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Innovative data solutions for fragile and conflict-affected settings

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This paper examines how innovative data solutions can complement traditional statistical systems in fragile and conflict-affected settings (FCAS). While these innovations cannot replace robust national data infrastructure and systems, they offer promising ways to generate timely, granular insights when standard methods are unfeasible

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Executive summary

Fragility increasingly shapes global development outcomes. As of 2025, 61 countries face high or extreme fragility, encompassing one-quarter of the world's population and nearly three-quarters of its extreme poor. Yet it is difficult to find reliable, timely and granular data from these countries due to insecurity, weak infrastructure, displacement, and institutional deficits. These gaps undermine efforts to understand evolving situations, target resources effectively, and measure impact.

Closing these data and evidence blind spots is essential for shaping effective responses in fragile contexts. Research plays a critical role: it offers innovative ways to collect and analyse the data that can inform policy decisions, build local capacity, and adapt interventions to uncertain situations. Beyond the immediate policy needs, such research deepens our understanding of what drives fragility and how institutions emerge. It also provides insights into how people behave in diverse political, economic, and social conditions, refining our broader understanding of how societies adapt to different and evolving equilibria.

This framing paper examines how innovative data solutions can complement traditional statistical systems in fragile and conflict-affected settings (FCAS). While these innovations cannot replace robust national data infrastructure and systems, they offer promising ways to generate timely, granular insights when standard methods are unfeasible.

The paper addresses the following core factors:

- **Barriers to data collection in FCAS**: Persistent insecurity, displacement, weak institutional capacity, and political sensitivities make conventional instruments such as censuses, household surveys, and administrative data costly, slow, and often impossible. These constraints lead to incomplete, biased, or outdated data which limits evidence-based decision making.
- **Emerging data innovations:**
    - **Mobile-phone-based approaches**: In a crisis, call detail records (CDRs) and rapid-response phone surveys enable real-time monitoring of poverty, displacement, and welfare. They offer scalability and cost-efficiency but face coverage gaps, model drift, and privacy risks.
    - **Satellite-based economic measurement**: Night-time lights and other remote-sensing indicators provide near real-time insights into economic activity, disaster impacts, and spatial development patterns. These tools are versatile and resistant to manipulation but require careful

calibration and "ground-truthing" to address biases in informal and rural economies.

- **Policy directions arising from the paper:**
    - Use innovative data sources as complements, not substitutes, for official statistics.
    - Prioritise hybrid approaches that combine mobile, satellite, and survey data to improve representativeness and reliability.
    - Invest in local capacity for data governance, bias adjustment, and ethical safeguards.
    - Establish clear protocols for privacy and data protection, particularly in politically sensitive environments.

Together, these strategies can help close evidence gaps, improve decision making in uncertainty, and support more timely policy responses in fragile contexts.

1. Introduction

Fragility is increasingly shaping global development outcomes. However, the evidence base needed to respond effectively remains limited. In fragile and conflict-affected settings (FCAS), insecurity, displacement, weak infrastructure, and political sensitivities make it difficult to collect reliable, timely, and granular data. As a result, policymakers and practitioners are often forced to make decisions with incomplete or outdated information; this limits their ability to target resources, adapt interventions, and evaluate impact.

How can we address these constraints? This paper examines how recent advances in data collection and analysis can help. It focuses on a set of emerging approaches – mobile phone data, rapid-response surveys, and satellite-based measurement – that offer new ways to generate insights in environments where traditional methods are unfeasible. While these innovations do not replace the need for national statistical systems, they provide complementary tools that can improve timeliness, granularity, and coverage where data gaps are most acute.

The value of these innovations lies not only in their technical capabilities, but in how they are deployed. Each approach involves trade-offs. Mobile data can be fast and scalable but may exclude the poorest. Satellite imagery offers broad coverage but requires careful interpretation. Phone surveys can generate rapid insights but raise concerns around representativeness and attrition. Understanding these limitations and designing hybrid approaches that combine multiple data sources is critical to ensuring that new data tools improve, rather than distort, decision making in fragile contexts.

The paper begins by outlining the key barriers to data collection in FCAS. It then examines three data innovations that have proven useful in data-scarce environments – mobile phone data, rapid-response surveys, and satellite imagery – highlighting their applications and their limitations. The paper concludes by emphasising that, while these approaches cannot substitute for strong administrative data systems, they serve as critical tools where conventional data collection is constrained or unfeasible.

2. Barriers to data collection in FCAS

Fragility is increasingly shaping global development outcomes: as of 2025, 61 countries face high or extreme fragility, encompassing one-quarter of the world's population and nearly three-quarters of its extreme poor (OECD, 2025). Yet gathering reliable, timely, and granular data from these contexts remains a pressing challenge due to limited statistical capacity, access constraints, and safety risks (Lwamba & Lee, 2025; OECD, 2025). Robust data is fundamental for effective development planning and policymaking. However, the processes of collecting and maintaining data and statistical systems face several unique and multifaceted challenges arising from persistent insecurity, displacement, institutional weaknesses, and the deterioration of infrastructure.

Security and inaccessibility

Active conflict and insecurity are among the most significant barriers to effective data collection in fragile settings. The prevalence of violence, the presence of disease and other dangers can make traditional face-to-face information gathering (such as household surveys) unfeasible, exposing enumerators to considerable risk. When insecurity escalates, enumerators and survey teams are often unable to reach many areas, especially those which are under the control of non-state actors or experiencing ongoing violence (Idris, 2019). Reports from the Sahel and other conflict-affected areas show that when access is restricted due to deteriorating security, this limits representative sampling and the collection of reliable information (Deb & Baudais, 2022). The constant risk to the safety of research staff inhibits not only household surveys but any in-depth or repeated studies. Disease outbreaks in such contexts, such as Ebola in West Africa, have exacerbated these limitations by making face-to-face interviews dangerous or impossible (Etang & Himelein, 2020). In Somalia, extended interview times for traditional household surveys were impossible due to the insecurity and threats to enumerators (Pape & Wollburg, 2019).

Lack of infrastructure and low government capacity

The physical and institutional infrastructure essential for systematic data collection is remarkably weak in these settings. Poor road conditions, unreliable telecommunications, and electricity shortages are routine, making large-scale surveys logistically challenging if not unfeasible (Hoogeveen & Pape, 2020). Furthermore, the ability of governments and local agencies to design, execute, and store high-quality data is often undermined by weak statistical systems, lack of technical skills, and the ongoing loss of personnel - a situation exacerbated by frequent unrest and brain drain (Idris, 2019). For example, during civil conflict in the Central African Republic, the destruction or theft of data infrastructure, such as records, computers, and maps, led to long-lasting setbacks (Hoogeveen & Pape, 2020).

Poor data quality

Even when data collection is possible, its quality is frequently questionable. Insecure environments result in incomplete responses, high rates of sample attrition, and coverage errors that result in findings that are not representative (Idris, 2019). Sampling frames are often outdated, lost, or rendered obsolete by mass displacement and changing demographics (Deb & Baudais, 2022; World Bank, 2024). As a result, surveys risk selection and survivor bias, where only more accessible or “surviving” populations are represented (Idris, 2019). Data may also be infrequently collected, poorly disaggregated by geography or group, and subject to manipulation or controversy, particularly on politicised topics (Defontaine, 2018; Idris, 2019).

Even in areas where data is collected, its quality can be undermined by factors such as:

- **Attrition and survivorship bias**: High levels of population movement and insecurity result in attrition, skewing results towards those who are accessible or have survived conflict.
- **Selection and response bias**: Samples may exclude harder-to-reach groups, while those included may shape their answers to align with perceived expectations or to avoid repercussions - especially regarding sensitive topics (for example, group affiliations or perception of authorities).
- **Data loss and system weaknesses**: The destruction or theft of equipment and data further limits comprehensive data gathering and continuity over time.

Displacement and mobility

Fragile settings are often characterised by large-scale internal displacement and population movement, either as a direct result of violence or as a survival strategy amid economic breakdown (Hoogeveen & Pape, 2020; Idris, 2019). This mobility disrupts established sampling frames and complicates efforts to ensure survey samples remain representative of the target population (Hoogeveen & Pape, 2020). As populations move, become dispersed, or congregate in displacement camps, the most vulnerable are often under-represented in national or regional datasets.

The challenge is compounded when using outdated or destroyed census data. Armed conflict can render official population numbers obsolete overnight, as occurred in the Central African Republic where much of the data infrastructure was lost during the civil war. Consequently, surveys risk systematic bias, particularly if access is feasible only in relatively secure "islands" and provides no basis for generalisation (Deb & Baudais, 2022).

Data collection as a political process

The politics of data collection further complicate research in these contexts. Governments may be less willing to collect or disclose data revealing abuses by official forces or information that might fuel opposition or unrest. Lebanon, for example, has not conducted a census since 1932 because the demographic data has sensitive political implications (Lebanese Information Center, 2013; Abrahams & Greenwald, 2021). The selective sharing or withholding of information, as well as divergent standards for reporting violence by (state vs. non-state) actors, can significantly bias what is known about conflict dynamics (Abrahams & Greenwald, 2021; Idris, 2019).

Mistrust of institutions and sensitivities of the questions

Mistrust of state authorities, outsiders, or international organisations makes respondents hesitant to answer candidly, especially on controversial or dangerous topics such as group loyalties, security conditions, or government performance (Nienaber, 2021; Idris, 2019). Concerns about confidentiality and fear of reprisal often lead to non-response or "strategic" reporting, undermining data reliability and completeness.

