

Remotely measuring populations during a crisis by overlaying two data sources

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Received 31 October 2014; revised 14 January 2015; accepted 15 January 2015

Background: Societal instability and crises can cause rapid, large-scale movements. These movements are poorly understood and difficult to measure but strongly impact health. Data on these movements are important for planning response efforts. We retrospectively analyzed movement patterns surrounding a 2010 humanitarian crisis caused by internal political conflict in Côte d'Ivoire using two different methods.

Methods: We used two remote measures, nighttime lights satellite imagery and anonymized mobile phone call detail records, to assess average population sizes as well as dynamic population changes. These data sources detect movements across different spatial and temporal scales.

Results: The two data sources showed strong agreement in average measures of population sizes. Because the spatiotemporal resolution of the data sources differed, we were able to obtain measurements on long- and short-term dynamic elements of populations at different points throughout the crisis.

Conclusions: Using complementary, remote data sources to measure movement shows promise for future use in humanitarian crises. We conclude with challenges of remotely measuring movement and provide suggestions for future research and methodological developments.

Keywords: Crisis, Mobile phones, Movement, Population density, Satellite imagery

Introduction

Estimating average population numbers and distributions at high spatial-resolution is difficult; measuring dynamic population sizes and densities is an even greater challenge.^{1–10} Movement and displacement across various scales can have important effects on health, including disease transmission and access to medical and social services. Understanding mobility surrounding disruptive events can improve the delivery of humanitarian aid. Measures of movement following a crisis can also guide rebuilding efforts.

The sizes, and occasionally the demographics, of displaced populations have been assessed using various sampling strategies,¹¹ including surveys,¹² camp registration data from internally displaced persons (IDPs),¹³ counting tent structures with high

resolution satellite imagery,¹⁴ long-term changes in vegetation patterns^{15,16} and, more recently, crowdsourcing efforts.^{17,18} Unfortunately, these methods of data collection are often labor intensive and may occur at a spatial or temporal scale that does not capture the full extent of the crisis event, making it difficult to inform a response strategy. Recently harnessed remote data streams, such as mobile phone call detail records (CDRs) and satellite nightlights imagery enable rapid, large-scale measures of populations and movements.^{1,19,20}

Mobile phone data

Mobile phones communicate with the nearest cell tower to send and receive signals. Each billable communication event between

a phone and a tower is recorded in the operator's database of CDRs so each user can be located to the nearest cell tower at the time of the event. CDRs provide very high spatial and temporal resolution data on movements in areas where mobile phones are used regularly and tower coverage is dense.

CDRs can be used to estimate aggregated time series of: 1. the number of users in the coverage area of each phone tower and 2. origin-destination matrices of the proportion of phone users moving between any two mobile tower coverage areas.²¹ Anonymized mobile phone data are a cost efficient proxy indicator for short-term recurring and non-recurring population movements, though such data have only been used for crises or displacement in limited situations, for example the analysis of the 2010 earthquake in Haiti.^{5,6}

There are some important practical limitations to CDRs. First, private companies own CDRs and gaining access usually requires a legal contract, including time-consuming negotiations, often with significant legal liabilities.²² Second, if access to CDRs is granted, most network providers operate within national boundaries and can grant access only to CDRs that occurred within those boundaries; crisis-time movement often intentionally occurs across national boundaries. Third, demographic differences in phone ownership and usage levels within a country can influence the reliability of relative mobility estimates derived from CDRs, for example measuring population movements across levels of wealth or rural and urban areas. Finally, phone operators do not often provide long-term data on phone usage, although there are some exceptions. Researchers might be granted access to approximately 12 months of CDRs, from which it is impossible to detect seasonal or other long-term cyclical movement patterns and distinguish them from movements due to one-time events; for this study we have 5 months of CDRs.

Satellite imagery

Satellite images detect settlements by capturing quantifiable, anthropogenically derived light emissions (electric lighting and fires).²³ Brightness values in images correlate to population presence and size; 'changes' in numerical brightness values or area lit, determined from serial images, reveal changes in population size and distribution. Images of nighttime lights brightness have been captured daily since 1992 by the Defense Meteorological Satellite Program (DMSP) at approximately 1 km spatial resolution.²⁴ The combined level of detailed, global coverage and long-running data collection of satellite images provide rare advantages in measuring populations. Despite this, these images have rarely been used to measure crisis-time displacement.^{25,26}

Important limitations of nighttime lights satellite imagery include sensitivity to environmental conditions, such as light contamination and cloud obstruction,²⁷ and difficulty with calibration to absolute population size. Both CDRs and nighttime satellite imagery are biased by wealth, most notably in low-income areas,^{21,28} and are sensitive to power outages, which can occur during natural disasters and crises.

