

Digital Observation Technologies for Human Security: Using Open Data and Artificial Intelligence

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Abstract

This article examines the methodological and technical constraints that have long impeded the quantitative measurement and analysis of human security and considers how digital observation technologies may help to overcome these barriers. It first reviews major attempts to index human security, arguing that the literature has repeatedly confronted a persistent measurement paradox: the difficulty of reconciling high-granularity observation of threats faced by individuals with scalable and sustainable data production. The article then surveys key open data sources relevant to human security, showing that georeferenced event data and GIS (Geographic Information Systems) data enable observation at substantially finer spatial and temporal resolutions than conventional country-year statistics. It contends that recent innovations—exemplified by Generative AI and AI agents—can automate workflows for data acquisition, data generation, and analysis, thereby easing the trade-off between granularity and sustainability. Finally, the article presents a case study of a system currently under development for the real-time detection of conflict events using large language models.

Introduction

Since its inception, numerous efforts have sought to operationalize human security and its associated threats for quantitative measurement and analysis. To date, however, no index has achieved broad acceptance in either academic or policy communities, and relatively few initiatives have produced continuous monitoring or sustained data generation based on such indicators. Given that the concept has attracted controversies and critiques regarding its definition and practical utility for more than three decades, this lack of

progress is not entirely surprising.¹ Yet the limited success of indexing reflects not only conceptual disagreement but also substantial methodological and technical constraints. Many prior initiatives, for example, have relied on conflict data or development statistics whose basic unit of observation is the

¹ For a well-known critique of the human security concept, see Paris (2001). The core of this critique is that the concept is too broad and ambiguous to be operationalized, rendering it unsuitable for either academic analysis or practical application. For fundamental critiques of the indexing of human security itself, see Grayson (2008) and Homolar (2015). A comprehensive overview of the trajectory of these controversies over the past 30 years, including such critiques, can be found in the introduction and appendix of Sakamoto and Kihara-Hunt (2024).

The views expressed in this report are those of the author(s) and do not necessarily represent the official positions of either JICA or the JICA Ogata Research Institute.

country-year. As a result, threats have been aggregated at the national level rather than observed at the level of individuals—the focal point that the human security concept was intended to foreground. In short, the prevailing data infrastructure and measurement technologies have not always matched the requirements and distinctive characteristics of the human security paradigm.

This article focuses on these methodological and technical constraints and examines how rapidly expanding digital data foundations and advancing data-processing technologies may be employed to address them. The central question is the extent to which public-domain open data and the rapid evolution of artificial intelligence (AI) can enable the observation of diverse risks and threats to human security with higher granularity and speed.²

The article proceeds as follows. Section 1 reviews past efforts to index human security and argues that limited spatial and temporal granularity, together with the high cost of data generation, have constrained both broad adoption and sustained observation. Section 2 introduces major open data sources that have expanded in tandem with the growth of digital data foundations. In domains such as armed conflict and selected development indicators, improvements in spatial granularity and update frequency have begun to create conditions more consistent with the conceptual and practical demands of human security. Section 3 considers how AI may further accelerate these trends. As innovation has progressed from Generative AI to AI agents, automation in data acquisition, data generation, and analysis has increasingly reduced costs. Drawing on a case study from a project in which the author participates, this section outlines a direction for leveraging these innovations in monitoring and (prospectively) forecasting human security risks. The conclusion addresses the inherent limitations and constraints of digital observation technologies.

² Throughout this paper, granularity refers to the degree of detail at which phenomena relevant to human security can be observed and measured, particularly in terms of spatial resolution (e.g., individuals or communities rather than countries) and temporal resolution (e.g., specific events rather than annual aggregates).