Note: There is also an important distinction between accuracy and precision in data systems. “Accuracy” refers to how closely estimates reflect underlying realities, whereas “precision” relates to the consistency and comparability of measurements across time and space. Many innovative data sources improve timeliness and coverage in FCAS but may introduce trade-offs in comparability or measurement stability, underscoring the need for hybrid data systems that combine traditional and non-traditional approaches to ensure both responsiveness and reliability.

3. Innovative solutions for data collection in FCAS

3.1 Mobile-phone-based innovations

This section examines how innovative, mobile-phone-based approaches can help to partially close these gaps. It focuses on three applications that have been tested in FCAS:

- targeting recipients of social protection programmes using mobile data;
- tracking mobility and displacement using call detail records (CDRs); and
- deploying rapid-response mobile phone surveys (RRPS) during crises.

While these approaches are not a substitute for robust statistical systems, they can complement traditional approaches and provide more timely, granular information when standard methods are unfeasible.

3.1.1 Targeting recipients of social protection programmes using mobile data

The policy challenge: identifying targets for social safety nets

A central challenge for social protection programmes is identifying who should receive benefits and who should not. The goal is to minimise two errors: including ineligible households and excluding households that should be included. For example, if the aim of the policy is to help the poorest households, it should not include wealthier households by mistake or exclude poor households in need. In low-income and fragile contexts, this task is especially difficult because governments lack reliable administrative data such as tax records or social registries on which to base their decision.

Proxy means testing (PMT) is one of the most common approaches used to determine eligibility. It uses detailed household surveys on assets and demographics to statistically predict income. Alternative methods include community-based targeting (CBT), in which local committees select beneficiaries; geographic targeting of poor areas; and universal basic income (UBI) schemes, which forego targeting altogether. Governments face a clear trade-off: for a fixed budget, they can invest heavily in identifying eligible households, leaving fewer resources for benefits, or reduce selection costs but risk including more ineligible households.

In FCAS, these traditional methods often break down. PMT surveys are expensive, logistically complex, and difficult to conduct in insecure regions. CBT assumes stable community structures and trust, which may be eroded during displacement or conflict. Geographic targeting or UBI may be fiscally unfeasible. The result is that programmes risk either failing to reach vulnerable groups or diverting limited resources to wealthier households.

The innovation: mobile data use

An emerging innovation uses mobile phone metadata or CDRs as a proxy for income and welfare. The data includes information on the number and location of calls made, the recipient’s location, and the number of texts. This approach builds on evidence that phone-use behaviour differs systematically across income groups (Blumenstock et al., 2015), allowing these patterns to serve as indirect indicators of living standards. Crucially, the approach first needs a small group of households for which both mobile phone records and reliable information on wealth are available. This data is used to learn how phone-use patterns differ between poorer and wealthier households. Once this relationship is established, it can be applied to mobile phone records for the wider population to estimate relative wealth levels at scale.

The approach typically works as follows:

1. Survey data on consumption or income are collected for a subset of the population.
2. These data are matched to mobile phone metadata, such as frequency of calls, airtime purchases, and mobility patterns.
3. A machine-learning model is trained to predict income or consumption.
4. The trained model is applied to all subscribers in the network, producing scalable poverty estimates.

This method has been tested in multiple countries. In Afghanistan, CDR-based targeting identified ultra-poor households nearly as accurately as traditional PMT (Aiken et al., 2023). During Covid-19 in Togo, mobile-based targeting enabled rapid delivery of emergency transfers (Aiken et al., 2022). Other pilots in Haiti (Barriga-Cabanillas et al., 2025) and Bangladesh (Aiken et al., 2025) demonstrate its potential to expand coverage quickly and at low cost.

There are several benefits to this approach:

- **High-frequency data:** Mobile data can be collected and updated frequently, enabling governments to design programmes that respond quickly to changing economic conditions. This is particularly relevant for FCAS, which experience frequent shocks.
- **Lower cost:** Screening households with CDR data is far cheaper than traditional methods. Aiken et al. (2023) estimate the cost per additional household screened at USD 2.20 for CBT and USD 4.00 for PMT, compared to negligible marginal costs for CDR-based targeting.
- **Scalability:** Once the algorithm is trained, it can be applied to millions of mobile subscribers at virtually no additional cost, making it well-suited for large-scale social protection programmes. This is particularly valuable during emergencies when rapid expansion of coverage is required.
- **Ability to reach hard-to-access areas**: Since mobile data are collected passively through telecom networks, they can provide coverage in remote or insecure areas where in-person surveys would be costly, dangerous, or impossible. This enables governments to extend targeting into regions that are typically excluded from household surveys.

Case Study 1: targeting recipients for Togo's Novissi social assistance programme[1]

The Covid-19 pandemic hit the poorest households hard. To help the government of Togo respond, researchers engaged with the government to help support the design of Novissi, an emergency social assistance programme. They leveraged machine-learning techniques and satellite and mobile phone data to target the programme.

Context

The policy was launched in April 2020 in response to the Covid-19 pandemic. It provided subsistence cash transfers to the most affected households. Beneficiaries received bi-weekly payments of around USD 10. Both enrolment and payments were conducted digitally to minimise in-person contact. At the time, Togo did not have a social registry that can be used to determine programme eligibility. The most recent census was conducted in 2011 and did not contain information on household poverty. Initially, eligibility was determined using a national voter registry. Households could receive the payment if they met three criteria: (i) they dialled into the Novissi platform and entered basic information about their mobile phone; (ii) they were registered to vote in specific regions (the programme initially focused on the Greater Lome region around the capital city); and (iii) they had declared that they worked in informal occupations when they registered to vote.

To better target poor households and expand the programme to rural areas, researchers collaborated with the Togo government to meet two policy goals: (i) to target the poorest geographic areas of the country; and (ii) to target the poorest mobile phone subscribers in those regions.

Policy design

The first step was to determine which regions were the poorest. To do so, the researchers divided Togo into cells of 2.4km by 2.4km. They then used high-resolution satellite imagery to construct micro-estimates of relative wealth in each of those cells. To convert these estimates to the local administrative units, they took the population-weighted average of the grid cells and obtained the average wealth of each canton (Togo's smallest administrative unit).

The second step was to determine, in those poorest areas, which mobile phone users were the poorest. To do so, the researchers estimated the average daily consumption of each mobile phone subscriber using metadata provided by Togo's two mobile phone operators. To estimate consumption, they conducted surveys with a representative sample of users to capture wealth and consumption, then matched those estimates to the subscribers' phone use data. They then trained a machine-learning algorithm that could predict wealth using mobile phone data; this allowed them to obtain wealth estimates for all mobile phone subscribers.

[1] Source: Aiken, E., Bellue, S., Karlan, D., Udry, C., & Blumenstock, J. E. (2022). Machine learning and phone data can improve targeting of humanitarian aid. Nature, 603(7903), 864-870

Based on these two steps, the government was able to target and distribute cash to 60,000 beneficiaries in Togo's 100 poorest cantons.

Benefits

The research design allowed the government to improve its targeting of poor households. The researchers compared their approach to three standard targeting procedures – geographic targeting, occupation-based targeting, and an approach that uses phone data but without machine learning. They found their approach to be more efficient than most other feasible targeting approach for a national anti-poverty programme. The only approach that slightly outperformed theirs was occupation-based targeting, targeting the poorest occupation (i.e., agricultural workers).

Limitations

The researchers highlight that the benefit of phone-based targeting increases when used within a homogenous population and when there is less variation in other factors used in other targeting approaches, such as place of residence. For example, when they restricted the targeting to the rural population, their algorithm was better at targeting the poorest households than when the population included rural and urban households. They also found that the algorithm performed better when the government aimed to target the extreme poor (so when the wealth threshold is lower). They noted that for the algorithm to perform well, the survey linking mobile use to wealth needed to be accurate before the policy rollout; a model trained on older data might not perform as well. When the model training or mobile data is 18 months out of date, the ability of the model to accurately determine a household's wealth decreases by 4-6% and precision falls by 10-14%.

Conclusion

Overall, this showed how non-traditional data sources can be leveraged to quickly develop and roll out a government programme in the face of an emergency, especially in data-scarce settings.

However, this approach faces several constraints:

- **Limited phone ownership:** Segments of the population, especially in FCAS, do not own mobile phones. The problem is most acute among the poorest households, who are typically the intended beneficiaries of social assistance programmes. Figure 1 shows mobile phone subscriptions per 100 people in fragile countries: only 33 of 70 countries exceed 90%, while 17 fall below 60%. Low ownership reduces the accuracy of CDR-based models, as they cannot capture the poorest households without phones. Aiken et al. (2023) find that excluding non-phone-owning households significantly weakens targeting performance.
- **Accuracy limitations:** Using mobile data to target vulnerable populations involves a trade-off: although it is cheaper and faster to