Instability and crisis: Côte d'Ivoire election

On 28 November 2010, the presidential election results from Côte d'Ivoire (Figure 1A) reported that the challenging candidate, Alassane Ouattara, narrowly defeated the incumbent president, Laurent Gbagbo²⁹ (Figure 1B). The results were widely disputed

and both candidates claimed victory. Political support for the two candidates divided the country geographically, coarsely separating the south from the north (Figure 1C). Armed conflict throughout the country began in December of 2010 and large numbers of people reportedly fled the violence.³⁰ In April of 2011, Ouattara's military forces surrounded Gbagbo in the president's residence, located in the largest city of Abidjan.³¹ During the year-long period of instability (Figure 1B), hundreds of thousands of Ivoirians sought refuge in neighboring Liberia,³² while thousands of others were internally displaced.³³

By April of 2012, the UN-backed pro-Ouattara military forces stabilized large parts of Côte d'Ivoire. As security improved, the United Nations High Commissioner for Refugees (UNHCR) and the International Organization for Migration (IOM) facilitated the return of refugees and IDPs, though large numbers are believed to have returned without external assistance, making official reports on return movements difficult to interpret.^{34,35}

For this study, the CDRs did not provide long-term data on population movements, a pre-conflict baseline or movement across national boundaries. Likewise, the satellite images did not provide high-resolution mobility traces and were sensitive to environmental factors. Taking the unique approach of using these two complementary data sets to overcome the limitations of each and remotely measure movement during the 2010–2012 political conflict in Côte d'Ivoire enabled measurements of average long-term population presence and dynamic measures of populations across spatial and temporal scales (Figure 1).

Materials and methods

Côte d'Ivoire administrative boundaries

Côte d'Ivoire is made up of 19 administrative regions, which are further divided into 255 subprefectures. In addition to these government recognized administrative units, Oxford University's Poverty and Human Development Initiative has clustered the 255 subprefectures into 11 regions that reflect similar poverty indices,³⁶ which are particularly relevant here because anthropogenic illumination, phone ownership and phone usage can be biased by wealth. Official election results were reported for the 95 departments in Côte d'Ivoire. The subprefectures are not perfectly nested within the 95 departments. The 12 largest cities based on population size estimates were located to measure urban population sizes.

Liberia administrative boundaries

Liberia is divided into 15 counties, which are each further divided into districts. Using brightness, we measured changes in population in the border districts of Grand Geddeh and Nimba, where the UN established refugee camps. Data on refugee camps were collected from UN reports.^{32,34,37}

Satellite imagery: pre-, during and post-conflict

Annual composites

Composite images are produced from a compilation of individual images that are captured daily over a certain period of time, high-lighting either stable lights or average light values. Because these are comprised of many individual images, they are more robust to the noise and light contamination that affect each individual

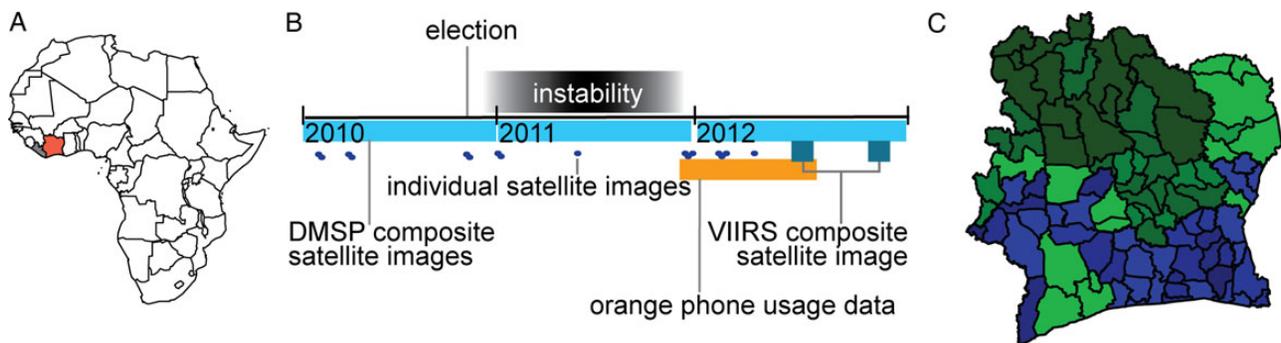


Figure 1. (A) Map of Africa with Côte d'Ivoire shaded in red and Liberia in light grey. (B) Timeline of events from 2010–2012 (above line) and time points of data collection (below line). A single point represents a single satellite image; these were often acquired in clusters of two or more consecutive cloud and moon-free days. (C) Election results from 95 departments (adapted from⁵¹), from official election results released by Commission Electorale Indépendante.⁵² Blue: Gbagbo; Green: Ouattara; darker shades indicate greater margin of victory.

image. These images have been collected since 1992, though the satellites drift over time and degrade and aging sensors are taken out of commission and replaced with new ones. Because these devices lack onboard calibration, the images, both individual and composited, must be calibrated after they are captured. This is done according to the methods presented in Elvidge et al.,²⁴ with details for calibrating more recent imagery found in Elvidge et al.³⁸ We analyzed annually composited images of stable lights, created from individual images captured during 1998 (to compare to 1998 census data, see [Supplementary materials](#)) 2010, 2011 and 2012 by the Operational Linescan System instruments onboard the DMSP satellite, and calibrated the extracted values.³⁸

