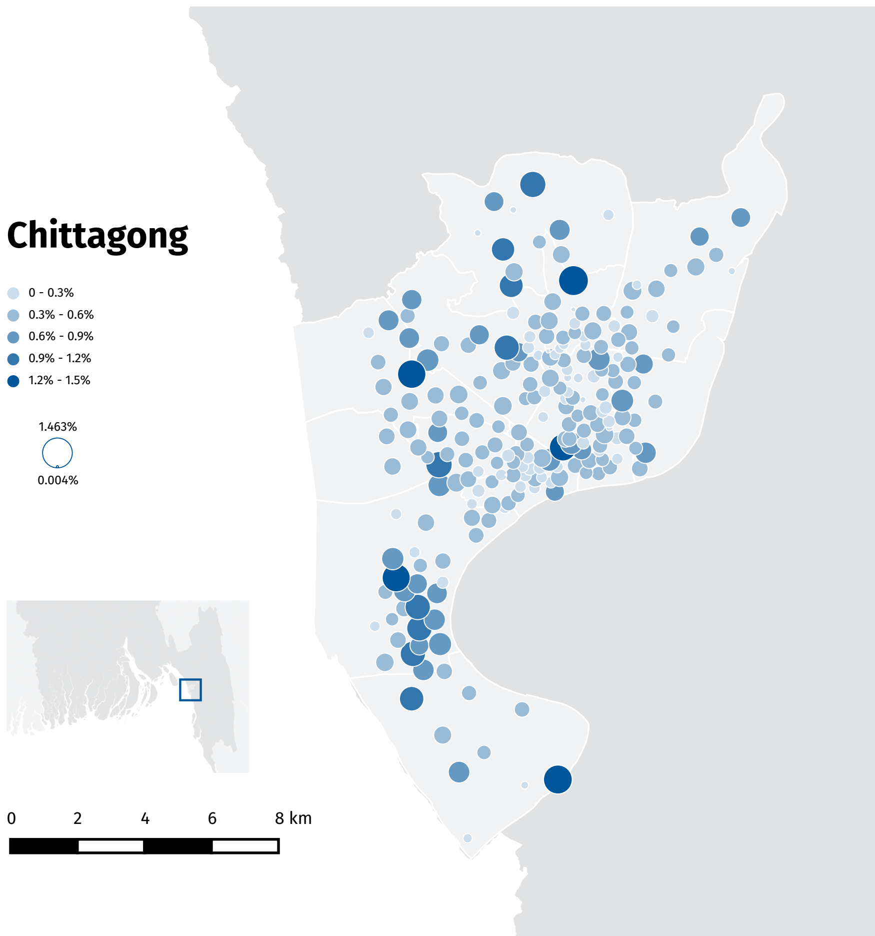


*Figure S3: **c,** The night time (9:00pm-6:00 am) distribution of subscribers arriving in Chittagong City between 16 May and 30 June, after Cyclone Mahasen.*

S4. Flow between Cyclone Affected Region and Other Regions

We then investigated flows of SIM cards in the cyclone impact area in the months immediately after the cyclone (May to July 2013) using Dataset D2. Figures S4 c and d show flow networks between the cyclone affected area and all other districts in the country during the period after Cyclone Mahasen, between May and July 2013. We see that the largest flows occured between the affected area and Dhaka, followed by the connections to Barisal City and Chittagong. We produced an identical flow network from the same time period in the previous year, 2012 (Fig S4 a, b), showing a very similar pattern.

We also compared specifically the flows from 2012 and 2013 between the cyclone-affected area and the country's two largest cities, Dhaka and Chittagong (Fig S4 e-g). This analysis shows that the relative flows between each three pairs of areas in the months after the cyclone (May to July 2013) are nearly identical to flows from the same time period the previous year (Fig S4 e). Relative flows from the cyclone affected areas to other areas are highly correlated between 2012 and 2013 (Fig S4 f); likewise, relative flows to the cyclone affected areas are highly correlated between 2012 and 2013 (Fig S4 g).