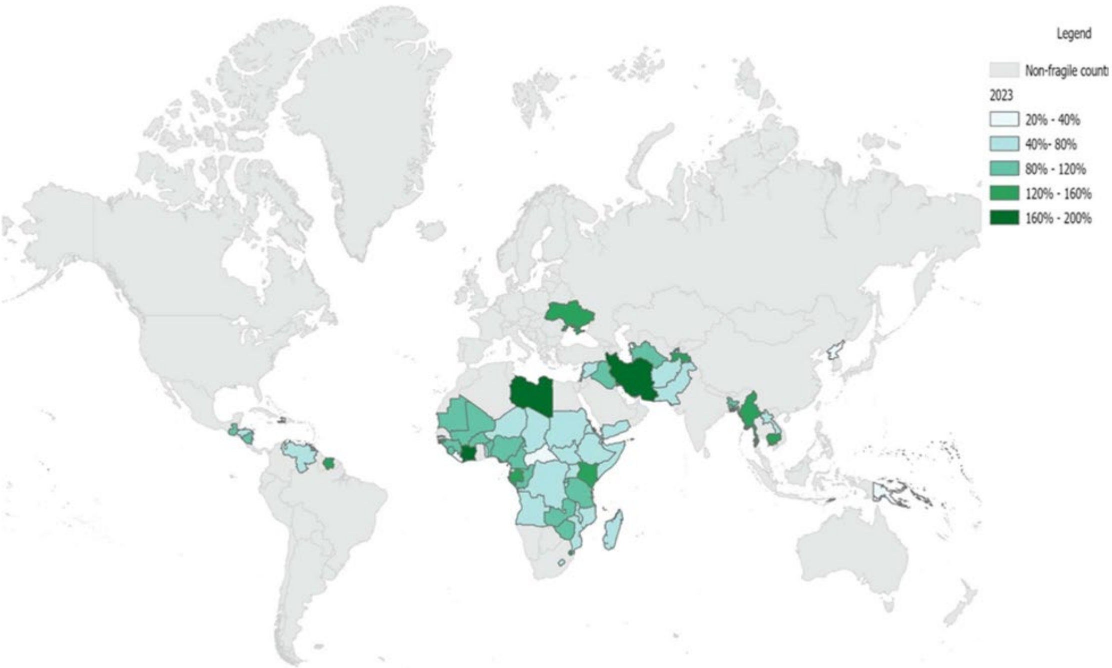
implement than PMT, it is generally less accurate at identifying poor households. Aiken et al. (2025) propose a framework for quantifying this trade-off as a function of programme scale: specifically, the budget available relative to the number of households screened for eligibility. Their analysis suggests that when budgets are large relative to the target population, PMT is the better investment, as higher accuracy justifies the cost. In contrast, when budgets are small relative to the number of households screened, mobile-based targeting is more suitable, given its near-zero marginal cost for assessing additional households

- **Model drifts:** The relationship between phone usage and poverty changes over time and across seasons, reducing accuracy if models are not updated regularly. Aiken et al. (2022) find that when the model or phone data are 18 months old, predictive accuracy falls by 4.6% and precision by 10–14%. At this point, CDR-based targeting performs no better than simple geographic targeting, implying that frequent recalibration is essential. Using CDR requires some data collection for training the model, making it less useful in extremely fragile settings where surveys are unfeasible.

- **Comparability across time and space**: In practice, estimates of eligible households are unlikely to be comparable over time and space. Over time, model drift, changes in phone ownership and usage patterns, and shifts in telecom market conditions can alter the relationship between observed phone behaviour and underlying welfare, weakening consistency unless models are regularly updated. Across space, comparability is further challenged by heterogeneity in phone access, usage norms, and network coverage, meaning that similar observed behaviours may correspond to different welfare levels in different regions. As a result, while mobile-based approaches can generate timely and internally consistent estimates within a given context, comparisons across periods or between markedly different areas should be interpreted with caution, and where possible complemented with additional data sources or local calibration.

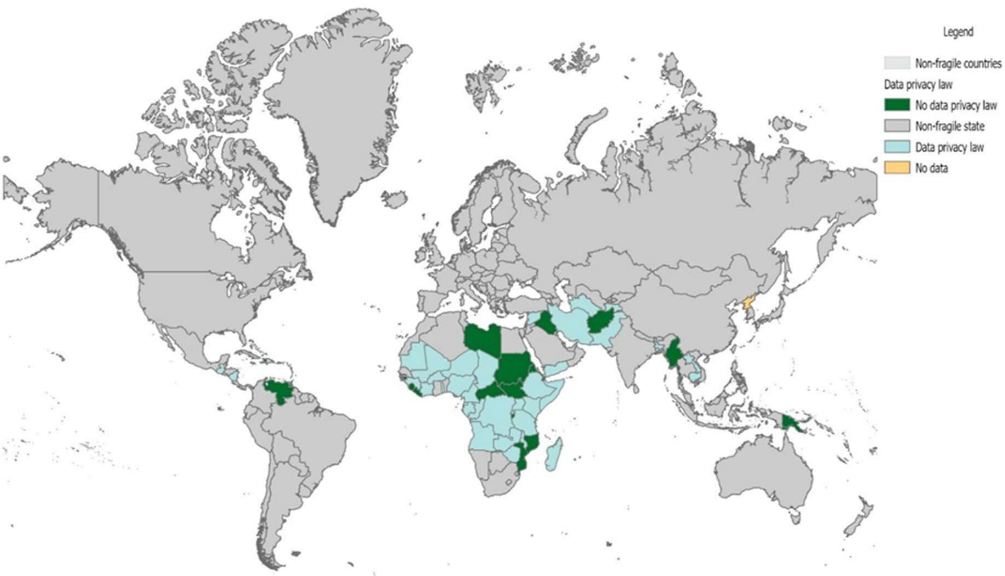
- **Ethical and privacy concerns:** CDRs contain highly sensitive information on individuals' behaviour and location. Without strict safeguards, there is a risk of data misuse or breaches. Governments and researchers must ensure robust data protection, informed consent processes, and clear limits on data use. As Figure 2 shows, very few fragile states have laws on data privacy, let alone the capacity to enforce them. The General Data Protection Regulation (GDPR) law that came into effect in 2018 in the European Union is held as a gold standard of data privacy protection.[2] To be GDPR compliant, the stakeholders using CDR data would have to request permission from each individual user to be able to use their data. The additional cost would have to be factored in, as every user in the database would have to be contacted.

Figure 1. Map of mobile phone penetration



Source: World Bank data, Mobile cellular subscription (per 100 people).

Figure 2. Map of country data privacy laws



Source: UNCTAD Data protection and privacy legislation worldwide

[2] See https://www.edps.europa.eu/data-protection/data-protection/legislation/history-general-dataprotection-regulation_en

Policy recommendations

Policymakers should consider mobile-based targeting when:

- budget constraints make traditional surveys unfeasible.
- rapid response is needed, such as during crises or displacement.
- in-person data collection is unsafe or logistically impossible.
- mobile penetration and network coverage are reasonably high.
- the target population is large and homogenous allowing cost-effective scaling.

They should avoid relying solely on mobile data when coverage gaps are severe, when poverty is highly correlated within populations with low levels of phone ownership, or where privacy frameworks are weak.

Future directions

Understanding model drift: Predictive models that use mobile data to estimate poverty or vulnerability can quickly lose accuracy. Aiken et al. (2022), for example, show that the model guiding Togo's targeting strategy had already deteriorated substantially within two years of its initial development. This raises a difficult question of whether targeting using mobile data is better than other forms of targeting. At present, we still have only a partial understanding of why these models drift and how to design systems that remain stable over time.

Further research should help us understand the reasons behind these drifts.

Ensuring privacy: CDRs contain highly granular data on individual behaviour, making privacy breaches a real and immediate risk. In many parts of Europe, strict data protection frameworks prevent governments or firms from using CDRs in the ways described above without explicit subscriber consent. By contrast, 23 fragile countries lack any formal legislation on data protection or privacy (see Figure 2). That gap matters: subscribers may have no information on how their data is being used, nor have access to any recourse if they object. Privacy-enhancing technologies (PETs) offer a promising way to reduce these risks while preserving analytical value. Institutions such as the Centre for Effective Global Action's (CEGA) Data Privacy Lab are helping advance PETs and train privacy engineers.

Building sustainable models: Given the sensitivity of mobile phone data, building sustainable systems requires careful institutional design. While governments ultimately need the capacity to use such data for policymaking, fully centralising technical capabilities may be neither feasible nor desirable in the short term, particularly in contexts with limited safeguards. Hybrid models, where telecom data are analysed by trusted intermediaries under strict governance frameworks, and governments engage as users and partners, offer a more viable pathway. Over time, this can support gradual capacity building within government while mitigating risks related to privacy, misuse, and public trust.

3.1.2 Tracking mobile populations using mobile phone data

The policy challenge: tracking mobility in fragile settings

Section 2 highlighted how displacement and mobility undermine the sampling frame, increase attrition, and induce survivorship bias. Quantifying migration and displacement remain difficult in FCAS. Traditional instruments, such as censuses, household surveys, and administrative registries, capture migration through questions on place of birth, residence, or duration of stay. While valuable, these methods are costly, slow, and quickly outdated. Attrition is high because those who move are least likely to be recontacted, leaving major gaps in understanding population flows.

This limits governments' ability to plan relief efforts or assess interventions in fast-changing contexts, whether during conflict, natural disasters, or epidemics. The challenge is especially acute in FCAS, where both violence and climate shocks trigger large-scale, sudden displacement. In the 2010s, an average of 600,000 people were affected by natural disasters annually across fragile states.[3] In 2024, FCAS recorded roughly 546,000 newly displaced people, both due to conflict and natural disasters.[4] Despite the high levels of need in many of these contexts, official monitoring systems remain weak or absent.

Mobile phone data offer a promising complement to traditional measures of migration. By capturing anonymised location and movement information from millions of users in near-real-time, they allow researchers and policymakers to observe mobility patterns at a higher temporal and spatial resolution. This capacity is particularly valuable in FCAS, where field surveys may be unsafe or unfeasible, and where humanitarian response hinges on understanding population movements as they unfold.

The innovation: how mobile phone data capture population movements

Mobile phone networks generate CDRs for every call, text, or data session. Each record contains a unique (anonymised) user ID, timestamp, and the

[3] Data from Our World in Data, People affected by natural disasters. Extracted 21 October 2025.
[4] Data from the Global Internal Displacement Database from the Internal Displacement Monitoring Centre. Extracted 21 October 2025.

approximate location of the nearest cell tower. Researchers can use this information to infer where people live, travel, and resettle.