Individual images

Anthropogenic brightness is most abundant in urban areas so we specifically analyzed phone tower density and changes in brightness values in the 12 largest cities in Côte d'Ivoire. We used non-composited, calibrated serial images from DMSP satellite sensor F18, acquired from the National Oceanic and Atmospheric Administration National Geophysical Data Center.³⁸ These raw images are captured daily and georeferenced and were obtained from the Space Physics Interactive Data Resource.³⁹ We selected images that were free of environmental contaminants, specifically: 1. lunar illumination (images captured during bright moon phases); 2. solar illumination (images captured during daylight); 3. cloud presence (as determined by the accompanying thermal-infrared images using a conservative numerical threshold of 200). Finally, to reduce the impact of variability in human behavior (extinguishing fires and reduced lights while sleeping), we included only images that were captured between 19:00 h and 22:00 h local time. We selected 16 individual images that were captured before, during and after the period of instability, from 2010 to 2012, to measure displacement and return. We used the same approach to measure population changes from 13 images in the two border counties of Liberia where the UN established refugee camps.

The sensors on board the satellites can fail to detect changes in brightness levels above a saturation threshold when pixels are very bright. They may also not be sensitive enough to detect settlements that emit very low light levels. Issues of saturation and sensitivity exist in both composite and individual images. In our images of Côte d'Ivoire, we observe saturated pixels in the largest city of Abidjan, the second largest city of Bouaké and the

capital city of Yamoussoukro. Pixels with a brightness value of zero are found in all administrative regions of the country; some of these pixels are locations where small settlements exist but cannot be detected by the satellite sensors.

Mobile phone call detail records

Orange mobile has approximately 5 million registered users in Côte d'Ivoire, an estimated one-quarter of the national population,⁴⁰ and has phone towers present in 237 of the 255 subprefectures. To assist in societal development, Orange mobile provided datasets of phone usage from 1 December 2011 to 28 April 2012. In addition to the location of the mobile phone towers, we used two Orange mobile provided datasets, described below, for this study.⁴¹

For the first dataset Orange mobile randomly selected 50 000 users every 2 weeks for 5 months from their 5 million registered users in Côte d'Ivoire and geolocated them to the nearest tower. Reselecting users every 2 weeks ensured that their privacy was not compromised, while still providing detailed movement patterns of the population (dataset 2).⁴¹ These data were compared to composite and serial measures of brightness values from satellite images across economic regions, administrative regions, subprefectures and in urban areas.

The second dataset is a random sample of 500 000 anonymized mobile phone users (dataset 3).⁴¹ Each user's location is reported daily at the level of the subprefecture. We used these data to measure average population sizes, net changes in population sizes over the 5-month period of phone data and designate subprefectures as population sources or sinks, calculated from SIMs (Subscriber Identity Modules; anonymous, unique identifiers of phone users).

Each data set presents the results of any billable event between a phone and a tower. This includes phone calls, text messages and data usage on smartphones. These Orange-provided phone usage datasets were largely collected after the crisis was officially declared over.

Analyses

To measure average population presence using CDRs and satellite imagery, we compared composited stable nighttime lights values from 2012 and 2010, the density of phone towers present, which are static, and the density of SIMs from data set 2 from December 2011 to April 2012 from the 11 poverty-indexed economic

regions,³⁶ 19 administrative regions and 255 subprefectures of Côte d'Ivoire. We also compared composited imagery to the most recent census, which was completed in 1998 (see [Supplementary material](#)).

Estimated net changes in subprefecture population sizes, measured over 5 months using CDRs (see next section) and over 2 years using brightness measures, were assessed as follows: 1. a linear regression model was fit to the stable brightness composites of 2011 and 2012 for the subprefectures; 2. a linear regression model was fit to the mean number of SIMs from phone data set 2 for the first week of December 2011 and the last week of April 2012 for the subprefectures; an additional linear regression model was fit to the mean number of SIMs for the month of December 2011 and the month of April 2012; 3. the correlation between the residuals from each regression was measured.

Population source and sink subprefectures were determined by removing the central 20% of the residuals from each of the above mentioned regressions. The remaining 80% of subprefectures were classified as population 'sources' (net exporters) or 'sinks' (net importers) based on net loss or gain of SIMs or brightness.

To look at net changes in population presence pre- to post-conflict, a linear regression model was fit to the stable brightness values from the annual composites of 2010 and 2012 for the subprefectures, and again all but the central 20% of the residuals were plotted as population sources or sinks. We compared the spatial patterns of population sources and sinks for both short and long-term movements, as measured by the CDRs and satellite images, respectively.

Using the locations of phone towers, we compared the density of towers in each of the 12 most populous urban areas to the

corresponding urban brightness values from individual images as well as annual composites to assess average population sizes. Using phone data set 1, we also calculated the mean number of SIMs accessing the towers of each urban area from December 2011 to April 2012. Finally, we measured the variance and mean in brightness for each city across the serially captured individual images. We also applied this approach to measure population size changes in the refugee camps in Liberia.