1. Indexing Human Security: Past Efforts and Bottlenecks

1.1. Early Indexing Initiatives

Efforts to visualize and analyze human security or insecurity using quantitative data have continued since the emergence of the human security concept.³ This subsection briefly reviews the trajectory of such efforts, with an emphasis on initiatives that sought to operationalize and measure human security in ways conducive to continuous monitoring.⁴

These initiatives gained momentum around the turn of the millennium. Bajpai (2000), for example, proposed a “Human Security Audit” framework intended to support annual measurement of human security through a quantitative indexing scheme. Lonergan and colleagues (Halle et al. 1999; Lonergan, Gustavson, and Carter 2000) likewise provided an empirical—albeit one-off—demonstration by quantifying human “insecurity” across countries using 16 indicators grouped into four categories: environment, economy, society, and institutions.

Among early contributions, the study by King and Murray (2001) remains particularly prominent. They offered an operational definition of human security as the “expectation of years of life without experiencing the state of generalized poverty.” Here, “generalized poverty” denotes falling below a specified threshold in any core domain of human well-being, including income, health, education, political freedom, and democracy. While the proposal is operationalizable given suitable data and thresholds, there is limited evidence that King and Murray themselves—or the many scholars who cite their work—have been able to translate this definition

³ The Human Development Report 1994 (UNDP 1994), which first introduced this concept, can be considered the pioneer of such efforts. The recent UNDP Special Report (UNDP 2022) even more prominently demonstrates this orientation toward visualization using diverse data sources.

⁴ For papers that review these early efforts, see Eldering (2010) and Togo (2011). Reinsberg, Shaw, and Bujnoch (2024), which will be discussed later, also contains an excellent review of indexing initiatives.

into sustained measurement or large-scale data generation.⁵

Subsequent proposals continued to proliferate. Hastings's "Human Security Index (HSI)" (2009; 2011) is one influential example.⁶ Designed as a composite measure spanning economic, environmental, and social dimensions, it draws on more than 30 existing datasets. Hastings used the index to compute HSI scores for roughly 230 countries and regions, enabling cross-national comparison. Nevertheless, this compilation and scoring exercise remained largely a one-time effort and did not develop into a system of continuous monitoring.

1.2. Pioneering Studies of Indexing

As noted above, many indexing attempts over the past quarter-century have remained at the level of proposals or single demonstrations. This does not, however, imply that earlier efforts offer no guidance for future measurement and observation. Several initiatives exhibit noteworthy characteristics and suggest possible pathways forward.

A relatively recent contribution by Reinsberg and colleagues (Reinsberg, Shaw, and Bujnoch 2024) is significant insofar as it establishes a basis for time-series measurement of human security. The authors constructed a "Human Security Index (HSI)" by extracting a single latent common factor through confirmatory factor analysis from 11 indicators. These indicators are drawn from widely used open data sources (including World Bank development statistics and the V-Dem project) and are selected to reflect both "freedom from want" (e.g., undernourishment, life expectancy, water access) and "freedom from fear" (e.g., homicide rates, conflict intensity, terrorist attacks). Using this approach, Reinsberg et al. computed annual HSI values for 216 countries from 1980 to 2020 and conducted panel analyses to assess the effects of IMF structural adjustment programs on human security. The study is notable for enabling continuous observation, cross-national comparison, and rigorous quantitative analysis using

broadly available time-series data.

At the same time, the approach has clear limitations. First, the index is computed at the country-year level using nationally aggregated data. Although this reflects the dominant structure of available open data, it necessarily attenuates the value added of human security for scholars who emphasize individual-level threats that are poorly captured by national averages. Second, the dimension often framed as "freedom to live in dignity" is intentionally excluded for analytical reasons. For perspectives that place particular weight on subjective and dignitarian aspects of human security, this omission constitutes a substantial gap.