To define a migration event requires:

- **Defining a home location**: usually where a user registers the most calls or texts.
- **Identifying destinations**: locations different from “home”, defined by distance and duration thresholds.
- **Determining migration events**: movements across administrative boundaries sustained over a minimum period.

These definitions can be tailored to short-term, seasonal, or permanent migration. Chi et al. (2020) propose a flexible three-step algorithm to systematically detect such movements in digital trace data, where users can flexibly define the three components listed above.

Empirical applications include:

- **Conflict-induced mobility:** Tai et al. (2025) used satellite and CDR data to study seasonal “poppy” migration in Afghanistan. They found that between 54,000 and 85,000 workers migrate annually for harvests, with flows resilient to violent events but responsive to Taliban control and government suppression efforts, demonstrating the potential of mobile data for monitoring illicit economies.
- **Response to conflict alerts:** In Ukraine, Van Dijcke, Wright and Polyak (2023) used high-resolution GPS data (not tower-based) to analyse civilian reactions to bombardment alerts. They found alerts initially triggered rapid movement, including measurable altitude changes consistent with sheltering underground, but effectiveness waned over time as “alert fatigue” set in.
- **Post-disaster displacement:** Bengtsson et al. (2011) tracked movements of 630,000 people who left Port-au-Prince after the 2010 Haiti earthquake; Wilson et al. (2016) replicated the approach in Nepal, following 12 million users in the nine days after the 2015 earthquake, enabling more targeted humanitarian responses.

Case Study 2: Tracking the conflict of seasonal migration in Afghanistan

Seasonal migration is a vital livelihood strategy for many households in low-income countries (Bryan et al., 2014). Yet, conflict can severely disrupt these flows of labour, cutting households off from essential income sources. Measuring such disruptions has long been difficult, as traditional data collection is often unfeasible in insecure regions.

In Afghanistan, Tai et al. (2025) combine CDRs and satellite imagery to study how violence affects seasonal labour migration to opium-producing districts over the eight years preceding the Taliban takeover in August 2021. Using satellite imagery, they first identify the timing of the peak harvest season in each district. They then analyse anonymised CDR data from over 11 million subscribers to map daily migration patterns across the country.

How migration is defined

- **Location**: Each subscriber's location is determined by the district where they make or receive the most calls or texts in a 24-hour period. To identify longer-term residence, the researchers group consecutive daily locations into week-long periods. This provides, for each subscriber, a timeline of the districts where they have spent at least one week, and the duration of each stay.

- **Migration event**: A migration event on a given day is recorded when a subscriber is in a different district than they were 30 days earlier. The 30-day window increases the likelihood that the analysis captures a person's true home district and final destination, rather than short visits or travel through intermediate areas.

Key findings

- **Scale of migration:** Between 54,000 and 85,000 seasonal migrants travel each year for the poppy harvest.

- **Limited sensitivity to violence:** Migration levels do not significantly change in response to fatal violent events, either in origin or destination districts – even when fatalities are high.

- **Policy effects:** Migration is higher in Taliban-controlled districts, reflecting the group's policies promoting poppy cultivation. Conversely, government-led eradication campaigns suppress both cultivation and migration.

This study demonstrates the value of combining satellite and mobile data to measure short-term, seasonal migration in data-scarce contexts. The high temporal frequency of CDRs makes it possible to detect movements that last only a few weeks, which is often unfeasible with traditional surveys. Since CDRs reveal who moved, but not why, the authors align migration timing with the poppy harvest period identified in satellite data to infer purpose with greater confidence.

Limitations

- **Crop identification:** The vegetation indices used to detect harvest timing cannot distinguish between different crops. As satellite resolution and image-processing techniques improve, future work will better differentiate crop types.

- **Motivation uncertainty:** Because CDRs are anonymised, researchers cannot confirm that detected movements are for seasonal work, nor can they observe migrants' characteristics (e.g. occupation). Restricting analysis to migration during the harvest season helps mitigate this concern.

- **Representativeness**: Mobile phone penetration in Afghanistan is about 66 percent, meaning CDR data may under-represent poorer or more remote households. If these groups migrate differently, estimates could be biased.

Overall, the study highlights how innovative data sources can illuminate economic behaviours, such as seasonal migration, that are otherwise invisible in FCAS.

Benefits and limitations

There are several benefits to this approach:

- **Timeliness:** Enables near-real-time monitoring of displacement during crises.
- **Granularity:** Offers fine-scale spatial and temporal data unavailable in censuses or surveys.
- **Scalability:** Covers millions of users, producing national or regional displacement maps.
- **Complementarity:** Strengthens traditional statistics by validating or updating survey-based migration estimates.

However, this approach faces several constraints:

- **Cost and access barriers:** Obtaining mobile phone data from telecommunications companies can be prohibitively expensive. In addition to the financial cost, data access is often hindered by resistance from private operators who may be concerned about reputational risks or potential government misuse of sensitive information. Negotiating data-sharing agreements requires both resources and trust.
- **Limited population coverage:** Mobile phone ownership and usage remain uneven across populations. The poorest, the elderly, women, and people living in rural or conflict-affected areas are often less likely

to own or regularly use a mobile phone. As a result, datasets derived from CDRs or mobile money transactions may systematically exclude the most vulnerable groups, introducing selection bias.

- **Dependence on telecommunications infrastructure:** The use of mobile phone data presupposes functioning network infrastructure. In conflict settings, such infrastructure is often damaged or deliberately targeted. In Ukraine, for instance, the International Telecommunication Union (ITU) estimated that as of July 2022, 12.2% of households had lost access to mobile communications and 20% of telecommunication infrastructure had been damaged or destroyed. In Gaza, the joint World Bank–EU–UN interim damage assessment (February 2025) found that 74% of ICT assets were completely destroyed and 16% partially damaged, severely limiting digital connectivity and data availability.

- **Privacy and data protection risks:** Mobile phone data are highly sensitive, revealing detailed information about individuals' movements, social networks, and economic activities. Without strong data governance frameworks, there is a risk of misuse – by governments, private actors, or armed groups – potentially endangering individuals' safety and violating privacy rights. Ensuring anonymisation, secure storage, and ethical use of such data is therefore paramount.

- **Accuracy:** Evidence from multiple settings suggests that mobile phone data can reliably capture the direction, timing, and relative intensity of population movements, often aligning closely with patterns observed in survey or administrative data. For instance, in Bengtsson et al. [2011], estimates using CDRs aligned with a subsequent large retrospective UN survey, but differed widely from official government estimates that were used at the time when humanitarian relief was allocated. However, estimates of absolute population levels are less accurate, as coverage gaps, SIM usage patterns, and methodological choices introduce systematic biases. As a result, CDR-based measures are best interpreted as accurate indicators of mobility dynamics rather than precise estimates of total displacement. To estimate the total number of affected people, governments typically need to rely on pre-event population figures from censuses or surveys and then combine these with CDR-based estimates to infer changes in population distribution.

- **Comparability over time and space:** Comparability of migration estimates across time and space is not guaranteed. Over time, changes in phone ownership, SIM usage, and network coverage, as well as behavioural responses to shocks, can affect who is observed and how movements are recorded, weakening consistency. Across space, differences in telecom infrastructure, market shares of operators, and patterns of phone use mean that mobility estimates may not be directly comparable between regions, particularly when coverage is uneven or populations differ systematically in access to phones. As a result, mobile data are often most reliable for identifying trends, directions, and relative changes in movement, rather than for making precise comparisons of displacement levels across periods or locations, and are best used alongside complementary data sources when such comparisons are required.

Policy recommendations

Policymakers should use mobile data to track displacement:

- **For rapid, large-scale displacement monitoring:** It is ideal for crises that evolve quickly (e.g. conflict outbreaks or natural disasters) where traditional surveys or censuses cannot provide timely information. It enables near-real-time estimates of the number and direction of people moving, supporting emergency logistics, such as shelter, food, and medical aid.

- **To complement, not replace, official statistics:** It is best used as a high-frequency supplement to census or survey data to validate or update displacement estimates between official rounds. It is particularly useful where household surveys have high attrition or where government administrative data are incomplete.

- **For evaluating the short-term effects of shocks or interventions:** It is appropriate for assessing how people respond to events such as conflict incidents, disaster alerts, or new border controls. It can provide behavioural insights - evacuation compliance or seasonal migration changes, for example - that help tailor policy responses.

- **In contexts with adequate network coverage and data governance:** It is most reliable when telecommunication infrastructure is largely functional and when there are trusted intermediaries (e.g. Flowminder) ensuring data protection and anonymisation.

Future directions

- **Using mobile phone data to estimate economic activity:** CDRs so far have estimated the movement of people. However, they can also be used to compute the impact of conflict on firms, such as in Herskowitz et al. (2024). By obtaining CDRs for corporate mobile phones, they are able to quantify how firms respond to violence in Afghanistan. They find that violence reduces entry and increases exit of firms in the district where the violence occurred, especially in the first month after the attack.

- **Leveraging the network data:** CDRs do not only have information on the individual who owns the phone, but also on whom they are in contact with. Using this data would allow researchers to determine the social network in which the subscriber is embedded. For example, Blumenstock et al. (2025) leverage CDRs of individuals in Rwanda to determine how social networks affect migration.