Results

Correlation between data sources: average population measures pre- and post-conflict

We found a strong positive correlation between the mean number of SIMs and the number of phone towers across the 5 months of CDRs in the economic regions ($\text{corr}=0.95$; $p<0.001$) and subprefectures ($\text{corr}=0.81$; $p<0.001$), but no correlation in administrative regions ($\text{corr}=-0.08$; $p=0.75$) (Figure 2A).

Comparing post-crisis population presence from data collected in 2012, we found a positive correlation between the density of towers and the mean composite brightness values from 2012 in the economic regions ($\text{corr}=0.96$; $p<0.005$), subprefectures ($\text{corr}=0.70$; $p<0.001$) and administrative regions ($\text{corr}=0.83$; $p<0.001$) (Figure 2B). We also found a positive correlation between the density of SIMs and the mean composite brightness values from 2012 in economic regions ($\text{corr}=0.96$; $p<0.005$), subprefectures ($\text{corr}=0.70$; $p<0.001$) and administrative regions ($\text{corr}=0.83$; $p<0.005$) (Figure 2C). It is possible that sensor saturation and sensitivity had an impact on the relationships seen in Figures 2B and C.

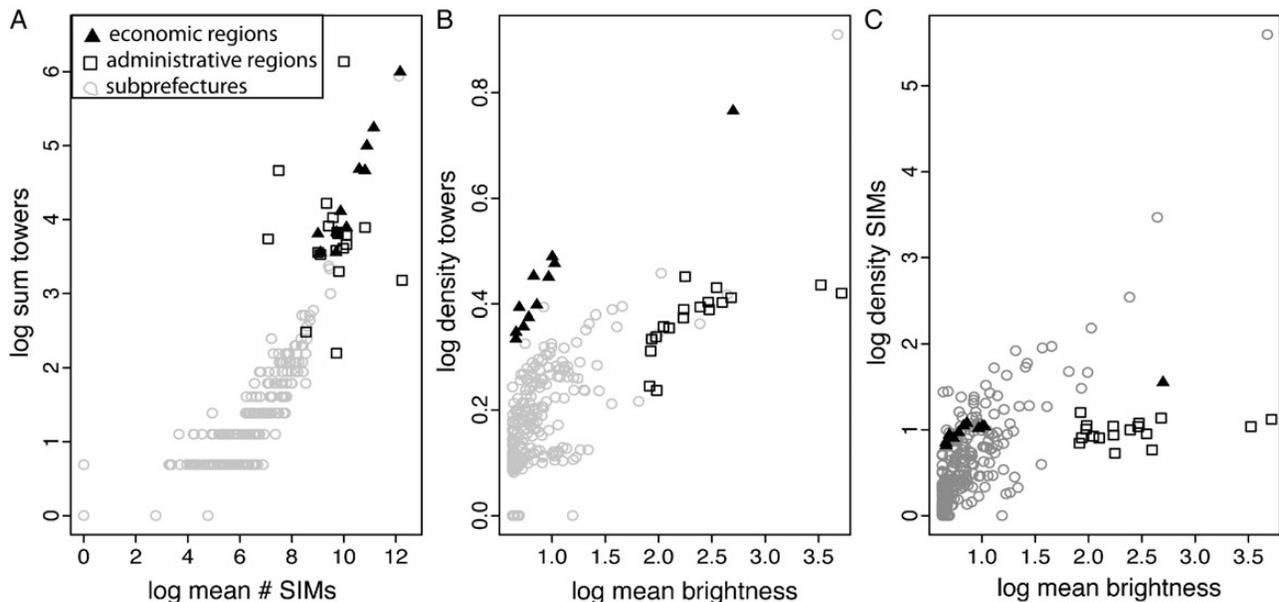


Figure 2. Stable measures of population presence. (A) Sum of phone towers against mean number of calling SIM cards from December 2011 to April 2012 for 11 poverty indexed regions³⁶ (black triangles, correlation=0.95), 255 subprefectures (grey circles, correlation=0.81) and 19 administrative regions (black squares, correlation= -0.08). (B) Mean density of towers against the mean nightlight image brightness values from the 2012 Defense Meteorological Satellite Program (DMSP) composite for 11 poverty indexed regions (correlation=0.96), 255 subprefectures (correlation=0.70) and 19 administrative regions (correlation=0.83). (C) Mean density of calling SIM cards from December 2011 to April 2012 against the mean nightlights brightness values from the 2012 DMSP composite for 11 poverty indexed regions (correlation=0.96), 255 subprefectures (correlation=0.70) and 19 administrative regions (correlation=0.83).

We found positive correlations between the density of towers and the mean composite brightness from 2010 across the economic regions ($\text{corr}=0.96$; $p<0.005$), subprefectures ($\text{corr}=0.70$; $p<0.005$) and administrative regions ($\text{corr}=0.82$; $p<0.005$). We also found positive correlations between the density of SIMs and mean composite brightness values from 2010, pre-conflict, in economic regions ($\text{corr}=0.96$; $p<0.005$) and subprefectures ($\text{corr}=0.82$; $p<0.005$), but only a weak correlation in administrative regions ($\text{corr}=0.23$; $p=0.35$).

