RESEARCH ARTICLE

Leveraging High-Frequency Digital Data to Analyze Forced Displacement Dynamics: A Case Study from the Gaza Strip

Edith Darin, Ridhi Kashyap and Douglas R. Leasure

The quantification and analysis of forced displacement, driven by political unrest or natural disasters, has become increasingly central to both humanitarian and demographic research. With displaced populations reaching record numbers, there is an urgent need for accurate and timely data on displacement patterns, particularly disaggregated by age and gender. This paper introduces an analytical toolbox designed to leverage the growing diversity of digital trace data that overcomes disruptions of traditional data collection systems during crises, enabling high-frequency monitoring of forced displacement. The toolbox enhances our understanding of the magnitude, pace, and subpopulation heterogeneity of displacement dynamics. We apply this toolbox to the Gaza Strip following the 2023 Hamas attack. Deriving population estimates using data from Facebook's marketing API in combination with pre-war population data, we demonstrate how this toolbox facilitates a multifaceted assessment of the consequences of war on population movement, connects mobility patterns to ground events, dissects displacement by gender, and enables cross-country comparisons. Ultimately, the analysis highlights the unparalleled relative magnitude of forced displacement in the Gaza Strip from October 7, 2023, to May 15, 2024, with up to 70 percent of the population displaced, alongside increasing volatility in population movements as the conflict persists.

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This article is part of the *Population and Development Review* special issue, **Social and Demographic Consequences of Political Conflict and Violence**.

Introduction

Quantifying and analyzing forced displacement, whether driven by political unrest or natural disasters, has gained increasing prominence in both the humanitarian agenda and demographic research in recent years. This growing focus is partly due to the global surge in displaced populations, which reached a record high of 117 million people in 2023 (United Nations High Commissioner for Refugees 2023). Additionally, there is a growing consensus that forced displacement presents significant challenges to achieving the Sustainable Development Goals for countries of origin and host nations of both international and internal migrants (Sarzin 2017). In displacement contexts with rapidly shifting demographic dynamics, geographically detailed population denominators by age and gender help to assess the needs of affected populations, to mobilize resources for them, and to implement and monitor the performance of services in these areas (Alburez-Gutierrez and García 2018).

Establishing an accurate picture of the scale, composition, and dynamics of forced displacement, however, has been extremely challenging as violent incidents tend to uproot traditional data collection systems led by national statistics offices such as censuses or routine household surveys (Alburez-Gutierrez 2019). Population size and composition are also likely to change rapidly due to evolving crises, and quantification can be challenging due to the fluidity and unpredictability of population movements and lack of access to affected areas. Collecting data on people displaced internally is even more complicated than collecting data on refugees because no international border is crossed, individual registration is uncommon,[1] and scattered resettlement is the norm (Sarzin 2017). It is almost impossible for field-based data collection systems to provide the basis for reliably quantifying population movement in near real time at subnational scales by age and gender, as this would require access to dangerous locations to conduct fieldwork and high-frequency longitudinal data systems to be set up at the start of the crisis (Williams et al. 2012).

The demographic data revolution, characterized by the increasing availability of automatically, routinely, and passively collected data generated from digital technologies (Kashyap 2021), offers analytical opportunities for the study of forced displacement of population at unprecedented levels of temporal, spatial, and demographic detail. As examples, satellite imagery (Rufener et al. 2024), Facebook marketing API (Leasure et al. 2023), Facebook connectedness index (Minora et al. 2023), and phone geolocation data (Iradukunda, Rowe, and Pietrostefani 2025; Shibuya, Jones, and Sekimoto 2024) have been leveraged to estimate population displacement in Ukraine with a temporal resolution of up to a daily update and a spatial resolution of up to 30 cm. Not only can digital data provide new levels of spatial and temporal resolution, but it also offers consistent and uniform coverage across regions and even countries, enabling the study of population-wide displacement and cross-national comparisons. The broader digital data revolution (Laney 2001) also fuels the increasing availability of data on conflict-related events such as airstrikes sourced from social media platforms (Airwars 2023) or building damages derived from satellite imagery (Ge, Gokon, and Meguro 2020), which in turn can help to better contextualize and identify population responses to crises as they unfold.

While digital trace datasets come in a variety of data types, the expanding availability of these high-frequency data benefits from a tailored and generalizable analytical toolbox to capture the magnitude, pace, concentration, and timing of displacement between groups, as well as their correlation with ground events. This article develops descriptive metrics that can offer an integrated overview of these different high-frequency data streams to help unlock additional, interpretive insights into population displacement following the onset of a crisis. We then apply this toolbox to build a comprehensive picture of the massive forced displacement inside the Gaza Strip that followed the 2023 Hamas attack.

Building on previous work in Ukraine (Leasure et al. 2023), we derive daily estimates of population change at the governorate level from October 7, 2023, to May 15, 2024, by combining near real-time data from Facebook's marketing API (Meta 2023) with pre-war population data. By monitoring daily changes in population dynamics across gender and subregional units, we provide a precise account of the consequences of Israeli military interventions on the timing and sequencing of population movement across governorates, a level of insight which is not possible to reach with traditional reporting methods such as produced by the United Nations. Our analysis reveals increasing volatility in population movement over time as the destruction of all remaining so-called "safe zones" unfolded (Forensic Architecture 2024). Through the creation of a global database of consistent and standardized social media audience data, we compare forced migration occurring in Gaza with internal mobility from neighboring countries that were not directly impacted by the war (Egypt and Jordan), and with another war setting (Ukraine). Lastly, correlating population changes through time and space with data on building damage, conflict events, fatalities, evacuation orders, and ground invasion highlights how the relationship between war events and displacement evolved through time. We demonstrate how the proposed analytical toolbox can leverage high-frequency data to provide a multifaceted assessment of the war and its consequences on population movement, highlighting the severity of forced displacement in Gaza proportional to its population in terms of magnitude, pace, sustained intensity, and increasing volatility.

New data streams: Towards high-frequency monitoring of forced displacement

Migration is inherently a challenging demographic process to capture due to its varying definitions, measures (as an event or a transition), geographical scope, and time frames. Internal migration is especially difficult to track, as it does not involve crossing national borders, occurs without formal registration and legal status, and is dependent on the geographical division being considered (Bell et al. 2002). In the case of forced internal migration triggered by war and natural disasters, the challenges are compounded as data collection systems themselves are disrupted and population movements often shift rapidly, unpredictably, continuously, and to unforeseen magnitudes, resulting in significant data gaps and inconsistencies (Reed, Haaga, and Keely 1998).

Previously, extensive pictures of internal forced displacement could be obtained only post hoc, through interview-based qualitative analysis (Lubkemann 2005; Steele 2009) or comparison between census and survey rounds (Czaika and Kis-Katos 2009), which constrained our ability to understand crises as they unfolded, and to anticipate future crises. On an operational level, relief workers currently rely primarily on key informant reports from strategic sites, habitation counts from satellite imagery, or registration, and sampling from camps (Abdelmagid and Checchi 2018). These methods, however, provide incomplete views of the full-scale of displacement patterns. International efforts to improve internal displacement data have accelerated with the creation of several initiatives, such as the Joint Data Centre on Forced Displacement (Brock and Mugera 2023) or the International Organisation for Migration (IOM) Displacement Tracker Matrix (Displacement Tracking Matrix 2023). However, this multiplication has led to a diversification of stakeholders employing different definitions and methodologies with varying scopes and geographic extents, as well as different political agendas, which in turn has led to the compilation of integrated databases (Internal Displacement Monitoring Centre 2023) with various degrees of completeness and coherence (Checchi and Koum Besson 2022).

In this context, the increasing availability of digital data presents opportunities to improve both temporal and geographical resolution for monitoring population displacement in real time, thereby supporting humanitarian response efforts, ensuring accountability, and supporting unprecedented in-depth analyses of individual decision-making in times of crisis. Digital trace data, digital traces of our online activity, offer the advantage of being continuously and passively collected from a large number of users (Salganik 2019). Since the use of mobile phone call detail records (CDR)—specifically the location from cell phone towers when users make calls or text messages—to estimate population displacement after the 2010 earthquake in Haiti (Bengtsson et al. 2011), both academic and humanitarian sectors have increasingly relied on digital trace data to track forced displacement. Mobile phone location data have since expanded to various emergency management areas, including traffic accidents, strikes, disease outbreaks, and violence, with its use accelerating during the COVID-19 pandemic (Y. Wang et al. 2020). The type of data gathered from phone activity has also diversified from CDR-based cell tower locations to single-app-based GPS locations through one platform, such as Facebook and multiple-app-based GPS locations aggregated across several third-party applications by data brokers (Yabe et al. 2022). Table 1 summarizes the various sources of high-frequency data (sub-quarterly) on population displacement, outlining their strengths and limitations in terms of spatial information (e.g., phone GPS vs. cell tower), spatial scale and extent (e.g., countrywide vs. sampled locations), access costs (monetary or time-related for setting up data pipelines), population coverage (likelihood of including the entire population), and data stream stability (likelihood of data continuity once the contract/pipeline is established). The data leveraged in this study, which is a platform marketing API, is highlighted in light gray.

An often-overlooked aspect in displacement studies utilizing digital trace data is the entity being observed. Researchers may not correct for the fact that a user account or a device does not always equate to an individual and that this individual is not representative of the entire population. As emphasized in the work of Leasure et al. (2023) and Iradukunda, Rowe, and Pietrostefani (2025), we stress that digital trace data require further modeling to enable population nowcasting through addressing biases related to what and who is represented in these datasets. For example, not everyone has a mobile phone, internet access, or uses social media, especially in data-scarce contexts typical of crisis settings. Moreover, while acknowledging the existing data gap, we emphasize the urgent need for scholarships focused on estimating near real-time displacement by age and gender, as these data are critical for monitoring high-risk groups—such as children under five, pregnant women, and the elderly—who require targeted health interventions but who may be under-represented or absent from many data sources.

In this article, we focus on population displacement estimates derived from the Facebook Marketing API, as this data source offers free daily monitoring of social media audiences by age and gender at the subnational level, with cross-country comparability (see the gray row in Table 1). However, it is important to acknowledge, as we also discuss later, that a feature of the API that made it particularly well-suited for monitoring population displacement has now been deprecated by Meta, highlighting the inherent fragility of pipelines relying on repurposed, proprietary streams of digital data.