Such constraints are not unique to Reinsberg et al.; rather, they apply to much of the indexing literature. A number of studies have therefore pursued higher-granularity approaches. One natural direction is to increase spatial granularity by combining GIS with subnational data. A pioneering example is Owen's "Human Security Mapping" (Owen 2003; Owen and Slaymaker 2005). Using Cambodia as a case, Owen identified "hotspots" of concentrated insecurity by overlaying district- and province-level data on landmine victims, poverty, malnutrition, crime incidents, dengue fever infections, and related indicators. Importantly, the threats mapped were not selected solely through a top-down research design; rather, they were identified from a "stakeholder perspective" through interviews with local experts (researchers, NGOs, government officials, and others). This approach is notable for incorporating stakeholder perceptions and subjectivities into the construction of indicators.⁷

In a different context and with distinct methods, the "Human Security in Japan" project led by the NPO Human Security Forum (HSF) similarly combines high-granularity measurement with attention to subjective dimensions (Takasu 2020; Takasu and Mine 2024). The project measures multidimensional human security at prefectural and municipal levels using more than 90 indicators across three domains—"Life," "Livelihood," and "Dignity." It also places emphasis on socially vulnerable populations, including children, older persons, women, persons with disabilities,

⁵ Examples include De Rivera (2004), Roberts (2008, chap. 2), Batniji et al. (2009), and Bambals (2015). However, many of these cite King and Murray (2001) rather critically, pointing out that their indicator is too narrow relative to the conceptual breadth of human security.

⁶ See also Werthes, Heaven, and Vollnhals (2011) and Koundouri and Dellis (2023).

⁷ Other studies that have attempted to understand or index human security from the perspective of stakeholders include Leaning and Arie (2000), Adger et al. (2020), and Hanatani (2024).

and disaster-affected communities. In addition to official statistics, the project employs original surveys to capture subjective aspects related to dignity and solidarity, thereby visualizing social issues in a developed-country setting through a human security lens.

These initiatives demonstrate that it is possible to move beyond national-level aggregation. Yet both Owen's work and the HSF project entail substantial costs and labor, including interviews and survey collection. Whether such fine-grained measurement can be deployed at scale—replicated across countries and regions—and sustained over time rather than implemented as a one-off exercise remains a key obstacle to broader academic and policy uptake. Owen's Cambodia mapping, for example, was not followed by a comparable series of applications elsewhere; to the author's knowledge, the published literature contains few reports of similar mapping conducted systematically across other settings.

1.3. Bottlenecks and Trade-offs

This review suggests that human security measurement has been shaped by a trade-off rooted in methodological and technical constraints, distinct from conceptual ambiguity or contestation. When efficient indexing and sustained observation are prioritized, researchers naturally rely on readily available datasets. Yet most such data share an aggregate structure—typically the country-year—making it difficult to achieve the spatial and temporal granularity embedded in the human security concept. By contrast, when conceptual fidelity is prioritized, existing datasets often prove insufficient, requiring the independent collection and construction of new data. This approach entails substantial financial and time costs and therefore limits scalable and continuous observation.

Importantly, this trade-off is neither inevitable nor immutable. It depends in large part on prevailing methodological and technical constraints (bottlenecks), including the dominant standards of available datasets and the precision and cost of observation technologies. The following sections therefore examine how rapid innovation in contemporary data foundations and observation technologies may help to overcome these bottlenecks and mitigate the associated trade-offs.

2. Expansion of Digital Data Foundations: Leveraging Diverse Open Data

Today, vast volumes of data are published and shared online by government agencies, international organizations, research institutes, and many research teams and individual scholars. Much of this information is provided as open data in formats that permit secondary use without restriction. With an internet connection, this data can be accessed for research and policy use via cloud platforms or local downloads. In fields closely tied to human security—such as international relations and development—standardized global open data now cover a broad range of phenomena, and both their volume and scope have expanded rapidly. Whether the aim is to construct indices of human security/insecurity or to analyze relationships among its components (for example, between conflict and poverty), the use of readily available open data often serves as the baseline for empirical analysis.

While quantitative work on human security has long relied on such open data (e.g., Reinsberg, Shaw, and Bujnoch 2024), the shared standards and structures of many datasets—especially national aggregation—have historically constrained measurement and analysis that more closely align with the core characteristics of the human security concept, as discussed above. Yet the expansion of digital data foundations has begun to yield datasets that alleviate some of these limitations.