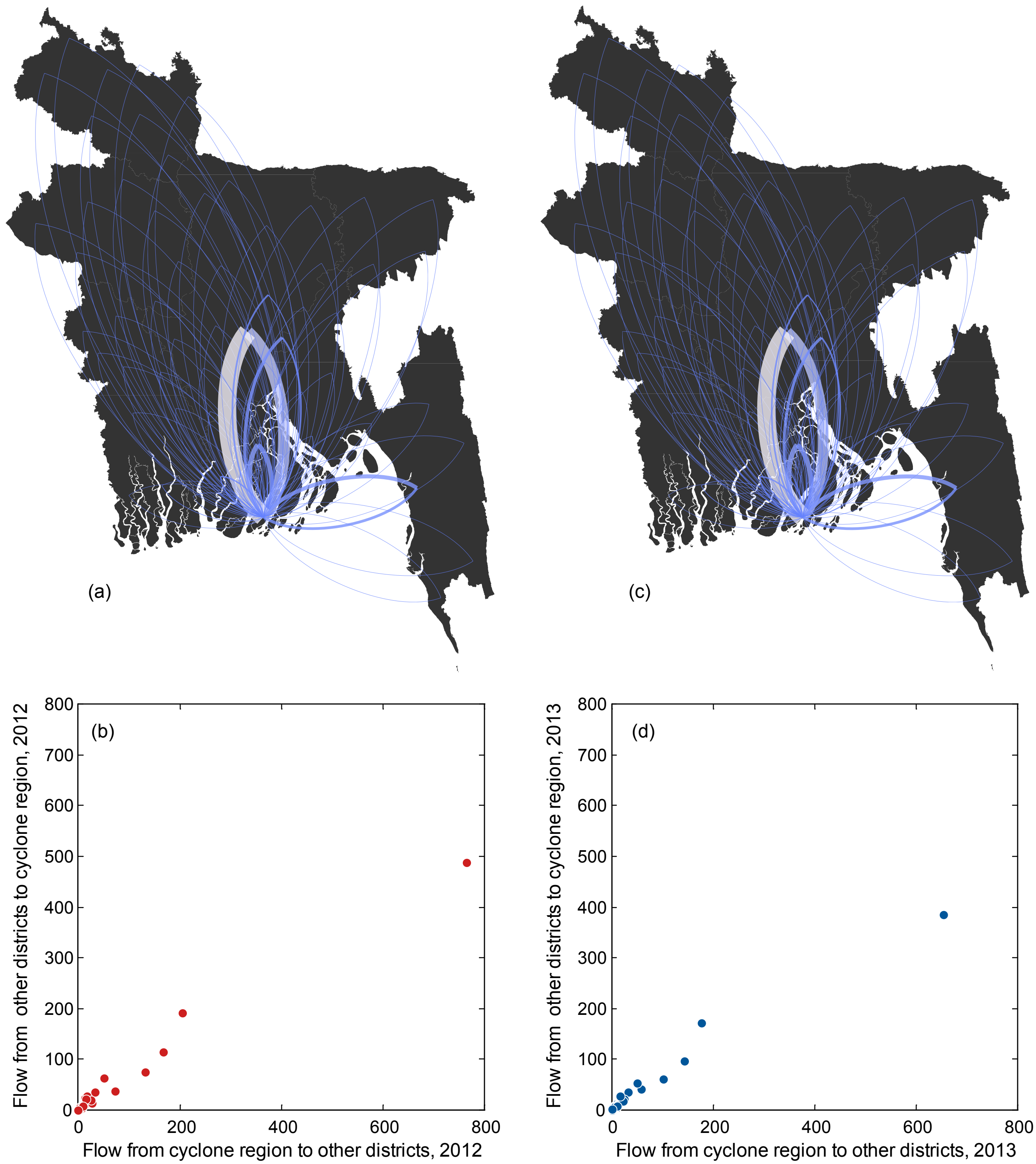


Fig S4: ***a,*** *Flow network between cyclone districts and other districts between May and July, 2012.* ***b,*** *Flow from all districts to the affected area plotted against flow from the cyclone affected are to all other districts, for the period from May to July in 2012 ($r=0.990$, $p<0.000$). Moving right to left, the dot farthest to the right represents Dhaka, followed by Barisal City, and then Chittagong.* ***c,*** *Flow network between cyclone districts and other districts between May and July, 2013.* ***d,*** *Flow from all districts to the cyclone affected area plotted against flows from the cyclone affected area to all other districts, for the period from May to July in 2013 ($r=0.986$, $p<0.000$). Moving right to left, the dot farthest to the right represents Dhaka, followed by Barisal City, and then Chittagong.*