- **Operational integration with humanitarian systems:** Government and humanitarian organisations are integrating the mobility data from mobile phones to better anticipate and allocate resources in times of disaster. An example is GiveDirectly's partnership with FlowMinder, in which they tracked internally displaced people in the Democratic Republic of the Congo (DRC) during the M23 attack in Eastern DRC and used the information to send them mobile money directly. FlowMinder is also partnering with the Mozambique government to develop a system to monitor disaster-driven displacement and recovery.

3.1.3 Deploying rapid-response mobile phone surveys during health or political crises

The policy challenge: crisis data collection

As discussed in Section 2, insecurity, health emergencies, and political crises make conventional face-to-face household surveys difficult or impossible in FCAS. Enumerators cannot safely visit households, fieldwork is expensive and slow, and traditional surveys typically deliver results only after months; whereas policymakers need timely data on socio-economic shocks, health behaviours, humanitarian needs, and welfare impacts.

Rapid-response phone surveys (RRPS) have emerged to address this fundamental policy challenge: obtaining timely and reliable data during emergencies when traditional evidence sources break down. Travel restrictions, security concerns, and population displacement mean that officials can neither reach affected communities nor quickly understand how socio-economic conditions are changing. At the same time, administrative data systems often fail under crisis pressure, leaving decision-makers with little insight into who needs help, where, and why.

This information gap creates serious obstacles for emergency policy responses. Governments and humanitarian actors must make critical choices - about food distribution, healthcare services, cash transfers, and other life-saving interventions - without up-to-date evidence about needs or whether their efforts are working. RRPS use the widespread reach of mobile phones in low and middle-income countries to collect data rapidly, even when in-person methods are impossible. By enabling real-time tracking of shocks, behaviours, and welfare outcomes, RRPS help ensure that scarce resources can be directed where they are most needed, supporting more effective and adaptive policy action amid crises.

The innovation

RRPS leverage the widespread penetration of mobile phone technologies in low and middle-income countries to conduct surveys via telephone rather than in-person. They are a cost-effective and flexible tool that can enable researchers and policymakers to generate near real-time data during health emergencies and episodes of political instability, filling in critical information gaps (World Bank, 2020; Dabalen et al., 2016). RRPS tools have played a key role in monitoring socio-economic shocks, public health behaviours, and humanitarian needs during health crises like the Ebola and COVID-19 pandemics, as well as during political upheavals and displacement (Cavallo et al., 2018; Palacios-Lopez et al., 2021).

RRPS typically use one of three modalities: (i) computer-assisted telephone interviewing (CATI), (ii) interactive voice response (IVR), or (iii) short message service (SMS). CATI involves trained enumerators calling respondents and conducting detailed interviews using laptop-based survey software, allowing for complex question branching, clarification of ambiguous responses, and data quality checks in real time. IVR systems automate the process, using recorded prompts and touch-tone responses to collect standardised data at scale without human intermediaries. SMS polling sends text-message questions to respondents, who reply via SMS, enabling rapid pulse checks and scalable data collection but with constraints on question complexity and respondent literacy. Among these, CATI is most commonly used and often the most suitable in FCAS due to its balance of data quality, ability to clarify questions, and reduced risk of literacy exclusions - critical in settings where educational attainment is low or languages are highly localised (GSMA, 2023).

The practical implementation of RRPS follows a structured process. Researchers begin by constructing a sampling frame – ideally drawing from recent, representative household censuses or surveys with mobile numbers. However, as discussed above, such frames are often non-existent or outdated in FCAS. As a result, researchers often resort to random digit dialling (RDD) or telecom operator lists, though these raise concerns of coverage and representativity, especially among rural, poorer or displaced households who most likely lack mobile access (Galperin & Viecens, 2023). Paradata collection - automated metadata on call attempts, durations, refusals, and technical failures - supports process evaluation and helps diagnose sampling and non-response issues.

Institutions such as the World Bank and World Food Programme (WFP) have increasingly deployed RRPS in FCAS to monitor welfare and inform humanitarian response. For example, the World Bank's Listening to Africa project combined baseline face-to-face interviews with subsequent mobile follow-ups to track shocks and welfare dynamics in real time (World Bank, 2025). Likewise, the WFP's mobile Vulnerability Analysis and Mapping (mVAM) system used CATI to collect data on food security among internally displaced people (IDPs) in refugee camps in eastern DRC and Somalia. The World Bank also implemented the Listening to Displaced People Survey, which gathered data on living conditions from the displaced population (IDPs and returnees) in Mali and refugees in camps in Mauritania and Niger who had been displaced by the crisis in northern Mali (Etang et al., 2015).

Case Study 3: Ebola outbreak in West Africa (2014-2015)

Between March 2014 and July 2015, the Ebola Virus Disease (EVD) outbreak in West Africa resulted in over 28,600 cases and 11,300 deaths across Guinea, Liberia, and Sierra Leone (WHO, 2016). The epidemic created an urgent need for real-time data to guide response efforts, but traditional face-to-face household surveys became impossible due to infection risks, travel restrictions, and widespread fear among communities and enumerators (Himelein et al., 2016). With healthcare systems overwhelmed and routine information systems failing, policymakers lacked critical data on employment impacts, food security, healthcare access, and health-seeking behaviours during the peak of the crisis.

The epidemic accelerated mobile phone survey innovation which were deployed across all three countries to monitor the crisis and its effects on food security and to provide estimates of its socio-economic toll. Different methodological approaches were used based on the local contexts and available infrastructure, but two primary modalities emerged: CATI for detailed household-level data and SMS polling for rapid, scalable tracking of specific health-seeking behaviours (Himelein et al., 2016; Feng et al., 2018).

Sampling frames were drawn from recent pre-crisis household surveys that had collected mobile phone numbers, enabling researchers to maintain some degree of national representativeness even under emergency/crisis conditions. In Liberia and Sierra Leone, approximately 57-66% of previously surveyed households had provided phone numbers, though coverage was highly uneven between urban (82%) and rural

(43%) areas (Etang & Himelein, 2020). Multiple survey rounds were conducted at high frequency (weekly or monthly) to track rapidly evolving conditions.

Key findings

The surveys provided timely insights that directly informed government and donor interventions. In Liberia, SMS polling revealed a sharp decline in facility-based deliveries, particularly in public health centres (Feng et al., 2018). This evidence prompted immediate public messaging campaigns and the deployment of mobile maternal health teams to restore essential services. Across the three countries, phone surveys documented severe economic disruptions including job losses, business closures, and sharp declines in agricultural production, with over 80% of respondents reporting lower yields (World Bank, 2015). High-frequency monitoring showed escalating food insecurity as households reduced meals, depleted savings, and sold assets to cope. These findings prompted emergency food distribution, agricultural input support, and cash transfer programmes targeting the most affected communities.

Methodological innovations and challenges

The Ebola experience demonstrated that, with appropriate weighting and bias adjustment, phone surveys could yield reasonably representative national estimates even in emergencies.

Researchers used propensity score matching and post-stratification weighting to align results with pre-crisis data (Feng et al., 2018). The dual use of CATI and SMS also proved valuable; CATI offered richer household data while SMS enabled rapid pulse checks at scale.

However, limitations persisted. Rural-urban disparities led to under-representation of poorer, remote populations. Attrition between survey rounds introduced non-response bias, with only about half of respondents completing all waves (World Bank, 2015). Despite this, interventions like airtime credit incentives post-interview, collecting preferred call times at baseline, minimising lags between rounds, and providing phone-charging support boosted initial response rates to around 80% for at least one round in Sierra Leone (World Bank, 2015). These constraints suggest that while phone surveys are powerful complementary tools, they cannot fully replace in-person data collection for comprehensive population coverage.

Case Study 4: SMS surveys and health-seeking behaviour during the Ebola crisis in Liberia (2015)

An IGC-funded project zoomed in on a complementary and under-examined question: what did Liberians actually know about Ebola, and how were their health-seeking behaviours changing as the outbreak moved into its recovery phase? Using a commercial SMS polling platform, the study surveyed approximately 10,000 Liberians across four rounds between March and June 2015. This was a period when new case counts were falling but the health system remained fragile, having lost approximately 8% of its workforce to the outbreak. By targeting a nationally distributed sample, including urban and rural populations across all counties, this project generated some of the first systematic evidence on public knowledge and healthcare utilisation during the post-peak recovery period.

Key findings

Three key findings emerged:

1. 85–89% of respondents across all four rounds correctly identified Ebola symptoms, indicating high public awareness even as the outbreak evolved.

2. personal exposure was limited and geographically concentrated: few respondents reported knowing someone who had contracted the disease.

3. institutional delivery rates remained robust - around 80% of households reporting a recent birth delivered in a public or private health facility - suggesting partial recovery of essential health-service utilisation by early Innovative data solutions for fragile and conflict affected settings 26 2015, despite workforce losses. This is not in tension with the earlier documented decline; rather it traces the arc from crisis to recovery, confirming that the emergency response and public messaging efforts had begun to restore confidence in health services.

Policy implications

The study highlighted three priorities for policymakers:

1. investing in mobile data infrastructure to enable real-time health monitoring during future crises

2. prioritising the rebuilding and retention of health workforce capacity in post-outbreak recovery phases; and

3. strengthening public communication strategies to maintain trust in health services during emergencies.

More broadly, the research established proof-of-concept that SMS-based surveys can provide timely, scalable, and reasonably representative data in contexts where face-to-face data collection is impossible.

Benefits and limitations

Beyond their operational feasibility, mobile phone surveys offer distinct advantages in these more challenging contexts (Dabalen et al., 2016):

- **Cost efficiency and speed:** Surveys can be rapidly designed and fielded with lower operational costs than face-to-face enumeration.