Table 1 lists key open datasets available as of late August 2025, selected according to the following criteria: (1) global coverage, (2) high reliability and broad use in the academic community, and (3) a preference, where feasible, for disaggregated data (e.g., subnational or GIS-based data) over purely aggregate indicators.⁸ The “Category” labels are used for convenience. “Peace” denotes datasets related to

⁸ Needless to say, this list is not exhaustive. While efforts have been made to make it as diverse and comprehensive as possible, it should be noted that it more or less reflects the author's specialization in International Relations.

Table 1 Major Open Data Sources Related to Human Security⁹

Dataset Name	Category	Phenomena Covered	Period Covered	Update Frequency	Spatial Granularity	URL
UCDP Georeferenced Event Dataset (GED)	Peace	Individual events of organized violence (state-based, non-state, unilateral)	1989–Present	Annual	Events (Point coordinates)	https://ucdp.uu.se/
Armed Conflict Location & Event Data Project (ACLED)	Peace	Individual events of political violence (battles, violence against civilians, etc.) and protests	1997–Present (Real-time)	Weekly	Events (Point coordinates)	https://acledata.com/
Global Terrorism Database (GTD)	Peace	Terrorist incidents	1970–Present (Except 1993)	Annual	Events (Point coordinates, city, country)	https://www.start.umd.edu/gtd/
Political Terror Scale (PTS)	Peace	State violations of physical integrity rights	1976–Present	Annual	National	https://www.politicalterrorsscale.org/
UNHCR Refugee Population Statistics Database	Peace	Forced displacement (refugees, IDPs, asylum seekers, etc.)	1951–Present	Annual	National (By origin/ asylum country)	https://www.unhcr.org/refugee-statistics
IDMC Global Internal Displacement Database (GIDD)	Peace	Global internal displacement (number of IDPs due to conflict/ disasters, etc.)	2008–Present	Annual	National	https://www.internal-displacement.org/database
World Bank Subnational Poverty Data (SPD)	Development	Poverty, Inequality (Monetary and Multidimensional)	c. 2000–Present	Irregular	Subnational (Administrative divisions)	https://pipmaps.worldbank.org/
The DHS Program (Demographic and Health Surveys)	Development	Household and individual-level indicators on health, population, and nutrition	1980s–Present (By country)	Approx. every 5 years	Survey clusters (Displaced point coordinates), Estimated grids (Approx. 5km)	https://dhsprogram.com/
IHME Global Burden of Disease (GBD) Study	Development	Burden of death and disability due to diseases, injuries, and risk factors	1990–Present	Annual	National, Subnational (Partial)	https://www.healthdata.org/gbd
FAOSTAT Suite of Food Security Indicators	Development	Food security indicators (undernourishment, food insecurity, etc.)	1990s–Present	Annual	National	https://www.fao.org/faostat/
EM-DAT International Disaster Database	Development	Occurrence and impact of natural and technological disasters	1900–Present	Ad hoc (Per disaster event)	National, Disaster event	https://www.emdat.be/
Varieties of Democracy (V-Dem) Project	Governance	Multidimensional aspects of democracy (electoral, liberal, participatory, deliberative, equal)	1789–Present	Annual	National	https://www.v-dem.net/
Polity5 Project	Governance	Global regimes (democracy/ autocracy scores, regime transitions)	1800–2018	Irregular	National	http://www.systemicpeace.org/polityproject.html
Worldwide Governance Indicators (WGI)	Governance	Six governance indicators (voice, stability, government effectiveness, etc.)	1996–Present	Annual	National	https://www.govindicators.org/
Freedom House - Freedom in the World	Governance	Political rights and civil liberties	1973–Present	Annual	National	https://freedomhouse.org/
Georgetown WPS Index (Component Indicators)	Governance	13 component indicators on women's inclusion, justice, and security	Recent years (by indicator)	Every 2–3 years	National	https://giwps.georgetown.edu/the-index/

Source: Compiled by the author.