Net population changes by subprefecture: pre- and post-conflict

The residuals from the linear regression of composite brightness from 2010 and 2012 were not correlated to the residuals from the linear regression of phone usage from the first and last week ($\text{corr}=0.16$; $p=0.009$) or the first and last month ($\text{corr}=0.14$; $p=0.03$) across subprefectures. This indicates that, although spatial resolution was consistent, movement patterns and changes in population size across subprefectures were different during these time periods, which reflect different points in the conflict. This would be expected if the conflict caused the movement patterns that disrupted stable populations.

The spatial redistribution of SIM users by subprefectures during the post-crisis period from the first week of December 2011 and the last week of April 2012 is patchy (Figure 3A). The 5-month period of phone data collection measured post-conflict movements only with no data from before or during the conflict for comparison. From December 2011 to the following April, the central and northern portions of the country increased in numbers of SIM users. In contrast, the residuals of a linear regression fit to the mean brightness of subprefectures from 2010 and 2012 (pre- to post-conflict) composite images showed a clustered decrease in brightness, or population sources, in the central subprefectures of the country, while the northern and western subprefectures showed

increases and were population sinks (Figure 3B). As expected, patterns of net population redistribution over the duration of the crisis and during the recovery period look different.

Urban areas by region: throughout conflict

We compared serial brightness levels to the mean number of urban SIMs across the 5 months of CDRs in the 12 largest urban areas of Côte d'Ivoire. Brightness values were extracted from non-composited satellite images of nighttime lights (Figure 4A), beginning 1 year before the election and ending about 1 year after the conflict was officially declared resolved. Election results were not correlated with the average population size for the cities of Côte d'Ivoire; the cities in which Gbagbo won the election ($n=6$) and the cities in which Ouattara won the election ($n=6$) showed no differences between the mean of log brightness (mixed effects model with a random effect for city, $p>0.05$). There was no significant difference in the coefficient of variance in log brightness values of cities voting for Gbagbo or Ouattara (t test; $p=0.27$).

Mean urban brightness values from individual images were correlated to the density of phone towers present (for all points $\text{corr}=0.85$; $p<0.001$; without largest city Abidjan $\text{corr}=0.31$; $p=0.35$) (Figure 4B); mean urban brightness values from 2010 and 2012 composite images were strongly correlated to the number of towers present ($\text{corr}=0.94$ and $\text{corr}=0.93$, respectively). Of the 12 cities, 9 have fewer than 15 towers and only 1 has more than 25 towers; the city of Abidjan is the largest city in Côte d'Ivoire and has nearly 400 mobile phone towers. The number of phone towers is strongly correlated to the mean number of SIMs ($\text{corr}=0.99$ with and without outlier, Abidjan). The correlation between the volume of SIMs and mean brightness value varies from 0.51 to 0.80, excluding and including the city of Abidjan, respectively, indicating that brightness, SIMs and tower locations are correlated in urban areas, with strong correlation in large urban areas.

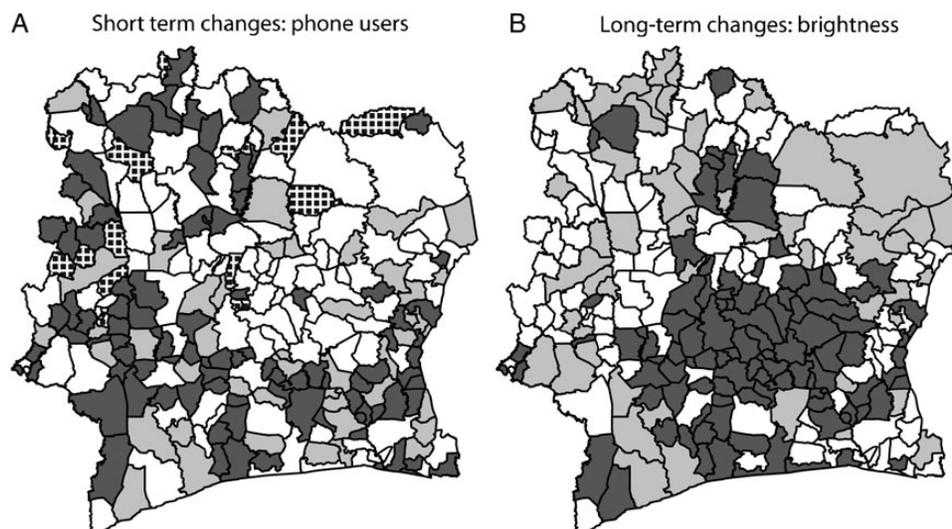


Figure 3. (A) Short-term redistribution of phone users by subprefecture between the first week of December 2011 to the last week of April 2012 showing decreases (black), increases (white), minimal change (central 20%) (grey) and no towers (checkerboard). (B) Long-term changes in stable brightness of subprefectures from a linear regression of 2010 and 2012 composite images showing decreases (black), increases (white) and minimal change (central 20%) (grey).