- **Geographic reach and remote area access:** Mobile phone surveys facilitate the survey of households in remote areas, enabling coverage of regions that are otherwise inaccessible due to security constraints or displacement patterns.
- **Real-time monitoring capability:** High-frequency survey rounds (weekly or monthly) allow for continuous tracking of rapidly evolving conditions.
- **Operational safety and feasibility:** Phone surveys eliminate infection and security risks to enumerators and respondents, making data collection viable during health emergencies, active conflict, and displacement when face-to-face methods are impossible or unethical.

However, such surveys also have their limitations.

- **Coverage bias:** As already highlighted above, individuals without mobile phones are systematically different from those with them. Mobile ownership often correlates with income, education, gender, and geography (Galperin & Viecens, 2023). Analysis consistently finds that survey respondents via mobile phones are more likely to be urban, male, wealthier, and better educated - risking underestimation of impacts among the poorest, least literate, or most isolated (Elkasabi & Khan, 2023; Gourlay et al., 2021; Gibson et al., 2021). For instance, in rural West Africa, households in the highest income quintile are up to 19 times more likely to have mobile access than the lowest (GSMA, 2023).
- **Non-response and attrition:** Contact and completion rates in FCAS are also lower than in stable, urban settings, with typical response rates ranging from 25%–50%, even after multiple attempts (Himelein et al., 2020). Non-response is driven by phone sharing, SIM rotation, network unreliability, and conflict-related displacement – all of which are prevalent among the most vulnerable groups (Labrique et al., 2017). Moreover, low literacy levels constrain SMS response rates, and gender gaps in mobile ownership exclude women, particularly in conservative or conflict-affected regions (GSMA, 2023). Evidence from Mozambique indicates that contact success rates improve substantially with multiple callbacks and flexible timing (de Weerdt et al., 2024).
- **Reduced data richness and question complexity:** While CATI allows clarification, the constraints of phone-based interaction - limited screen time, network interruptions - restrict survey length and complexity

compared to face-to-face interviews, potentially limiting the depth of data collected on complex topics.

- **Dependence on sampling frame quality and auxiliary data for bias correction:** Without recent household survey frames with embedded phone numbers, researchers resort to random digit dialling or telecom lists, further compromising representativeness. Post-stratification and related techniques (e.g., calibration, raking) can partially adjust for these biases using external demographic data, but such auxiliary datasets are frequently outdated or misaligned in FCAS. Moreover, these methods only correct for observable characteristics, leaving unobserved differences - such as income volatility, marginalisation, or attitudes - uncaptured, meaning that some degree of bias remains unavoidable in data-poor settings even after applying corrective strategies.

Integration with other data sources and future directions

Mobile phone surveys are evolving rapidly and increasingly being integrated into hybrid data collection ecosystems. Remote sensing (satellite imagery), administrative data, and passive mobile data (call detail records, CDRs, and network patterns) enable triangulation and situational awareness even when no survey or ground-based method is fully viable (Quinn et al., 2018). Innovations like “adaptive sampling”, where survey samples are continuously reweighted by auxiliary data streams, may reduce bias and improve representativeness by correcting for coverage gaps in near real time.

Stronger frameworks for participant protection, data ethics, and confidentiality are urgently needed, particularly as RRPS become institutionalised and the risk of misuse grows - political targeting, surveillance, or data being weaponised. An emerging concern is also phishing and impersonation: as mobile surveys become more common, respondents may struggle to distinguish legitimate requests from scams, especially via SMS, undermining trust and participation. Leading organisations are responding by developing clearer governance frameworks specifying data access and use, strengthening security protocols, and introducing measures such as registered caller IDs, shortcodes, and clear messaging to help verify survey legitimacy, alongside more transparent and meaningful consent processes for participants.

The COVID-19 experience has catalysed the institutionalisation of RRPS in statistical offices, with many now running regular phone panels alongside restored in-person enumeration (World Bank, 2020). Methodological experimentation in FCAS will likely focus on combining RRPS with geospatial, social media, and macroeconomic indicators, alongside the development of stronger frameworks for participant protection, data ethics, and confidentiality, especially in volatile political environments.

Policy recommendations

- **Invest in maintaining nationally representative sampling frames with phone numbers:** Governments and statistical offices should embed mobile numbers into routine household surveys and census updates. This dramatically improves representativeness during crises and reduces reliance on biased methods like random digit dialling.
- **Use hybrid, multi-modal data systems to reduce coverage gaps:** Combine CATI with SMS/IVR, administrative data, geospatial indicators, and community-level monitoring to reach populations without mobile phones and triangulate results in real time - especially for rural, remote, or displaced groups.
- **Strengthen bias adjustment capacity within national statistical systems:** Build local capacity to implement post-stratification, calibration, and adaptive weighting methods, and create protocols to regularly assess remaining unobservable biases.
- **Establish clear data-protection, ethical, and verification frameworks:** Introduce registered caller IDs, shortcodes, clear consent protocols, data-use safeguards, and anti-fraud messaging to help respondents verify survey legitimacy and protect against misuse, which is critical in fragile or politically sensitive environments.

RRPS surveys have fundamentally reshaped crisis data collection in FCAS. Their success, evidenced by robust adoption in crises from Ebola to COVID-19, rests on their speed, relative safety, scalability, and ability to provide actionable policy information when traditional methods are not feasible. However, maximising their value – and ensuring the sustainability of RRPS systems – depends on embedding them within national data systems rather than deploying them as ad hoc tools. This requires maintaining updated sampling frames and managing attrition and bias over time, alongside rigorous bias diagnostics and strong ethics and security frameworks. It also depends on building capacity within national statistical systems to design and use phone surveys routinely, as well as ensuring that repeated survey rounds and incentives are financially sustainable. Political economy factors (trust, consent, risks of survey fatigue or misuse) must also be carefully managed. In an era of complex and overlapping crises, RRPS represent not just a temporary workaround but a critical pillar of resilient, adaptive, and inclusive data systems.

To summarise, mobile phone-based data such as CDRs and RRPS offers specific benefits in FCAS. Such approaches are versatile and can be deployed to address several high-impact policy challenges. However, they require some degree of infrastructure and privacy safeguards, which may not always be available.

3.2 Leveraging satellite data to measure economic activity

The policy challenge: measuring economic activity

Macroeconomic data such as GDP and national accounts are essential for governments and humanitarian actors to monitor economic activity and respond effectively to crises. Yet, as discussed in Section 2, statistical systems in FCAS are often constrained by insecurity, displacement, and institutional breakdown. Countries like Yemen have not published complete national accounts since the conflict began in 2015 (World Bank, 2022). Traditional approaches, such as household surveys or administrative data, are often resource-intensive, infrequent, slow, and logistically difficult in these settings. As a result, there is growing interest in alternative approaches that can provide accurate, timely and granular information into economic conditions, especially during periods of disruption.

The innovation: satellite-based economic measurement and analysis

Satellite-derived data, particularly night-time lights (NTL) imagery, has emerged as a promising innovation for estimating economic activity, particularly in data-scarce environments. This is because NTLs are strongly associated with human economic activity as the development of public infrastructure (e.g., lighting) and light-intensive capital investments (e.g., industrial facilities) typically coincides with increases in economic production (McCord and Rodriguez-Heredia, 2022). This relationship has increasingly underpinned satellite-based measures of economic activity, featuring in over 150 publications in economic journals (Gibson et al., 2020).

Beyond NTLs, other types of satellite-enabled data relevant for GDP and national accounts include vegetation indices, atmospheric pollutants such as nitrogen dioxide, land cover/use, and maritime activity captured through satellite Automatic Identification System (AIS) signals, which provide insights into trade flows (Cerdeiro et al., 2020). These approaches provide a versatile alternative to traditional statistics due to their high frequency, broad geographic reach, and low cost. Consequently, they have been used both to estimate components of GDP and, beyond GDP measurement, to inform broader economic and policy analyses across key sectors of the economy.

Satellite-based data have proven particularly useful in FCAS contexts, where obtaining accurate and timely information with broad geographic coverage is often a major challenge. For example, recent IMF analysis (2024) used satellite imagery to monitor economic activity in Somalia. It examined vegetation patterns as proxies for agricultural output and NTL and land cover as indicators of urbanisation and economic development, helping to inform macroeconomic policy design. Similarly, the World Bank (2024) used NTL data to assess Afghanistan's economic dynamics after the Taliban takeover. This approach revealed not only the depth of the initial shock but also the pace and uneven nature of recovery. These examples show how satellite-based data can uncover trends and vulnerabilities that traditional indicators often miss, offering useful information for policy design in fragile contexts.

Methodological approaches

For many years, the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) was the main source, offering continuous, annual time series data between 1992 and 2013 (Henderson et al., 2012). While DMSP-OLS showed promising early economic applications, its inconsistencies, saturation, and limited range prompted the transition to the Visible Infrared Imaging Radiometer Suite (VIIRS), which provides better resolution, high spatial accuracy, and continuous monitoring made possible by daily global observations (Elvidge et al., 2013; Gibson et al., 2021).

Advances in satellite technology have enabled economic researchers to increasingly use NASA's unsaturated NTL dataset, known as Black Marble, and other high-performing commercial alternatives. Building on VIIRS observations, Black Marble generates 15 arc-second resolution (about 450-500 meters) and corrects for noise and temporary illuminations, producing more reliable measures of human activity (Rossi-Hansberg and Zhang, 2025).

In FCAS, satellite-based data offer unique advantages for research and policy analysis. They are particularly useful in three areas: (1) assessing aggregate and subnational economic activity where conventional data are limited or unreliable, (2) monitoring shocks and disasters that disrupt livelihoods and overall welfare, and (3) supporting sectoral analysis critical for economic recovery and development.