TABLE 1 Overview of strengths and limitations of available digital data for high-frequency monitoring of population displacement.

Data type	Provider	Observed entity	Spatial information	Data access	Population coverage	Data stream stability	Examples (provider)
Repurposed call details records	Mobile phone provider	SIM card (no age and gender so far)	Source: phone tower Resolution: ~1 m Extent: country	High cost High processing	Lower	Very high (*once the contract is set up*)	Haiti earthquake (Digicel), Rwanda flood, Afghanistan violence (Bengtsson et al. 2011; Ghurye, Krings, and Frias-Martinez 2016; Tai, Mehra, and Blumenstock 2022)
Preprocessed single app	Platform data for good teams	User account (no age and gender information available)	Source: GPS Resolution: ~5 km Extent: country	No access to raw data Free and no processing	Higher	Ad hoc (*subject to company strategy*)	Disaster map (Facebook) (Maas et al. 2019)
Repurposed single app	Platform posts	Post (age and gender inferred)	Source: GPS Resolution: ~1 m Ex tent: country	Free High processing	Higher	Medium (*subject to company strategy*)	Hurricane Sandy (Twitter)(Q. Wang and Taylor 2014)
Repurposed single app	Platform marketing API	User account (age and gender inferred)	Source: GPS Resolution: ~1m Extent: country	Free High processing	Higher	Medium (*subject to company strategy*)	Ukraine war (Facebook) (Leasure et al. 2023) Hurricane Maria (Facebook) (Alexander, Polimis, and Zagheni 2019) Venezuela exodus (Facebook) (Palotti et al. 2020)
Repurposed multiple apps	Intelligence firm	Mobile device (no age and gender information available)	Source: GPS Resolution: ~1m Extent: country	High cost High processing	Higher	High (*opaque sector*)	Ukraine war (Outlogic) (Iradukunda, Rowe, and Pietrostefani 2025; Shibuya et al. 2024)
Repurposed satellite images	Satellite imagery provider	Cars	Source: satellite Resolution: ~10 m Extent: sample	High cost High processing	Low	Very High (*once the contract is set up*)	Ukraine war (Maxar) (Rufener et al. 2024)
Preprocessed Wi-Fi	Institution	Individual (age and gender reported)	Source: GPS Resolution: ~1 m Extent: country	High cost Low processing	Lower	Very high (*once the system is set up*)	Colombia-Venezuela (IOM)(International Organisation for Migration 2021)

NOTE: The “data type” refers to the nature of the data distinguishing between preprocessed (by the company) and repurposed (by the researcher), “ provider” is the data supplier type, “observed entity” refers to the object measured, “spatial information” specifies the source that captured the geographical, the spatial sale, and the extent of the data, “data access” indicates the ease of obtaining the data, “population coverage” assesses representativeness and levels of population inclusion, “data stream stability” refers to the consistency and reliability of the data stream over time, and “examples” provide specific use with data providers in parenthesis. Highlighted in light gray is the data used in this study.

Data

Demographic data for the Gaza Strip

We used four data sources for estimating population displacement by age and gender: (1) pre-war population estimates, (2) daily counts of monthly active users on Facebook, (3) monthly deaths, and (4) border crossings.

Pre-war population. The pre-war population consists of the 2023 Gaza-wide population by age and gender as compiled in the Common Operational Dataset and results from the 2017 census projection (Palestinian Central Bureau of Statistics 2023). Governorate-level population estimates from 2023 for men and women were obtained from the Palestinian Central Bureau of Statistics (2024).

Facebook users. We collected daily counts of Facebook users who were active on the platform over the previous 30-day window in the Gaza Strip for the six areas (Beit Lahia, Beit Hanoun, Gaza City, Bureij, Khan Younis, Rafah) available from the Facebook marketing API (Meta 2023), using pySocialWatcher software (Araujo et al. 2017). Since no boundaries were made available through the Facebook marketing API, we assumed that these six areas were indicative of the dynamics in the five governorates (North Gaza, Gaza, Deir al-Balah, Khan Yunis, and Rafah). The data were automatically collected every day from October 7, 2023, until May 15, 2024, at which point the Facebook Marketing API implemented a planned global change that no longer provided audience counts based on the current location of users. Until then, we collected aggregate data for users aged 13 and older, disaggregated by gender and age group. These counts included all Facebook users whose "recent" location was in a given governorate, as determined by their device data (Meta 2023). We collected similar data over the same period for 27 governorates of Egypt and 11 governorates of Jordan, as well as 22 oblasts of Ukraine, between February 27, 2022, and May 15, 2024. Data from the Facebook Marketing API, accessible to anyone with a Facebook account, provide audience sizes for targeted ads on the platform by counting active accounts rather than individual users. Additionally, the data are censored for queries returning fewer than 1,000 user counts, making it unreliable for small population subgroups, such as age-specific groups. For this study, we considered only data for users aged 18 and above to align with official population estimates, as well as because users must be at least 13 years old to set up a Facebook account. As a result, data on under-13 are not provided by the platform API.

Deaths and border crossings. To update the Gaza Strip population totals, we retrieved data on casualties by age and gender from the Palestinian Ministry of Health (2025) and on Rafah border crossings from UN OCHA (2025). We decompose border crossings by age and gender using the pre-war Gaza-wide population.

Estimates of displaced population. The United Nations Relief and Works Agency for Palestine Refugees (UNRWA) published situation reports that summarized the humanitarian situation and response in the Gaza Strip and the West Bank for the first two months of the war every day and then every three days. One hundred seven reports were released for the period from October 7 to May 15. They contained three types of population displacement estimates: general estimates of the number of people displaced in the Gaza Strip, estimates of the number of people hosted in UNRWA shelters, and estimates of the number of people receiving UNRWA assistance.

Contextual data on forced displacement

We compiled a set of daily contextual data to understand the dynamics of forced displacement in the Gaza Strip from four data providers.

Conflict events. We used the locations of conflict events as recorded manually by the Armed Conflict Location & Event Data project (Raleigh et al. 2010) and compiled from it the daily number of conflict events, events with fatalities, and events targeting civilians for each governorate.

Evacuation orders. We retrieved a register of the daily areas under evacuation orders as reported on X (formerly Twitter) and Facebook by the Israeli military and areas under ground invasion (Institute for the Study of War and AEI's Critical Threats Project 2024) as compiled in the "General Cartographic Database" (Forensic Architecture 2024).

Building damage. We computed building damage as detected from the imagery provided by the European Space Agency Copernicus Sentinel-1 A synthetic aperture radar by two different algorithms: multi-temporal coherent change detection (Asi et al. 2024) and pixel-wise *t*-test (Ballinger 2024). The data from Asi et al. (2024) are not openly available and were provided through a conflict damage layer similar to the one described in Scher and Van Der Hoek (2025) at 10 m spatial resolution every five days which corresponds to a binary pixel-level outcome damage/undamaged from which we derived the sum and the proportion of pixels considered as impacted per governorate per day. The algorithm from Ballinger (2024) is openly available and produces a conflict damage layer with 10 m spatial resolution every month that corresponds to a pixel-level damage intensity metric that we summed up per governorate per day. All indicators were linearly interpolated to produce daily estimates of building damage.

Methods

Analyzing high-frequency displacement data: The multidimensional crisis analytics toolbox

To make sense of the increasing availability of high-frequency displacement data, we develop a multidimensional crisis analytics toolbox, summarized

TABLE 2 Toolbox of crisis analytics for high-frequency displacement data

		At subnational level	At national level
ACROSS TIME	**Magnitude**	Absolute displacement: The population at time *t* compared to pre-crisis. $displaced_{i,t} = pop_{i,t} - pop_{i,t_0}$ *Note:* - $displaced_{i,t} > 0$ *represents incoming displacement* - $displaced_{i,t} < 0$ *represents outgoing displacement*	$displaced_t = \sum_{i \in I} displaced_{i,t} \mathbb{1}_{displaced_{i,t} \geq 0}$
		Relative displacement: The percentage of displaced population. $displaced\_perc_{i,t} = \frac{displaced_{i,t}}{pop_{i,t_0}}$	$displaced\_perc_t = \frac{displaced_t}{\sum_{i \in I} pop_{t_0}}$
	Pace	Absolute displacement rate: The time-to-time population change. $disp\_rate_{i,t} = \frac{pop_{i,t} - pop_{i,t-\Delta}}{\Delta}$	$disp\_rate_t = \sum_{i \in I} disp\_rate_{i,t} \mathbb{1}_{disp\_rate_{i,t} \geq 0}$
		Relative displacement rate (in %): The percentage of time-to-time change compared to the total population.	$disp\_rate\_perc_t = \frac{disp\_rate_t}{\sum_{i \in I} pop_{t_0}}$
ACROSS SPACE	**Concentration**	Spatial autocorrelation (Moran's I): The distance-based correlations in displacement patterns across subnational units. It ranges between -1 and 1 where 0 is no clustering. $local\_Moran\_I_{i,t} = \frac{(d_{i,t} - \bar{d}_t) \sum_{j \in I} w_{i,j} (d_{j,t} - \bar{d}_t)}{\sum_{i \in I} (d_{i,t} - \bar{d}_t)^2 / card(I)}$	$global\_Moran\_I_t = \sum_{i \in I} \frac{local\_Moran\_I_{i,t}}{card(I)}$ with $d_{i,t}$ adisplacement metric, $w_{i,j}$ matrix-based spatial weight, $card(I)$ the number of locations
ACROSS GROUPS	**Relative timing**	Time gap Relative timing of displacement between groups (e.g. female, male). If positive, group 1 was displaced before group 2.	$gap_{i,d}(g_1, g_2) = t_{i,d,g_1} - t_{i,d,g_2}$ with d a relative displacement metric
WITH CONTEXT	**Correlates**	Temporal cross-correlation The correlation between population displacement and past/current/future events (e.g. evacuation orders, bombardments).	$temp\_xcorr_{i,\delta} \approx \text{corr}(X_{i,t+\delta}, disp\_rate_{i,t})$* with $t \in (max(1, -\delta), min(T - \delta, T))$ *see text for exact expression
WITH OTHER INFORMATION	**Reliability**	Triangulation**:** Summarise the displacement estimates to compare with other sources of information Alternative scenario: Create alternative scenarios to test model assumptions	

NOTES: i represents the subnational level, I all subnational units, t timesteps, t_0 pre-crisis timestep, δ time gap, T the total number of timesteps, and g_1 and g_2 two subpopulations. $displaced_{i,t} > 0$ represents incoming displacement. $displaced_{i,t} < 0$ represents outgoing displacement.

in Table 2, that offers a set of metrics for analyzing population displacement patterns across time, space, subpopulation, and in relation to external events.