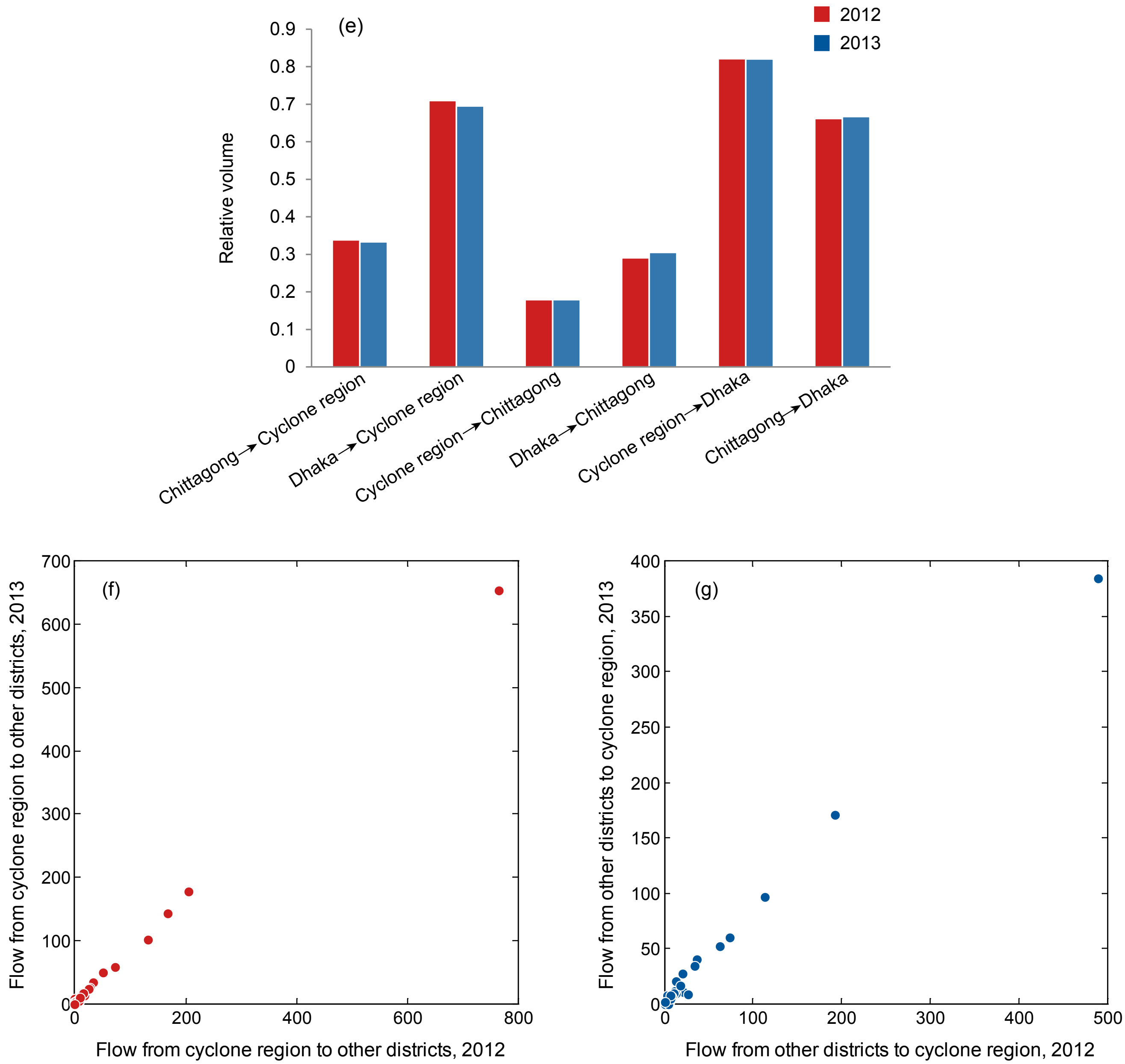


Fig S4: ***e,*** *Relative flow between the cyclone affected area, Chittagong and Dhaka, May-July 2012 compared to May-July 2013.* ***f,*** *Flow from affected districts to all other districts, for the period from May to July in 2012 and 2013. The correlation between absolute volume of flow in 2012 and 2013 are calculated ($r=0.999$, $p<0.000$). The dot to the extreme right represents Dhaka.* ***g,*** *Flow from all districts to the cyclone affected area, for the period from May to July in 2012 and 2013 ($r=0.997$, $p<0.000$).*

S5. Seasonality

In Figure 3, we show the correlation between netflow in 2012 and 2013 for each month and district. Here we show the same correlation for outflow and inflow, separately. By comparing the location of each SIM card in D2 at the beginning and end of each year (January and November, respectively), for each district, we calculate the inflow and outflow. From Figs. S5a, b, we can see that both inflows and outflows in 2012 are highly correlated to those in 2013, a correlation coefficient close to one, indicating a strong similarity of mobility patterns from year to year.

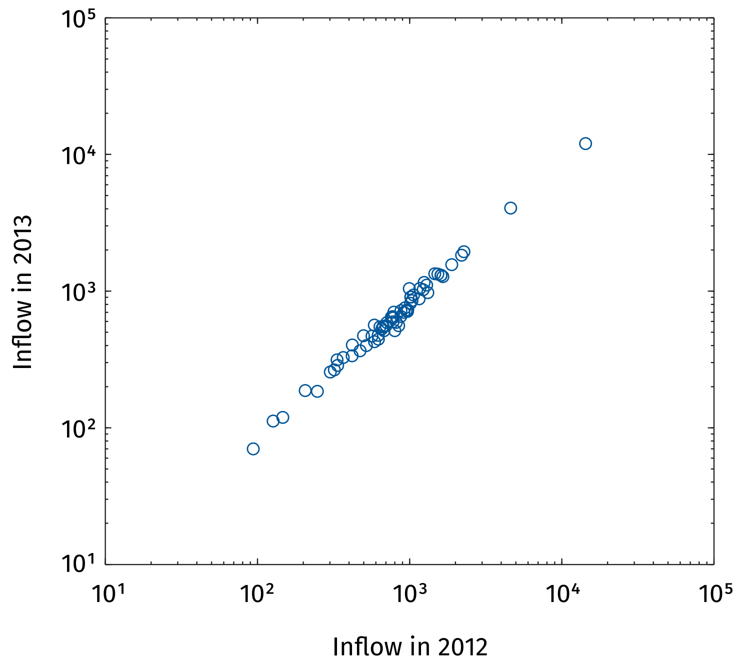


*Figure S5: **a,** A comparison of inflow for each district based on the location of each SIM card at the beginning and end of each year (January and November) (r=0.999, p<0.001)*