In relation to overall economic activity, the most common approach involves regressing changes in NTL intensity on changes in GDP using either annual or quarterly data and controlling for country fixed effects and time effects (Henderson et al., 2012; Beyer et al., 2022). Beyond regression analysis, recent advances demonstrate that integrating NTL with national accounts and contextual factors (e.g., geography) can produce more robust measures of economic activity (Hu and Yao, 2019). NTL data are not only useful for validating aggregate economic activity but can also serve as outcome variables to explore the drivers of spatial and subnational economic dynamics (Hodler and Raschky, 2014; Henderson et al., 2018; McCord and Rodriguez-Heredia, 2022).

The use of satellite data depends on assumptions about consistency across urban, rural, and informal settings, temporal stability, and adequate spatial resolution; these conditions are often challenging in fragile contexts. Advances in sensor technology, such as VIIRS day/night band instruments, have improved measurement quality (McCord and Rodriguez-Heredia, 2022; Rossi-Hansberg and Zhang, 2025). To address remaining limitations, researchers increasingly integrate NTL with daytime imagery, machine learning, and complementary datasets like land use, census, and emissions data (Jean et al., 2016; Engstrom et al., 2022; Rossi-Hansberg and Zhang, 2025). These hybrid approaches enable richer insights into economic well-being, as illustrated by applications that predict asset wealth at fine spatial scales using deep-learning models trained on multispectral imagery and NTL (Yeh et al., 2020).

The ability to access satellite data within days enables near-real-time analysis. This is a critical advantage in FCAS where shocks and crises demand rapid analysis, as in the case of the onset of the war in Sudan in 2023. For example, sharp declines in VIIRS NTLs following the February 2023 earthquake in Turkey and Syria highlighted disruptions to infrastructure, service delivery, and economic activity, offering an early signal of impacts on household well-being and recovery prospects (Yuan et al., 2023; World Bank, 2023). These tools have also been deployed for disaster impact assessments in contexts such as Nepal and Haiti, where satellite imagery helped quantify economic disruption in the absence of timely ground data (Zhao et al., 2018; Mohan & Strobl, 2017) and in Sudan following the outbreak of the conflict in 2023 (Guo et al., 2024). Unlike official indicators such as GDP or consumption, which often take months to compile, satellite-based monitoring provides timely information for decision-making in dynamic and fragile contexts.

Other applications underscore the versatility of satellite-based tools in supporting sector-specific policies. These include monitoring trade, assessing infrastructure development, and tracking dynamics in agriculture, mining, energy, and transportation. Such capabilities expand the evidence base for targeted interventions and policy decisions in FCAS. An illustrative example is Vogel et al. (2024), who use satellite imagery to calibrate a spatial general-equilibrium model for welfare analysis and highway impacts. Unlike reduced-form regressions that relate NTL to GDP, this structural approach demonstrates how satellite data can inform complex policy questions.

Analytical advances and future directions

While improvements in spatial resolution, temporal stability, and the frequency and precision of observations are likely to expand possibilities in the future, the most transformative opportunities lie on the analytical front. This is because researchers will increasingly be able to move beyond annual and monthly aggregates toward daily and even hourly analysis. This shift will significantly improve the capacity to monitor economic activity, crises, and shocks in real time, enabling quicker and more dynamic policy and humanitarian responses (Sabri et al., 2022).

However, while monitoring is very useful in FCAS, forecasting and policy simulation arguably offer more opportunities for timely policy interventions. There is great potential to leverage machine learning and deep learning on satellite-based imagery for assessing localised shocks, broader welfare analysis and microspatial economic forecasting (Khachiyan et al., 2022; Yeh et al., 2020; Dell, 2025). At the macro-level, Bayesian state-space models can provide a framework for integrating satellite-derived indicators into macroeconomic forecasting (Chan and Strachan, 2023), while synthetic control method can be used for assessing policy impacts using satellite data (Abadie, 2021). Alongside these approaches, future developments will, to a greater extent, be able to integrate satellite data with other sources of data to build more comprehensive economic data systems. Taken together, these possibilities present great opportunities for FCAS, potentially enabling more targeted policy design as well as more adaptive and responsive policymaking.

Case Study 5: Assessing oil and non-oil GDP from space in Yemen

This case study draws on Debbich (2019), which applied satellite-derived NTL and gas flaring data to estimate oil and non-oil GDP in Yemen during the conflict period of 2015-17.

Background

Yemen's ongoing cycle of conflict and political instability goes back to the aftermath of the Arab Spring in 2011. Internal disagreements and hostilities escalated, culminating in a military intervention by a coalition of Arab countries in 2015. This intervention caused severe economic and humanitarian crises and led to significant fragmentation of statistical and institutional capacity. Key institutions such as the Ministry of Finance and the Central Bank, along with much of the government, relocated from Sana'a to Aden in 2016. As a result, the production of country-wide national accounts and economic data was suspended after 2014. To address this gap, humanitarian actors and donors required reliable information on the impact of the conflict on overall economic activity and its regional distribution. Researchers, including those at the IMF, responded by applying NTL and gas flaring data to estimate both oil and non-oil GDP (Debbich, 2019).

Methodology

NTLs were used as a proxy for non-oil GDP through elasticity models that link changes in light intensity to economic activity. These models were calibrated using real GDP data from 72 countries and historical Yemeni data. Similarly, gas flaring intensity was used as a proxy for oil GDP benchmarked against 28 comparable countries. In both cases, potential biases were mitigated through temporal smoothing and cross-validation with limited official data, reducing sensor noise and seasonal variation.

Key findings

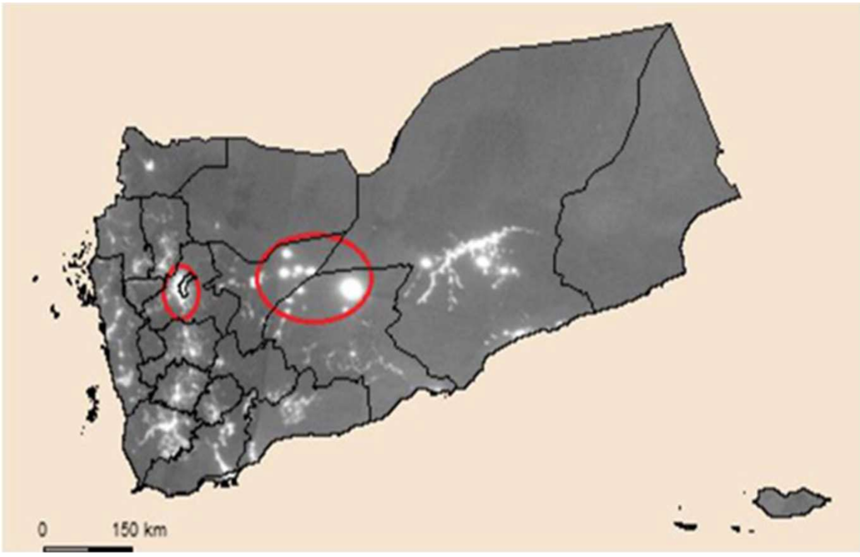
NTL-based estimates revealed sharp contractions in non-oil output following the conflict, capturing the magnitude of Yemen's economic collapse. Real GDP is estimated to have declined by approximately 24%, with a lower-bound estimate suggesting a contraction of up to 34% during 2015–2017. Oil GDP fell even more sharply, with a cumulative decline of about 72%, driven by global price shocks and local production collapse. VIIRS composite images (shown below) illustrate that reductions in light intensity were particularly pronounced in urban centres and oil-producing regions, both of which suffered heavily during the conflict.

Challenges

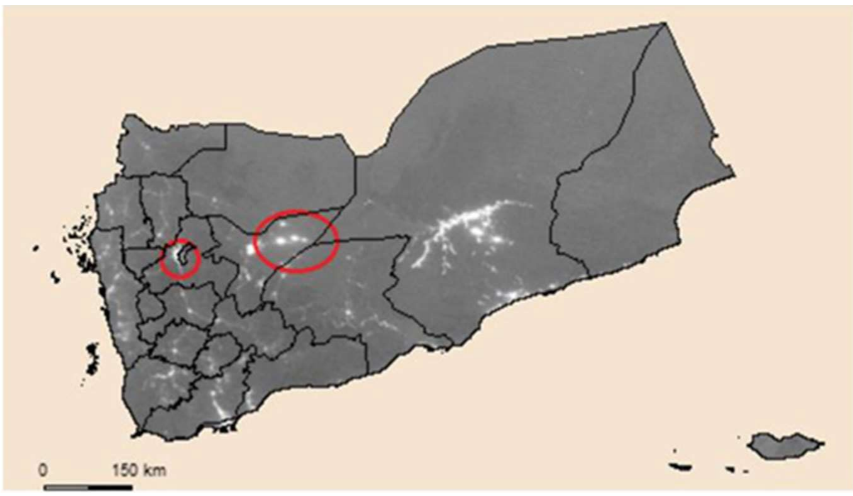
Despite providing valuable insights into the effects of the conflict on aggregate economic activity and its regional distribution, the approach has limitations. Yemen's low rural electrification means that NTLs likely understate informal economic activity (see Figure 3 below), which should be sizable in Yemen. Moreover, changes in brightness may reflect energy supply shocks as much as actual economic performance.

Nonetheless, this case demonstrates that in FCAS, satellite-derived data can be a useful tool for assessing economic activity during data blackouts, provided that careful calibration is applied. These insights can provide much-needed information on the living conditions of households.