⁹ All URLs accessed August 28, 2025.

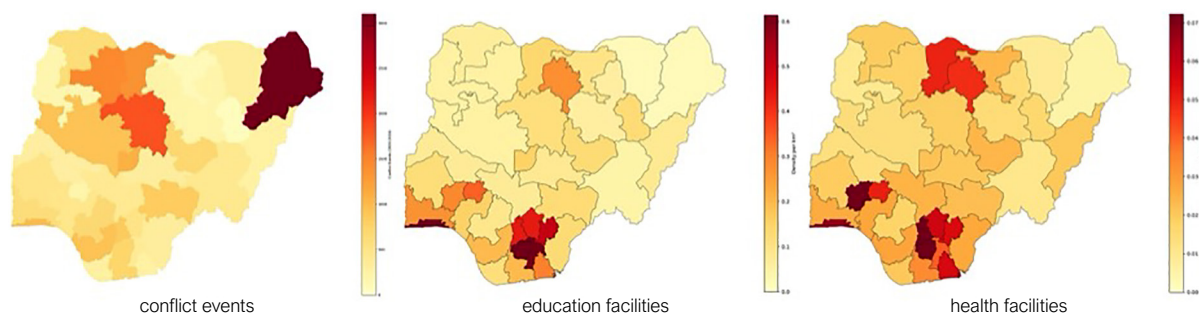


Figure 1 Number of Conflict Events (2020–2024), Education Facility Density, and Health Facility Density in Nigerian States

Source: Compiled by the author from ACLED, GRID3, and Maina et al. (2019) data.

events that generate “fear,” such as armed conflict and terrorist attacks, as well as their consequences, including refugees and internally displaced persons. “Development” denotes datasets related to “want,” including poverty, disease, and food insecurity. “Governance” denotes legal and institutional conditions that can shape both “fear” and “want,” and potentially “dignity” as well.

These sources include substantial numbers of disaggregated observations with high spatial and temporal granularity, rather than relying exclusively on the country-year unit. In particular, datasets on armed conflict and political violence—such as UCDP-GED, ACLED, and the GTD—are organized around individual events. They record geospatial information, including latitude and longitude coordinates and administrative divisions for event locations. Datasets related to poverty and health, such as the World Bank’s SPID and the DHS, likewise draw on detailed household survey infrastructures; their web portals provide subnational aggregates and high-resolution grid estimates for key indicators.¹⁰

By combining georeferenced event and survey data—either with one another or with additional geospatial information—human security measurement and analysis can be

conducted at finer spatial scales more efficiently and, in some settings, at greater scale. Parallel to the diffusion of GIS tools, open geospatial datasets have also expanded rapidly. These include, for example, annually updated gridded population estimates (WorldPop Gridded Population Data);¹¹ settlement extents and points inferred from satellite imagery (GRID3 Settlement Extents/Points);¹² infrastructure networks such as roads and power grids; and geocoded distributions of health and educational facilities. Many such datasets are accessible through portals such as the Humanitarian Data Exchange (HDX).¹³

Figure 1 illustrates, using Nigeria as an example, recent data (January 2020 to December 2024) on the number of armed conflict and political violence events (ACLED), educational institution density (GRID3), and health facility density (Maina et al. 2019), each aggregated by subnational state and projected onto a map. This type of visualization makes it possible to depict the spatial maldistribution of “fear” and “want” in a multidimensional manner. When combined with population and settlement distribution data, such approaches also enable more refined estimates of where—and approximately how many—people face varying degrees of security or insecurity. In effect, a simplified version of Owen’s “Human Security Mapping” can be implemented for many settings where relevant data are available.

Significant constraints nonetheless remain. For GIS

¹⁰ Although satellite imagery is not covered in this paper, satellite images of “nighttime lights” are sometimes used as a potent proxy indicator for the geospatial distribution of social and economic activities (Henderson, Storeygard, and Weil 2012). Various satellite images, including such data, are also widely (and freely) available for academic purposes, subject to certain restrictions, through platforms such as Google Earth Engine (<https://earthengine.google.com/>; accessed August 28, 2025).