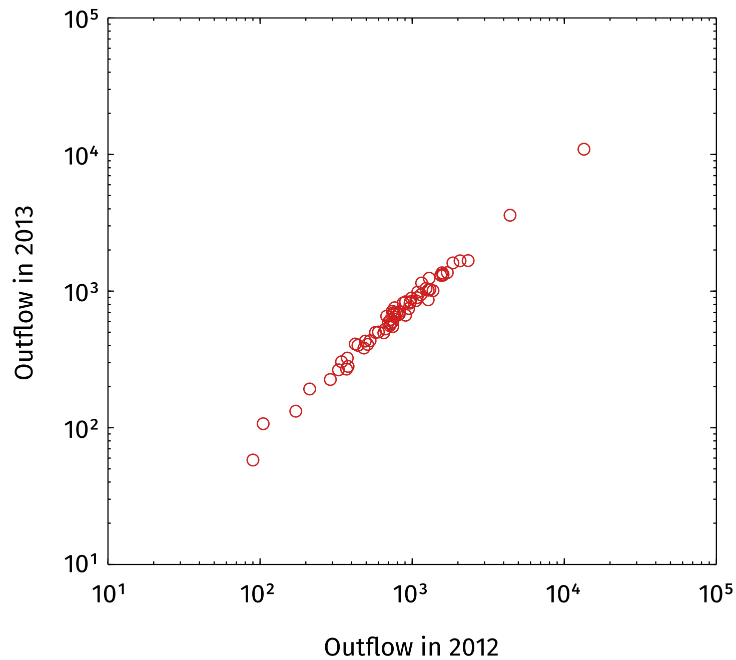


Figure S5: ***b,*** *A comparison of outflow for each district based on the location of each SIM at the beginning and end of each year (January and November) (r=0.999, p<0.001).*

S6. Sensitivity Analysis: Outside Proportion of Population versus Time Spent Outside

Next we test whether the specific period in which we calculated the outside ratio and outside time in the main manuscript (May through November) affected the correlation (e.g. due to holidays and other celebrations). For users located in the same district during January to April, the change in location (if such occurred) was calculated for the following periods: from May-June, from May-August, and from May-October (Figs. S6a-c). The correlation remains high across the different periods. We also show results where we require users to have moved out at least one or at least two months (two months is shown in the main manuscript).

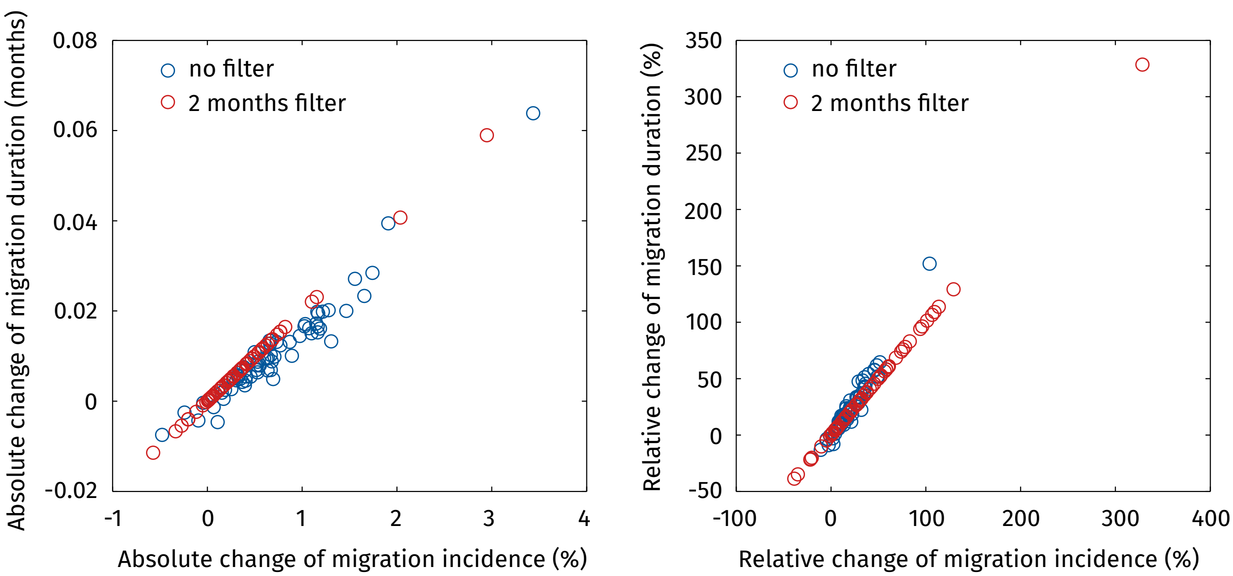


*Figure S6: **a,** May-June: The left figure shows the correlation for absolute differences in migration incidence and duration. The right figure shows the relative changes. The filter for the red data points (two months) means that they per definition end up on a straight line (since the time period considered has a length of two months).*