Magnitude. To estimate the subnational magnitude of displacement, we suggest using the difference between the current subnational population estimates and the subnational pre-crisis population. To obtain the national magnitude, that is, the total number of displaced people, we sum the positive changes.

Pace. To study the pace of displacement, we suggest computing the displacement rate as the time-to-time differences of subnational population sizes, in our case, day-to-day. To obtain a nationwide metric, we then sum the positive rate of displacement. To enable cross-country analysis of the pace of displacement, we calculate the nationwide displacement rate as a percentage of the total population, thus providing an estimate of the proportion of people who move at each timestep.

Concentration. We can also explore the spatial dynamics of displacement by quantifying its spatial autocorrelation using local Moran's I, which highlights clusters of similar displacement metrics, and global Moran's I to describe the overall clustering pattern. However, in the Gaza Strip, since there are only five spatial units, we have not explored that dimension.

Relative timing. Once the temporal and spatial dynamic of displacement is established, we propose a metric to explore displacement patterns for specific subpopulations (e.g., women/men). This metric measures the number of timesteps required for a specific population change (e.g., a 10 percent increase) to occur for two subpopulations, which corresponds to the temporal distance between their respective population time series. The sign of the metric indicates which group moved first.

Correlates. Then, to link population displacements with events happening on the ground, including lagged and anticipatory effects, we suggest using the temporal cross-correlation between population change at time t compared to the occurrence of the event at time $t, t-1, \ldots, t-\delta, t+1, \ldots, t+\delta$. The exact formula is the following:

$$\text{temporal\_xcorr}_{\mathrm{i},\delta} = \frac{1}{C}\frac{1}{T}\sum_{t=\max(1,-\delta)}^{\min(T-\delta,T)} \left(X_{t+\delta} - \bar{X}\right)\left(disp\_rate_t - \overline{disp\_rate}\right)$$

$$\text{with } C = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(X_t - \bar{X}\right)^2 \frac{1}{T}\sum_{t=1}^{T}\left(pop_t - \overline{disp\_rate}\right)^2}.$$

While temporal cross-correlations are not suited for assessing causal relationships as they are computed for each timestep independently, masking thus temporal correlations, they are useful to study the strength and direction of the link between the pace of population change and potential drivers. To get a more precise picture of those interactions, we processed the covariates to derive (1) their cumulative effect, by summing them over different time windows w, ($Y_{i,t} = \sum_{u=t-w}^{t} X_{i,u}$), referred to as "cumulative covariate"; (2) their time-relative effect by centering them through time ($Y_{i,t} = X_{i,t} - \frac{1}{w}\sum_{t-\mathrm{w}}^{t} X_{i,u}$), to capture temporal intensification of the covariate, referred to as "temporal scaling"; and (3) their spatial-relative effect, by centering them through space ($Y_{i,t} = X_{i,t} - \frac{1}{card(I)}\sum_{j\epsilon I} X_{j,t}$) to detect spatial intensification of the covariate compared to other locations, referred to as "geographical scaling." A more advanced framework would be to use Granger causality.

Reliability. Finally, it is key to provide metrics that convey the reliability of the displacement analysis. In crisis settings, reliable confidence intervals are hard to estimate due to the lack of ground truth data. We suggest two alternative methods: (1) triangulation with other forms of data that are either on a lower time resolution (e.g., IDP registration) or on a population subset (e.g., shelter monitoring, key informant surveys) and (2) internal checks by testing the sensitivity of critical parameters to violations of assumptions by simulating different data scenarios.

Estimating daily displacement in the Gaza Strip

To account for biases in the Facebook active user population and thus extrapolate population change to the non-Facebook population, we adopted the deterministic model that was developed to estimate the daily population sizes by the age-gender demographic group in each subdivision of Ukraine following the Russian invasion (Leasure et al. 2023).

We calculated current population sizes $N_{i,g,t}$ by location i, gender g, and time t as

$$N_{i,g,t} = \frac{F_{i,g,t}}{\theta_{g,t}} ,$$

where $F_{i,g,t}$ is the number of monthly active users on Facebook. $\theta_{g,t}$ represents the average Facebook penetration rates across governorates for each time step t and gender g, defined as

$$\theta_{g,t} = \frac{\sum_{i \epsilon I} F_{i,g,t}}{P_g - D_{g,t} - M_{g,t}}$$

This formulation ensures that the aggregated gender-specific population estimates align with the total pre-war population of the Gaza Strip P_g, adjusted for deaths $D_{g,t}$, and net migration out of the territory $M_{g,t}$. In the Gaza Strip, data on migration outside the territory and deaths during the first six months of the war are available only at the aggregated level; we are therefore assuming uniform death and migration rates across all governorates.

Leasure et al. (2023) include pre-war subnational location-specific penetration rates that are the ratio of the Facebook user population to the resident population prior to the onset of the crisis and apply these rates consistently throughout the crisis. However, in the case of the Gaza Strip, we contend that due to the territory's small size and the rapid pace of displacement, the pre-war location-specific penetration rate would quickly become outdated as individuals move between locations. Consequently, we chose not to include these rates in our analysis but included a detailed assessment of the impact on displacement estimates in the Online Appendix, Section A2. Finally, we smoothed the estimates by computing the two-day rolling average to reduce noise caused by inconsistencies in the API data.

This methodology for estimating population assumes that the age of the population did not evolve during six months and that penetration rates varied only by time and gender. This approach is vulnerable to time and location-specific variations of penetration rates (1) due to the environment, such as network damage (see Sections A4 and A5 in the Online Appendix) and (2) due to changes in user behavior. For the latter to have an impact, it needs to affect both the penetration rate and the spatial relocation of the population, for example, a difference in user behavior according to economic status that is not uniform across governorates, due to where those users have clustered (see Section A1 in the Online Appendix). The importance of this assumption is reduced in the Gaza Strip due to the large-scale displacement that led to an unusually high mixing of populations. Lastly, we consider that all population changes at the governorate level are due to forced migration imposed by the war rather than other forms of mobility.

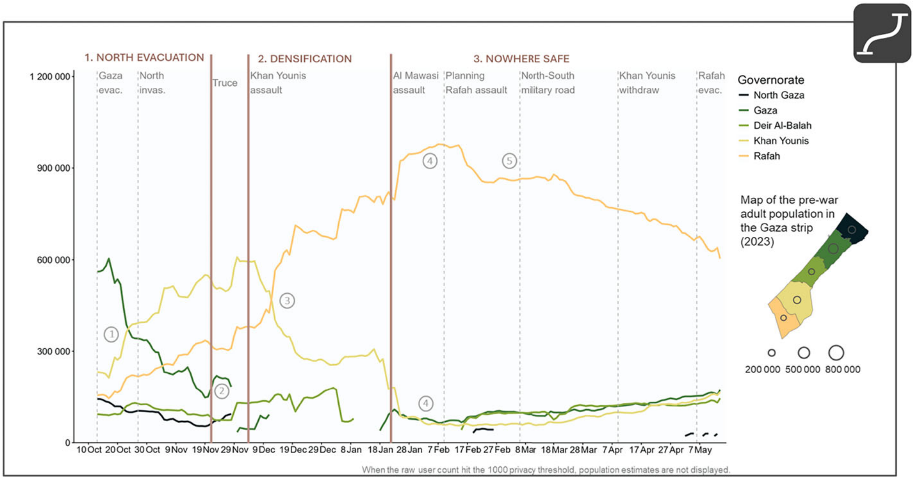
Results

Timeline of the war from the lens of population change

Following the Hamas attack on Israel on October 7, 2023, the war escalated rapidly, leading to a series of retaliatory military actions and forced rapid evacuations in the Gaza Strip. Figure 1 illustrates how our method was able to capture population changes in the five governorates at a daily resolution, allowing us to study the impact of the Israeli military interventions on the forced movement of the adult population (above 18 years old).

The forced displacement started with the first Israeli military orders instructing all people residing in the northern parts of the Gaza Strip to move South, a phase we named "North Evacuation." As shown in Figure 1, marker 1, we estimated that North Gaza and Gaza saw their populations dropping, respectively, by -87,000 and -412,000 residents between October 14 and November 20, which represent 61 percent and 73 percent of their pre-war resident population, with corresponding increases in the southern governorates of Khan Younis and Rafah. Figure 1 shows the effect of the temporary ceasefire (November 24–30), highlighted by marker 2, where the population increased in Gaza up to +69,000 and in North Gaza by up to +38,000 people compared to pre-truce levels (November 20). We observe that this reversal in trend began three days before the truce took effect, as people anticipated the agreement. It lasted only for the first four days of the ceasefire (initially announced for four days, later extended by three), with an increase in population numbers in the other governorates starting on November 28. This highlights the difference in displacement decision-making in conflict settings between the beginning of a truce and

FIGURE 1 Timeline of the estimated population change in the five governorates of the Gaza Strip

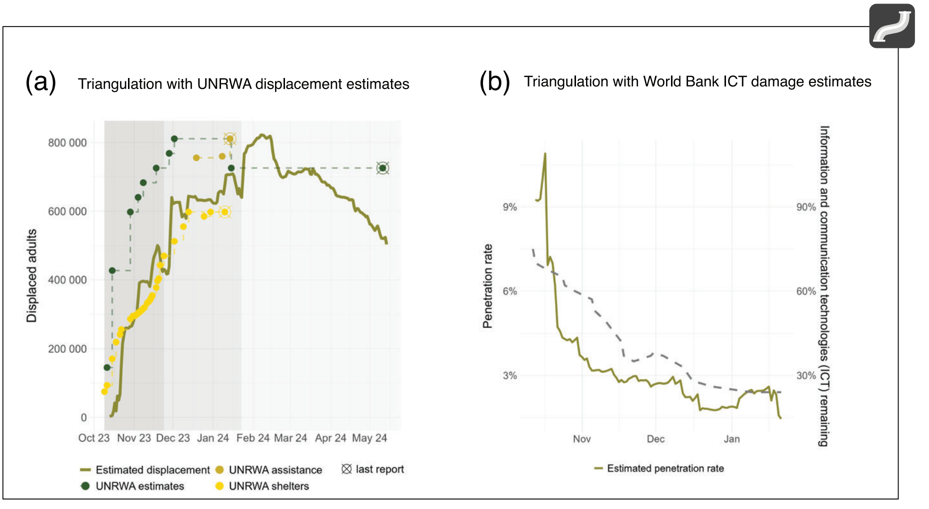


its last-minute extension. On December 1, an evacuation grid with over 600 numbered blocks was posted on the Israeli military website, marking the start of the invasion of Khan Younis as well as the shift to a more sporadic, fragmented, and localized attack strategy, blurring the lines of the safe zones (Forensic Architecture 2024), a phase we labeled "Densification." The population of Khan Younis which, during the first phase of the war, had more than doubled (from 230,000 to 515,000 on November 28), shrank back to its pre-war level (224,000) on January 20 (Figure 1, marker 3), while Rafah saw its population increase by more than five times during the same period, as it became the safest place to be in the Gaza Strip.