¹¹ WorldPop: <https://www.worldpop.org/> (accessed August 28, 2025).

¹² GRID3: <https://grid3.org/> (accessed August 28, 2025).

¹³ All GIS data mentioned in this paper are available from HDX. HDX: <https://data.humdata.org/> (accessed August 28, 2025).

data, availability varies markedly across countries and regions, and datasets that track spatial distributions over time are limited to a small number of sources, such as WorldPop. Moreover, while many datasets in **Table 1** constitute cross-sectional time series spanning decades or longer, most are updated only annually and therefore lack timeliness or genuine real-time capabilities. ACLED is exceptional in update frequency, but even there, a lag of several days to weeks can arise before events appear in the dataset. Given that human security concerns not only “chronic threats” such as hunger and poverty but also “sudden and hurtful disruptions” such as disasters and humanitarian crises (UNDP 1994, 23), limitations in temporal granularity and near-real-time availability can substantially hinder observation, analysis, and subsequent policy response. Thus, despite the rapid expansion of digital data foundations through the growth and diversification of open data, important obstacles must still be addressed before human security monitoring can be fully realized upon these foundations.

3. Advancements in Digital Observation Technologies: Automating Data Acquisition, Generation, and Analysis Using AI

3.1. Background: AI and the Automation of Data Processing

Artificial intelligence (AI) can play a major role in addressing the challenges identified above. The rapid global diffusion of Generative AI, catalyzed by the release of the language model “ChatGPT 3.5” in November 2022, has been reshaping the processing of diverse data modalities, including text, audio, images, and video.¹⁴ Although the trajectory of these changes remains uncertain, one widely

cited development as of late August 2025 is the rise of AI agents, with 2025 often described as the “First Year of AI agents.” In brief, an AI agent is a system that autonomously executes tasks toward human-defined objectives. Building on Generative AI (large language models), AI agents are characterized by the capacity to perform complex tasks—sometimes via collaboration among multiple agents—by incorporating multi-stage reasoning and by accessing external data and tools such as web search (Sapkota, Roumeliotis, and Karkee 2025).

These innovations have already affected many domains, including academic data analysis.¹⁵ Efforts to automate data generation—for example, replacing expert manual coding with Generative AI—have advanced rapidly.¹⁶ It has also become increasingly common for AI agents equipped with code-generation and mathematical reasoning capabilities to assume substantial portions of end-to-end workflows, including data acquisition, analysis, and visualization. In machine learning and the life sciences, moreover, initiatives have emerged in which multiple AI agents undertake broad segments of the research process, from conceptualization and literature review to hypothesis generation, manuscript drafting, and even responses to peer review (Lu et al. 2024; Swanson et al. 2024; Schmidgall et al. 2025).

Two additional trends are particularly relevant for data processing and analysis. The first is the expansion of multimodal AI, which can process multiple data types (e.g., text, images, and audio) within a unified framework, and multilingual AI, which can handle many languages—with some models reportedly supporting more than 100 languages. These capabilities, for example, make it possible to estimate the scale of conflict or disaster by integrating multilingual reporting with satellite imagery. The second trend is the steady improvement of high-performance, lightweight open models that run locally (e.g., the gpt-oss series, Gemma series, and Mistral Small series), alongside the continued prominence of large commercial models (e.g., OpenAI’s GPT

¹⁴ Today’s Generative AI is broadly based on deep learning technology, and if the recent boom is understood through text generation, it is largely driven by large language models (LLMs). While many introductory books are available, Chollet (2021) and Raschka (2025) are recommended for readers who prefer a hands-on approach.

¹⁵ For a review of recent AI trends in quantitative text analysis—especially in political science and international relations—see Sakamoto (2026).

¹⁶ Examples of political text classification include Heseltine and Clemm von Hohenberg (2024) and Le Mens and Gallego (2025).