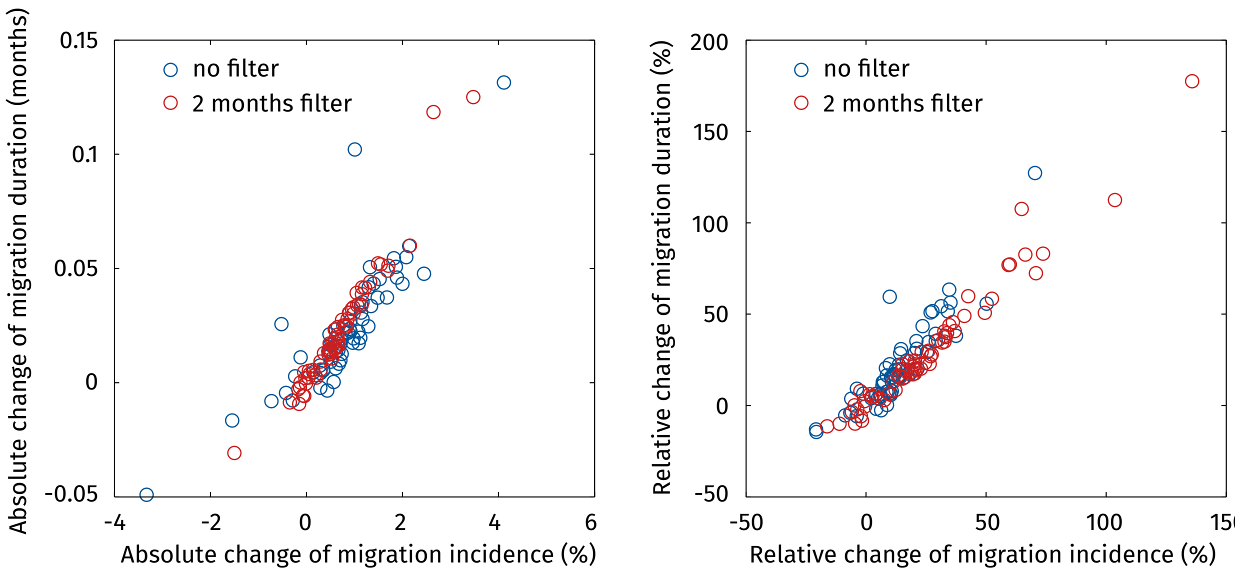


*Figure S6: **b,** May - August: The left figure shows the correlation for absolute differences in migration incidence and duration. The right figure shows the relative changes.*

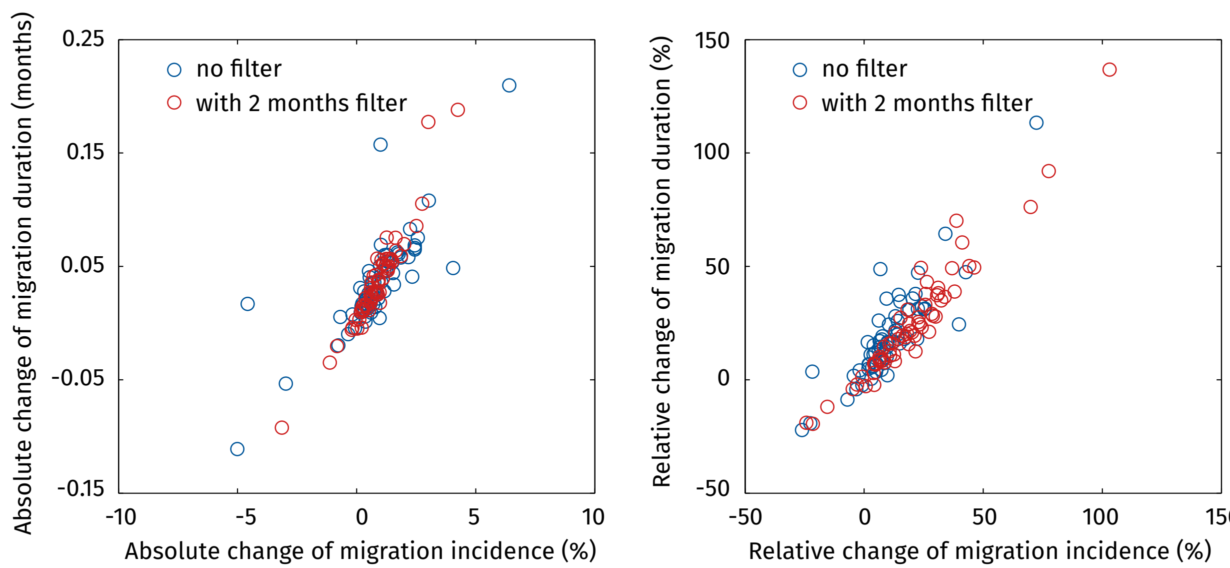


*Figure S6: **c,** May - October: The left figure shows the correlation for absolute differences in migration incidence and duration. The right figure shows the relative changes.*

As major flows appear to coincide with Eid celebrations, it is possible that a portion of the difference in flows between 2012 and 2013 can be explained by the timing of holidays. However Eid moved only by ten days within August between 2012 and 2013, and thus year-to-year differences were contained within August. With this exception, most calendar celebrations fell on similar days (Table S6).

Table S6: Holiday Calendar, August 2012 and August 2013.

August 2012	**August 2013**
09 Thursday: Krishna Janmashtami	02 Friday: Jumatul Wida
15 Wednesday: National Mourning Day	06 Tuesday: Shab-e-Qadar
16 Thursday: Shab-e-Qadar	**08 Thursday: Eid Ul Fitr (Rojar Eid)**
17 Friday: Jumatul Wida	**09 Friday: Eid Ul Fitr (Rojar Eid)**
19 Sunday: Eid Ul Fitr (Rojar Eid)	**10 Saturday: Eid Ul Fitr (Rojar Eid)**
20 Monday: Eid Ul Fitr (Rojar Eid)	15 Thursday: National Mourning Day
21 Tuesday: Eid Ul Fitr (Rojar Eid)	28 Wednesday: Krishna Janmashtami

S7. Sensitivity Analyses: Correlation between Changes in Inflows and Outflows (relating to Fig. 4 main manuscript)

First we determined, for each district in Bangladesh, the total number of moves out of each district between February to October 2012 and between February to October 2013 (per definition January and November lacks either inflow or outflow for both years). We then calculated the ratio between the values of outflow for the two years. We performed the same analysis for the total number of moves *into* each district and plotted the relationship between the change in inward movements and outward movements (Fig. S7a). We see that *changes in outgoing moves* per districts in 2013, as compared to 2012, are strongly positively correlated with *changes in inwards moves* into the same districts (r=0.775, p<0.001). This is the opposite pattern compared to the on analysis (negative correlation) shown in Fig. 4 (main manuscript). However, this positive pattern is largely caused by subscribers traveling repeatedly back and forth across district borders and is thus likely unduly influenced by highly mobile subscribers.