On January 22, 2024, however, the ground invasion of Al Mawasi was launched, an area stretching along the sea west of Khan Yunis, and designated by the Israeli army as a "humanitarian zone," which started the third phase of the war that we labeled as "Nowhere safe". This attack only reinforced the surge of the Rafah population (Figure 1, marker 4) that reached its peak on February 7 with 979,000 adults, representing six times its pre-war level and 85 percent of the total Gazan adult population. From February on, nonetheless, started the rhetoric made by Israeli officials about the invasion of Rafah which led to the steady decrease in its population (Figure 1, marker 5). Because of the strong enforcement of a North–South divide by the Israeli military, the observed increase in population in Khan Younis and Deir Al-Balah can be linked back to the decrease in the Rafah population, whereas the population increase in the Gaza governorate is likely due to fresh evacuation orders in North Gaza.

We were unable to detect an accelerated departure from Rafah following its invasion starting on May 6. Changing Rafah's population by 200,000

FIGURE 2 Triangulation of crisis analytics



people took 19 days before the peak (starting on January 19) and 58 days after the peak (until April 5).

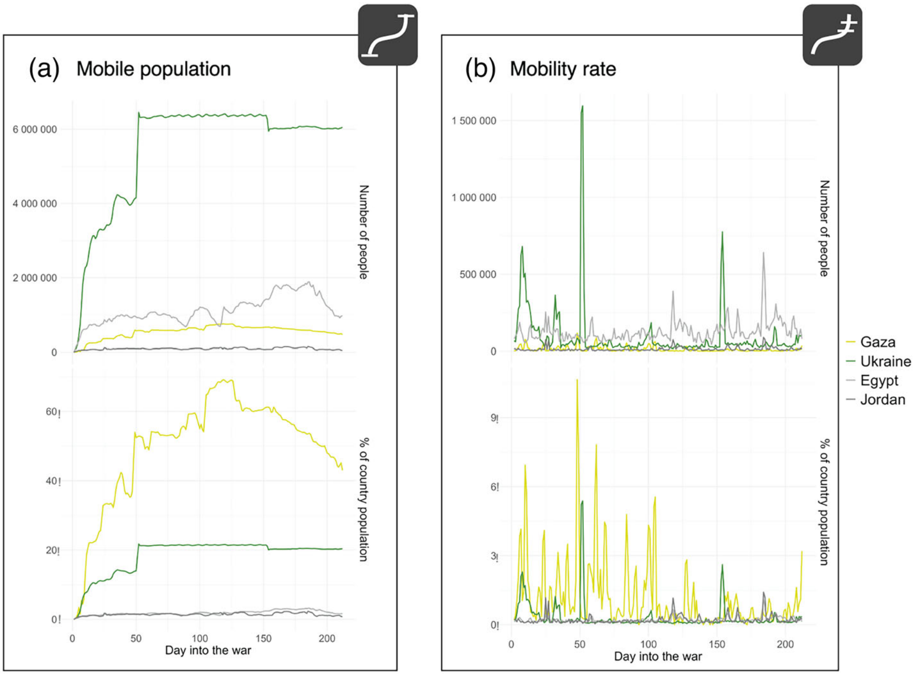
The estimated displaced population is in line with external reports

Figure 2a illustrates how the Facebook-derived estimated displaced population closely follows the trend of UNRWA estimates. In the first three months, the estimates align more closely with those derived from UNRWA shelters, as (1) Facebook-derived estimates capture displacement only between governorates and (2) UNRWA shelters may be more suitable for the inter-governorate displaced population who cannot seek refuge in the homes of neighboring households.

However, starting in December, Facebook-derived estimates depart from shelter-based figures to align more and more closely with UNRWA's population estimate, as the displaced population exceeded UNRWA shelters' capacity by more than four times (United Nations Relief and Works Agency for Palestine Refugees 2024). Figure 2b illustrates how the penetration rate (θ_t) closely follows estimates of damages to the information and communication technologies (ICT) infrastructure (World Bank et al. 2024) between November 2023 and February 2024. It is interesting to note that the penetration rate did actually increase at the very beginning of the war, likely due to the extreme need for internal and external communication, but then as the network damages occurred the penetration rate decreased with a small uptick when the network was briefly reconstructed in December.

Beyond coherence with external information, Figure 2 also highlights the frequency and the sustained availability of displacement estimates

FIGURE 3 Comparison of the magnitude and the day-to-day pace of displacement across four settings



derived from social media data compared to UNRWA reports, which cannot always update figures due to difficulty collecting data on the ground. Facebook-derived estimates, however, fail to capture intra-governorate displacement or displacement between locations that are not one of the six cities representing the governorates, and they assume that a governorate's population returning to pre-crisis levels reflects return migration rather than ongoing displacement. These two limitations are likely to lead to an underestimation of displaced adult populations, particularly during the third phase of the war, when the spatial distribution of forced migration was reversed.

Comparing the magnitude and pace of displacement across wars

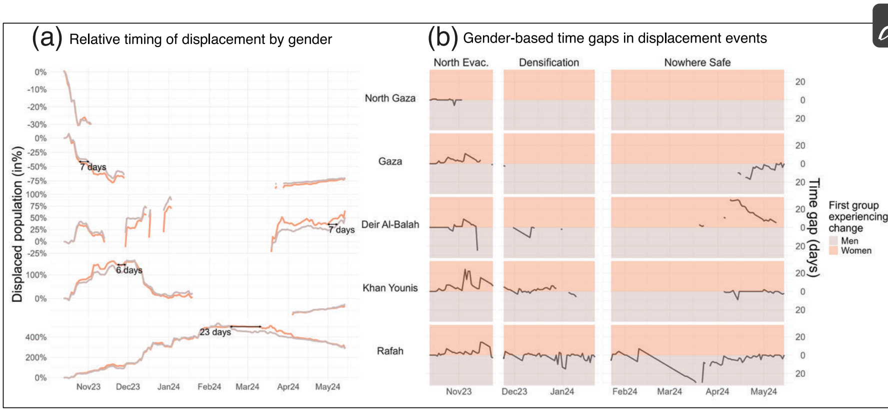
Figure 3 illustrates how Facebook-derived daily population estimates allow us to study cross-country patterns of mobility. We selected three countries to compare with the Gaza Strip: two neighboring countries (Egypt and Jordan) that did not have displaced populations due to the war, to understand how our methodology captures mobility in a peaceful context, and one country that had also experienced a full-scale war (Ukraine) to compare the population impact of the war in the Gaza Strip. We derived population estimates for 20 years old and older following the same methodology as explained in Section 2.1.1. We considered the first date for which we had collected subnational estimates as day 1 of the war, that is, for Ukraine, February 27, 2022, and for Jordan and Egypt, the same as for the Gaza Strip, that is, October 7, 2023.

We see that our methodology captures mobility for the two peaceful countries, especially in Egypt, around the 180th day into the war, which corresponds to the beginning of the Eid Al-Fitr national holiday. But once compared to the total population, we see that in Figure 3a the daily mobile population is at most 3 percent and in Figure 3b the day-to-day mobility rate is at most 1.4 percent for both countries during the 200 days. In contrast, Figure 3a shows that the displaced population in Ukraine and in the Gaza Strip reached up to 22 percent and 70 percent of the total population during the period, which represents 6.45 million and 0.75 million people, respectively. Figure 3b indicates that while in Ukraine we observe a rapid day-to-day displacement rate over 1.5 percent for only 14 days (at the beginning of the full-scale invasion, around the 52nd day, around the 154th day), in Gaza it is for 71 days, that is for 33 percent of the time, spread across the entire period. Relative to the size of the pre-war population, the displacement is three times higher, eight times quicker, and five times more sustained on average in Gaza than in Ukraine. The three times higher estimate is derived from the average daily ratio of Gaza to Ukraine displacement in percentage, the eight times estimate is derived from the average daily ratio of the day-to-day displacement rate in percentage, and the five times more sustained estimate is derived from the number of days that the displacement rate in percentage is above 1 percent. In absolute terms, however, the full-scale invasion of Ukraine had a greater toll on population size, with up to 6,451,000 displaced individuals on April 20, 2024, and as many as 1,595,000 people displaced in a single day on the same date.