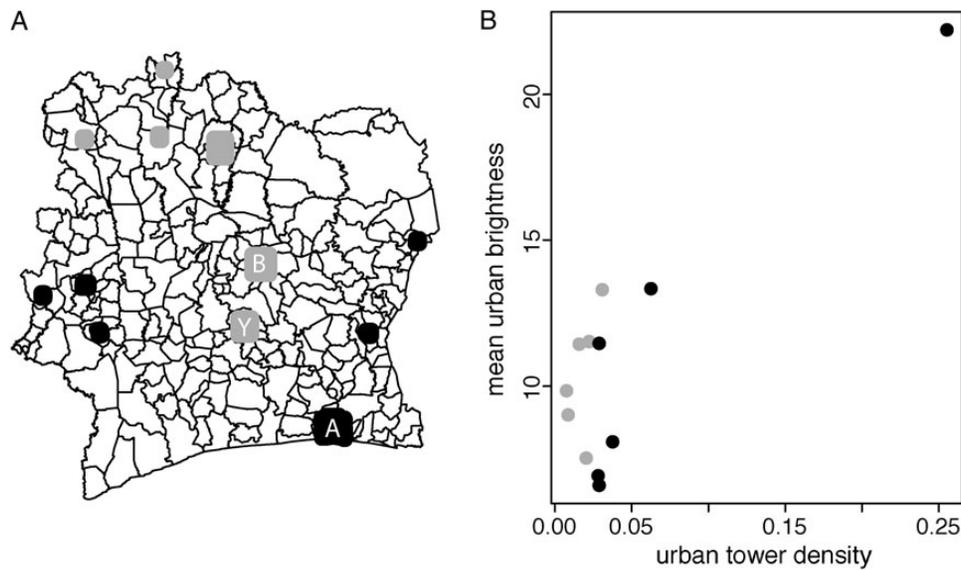


Figure 4. (A) Map of Côte d'Ivoire's subprefectures and 12 largest cities; the largest city Abidjan, the second largest city of Bouaké and the capital city Yamoussoukro are labeled with an A, B and Y, respectively. (B) Mean urban brightness against the density of phone towers. Colors indicate election results: grey: Outtara; black: Gbaggo.

Refugee camps: detection, growth and decrease throughout conflict

Because phone usage data did not provide information beyond the national boundaries of Côte d'Ivoire, we compared UN records to brightness values from satellite images to detect the hundreds of thousands of international refugees who crossed Côte d'Ivoire's border into two counties of Liberia. At the height of the instability, over 175 000 Ivorian refugees were reportedly living in Liberia, largely in the counties of Grand Gedeh and Nimba (Figure 5A, B).³² Using serial nighttime light satellite images, we measured the mean brightness levels of each of these two Liberian counties before, during and after the instability in Côte d'Ivoire (Figure 5C, D). Despite temporal gaps in usable imagery due to cloud cover, we found that the increases in brightness for Grand Gedeh and Nimba occurred at the same time as the increase in the number of UN recorded refugees crossing the border into Liberia. The increase in brightness and the beginning of the decrease in brightness coincided with the timing of the increase in refugee records in both areas. The proportional decrease in brightness following the period of instability is greater and more rapid than the UNHCR recorded number of refugees leaving Liberia through the end of 2011 (data on refugees leaving Liberia are not available past 2011). According to UN reports, refugees remained in Liberia until after December of 2011,⁴² but the brightness of the two Liberian counties had decreased to pre-instability levels by the end of 2011. This discrepancy may be due to the large numbers of refugees who reportedly returned to Côte d'Ivoire without external assistance and may have been unaccounted for in official reports.⁴³ The refugees entered and exited Liberia throughout 2011 so annually composited imagery cannot provide additional information in this case.

Discussion

Using two remotely acquired data streams, we measured average population sizes and population movements at different spatial

and temporal scales during a period of political and societal instability. Using satellite imagery, we established pre-conflict baselines of brightness at various spatial scales and compared relative brightness levels across multiple years and across international boundaries. We also used the 1998 census in conjunction with satellite imagery to understand the relationship between composite brightness levels and population numbers in the 19 administrative regions of Côte d'Ivoire (see [Supplementary material](#)). Mobile phone derived CDRs allowed us to look at high-resolution changes in absolute numbers of population size for a short period of 5 months during the recovery period in the Côte d'Ivoire. This is the first time satellite imagery and mobile phone usage data have been used together to measure populations and movement.

Phone towers and SIMs showed a stronger correlation in the few locations where many towers were present; this relationship was not as strong for low or intermediate levels of tower coverage. Only large urban areas have a high density of towers, which are accessed by a lot of SIMs, while many locations have a few towers that can provide sufficient coverage for both large and small numbers of SIMs. Stable or average measures of populations were strongly correlated between phone and satellite measures across economic regions and subprefectures, indicating that the two proxy data sources were measuring stable human presence similarly. These measures were not as strongly correlated across the large administrative units of the country, likely because administrative units aggregate across varying levels of wealth and access to resources that differ between these two proxy measures.