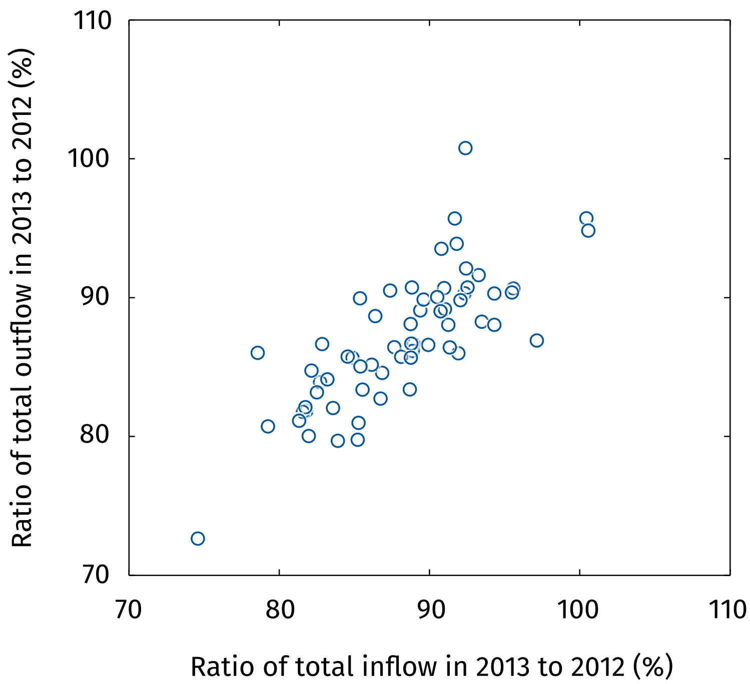


Figure S7: ***a,*** *Scatterplot showing, for each district, the change in incoming moves (comparing 2012 and 2013), with the corresponding change in outgoing moves between the same years. For each district, the total inward and outward moves are calculated by summing up all moves out of, and all moves into, the district between February and October each year (r =0.775, p<0.001).*

To better capture relevant migration patterns we therefore selected the subset of subscribers who had a stable home location prior to Mahasen, defined as being located each month in the same district during January to April. We then calculated, for this subset of subscribers and for each district, the number of subscribers located outside the district at the end of the year (in November). We determined the corresponding change in inflow (i.e. among users not present in the district during January to April but who had moved in by November). The number of migrating subscribers per district, according to these definitions, varied between 21 and 6,317 (Fig. S7b).