Women move first when the move is less risky

The analysis of population displacement by gender, as illustrated in Figure 4, provides valuable insights into the subgroups driving demographic changes during the conflict. In the initial phase, women accounted for 68 percent of the population displacements, compared to 5 percent for men, moving on average five days earlier across all governorates (the rest being moves done together). The second phase exhibited a more balanced distribution of displacement, with men leading 46 percent of the movements, averaging four days before women, particularly concentrated in Deir Al-Balah and Rafah. In the last phase, men continued to dominate population displacement in Rafah during the period for which we had data (until May 14, 2024), with a lesser extent observed in Gaza. Figure 4a shows, however, that this phase encompasses two distinct periods marked by a turning point on April 25 when Israel intensified airstrikes on Rafah (Al-Mughrabi 2024). During the

FIGURE 4 Gendered patterns of displacement



first period, when the Rafah invasion was present in the public rhetoric but not enacted, in Rafah, men were the first to move out (80 percent of the time), while after the strikes intensified, they led only 44 percent of the displacements in Rafah, resulting in the positive time gap depicted in Figure 4b. However, our data stream ends before the most intensive part of the Rafah evacuation, limiting our conclusions to only a partial understanding of this stage of the war.

Overall, the observed gendered pattern of displacement suggests that women may be more likely to initiate movement in contexts where the outcomes are perceived as less uncertain. In the early phase of the conflict, it was easier to identify relatively safe areas to move into, while the subsequent phases presented less clarity regarding safe directions (Forensic Architecture 2024).

Evolution of the association between correlates and displacement

Tables 3 and 4 show temporal correlations between the detected events and the outgoing or incoming displacement, respectively. This correlation is measured across 11 timesteps—five in the past and five in the future—, using the Pearson correlation coefficient (r), scaled to range between -100 and 100. It offers a description of the daily sequencing of events across the three phases of the war, as well as several lessons to learn for modeling forced displacement with covariates.

Table 3 teaches us that during the first phase of the war, conflict events with fatalities had the largest positive correlation with populations leaving their governorates ($r = 31$), this effect being stronger with cumulated days of high occurrences of deadly events ($r = 38$) as well as when the governorate experienced more conflict events than the other governorates ($r = 33$). The strongest association, however, is on the following three days

TABLE 3 Temporal cross-correlation of various covariates with outgoing displacement during the three phases of the war

		13 Oct-24 Nov										
		Past						Future				
	Window	-5	-4	-3	-2	-1	0	1	2	3	4	5
Raw covariate												
ACLED - All		14	17	24	27	25	**32**	33	28	26	26	21
ACLED - Fatalities		20	21	27	30	24	**31**	35	39	42	29	18
Cumulative covariate												
ACLED - All	7days	8	13	19	24	29	**33**	34	35	35	33	27
ACLED - All	14days	7	14	21	26	31	**37**	35	35	35	32	27
ACLED - Fatalities	7days	12	20	27	30	34	**38**	38	43	48	46	41
ACLED - Fatalities	14days	9	18	28	30	36	**43**	40	42	44	42	38
FA - Evacuation orders	7days											
FA - Evacuation orders	14days	-5	1	9	0	-7	**-5**	-6	-10	-6	1	10
FA - Evacuation orders	30days											
FA - Ground operations	7days	-6	-3	0	1	5	**6**	4	9	11	6	2
FA - Ground operations	14days	-8	-5	-3	-2	1	**4**	1	5	9	5	1
Temporal Scaling												
CD - Building damages	7days	8	8	12	15	15	**18**	16	10	4	-3	-5
CD - Building damages (prop)	7days	8	8	11	14	14	**17**	15	9	3	-4	-6
CD - Building damages (prop)	14days	14	3	-10	-10	-14	**-16**	-15	-8	0	-3	-3
PWTT - Building damages	14days											
Geographical Scaling												
ACLED - All		10	18	30	31	31	**40**	39	33	32	33	27
ACLED - Fatalities		15	20	27	26	22	**33**	34	37	45	34	23

		24 Nov-22 Jan										
		Past						Future				
	Window	-5	-4	-3	-2	-1	0	1	2	3	4	5
Raw covariate												
ACLED - All		8	25	29	29	32	**33**	36	18	0	1	0
ACLED - Fatalities		20	21	18	25	25	**20**	19	11	-5	-1	-6
Cumulative covariate												
ACLED - All	7days	5	12	21	30	37	**40**	40	30	22	13	5
ACLED - All	14days	-5	1	10	18	26	**31**	32	30	28	24	17
ACLED - Fatalities	7days	3	16	25	29	34	**34**	32	30	28	18	6
ACLED - Fatalities	14days	-8	0	10	18	27	**32**	31	27	27	24	19
FA - Evacuation orders	7days	29	50	56	39	14	**10**	20	17	-6	-10	-5
FA - Evacuation orders	14days	20	45	47	42	42	**31**	31	32	22	14	5
FA - Evacuation orders	30days	8	21	28	32	34	**37**	35	23	10	8	10
FA - Ground operations	7days	2	14	20	20	29	**37**	32	21	8	11	1
FA - Ground operations	14days	-3	9	18	22	27	**32**	34	29	26	30	24
Temporal Scaling												
CD - Building damages	7days	13	20	13	15	10	**21**	37	33	18	16	17
CD - Building damages (prop)	7days	12	19	11	13	7	**21**	44	36	15	13	15
CD - Building damages (prop)	14days	2	9	8	8	6	**13**	35	40	30	28	22
PWTT - Building damages	14days	27	25	25	22	14	**11**	3	17	36	20	5
Geographical Scaling												
ACLED - All		6	16	21	26	30	**29**	35	26	16	17	11
ACLED - Fatalities		13	11	13	24	22	**17**	22	21	14	12	1

		23 Jan-14 May										
		Past						Future				
	Window	-5	-4	-3	-2	-1	0	1	2	3	4	5
Raw covariate												
ACLED - All		-8	-5	-11	-15	-3	**9**	2	8	12	10	9
ACLED - Fatalities		-6	7	2	0	7	**14**	6	4	5	13	12
Cumulative covariate												
ACLED - All	7days	-15	-10	-6	-4	1	**4**	3	5	4	3	4
ACLED - All	14days	-18	-15	-11	-8	-3	**1**	2	3	3	3	4
ACLED - Fatalities	7days	-8	-1	2	5	11	**16**	14	14	10	9	11
ACLED - Fatalities	14days	-19	-12	-7	-1	7	**15**	14	13	12	10	11
FA - Evacuation orders	7days	-1	14	15	20	30	**20**	21	23	16	15	15
FA - Evacuation orders	14days	-3	10	11	16	27	**34**	22	27	21	18	18
FA - Evacuation orders	30days	-6	5	6	11	26	**38**	29	34	31	30	27
FA - Ground operations	7days	-5	0	26	52	40	**29**	9	12	10	7	8
FA - Ground operations	14days	-7	-1	22	44	36	**33**	16	21	18	13	13
Temporal Scaling												
CD - Building damages	7days	-4	-3	-1	0	10	**20**	22	20	23	29	33
CD - Building damages (prop)	7days	-3	-2	0	1	11	**21**	22	20	23	29	33
CD - Building damages (prop)	14days	3	2	2	1	11	**21**	23	23	24	26	28
PWTT - Building damages	14days	-1	-2	-2	-3	-10	**-18**	-19	-19	-18	-18	-18
Geographical Scaling												
ACLED - All		-7	-3	-8	-14	-4	**6**	-2	3	3	-1	2
ACLED - Fatalities		-3	7	1	0	3	**14**	9	7	4	8	10

Past indicates correlation between displacement rate and lagged value of covariate (in days). Future indicates correlation between displacement rate and future value of covariate (in days) Darker red indicates high positive correlation (up to 100), darker blue high negative correlation (up to -100). Grey indicates lack of variables during the given phase. Covariates that had all their correlation values below 35 have been removed.

($r = 42$, 48, and 45, respectively), which could be interpreted as anticipatory moves or an increase in the number of conflict fatalities once a greater number of people have left the governorate. In the second phase of the war, evacuation orders now show the strongest association with population outflows—not through their direct occurrences, but through their cumulative effect over 7- and 14-day periods. This correlation is higher ($r = 56$ and $r = 47$) three to four days before the population begins to leave, indicating a delay as individuals prepare for displacement. The second phase is also the only phase with a clear association between building damage and outgoing displacement. A higher proportion of building damage, compared to the previous seven days, shows a strong correlation in the next one or two days after people have left their governorate ($r = 44$ and $r = 36$). This suggests either anticipatory moves or strikes occurring after the population has departed, with the latter interpretation aligning with the observed strong effect of past cumulative evacuation orders. Finally, the third phase shows

TABLE 4 Temporal cross-correlation of various covariates with incoming displacement during the three phases of the war

13 Oct-24 Nov

Covariate	Window	-5	-4	-3	-2	-1	0	1	2	3	4	5
		Past						Future				
Raw covariate												
CD - Building damages		42	32	15	16	9	**0**	-1	-10	-15	-10	-9
Cumulative covariate												
ACLED - All	7days	41	30	21	16	8	**3**	0	-5	-6	-2	0
ACLED - All	14days	44	33	24	21	13	**6**	2	-5	-9	-5	-4
ACLED - Against civilians	7days	38	33	38	28	15	**11**	2	-7	-13	-16	-10
ACLED - Against civilians	14days	45	43	32	40	32	**19**	15	-3	-17	-12	-15
ACLED - Fatalities	7days	39	30	24	24	19	**14**	14	10	3	4	4
ACLED - Fatalities	14days	40	30	24	25	19	**12**	11	5	0	3	3
ACLED - Fatalities	30days											
FA - Evacuation orders	14days	0	17	40	22	7	**18**	6	3	9	-6	-15
CD - Building damages	7days	45	34	17	18	10	**-2**	-4	-13	-19	-14	-14
CD - Building damages	14days	44	37	25	28	23	**12**	9	-7	-19	-14	-16
PWTT - Building damages	30days											
Temporal Scaling												
FA - Evacuation orders	14days	0	-17	-40	-22	-7	**-18**	-6	-3	-9	6	15
CD - Building damages	7days	0	1	-3	-7	-4	**4**	12	14	15	17	19
CD - Building damages (prop)	7days	-1	0	-4	-8	-5	**3**	10	13	14	16	18
CD - Building damages (prop)	30days											
Geographical Scaling												
ACLED - All		27	18	16	11	10	**5**	1	3	-1	3	3
ACLED - Fatalities		28	15	21	17	14	**5**	4	1	-6	2	2
CD - Building damages		37	30	21	21	14	**5**	4	-4	-10	-7	-5