There was no detectable relationship between the mean or variance of urban population sizes and election results. Further, the displacement that reportedly occurred in many cities was not detectable by either of the methods used here. IDPs were said to seek shelter at local camps and religious centers by the thousands but did not necessarily leave the immediate area of their homes⁴⁴ because many UN IDP camps were located at the

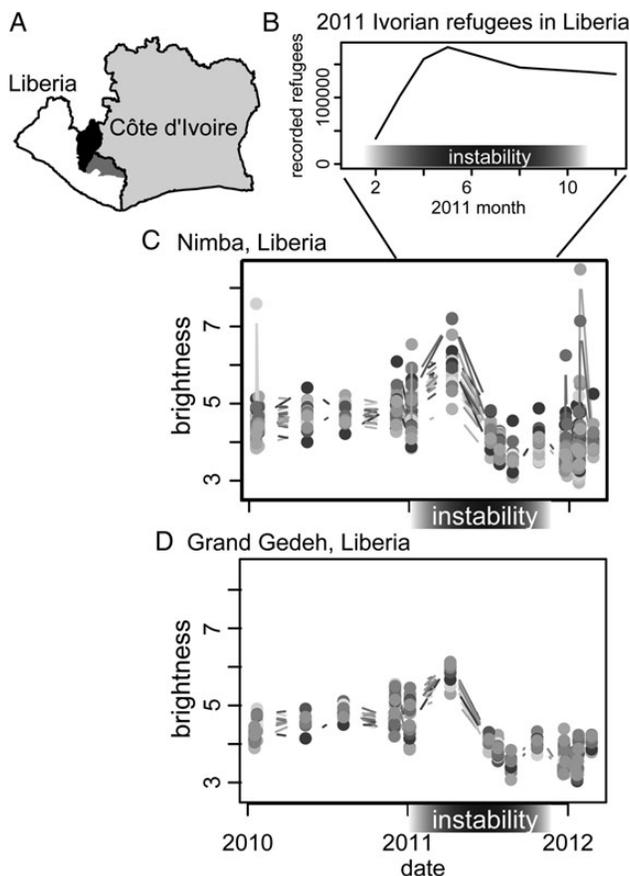


Figure 5. (A) Map of Côte d'Ivoire and Liberia with border counties Nimba (black) and Grand Gedeh (grey) shaded. (B) UNHCR recorded numbers of refugees crossing the border monthly from Côte d'Ivoire into Liberia for 2011. (C) Brightness values from the districts within Nimba and (D) Grand Gedeh from individual images captured between 2010–2012; period of conflict noted along x-axis in each plot.

outskirts of big cities during the conflict.⁴⁵ These aggregations of displaced persons may also emit anthropogenic light patterns indistinguishable from a previously stable settlement. Additionally, in some cases, internally displaced mobile phone users would likely continue to rely on the same nearby urban towers that they were previously accessing. Even with additional data, brightness and CDRs may not accurately reflect this displacement. This highlights the need to understand the relationship on the ground between the usage and availability of the resources captured by proxy measures in remote analyses of human presence and movement.

To understand potential biases in estimates of displacement numbers from proxy measures and to acquire a contextualized understanding of the development of the crisis, we performed informal interviews with staff at the UN Office for the Coordination of Humanitarian Affairs, IOM and UNHCR in Abidjan, Côte d'Ivoire during 6 to 8 February 2013. From these interviews, we learned that Orange mobile is perceived as the premium phone provider in the country and their subscriber base is skewed towards higher income levels. It is possible that the movement patterns derived from the Orange mobile CDRs are not representative of the entire population, particularly the individuals with low

income. Additionally, the interviews confirmed that phone networks and electrified lighting may be rendered temporarily inoperational in areas with violent conflicts, due to power outages or forced shutdowns by fighting parties.

The long-term and short-term spatial patterns of population sources and sinks by subprefecture were different. Satellite imagery shows a net population loss from 2010 to 2012 in the centrally located subprefectures of the country where political support is mixed; the 5 months of CDRs following the crisis show a net gain in SIMs in the same central part of the country. This may indicate that the CDRs are capturing the beginning of return movements to areas where the largest numbers of people left, as detected by the satellite images. By contrast, some of the subprefectures in the northwest of the country show long-term increases and short term decreases; these may be subprefectures to which people were displaced during the crisis and to which they returned following the period of instability. Unfortunately, there are no additional data on internal movements to confirm this hypothesis.

Following a long period of instability and large-scale displacement, the ability to measure both short- and long-term changes in populations at the subprefecture level would be incredibly useful for providing aid and national rebuilding efforts. In the months immediately following the Côte d'Ivoire's political crisis, phone usage data showed the movement of people and the locations where resources may be needed rapidly. On the other hand, the long-term redistribution in populations by subprefecture reflects patterns of resettlement and can help guide the allocation of resources for the new levels of catchment and demand for schools, healthcare facilities, public transportation and even road networks.

Strengths, limitations and uncertainties

The approach detailed here couples two powerful and technologically advanced data sources to address movement and displacement in conflict areas. Both data sources offer the potential of remote, near-real time situational awareness. While very promising, each of these data sources presented biases and limitations in this study.