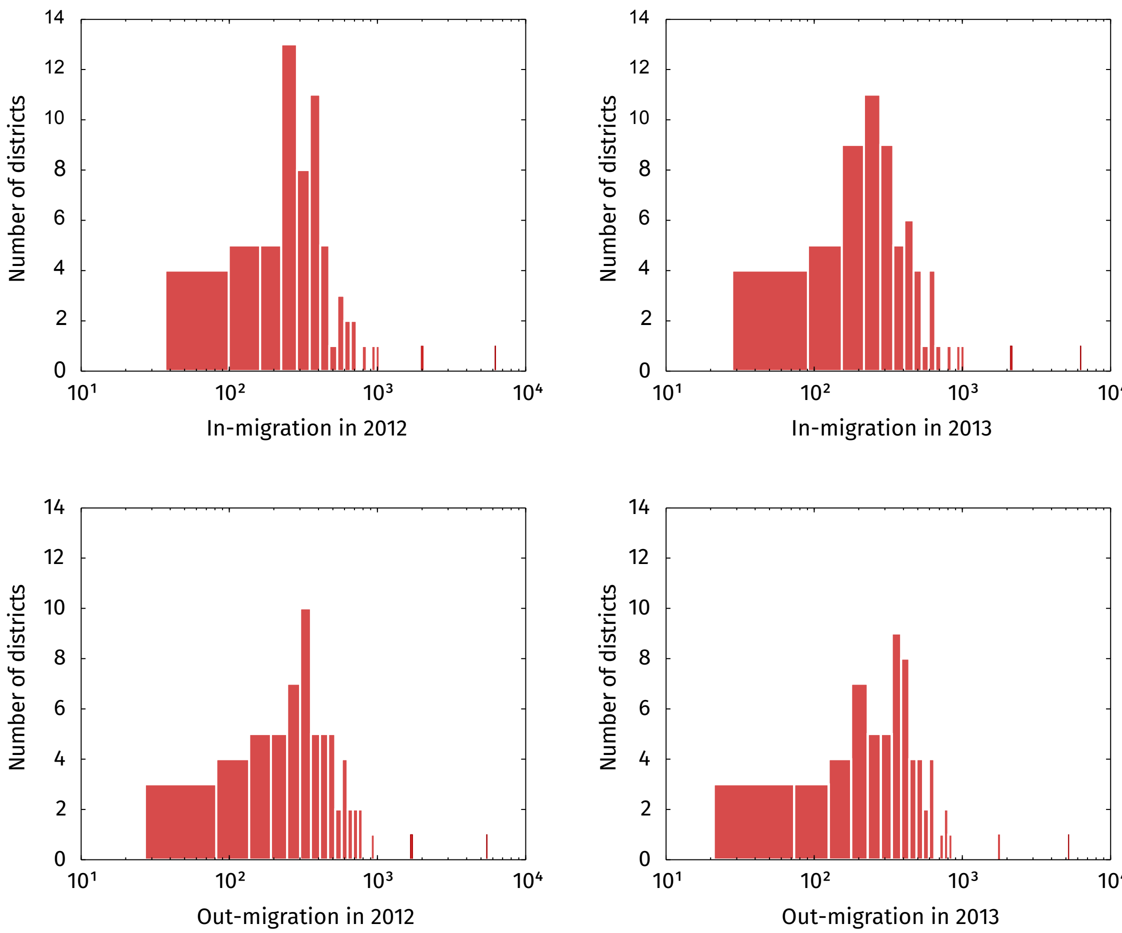


*Figure S7: **b,** Frequency distribution of the number of in and out-migration events per district in 2012 and 2013. Five out of sixty-four districts had less than 100 migrants in any of the above distributions. Fig. 4, main manuscript excludes districts with less than 200 migrants for any of the above periods and analyses.*

We plot the changes in the absolute values of change of in- and out-migration (comparing 2012 and 2013) versus the total number of in- and out-migrations taking place in 2012 (Fig. S7c). After removing extreme values for which migration is larger than 1000 per district, the linear correlation coefficient for in-migration is 0.15 ($p=0.237$) and for out-migration 0.49 ($p<0.001$). Interestingly, the changes in the number of migrants, comparing 2012 and 2013, are thus largely independent from the absolute number of outgoing migrants in 2012.

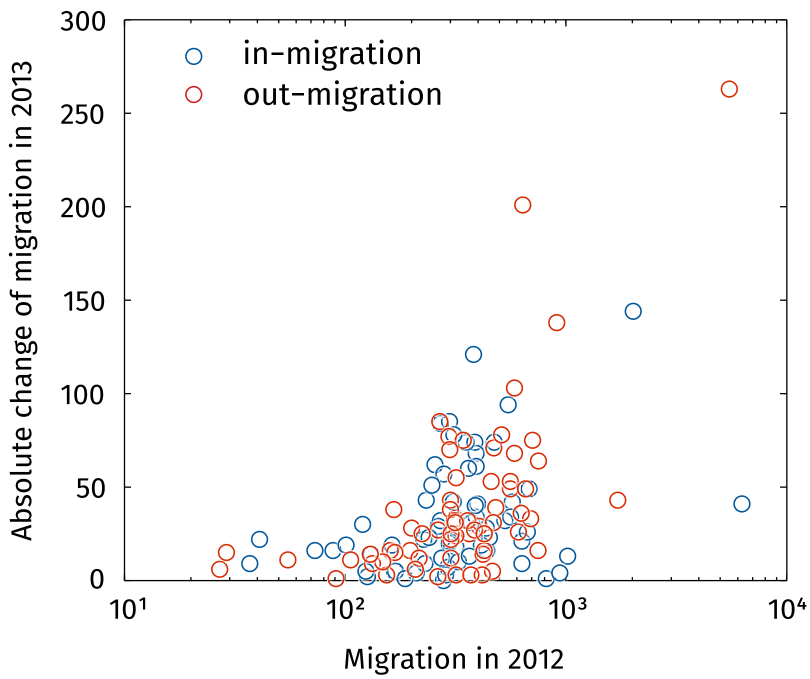
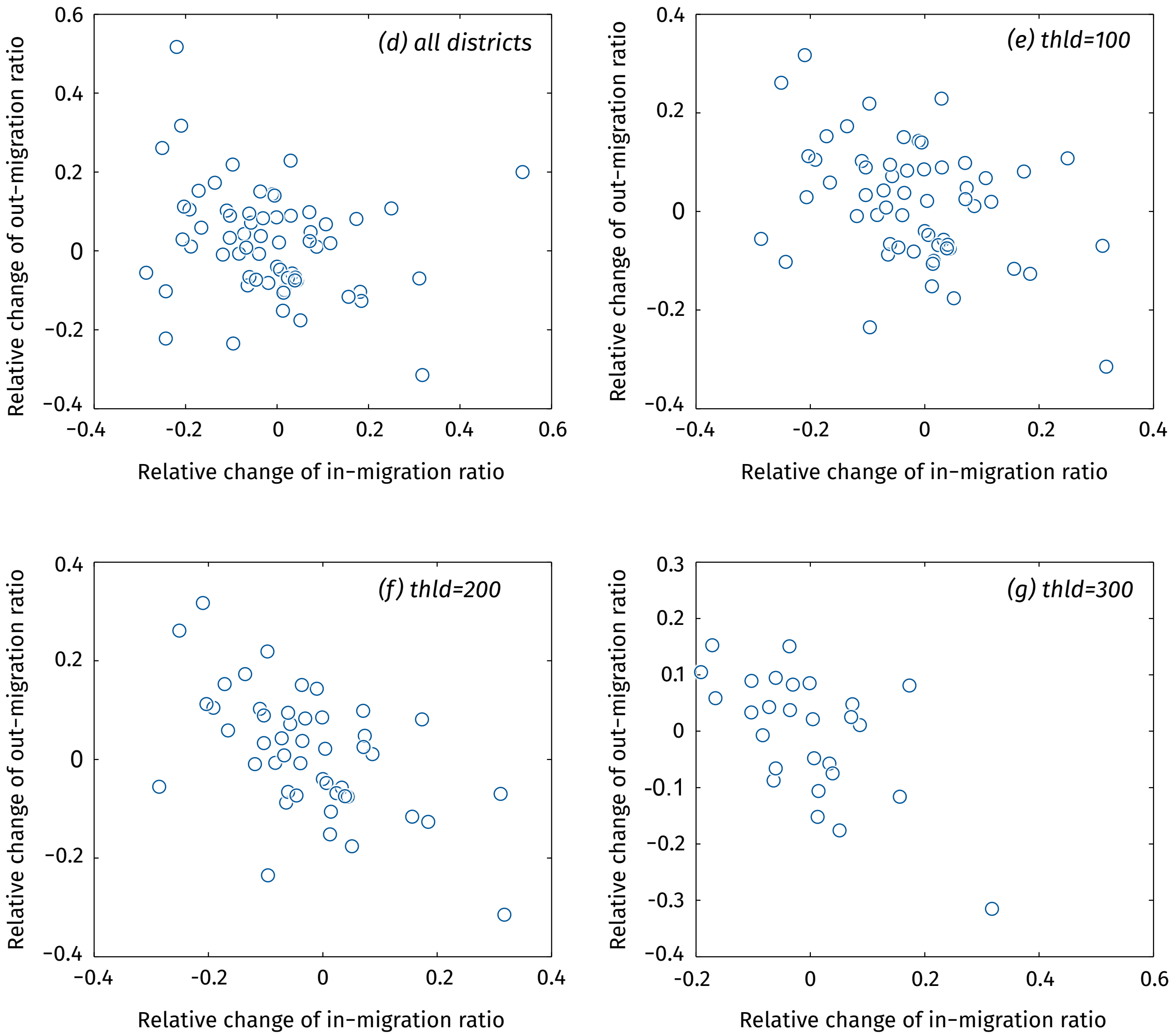