24 Nov-22 Jan

Covariate	Window	-5	-4	-3	-2	-1	0	1	2	3	4	5
		Past						Future				
Raw covariate												
CD - Building damages		-5	-12	-25	-26	-23	**-22**	-21	-22	-23	-23	-21
Cumulative covariate												
ACLED - All	7days	-18	-21	-27	-30	-33	**-35**	-35	-28	-19	-18	-23
ACLED - All	14days	-24	-26	-32	-34	-34	**-35**	-33	-31	-31	-26	-25
ACLED - Against civilians	7days	-4	-5	-5	-4	-3	**2**	4	-1	-7	-10	-15
ACLED - Against civilians	14days	4	2	-3	-5	-3	**-3**	-3	-6	-8	-6	-10
ACLED - Fatalities	7days	-13	-16	-22	-26	-30	**-34**	-35	-28	-18	-13	-19
ACLED - Fatalities	14days	-22	-23	-28	-32	-33	**-34**	-32	-30	-30	-26	-27
ACLED - Fatalities	30days	-23	-24	-29	-33	-33	**-34**	-34	-34	-36	-32	-29
FA - Evacuation orders	14days	-29	-31	-31	-29	-30	**-29**	-29	-24	-15	-16	-22
CD - Building damages	7days	-4	-11	-24	-25	-22	**-21**	-20	-22	-23	-23	-21
CD - Building damages	14days	-3	-9	-24	-24	-21	**-19**	-19	-20	-22	-23	-21
PWTT - Building damages	30days	-23	-27	-31	-31	-39	**-45**	-44	-43	-42	-39	-31
Temporal Scaling												
FA - Evacuation orders	14days	-3	1	4	1	3	**2**	3	3	-7	-3	-2
CD - Building damages	7days	-24	-26	-23	-26	-29	**-24**	-15	-12	-12	-7	-3
CD - Building damages (prop)	7days	-25	-28	-25	-27	-31	**-26**	-16	-13	-13	-8	-4
CD - Building damages (prop)	30days	-24	-27	-32	-35	-35	**-36**	-33	-32	-32	-24	-17
Geographical Scaling												
ACLED - All		-27	-33	-38	-32	-30	**-27**	-27	-23	-28	-33	-37
ACLED - Fatalities		-22	-32	-36	-32	-31	**-19**	-24	-27	-22	-22	-32
CD - Building damages		-4	-8	-20	-23	-21	**-22**	-22	-23	-27	-27	-26

23 Jan-14 May

Covariate	Window	-5	-4	-3	-2	-1	0	1	2	3	4	5
		Past						Future				
Raw covariate												
CD - Building damages		-5	-6	-7	-8	-14	**-22**	-21	-21	-21	-21	-2
Cumulative covariate												
ACLED - All	7days	-16	-18	-19	-16	-18	**-23**	-21	-20	-18	-17	-1
ACLED - All	14days	-17	-18	-20	-19	-21	**-24**	-22	-21	-21	-21	-1
ACLED - Against civilians	7days	-8	-9	-9	-9	-10	**-12**	-10	-9	-8	-6	0
ACLED - Against civilians	14days	-7	-10	-11	-11	-10	**-11**	-11	-11	-10	-9	-5
ACLED - Fatalities	7days	-19	-20	-21	-17	-17	**-19**	-17	-15	-13	-15	-1
ACLED - Fatalities	14days	-19	-22	-23	-21	-19	**-20**	-16	-15	-15	-16	-1
ACLED - Fatalities	30days	-25	-27	-26	-25	-23	**-22**	-19	-19	-18	-17	-1
FA - Evacuation orders	14days	1	1	2	10	9	**2**	-1	3	5	1	1
CD - Building damages	7days	-5	-5	-7	-8	-14	**-22**	-21	-21	-21	-22	-2
CD - Building damages	14days	-5	-5	-7	-8	-14	**-22**	-21	-21	-21	-22	-2
PWTT - Building damages	30days	-5	-2	-3	-4	-7	**-13**	-13	-13	-13	-14	-1
Temporal Scaling												
FA - Evacuation orders	14days	0	0	5	-3	-2	**4**	0	2	-1	-3	-4
CD - Building damages	7days	-5	-4	-2	-2	2	**6**	11	11	15	28	42
CD - Building damages (prop)	7days	-5	-4	-2	-2	3	**7**	12	12	16	29	45
CD - Building damages (prop)	30days	-9	-9	-6	-6	5	**16**	22	19	20	23	25
Geographical Scaling												
ACLED - All		-14	-17	-18	-13	-16	**-21**	-19	-18	-20	-17	-1
ACLED - Fatalities		-12	-15	-18	-14	-12	**-18**	-8	-11	-13	-18	-1
CD - Building damages		-5	-6	-7	-8	-14	**-20**	-19	-19	-19	-19	-2

Past indicates correlation between displacement rate and lagged value of covariate (in days). Future indicates correlation between displacement rate and future value of covariate (in days) Darker red indicates high positive correlation (up to 100), darker blue high negative correlation (up to -100). Grey indicates lack of variables during the given phase. Covariates that had all their correlation values below 35 have been removed.

a shift in the association structure: population decreases are strongly correlated only with cumulative ground operations over the past seven days, observed in the last two days ($r = 52$), or with cumulative evacuation orders on the day ($r = 38$), indicating a shortening of the decision-making process. Associations with all other covariates fall below 35, a weakening of correlations that points towards the high level of volatility of the "Nowhere Safe" phase.

The relationships between covariates and incoming displacement are different, as shown in Table 4. During the first phase of the war, population increases were not linked to any incidents on the day itself but rather to a decrease of evacuation orders compared to the past 14 day ($r = 40$) in the last three days and to higher cumulative amounts over the past 14 days of conflict incidents, targeting civilians, inducing fatalities, and building damages that occurred five days ago ($r = 44, 45, 40, 44$), speaking for an arrival of population after war-related incidents eased. The second phase of the war offers a homogeneous picture across all covariates where almost all correlations are negative and larger at a time lag of 0 days, suggesting that displacement destinations were associated with the immediate war situation, with little room for preparation or anticipation. Finally, the third phase of the war shows similar patterns as the analysis of outgoing displacement, with a weakening of the correlation with covariates—except for the unexpectedly strong positive relationship with higher building damages in the next five days than in the last seven days ($r = 45$), suggesting that higher measures of building damage follow influxes of population.

Reliability of the analysis

As demonstrated in the Online Appendix, Section A1, population estimates and thus the derived displacement metrics are not sensitive to differences in social media activity across social groups as long as the social media activity changes are uniform across governorates. Conversely, changes in social media penetration rates that are nonuniform across governorates bias the subnational population estimates with a proportional error structure. However, as the method for deriving gender- and time-specific penetration rates based on the total population, this error is distributed through all governorates, thus reducing its impact on the governorate that has seen the specific change in social media activity (see Online Appendix Sections A4 and A5). Finally, as the war unfolds, figures on death and border crossing can be either hard to access or highly disputed and thus hard to reuse. We show, nonetheless, in Section A6 that not taking into account those drivers of population change artificially increases the internal displacement metrics.

Discussion and concluding remarks

Armed conflict rapidly transforms the spatial distribution and demographic composition of populations, posing major challenges to the timely and effective delivery of humanitarian assistance, which requires up to daily situation updates (United Nations Relief and Works Agency for Palestine Refugees 2024). Although the demographic data revolution (Kashyap 2021) has produced a growing array of high-frequency data sources, analytical frameworks for translating these data into informative assessments of displacement remain limited. This study contributes to this effort by introducing an analytical toolbox for the timely study of short-term population displacement in contexts of ongoing armed conflict.

Applied to the Gaza Strip, the toolbox integrates freely accessible Facebook marketing data with pre-war population estimates and contextual covariates derived from satellite imagery (building damage products), social media platforms (evacuation orders and ground invasions from X and Telegram), and news outlets (conflict intensity). The resulting estimates capture governorate-level population dynamics throughout the war and closely align with UNRWA's displacement figures. Temporal analyses further reveal the evolution of migration dynamics over the course of the conflict and gender-differentiated patterns of mobility, with women more likely to leave high-risk areas earlier. This contributes to a small but growing literature highlighting gender-specific responses to an unfolding crisis in near real time (Anastasiadou et al. 2024).

Applying the measures from the toolbox to consistent data from Facebook's marketing API and pre-war population estimates, we highlight the distinct nature of the Hamas–Israel war compared to Russia's full-scale invasion of Ukraine. Population displacement in the Gaza Strip impacted a three times greater proportion of the population, unfolded eight times faster, and with a duration that was five times more constant than in Ukraine. In absolute numbers, population displacement in Ukraine impacted over six million people, three times the population of the Gaza Strip, with individual displacement events rapidly affecting hundreds of thousands of people. These differences quantify unique characteristics of each crisis, which can provide real-time insights into population movements and decision-making that may help shape more tailored humanitarian responses.

Having access to daily estimates of displacement at the subnational level for a conflict-affected territory is a rare data opportunity to get a deeper understanding of the short-term dynamics of war-induced population movements, especially in relationship with covariates that are correlated with displacement (Zens and Thalheimer 2024). We showed that in Gaza, the association between conflict events, building damage, evacuation orders, ground invasions and population changes differed between population increases (i.e., destination locations) and population decreases (i.e., origin locations) with building damages (or rather the lack of) being more correlated with a surge of people, while decreases were more tied with evacuation orders and ground invasions. The association was also nonlinear across war phases and time, with more immediate response between events and population decrease and less anticipatory movement as the war unfolded.

The phase-based analysis of Facebook-derived population estimates (October 7–December 1 for the "Evacuation of the North," December 1–January 22 for the "Densification," and January 22–May 15 for the "Nowhere safe" phase) aligns well with Forensic Architecture's classification of evacuation orders, "Evacuating the North," "The Evacuation Grid," and "Forceful Evacuation of the 'Safe Zones'" and demonstrates their direct impact on population movements, as exemplified in Khan Younis, where population sizes steadily increased in the first phase, sharply declined in the second, and recovered slowly in the third when "nowhere was safe anymore" (Asi et al. 2024). This phase-based framework also proved useful in identifying the changing relationship between displacement and co-variates. For example, associations generally weakened in the third phase, reflecting heightened volatility, except for the higher level of continuous ground operations in the last seven days, which was linked to a greater population decrease, and the higher level of continuous building damage in the next seven days, which was associated with a population increase. Articulating different data streams through an integrated crisis analytics toolbox is able to reveal shifts in the nature of the Hamas–Israel war.