The primary limitation for both data sets in this study was availability. Temporally, although the satellite images were available dating back to 1992, the phone usage data were available only for 5 months, following the Côte d'Ivoire's period of instability, permitting high spatial resolution analyses of movement patterns after the conflict, but no comparable data from before or during the displacement. This limited our ability to interpret the phone usage data to understand how movement patterns and settlement sizes were altered by the conflict.

The primary spatial limitation for CDRs was that they could not capture cross-border movement and we were specifically interested in the large-scale movement of Ivorian refugees into neighboring Liberia. As a result, we compared satellite imagery to UN records to assess population changes in these locations. Although this analysis would have been improved with more frequent measures of brightness values, which could not be obtained due to cloud cover, these images were useful for detecting changes in population size and area in Liberian counties, which aligned with UN camp registrations.

Despite daily capture, few satellite images were available in this area due to frequent cloud presence along the coast of

Côte d'Ivoire and Liberia; serial measures of brightness were sparse. To overcome this problem, we used annual composites of satellite imagery, but these 12-month composites aggregated over much of the movement during the period of conflict and instability. Additionally, these annual composites were not comparable with the 5 months of phone usage data. Areas with consistent cloud cover remain difficult to visualize with satellite imagery, even as image resolution increases and sensitivity improves with new sensors.

The relationship between brightness and population size is non-linear; changes in brightness are interpreted as relative changes in population size instead of absolute changes in population size. The exact relationship is influenced by local factors, including wealth, light source and sensor saturation. Wealth biases light emissions across both small and large scales; GDP and brightness are strongly correlated,^{28,46} emphasizing the value of ground truthing or locally calibrating changes in brightness with other measures of changes in population size. To both satellite images and CDRs, very small villages and nomadic populations are undetectable; areas with small populations fall below the detection threshold for brightness and mobile phone towers do not provide coverage in these areas. In fact, many densely populated urban areas have only a few towers to cover an entire city.

Cell phone usage, though more biased by wealth and development than light-usage, continues to increase in under-resourced areas, where reliance on mobile technology is high because communications infrastructure has been lacking.⁴⁷ With rising ownership, phone usage data becomes increasingly informative for movement patterns and less biased by wealth.²¹ The high spatial and temporal resolution of phone records provides detailed information that cannot be matched by other data sources at large spatial scales. For future studies, we expect that tower presence will continue to increase with call volume and phone ownership throughout stably populated areas.

Although rapid and short term population changes in areas with consistent cloud cover will remain challenging to measure with satellite imagery, additional satellites continue to capture visible nighttime imagery⁴⁸ rapidly producing composites that cover relatively short time periods at high resolution, which can help overcome cloud cover issues. One promising advance towards measuring high-resolution changes in anthropogenic brightness is the high resolution and increased sensitivity of new satellites. Since 2012, the Visible Infrared Imaging Radiometer Suite (VIIRS) onboard the Suomi National Polar-orbiting Partnership Satellite⁴⁹ has captured images daily at approximately 750 m spatial resolution. These images make it possible to detect changes at smaller spatial scales than DMSP imagery allows, particularly in low-lit settlements and at the edges of brightly lit settlements, which have been difficult to distinguish from light 'blooms'. Unfortunately for this study, these images were not available until the satellite began capturing images consistently in 2012 (Figure 1B), but there are many potential uses for these data in future health and crisis interventions.

Finally, due to privacy concerns and data ownership, phone companies independently determine the availability and distribution of their customers' phone usage data. Users are divided among competing companies in many markets, and with no monetary incentives to share phone records, the availability of these data are currently dependent on the goodwill of phone companies and are not reliably available during times of crisis.⁵⁰ This can vary

greatly between countries and service providers. Going forward, an area of great potential growth is the mapping of cross-border movement from phone usage data, which will require more complex agreements and coordination with multiple operators.

Conclusions

In measuring proxies for human presence and movement, phone usage data and nighttime light satellite imagery showed strong agreement for average measures of populations and provided complementary information on dynamic measures of populations across spatial and temporal scales. Using two very different data sources provided information that extended beyond the spatial and temporal limitations of each data set. This approach has promising future applications and we aim to develop a formalized method for combining complementary data sources like these.

Supplementary data

Supplementary data are available at International Health Online (<http://inthehealth.oxfordjournals.org/>).

Authors' contributions: NB and AJT conceived the study; NB, XL, LB, EW, and AJT conceived the statistical analyses; NB and XL carried out the statistical analyses; LB carried out the field interviews; NB drafted the manuscript. All authors read and approved the final manuscript. NB is the guarantor of the paper.

Acknowledgements: The CDRs were provided by the D4D Challenge (<http://www.d4d.orange.com>). This paper forms part of the output of the Human Mobility Mapping Project (www.thummp.org).

Funding: This work was supported by Branco Weiss–The Society in Science to NB. This work was also supported by RAPIDD program of the Science and Technology Directorate, Department of Homeland Security; the Fogarty International Center, National Institutes of Health; NIH/NIAID [U19AI089674] and the Bill & Melinda Gates Foundation [#49446 and #1032350] to AT. This work was also supported by the National Natural Science Foundation of China [71301165] to XL.

Competing interests: None declared.

Ethical approval: Not required.

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