*Figure S7: **c,** Scatterplot showing, for each district, on the y-axis, the absolute values of change (ignoring whether being positive or negative) in in-migration between 2012 and 2013, compared to on the x-axis the absolute numbers of migrant coming into the district in 2012 (green circles). The same analysis for out-migration is shown in red.*

Fig. 4 in the main manuscript shows the correlation between changes in in- and out-migration comparing 2012 and 2013 for districts with at least 200 migrants both years. Below we show how this relationship is influenced by removing districts with fewer migrants (Figs. S7d-g). The negative correlation is stable but considerable variation remains also when keeping only districts with at least 300 migrants both years.



Figures. S7: ***d-g,*** *Analyses as defined for Fig. 4 (main manuscript) with varying selection criteria;* ***d,)*** *all districts (r=-0.245, p=0.051);* ***e,*** *districts with at least 100 migrants both years (r=-0.391, p=0.002);* ***f,*** *districts with at least 200 migrants both years (r=-0.561, p<0.001); and* ***g,*** *districts with at least 300 migrants both years (r=-0.633, p<0.001).*

References

Associated Press, (2013) Cyclone Mahasen hits coast of Bangladesh, Associated Press. Telegraph, London.

Bengtsson, L., Lu, X., Thorson, A., Garfield, R., Von Schreeb, J. (2011) Improved response to disasters and outbreaks by tracking population movements with mobile phone network data: a post-earthquake geospatial study in Haiti. PLoS medicine 8, e1001083.

Government of Bangladesh, (2008) Cyclone Sidr in Bangladesh: Damage, Loss and Needs Assessment For Disaster Recovery and Reconstruction, Dhaka, Bangladesh.

Government of Bangladesh, (2009) In-depth Recovery Needs Assessment of Cyclone Aila Affected Areas, Dhaka, Bangladesh.

Gutro, R., Pierce, H., (2013) NASA Sees Cyclone Mahasen Hit Bangladesh, in: NASA (Ed.), Goddard Space Flight Center, Greenbelt, MD.

Lucini, B., Hatt, T., (2014) GSMA Intelligence Report: Country Overview: Bangladesh, London.

National Institute of Population Research and Training (NIPORT), M.a.A., and ICF_International (2015) Bangladesh Demographic and Health Survey 2014: Key Indicators. National Institute of Population Research and Training (NIPORT), Mitra and Associates, and ICF International, Dhaka, Bangladesh and Rockville, Maryland.

REACH Initiative, (2013) Tropical storm Mahasen final assessment report (Phase 3 Shelter, WASH, Early Recovery Detailed Assessment) Bangladesh 2013, Dhaka, Bangladesh.

Telenor, (2013) Grameenphone, Bangladesh: In Bangladesh, Grameenphone is the leading provider of mobile communications services.

Wesolowski, A., Eagle, N., Noor, A.M., Snow, R.W., Buckee, C.O. (2013) The impact of biases in mobile phone ownership on estimates of human mobility. Journal of the Royal Society Interface 10, 20120986.

Wesolowski, A., Eagle, N., Tatem, A.J., Smith, D.L., Noor, A.M., Snow, R.W., Buckee, C.O. (2012) Quantifying the impact of human mobility on malaria. Science 338, 267-270.