The population data presented in this paper have been considered sufficiently reliable to be included in an assessment of the public health impacts of the war (Igusa et al. 2024) and to directly guide the allocation of resources. They can be further reused for any assessments that require a population denominator, or any causal study that requires population displacement as an explanatory variable or as a target variable. But they come with several limitations that must be acknowledged. First, the data are provided at a sample of locations and thus do not have full coverage of the Gaza Strip or capture more localized movements, which may result in a conservative estimate of conflict-induced displacement. Second, the data do not capture individuals under 13 years old and thus miss 40 percent of the Gaza Strip population (Palestinian Central Bureau of Statistics 2023). Third, the approach derives displacement from raw population changes and therefore cannot distinguish forced displacement versus other sources of demographic change, such as other types of migration, births, and deaths at the subnational level. Lastly, the approach captures net population change based on stocks rather than flows, meaning it cannot differentiate between returnees and newcomers or detect changes when inflows equal outflows. As a result, it likely underestimates the toll of displacement and cannot track over time the displaced population separately from the resident population (Baroud 2024).

Another critical limitation concerns whether the observed results reflect actual population displacement or are instead influenced by the use of Facebook during the war. Disruptions in mobile phone connectivity and electricity pose challenges to the accuracy and completeness of digital data collection. However, as our methodology relies on the relative proportion of social media audience across governorates, uneven variations in social media activity between regions would affect population estimates, though homogeneous changes in online activity would have no effect. Furthermore, accessing the internet became vital for the population, as a crucial tool for communication both within their communities and beyond Gaza's borders to raise awareness and amplify their plight to the outside world. This dual role, data source, and lifeline underscores the importance of digital platforms in providing near-real-time insights into population displacement, even amidst the disruptions of war.

However, social media platforms are evolving rapidly, with sudden changes to APIs, such as Twitter ending free API access in February 2023 and Facebook restricting access to "recent" audience location data in May 2024, making these data sources increasingly unstable. The next critical research step is thus to develop models to estimate population displacement that are able to integrate those multiple incomplete and indirect data sources. As our findings show, this will be a significant challenge because the relationship between war events and displacement is nonlinear across time and space.

Nonetheless, we have demonstrated how the digital revolution has expanded capacity for fine-grained, extensive recording of war-related events. To offer an integrated understanding of those varied data streams, we designed a dedicated analytical toolbox aimed at describing population responses to conflict along three dimensions: across space, time, and demographic subgroups. Such analytics are essential for operational purposes, such as resource allocation and adapting funding calls, as well as for preparedness. By allowing a deeper understanding of population movements and behaviors, this framework can guide policy responses and improve humanitarian efforts, ultimately contributing to more effective conflict management and recovery planning.

Acknowledgments

The authors would like to express their gratitude to the feedback provided by Dr Elisabetta Pietrostefani and Prof. Franscisco Rowe on the crisis analytics toolbox. We also would like to thank the Conflict Ecology Lab and, in particular, Dr Corey Scher and Asst Prof Jamon Van Den Hoek for providing six months of building damage maps, and Dr Ollie Ballinger for presenting to us his methods and open-source code for detecting building damage from satellite imagery. We also would like to mention the use of LLM, mainly the ChatGPT 5.2 model, to assist with manuscript editing and proofreading.

Funding statement

This work was supported by the Leverhulme Trust under Grant RC-2018-003 for the Leverhulme Centre for Demographic Science. We gratefully acknowledge the resources provided by the International Max Planck Research School for Population, Health and Data Science (IMPRS-PHDS).

Conflict of interest statement

Prof Ridhi Kashyap is part of the Editorial Committee of the *Population and Development Review*.

Ethics approval statement

It was not possible for the authors to request consent from Facebook users whose anonymized and aggregated data were used for this study. These users consented to the Meta Platform Terms, which include consent for their data to be used for marketing purposes. We accessed counts of daily and monthly active Facebook users in the six main cities of the Gaza Strip for five-year age-gender groups from Facebook's marketing tools, which are available to anyone with a Facebook account.

Data availability statement

The data and code to reproduce the article's results can be retrieved from the following Open Science Framework repository: https://doi.org/10.17605/osf.io/k2qyw

Note

1 Except in the case of Colombia (Ibanez 2009) or the Philippines (Essig and Moretti 2020).

References

Abdelmagid, Nada, and Francesco Checchi. 2018. "Estimation of Population Denominators for the Humanitarian Health Sector." Guidance for Humanitarian Coordination Mechanisms. Health Cluster, World Health Organisation. https://healthcluster.who.int/publications/m/item/estimation-of-population-denominators-for-the-humanitarian-health-sector.

Airwars. 2023. "Methodology Note: Civilian Harm from Explosive Weapons Use in Gaza." https://airwars.org/research/methodology-note-civilian-harm-from-explosive-weapons-use-in-gaza/.

Alburez-Gutierrez, Diego. 2019. "Blood Is Thicker than Bloodshed: A Genealogical Approach to Reconstruct Populations after Armed Conflicts." *Demographic Research* 40 (March): 627–56. https://doi.org/10.4054/DemRes.2019.40.23.

Alburez-Gutierrez, Diego, and Carlota Segura García. 2018. "The UNHCR Demographic Projection Tool: Estimating the Future Size and Composition of Forcibly Displaced Populations." UNHCR Statistics Technical Series: 2018/1. New York: UNHCR.

Alexander, Monica, Kivan Polimis, and Emilio Zagheni. 2019. "The Impact of Hurricane Maria on Out-Migration from Puerto Rico: Evidence from Facebook Data." *Population and Development Review* 45 (3): 617–30.

Al-Mughrabi, Nidal. 2024. "Israel Intensifies Strikes on Rafah Ahead of Threatened Invasion." Middle East. Reuters, April 25. https://www.reuters.com/world/middle-east/israel-intensifies-strikes-gazas-rafah-ahead-threatened-invasion-2024-04-25/.

Anastasiadou, Athina, Jisu Kim, Ebru Sanlitürk, Helga A. G. de Valk, and Emilio Zagheni. 2024. "Gender Differences in the Migration Process: A Narrative Literature Review." *Population and Development Review* 50 (4): 961–96. https://doi.org/10.1111/padr.12677.

Araujo, Matheus, Yelena Mejova, Ingmar Weber, and Fabricio Benevenuto. 2017. "Using Facebook Ads Audiences for Global Lifestyle Disease Surveillance: Promises and Limitations." In *Proceedings of the 2017 ACM on Web Science Conference*, 253–57. New York: ACM.

Asi, Yara, David Mills, and P. Gregg Greenough., et al. 2024. "'Nowhere and No One Is Safe': Spatial Analysis of Damage to Critical Civilian Infrastructure in the Gaza Strip during the First Phase of the Israeli Military Campaign, 7 October to 22 November 2023." *Conflict and Health* 18 (1): 24. https://doi.org/10.1186/s13031-024-00580-x.

Ballinger, Ollie. 2024. "Open Access Battle Damage Detection via Pixel-Wise T-Test on Sentinel-1 Imagery." Preprint, arXiv, May 10. https://doi.org/10.48550/arXiv.2405.06323.

Baroud, Rita. 2024. "I Have Been Forcibly Displaced 12 Times by Israel's War in Gaza." The New Humanitarian, August 20. https://www.thenewhumanitarian.org/opinion/first-person/2024/08/20/i-have-been-forcibly-displaced-12-times-israel-war-gaza.

Bell, M., M. Blake, and P. Boyle., et al. 2002. "Cross-National Comparison of Internal Migration: Issues and Measures." *Journal of the Royal Statistical Society Series A: Statistics in Society* 165 (3): 435–64. https://doi.org/10.1111/1467-985X.t01-1-00247.

Bengtsson, Linus, Xin Lu, Anna Thorson, Richard Garfield, and Johan von Schreeb. 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(8): e1001083. https://doi.org/10.1371/journal.pmed.1001083.

Brock, Patrick Michael, and Harriet Kasidi Mugera. 2023. "Accelerating and Enhancing the Generation of Socioeconomic Data to Inform Forced Displacement Policy and Response." *Data & Policy* 5 (January): e42. https://doi.org/10.1017/dap.2023.47.

Checchi, Francesco, and Emilie Sabine Koum Besson. 2022. "Reconstructing Subdistrict-Level Population Denominators in Yemen after Six Years of Armed Conflict and Forced Displacement." *Journal of Migration and Health* 5 (January): 100105. https://doi.org/10.1016/j.jmh.2022.100105.

Czaika, Mathias, and Krisztina Kis-Katos. 2009. "Civil Conflict and Displacement: Village-Level Determinants of Forced Migration in Aceh." *Journal of Peace Research* 46 (3): 399–418. https://doi.org/10.1177/0022343309102659.

Displacement Tracking Matrix. 2023. "DTM Global Infosheet." International Organization for Migration, January 2023. https://dtm.iom.int/sites/g/files/tmzbdl1461/files/DTM%20Global%20Infosheet%20-%20January%202023.pdf.

Essig, Barbara, and Sebastien Moretti. 2020. "Preventing and Preparing for Disaster Displacement." Forced Migration Review. https://www.fmreview.org/essig-moretti-pdd/.

Forensic Architecture. 2024. "Humanitarian Violence: Israel's Abuse of Preventative Measures in Its 2023–2024 Genocidal Military Campaign in the Occupied Gaza Strip." https://forensic-architecture.org/investigation/humanitarian-violence-in-gaza.

Ge, Pinglan, Hideomi Gokon, and Kimiro Meguro. 2020. "A Review on Synthetic Aperture Radar-Based Building Damage Assessment in Disasters." *Remote Sensing of Environment* 240 (April): 111693. https://doi.org/10.1016/j.rse.2020.111693.

Ghurye, Jay, Gautier Krings, and Vanessa Frias-Martinez. 2016. "A Framework to Model Human Behavior at Large Scale during Natural Disasters." *2016 Proceedings of the 17th IEEE International Conference on Mobile Data Management (MDM)*, June 1, 18–27. Piscataway, NJ: IEEE. https://doi.org/10.1109/MDM.2016.17.