Figure 3. VIIRS composite images of Yemen



December 2014



December 2017

Source: Debbich, M. (2019). Assessing oil and non-oil GDP growth from space: An application to Yemen 2012–17. IMF Working Papers, 19(89). International Monetary Fund. https://doi.org/10.5089/9781498319824.001

Benefits and limitations of satellite-based approaches

Over the past two decades, the use of satellite-based data has expanded across countries, sectors, and contexts. Despite its impressive promise, integrating it into policy processes raises critical questions about feasibility, reliability, and political economy.

Key benefits include (Sabri et al., 2022):

- **Early-warning capabilities, sectoral agility, and adaptability:** The speed and continuity of satellite data enable near-real-time analysis while its versatility can support sector-specific analysis and more effective policy design. This adaptability makes it increasingly indispensable in data-scarce environments.
- **Geographic reach in insecure areas:** Satellite imagery is passively collected across all territories, including contested zones. This is especially valuable in FCAS where ground surveys may be dangerous or impossible. Moreover, advances in image processing now allow basic welfare analysis in off-grid and rural areas, though ground truthing remains essential.
- **Resistance to manipulation:** Unlike administrative data, satellite imagery is collected independently and is less vulnerable to political interference. This makes it a useful credibility check in FCAS where official statistics may be incomplete or politically compromised. However, findings that contradict national narratives can trigger political sensitivities.
- **Minimal cost barrier and anonymity:** Open-access platforms such as VIIRS (NASA/NOAA) and Sentinel (ESA/Copernicus) provide free satellite data, making these resources accessible to governments and researchers in resource-constrained settings. Also, its anonymity means that there are fewer privacy risks.

Key limitations include (Gibson et al., 2025):

- **Coverage bias and representativity:** NTLs primarily capture activity in electrified, urban, and industrial areas. Informal and rural economies, common in FCAS, are often underrepresented. Subsistence farming, informal trade, and illicit activities may go undetected. Newer satellite systems, data combinations and machine learning can help address some of these gaps but often require survey data that may be unavailable. Also, the inconsistency issue remains a concern.

- **Technical and interpretive limitations:** Sensor saturation in bright urban zones and under-representation in low-light areas can distort analysis. Environmental factors such as cloud cover and seasonal variation introduce “noise”, although newer sources may reduce these. Changes in light intensity may reflect migration, repression, or outages, not necessarily economic shifts. NTLs also blend residential, commercial, and industrial activity, limiting sectoral precision.

- **Political economy and ethical concerns:** Satellite findings can challenge official narratives, creating political sensitivities. Access to high-resolution imagery may be restricted due to sanctions, forcing reliance on lower-resolution data. Ethical risks include exposing vulnerable communities through geo-referenced maps and reinforcing imbalances in data ownership.

- **Process rigour and interdisciplinary disconnects:** There is a growing gap between economists using NTLs and remote sensing scientists who develop these datasets. Misinterpretation and methodological mismatches can lead to misleading results. Ground-level validation – via phone surveys or key-informant interviews – remains essential.

To summarise, satellite-based data offers significant advantages in FCAS, being faster and more cost-effective than traditional national accounts. However, such data tend to be noisier and less precise. Satellite-based data cannot fully replace conventional statistics, but can help narrow information gaps and support policy and humanitarian responses, especially when used appropriately.

To ensure the sustainability of satellite-derived data, it is important to design approaches that minimise dependence on external expertise. This can be done through analytical pipelines which local statistical offices can easily maintain with modest training (e.g., simple VIIRS composites, basic radiance-GDP elasticities). This can be further enhanced using open-access sources (e.g., Sentinel, VIIRS) that are unlikely to be discontinued. Creating documentation and reproducible workflows (R scripts, Python notebooks) can improve the sustainability of these approaches. More importantly, co-designing indicators with national statistics offices can ensure that these approaches map onto national statistical frameworks (e.g., national poverty maps, GDP components, crop assessments) or can be integrated into national hybrid systems (e.g., administrative data, phone surveys). Lastly, data governance arrangements and ethical guidelines can be co-generated with local institutions, particularly when satellite data interact with sensitive geographic factors, such as IDP camps or mining sites, rather than donor-driven compliance frameworks.

Policy recommendations

To maximise the value of satellite-based data in FCAS, policymakers and researchers should prioritise the following:

- **Integrate and validate:** Combine satellite indicators with local insights, such as rapid phone surveys or key informant interviews, to correct biases and strengthen interpretability.
- **Apply ethical and political safeguards:** Respect political economy dynamics, ensure data ownership transparency, and protect vulnerable communities from exposure through geo-referenced outputs.
- **Use under clear conditions:** Deploy satellite-based measures when official data are missing or unreliable, when bias-corrected approaches are feasible, and when uncertainty bands accompany estimates to guide decision making.
- **Leverage for timeliness, not absolutes:** Use near-real-time insights for monitoring and early warning but apply caution in translating these into policy actions without rigorous validation.

Case Study 6: Using satellite imagery to inform urban policy in Ethiopia[5]

Nearly two decades have passed since Ethiopia's last census in 2007, leaving critical gaps in understanding the country's urban transformation. Policymakers lack reliable data on Ethiopia's current degree of urbanisation, how many urban centres exist, where growth is concentrated, and crucially, what factors explain why urbanisation is advancing rapidly in some locations but slowly in others.

In the absence of census data, policymakers have had to rely on model-based projections and regional administrative classifications. However, these sources produce markedly different estimates: roughly 900 versus 2,600 urban centres. Neither provides the spatial granularity required for infrastructure planning, service delivery, or fiscal allocation. At the request of Ethiopia's policymakers, the research team set out to establish how urbanised the country is, where urban growth is occurring, and why expansion appears concentrated in some locations but not others.

To address the data gap, the study uses satellite-based, globally available geospatial datasets to directly measure the location and expansion of built-up areas over the past two decades. The approach identifies urbanisation through observable changes in land cover and settlement patterns. This enables a spatially consistent definition of "urban" that can be compared across regions and over time. Importantly, the method

[5] The study is currently being finalised and has not yet been published; readers interested in forthcoming findings are encouraged to keep an eye on the Ethiopia country team page on the IGC website, where updates will be shared once the report is released.

is designed for contexts where urban growth is fragmented, partly informal, and not always captured in official statistics. These are characteristics common in many developing countries, and particularly in fragile and conflict affected settings.

This research can directly inform policy, helping governments to capture fast-growing secondary towns that may otherwise be overlooked. This then helps the government to better allocate transfers and prioritise infrastructure development. Since the data is globally accessible, it is replicable in other countries that face outdated census data. In this sense, the Ethiopia application serves as a proof of concept for how remote sensing can strengthen state capacity in data-scarce environments.

Table 1. Comparative advantages and limitations of innovative data tools in FCAS

Data innovation	Comparative advantages	Key limitations
CDR-Based Social Protection Targeting	• High frequency data: responsive to changing conditions • Near-zero marginal cost vs. ~$4 per household for PMT • Scales to millions of subscribers at negligible extra cost • Ability to reach hard-to-access areas	• Excludes the poorest, who often lack phones • Lower accuracy than PMT for large-budget programmes • Model drift: accuracy typically falls 4–6% after 18 months • Ethical and privacy risks without strong data-protection laws
CDR-Based Mobility & Displacement Tracking	• Near real-time monitoring of population flows • Higher spatial and temporal detail than censuses or surveys • National-scale coverage of millions of users across national geographies • Helps validate or update official migration/displacement estimates	• Expensive and difficult to acquire data from telecoms • Under-represents poorest, rural, and displaced groups • Relies on infrastructure that is often disrupted in conflict • High privacy and data protection risks without governance frameworks
Rapid Response Mobile Phone Surveys (RRPS)	• Fast and cost-efficient • Strong geographic reach and remote access • Safe for data collection in conflict or epidemics (no enumerator exposure) • Enables weekly/monthly high-frequency monitoring • Captures behaviour-level data (health-seeking, coping strategies)	• Coverage bias: respondents skew urban, male, and wealthier • Non-response and attrition: response rates low in FCAS (25–50%) • Less depth than face-to-face surveys • Requires sampling frames that may be outdated or absent
Satellite-Based Economic Measurement (Night-time Lights and Remote Sensing)	• Excludes the poorest, who often lack phones	• Ability to reach hard-to-access areas

4. Conclusion

This paper has examined how innovative data solutions can help address persistent evidence gaps in fragile and conflict-affected settings, where traditional data systems are often constrained or unavailable. Data collection in these environments is shaped by insecurity, weak infrastructure, and institutional limitations, which continue to affect the availability, quality, and reliability of data. Displacement, political sensitivities, and mistrust in institutions further complicate efforts, particularly when collecting information on sensitive topics.

Against this backdrop, this paper highlights three broad modalities - mobile phone data, rapid-response surveys, and satellite-based measurement - as practical tools for generating timely, granular, and policy-relevant insights. These approaches demonstrate how data can still be collected and used to inform decision making in rapidly evolving and data-scarce environments.

However, these innovations involve important trade-offs: between speed and comparability, coverage and representativeness, and innovation and governance. These must be carefully managed. The effectiveness of the innovations lies not in standalone application, but in how they are combined and adapted to local contexts, requiring integration into broader data systems alongside investments in sampling frames, bias adjustment, and local capacity.

Taken together, this reinforces a central message: innovative data solutions are complements, not substitutes, for traditional statistical systems. When embedded within hybrid data ecosystems and supported by strong governance and ethical safeguards, they can enable more adaptive, responsive, and evidence-driven policymaking in fragile contexts.

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