Holail, Shimaa, Tamer Saleh, Xiongwu Xiao., et al. 2024. "Time-Series Satellite Remote Sensing Reveals Gradually Increasing War Damage in the Gaza Strip." *National Science Review* 11 (9): nwae304. https://doi.org/10.1093/nsr/nwae304.

Ibanez, Ana Maria. 2009. "Forced Displacement in Colombia: Magnitude and Causes." *The Economics of Peace and Security Journal* 4 (1): 48–54. https://doi.org/10.15355/epsj.4.1.48.

Igusa, Tak, Zhixi Chen, Anika Gnaedinger, Francesco Checchi, and Paul B. Spiegel. 2024. "Crisis in Gaza: Projected Deaths Due to Traumatic Injuries in the Rafah Governorate." Report 2: 20 May to 17 August 2024. Baltimore: Center for Humanitarian Health at the Johns Hopkins University and the London School of Hygiene and Tropical Medicine. https://gaza-projections.org/docs/report2/traumatic_injuries_rafah.pdf.

Institute for the Study of War, and AEI's Critical Threats Project. 2024. "Interactive Map: Israel's Operation in Gaza." ArcGIS StoryMaps, May 14. https://storymaps.arcgis.com/stories/2e746151991643e39e64780f0674f7dd.

Internal Displacement Monitoring Centre. 2023. "25 Years of Progress on Internal Displacement 1998–2023." Geneva: Internal Displacement Monitoring Centre.

International Organisation for Migration. 2021. "Informe de Análisis de Movimientos Migratorios Mediante Analítica de Wi-Fi OIM-GIFMM." Grupo Interagencial sobre Flujos Migratorios Mixtos en Colombia. https://www.r4v.info/es/document/colombia-informe-de-analisis-de-movimientos-migratorios-mediante-analitica-de-wifi-julio.

Iradukunda, Rodgers, Francisco Rowe, and Elisabetta Pietrostefani. 2025. "Estimating Internal Displacement in Ukraine from High-Frequency GPS Mobile Phone Data." *Humanities and Social Sciences Communications* 12 (1): 1863. https://doi.org/10.1057/s41599-025-06137-4.

Kashyap, Ridhi. 2021. "Has Demography Witnessed a Data Revolution? Promises and Pitfalls of a Changing Data Ecosystem." *Population Studies* 75 (supp. 1): 47–75. https://doi.org/10.1080/00324728.2021.1969031.

Laney, Doug. 2001. "3D Data Management: Controlling Data Volume, Velocity and Variety." *ETA Group Research Note* 6 (70): 1.

Leasure, Douglas R., Ridhi Kashyap, Francesco Rampazzo., et al. 2023. "Nowcasting Daily Population Displacement in Ukraine through Social Media Advertising Data." *Population and Development Review* 49 (2): 231–54. https://doi.org/10.1111/padr.12558.

Lubkemann, Stephen C. 2005. "Migratory Coping in Wartime Mozambique: An Anthropology of Violence and Displacement in 'Fragmented Wars'." *Journal of Peace Research* 42 (4): 493–508.

Maas, Paige, Shankar Iyer, Andreas Gros., et al. 2019. "Facebook Disaster Maps: Aggregate Insights for Crisis Response & Recovery." In *KDD '19: Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 3173. New York: Association for Computing Machinery.

Meta. 2023. "Meta Marketing API. V. v18." Released. Menlo Park, CA: Meta.

Minora, Umberto, Martina Belmonte, Claudio Bosco., et al. 2023. "Migration Patterns, Friendship Networks, and the Diaspora: The Potential of Facebook Social Connectedness Index to Anticipate Displacement Patterns Induced by Russia Invasion of Ukraine in the European Union." Migration Research Series, No. 73. Geneva: International Organization for Migration. https://publications.iom.int/books/mrs-no-73-war-ukraine-and-potential-facebooks-social-connectedness-index-anticipate-human.

Palestinian Central Bureau of Statistics. 2023. "State of Palestine - Subnational Population Statistics." Humanitarian Data Exchange (HDX). New York: UN OCHA. https://data.humdata.org/dataset/cod-ps-pse.

Palestinian Central Bureau of Statistics. 2024. "Revised Estimates Based on the Final Results of the Population, Housing and Establishments Census 2017." Personal communication. Ramallah, Palestine: Palestinian Central Bureau of Statistics.

Palestinian Ministry of Health. 2025. "Palestinian Casualties." Microsoft Power BI. October 20. Ramallah, Palestine: Palestinian Ministry of Health. https://app.powerbi.com/view?r=eyJrIjoiODAxNTYzMDYtMjQ3YS00OTMzLTkxMWQtOTU1NWEwMzE5NTMwIiwidCI6ImY2MTBjMGI3LWJkMjQtNGIzOS04MTBiLTNkYzI4MGFmYjU5MCIsImMiOjh9&disablecdnExpiration=1760918802.

Palotti, Joao, Natalia Adler, Alfredo Morales-Guzman., et al. 2020. "Monitoring of the Venezuelan Exodus through Facebook's Advertising Platform." *PLoS ONE* 15 (2): e0229175. https://doi.org/10.1371/journal.pone.0229175.

Raleigh, Clionadh, Andrew Linke, Håvard Hegre, and Joakim Karlsen. 2010. "Introducing ACLED: An Armed Conflict Location and Event Dataset: Special Data Feature." *Journal of Peace Research* 47 (5): 651–60.

Reed, Holly, John Haaga, and Charles Keely. 1998. *The Demography of Forced Migration: Summary of a Workshop*. Washington, DC: National Academies Press. https://doi.org/10.17226/6187.

Rufener, Marie-Christine, Ferda Ofli, Masoomali Fatehkia, and Ingmar Weber. 2024. "Estimation of Internal Displacement in Ukraine from Satellite-Based Car Detections." *Scientific Reports* 14 (1): 31638. https://doi.org/10.1038/s41598-024-80035-8.

Salganik, Matthew J. 2019. *Bit by Bit: Social Research in the Digital Age*. Princeton: Princeton University Press.

Sarzin, Zara Inga. 2017. “Stocktaking of Global Forced Displacement Data.” Policy Research Working Paper No. 2931796. Washington, DC: World Bank. https://papers.ssrn.com/abstract=2931796.

Scher, Corey, and Jamon Van Den Hoek. 2025. “Nationwide Conflict Damage Mapping with Interferometric Synthetic Aperture Radar: A Study of the 2022 Russia-Ukraine Conflict.” *Science of Remote Sensing*, 11: 100217. https://doi.org/10.1016/j.srs.2025.100217.

Shibuya, Yuya, Nicholas Jones, and Yoshihide Sekimoto. 2024. “Assessing Internal Displacement Patterns in Ukraine during the Beginning of the Russian Invasion in 2022.” *Scientific Reports* 14 (1): 11123. https://doi.org/10.1038/s41598-024-59814-w.

Steele, Abbey. 2009. “Seeking Safety: Avoiding Displacement and Choosing Destinations in Civil Wars.” *Journal of Peace Research* 46 (3): 419–29. https://doi.org/10.1177/0022343309102660.

Tai, Xiao Hui, Shikhar Mehra, and Joshua E. Blumenstock. 2022. “Mobile Phone Data Reveal the Effects of Violence on Internal Displacement in Afghanistan.” *Nature Human Behaviour* 6 (5): 624–34. https://doi.org/10.1038/s41562-022-01336-4.

United Nations High Commissioner for Refugees. 2023. “Refugee Data Finder.” New York: UNHCR. https://www.unhcr.org/refugee-statistics/.

United Nations Office for the Coordination of Humanitarian Affairs. 2025. “Gaza Crossings: Movement of People and Goods.” Microsoft Power BI. October 20. New York: United Nations Office for the Coordination of Humanitarian Affairs. https://www.ochaopt.org/data/crossings.

United Nations Relief and Works Agency for Palestine Refugees. 2024. “UNRWA Situation Report #59 on the Situation in the Gaza Strip and the West Bank, Including East Jerusalem.” January 2. Gaza City: United Nations Relief and Works Agency for Palestine Refugees. https://reliefweb.int/attachments/d68f957f-9c73-45ad-af17-bf98a9769738/unrwa_gaza_sitrep_59_2_jan_2024_eng.pdf.

Wang, Qi, and John E. Taylor. 2014. “Quantifying Human Mobility Perturbation and Resilience in Hurricane Sandy.” *PLoS ONE* 9 (11): e112608. https://doi.org/10.1371/journal.pone.0112608.

Wang, Yanxin, Jian Li, Xi Zhao, Gengzhong Feng, and Xin (Robert) Luo. 2020. “Using Mobile Phone Data for Emergency Management: A Systematic Literature Review.” *Information Systems Frontiers* 22 (6): 1539–59. https://doi.org/10.1007/s10796-020-10057-w.

Williams, Nathalie E., Dirgha J. Ghimire, William G. Axinn, Elyse A. Jennings, and Meeta S. Pradhan. 2012. “A Micro-Level Event-Centered Approach to Investigating Armed Conflict and Population Responses.” *Demography* 49 (4): 1521–46. https://doi.org/10.1007/s13524-012-0134-8.

World Bank, European Union, and United Nations. 2024. *Gaza Strip Interim Damage Assessment*. Washington, DC: World Bank Publications. https://thedocs.worldbank.org/en/doc/14e309cd34e04e40b90eb19afa7b5d15-0280012024/original/Gaza-Interim-Damage-Assessment-032924-Final.pdf.

Yabe, Takahiro, Nicholas K. W. Jones, P. Suresh C Rao, Marta C. Gonzalez, and Satish V. Ukkusuri. 2022. “Mobile Phone Location Data for Disasters: A Review from Natural Hazards and Epidemics.” *Computers, Environment and Urban Systems* 94 (June): 101777. https://doi.org/10.1016/j.compenvurbsys.2022.101777.

Zens, G., and L. Thalheimer. 2024. ‘The Short-Term Dynamics of Conflict-Driven Displacement: Bayesian Modeling of Disaggregated Data from Somalia’. Monograph. WP-24-002, January 17. https://iiasa.dev.local/.