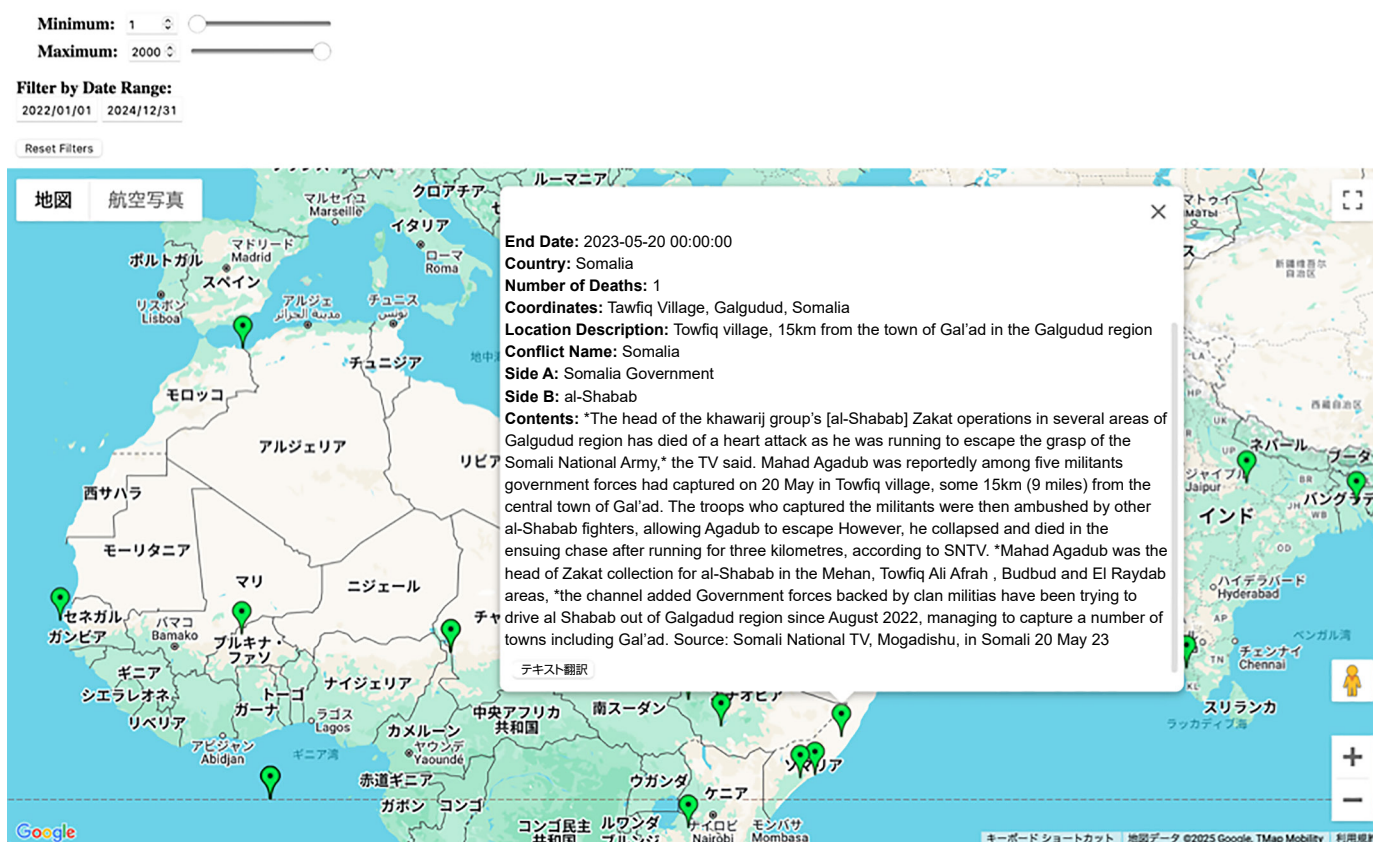


Figure 2 Screenshot of an automated event detection system from a news stream (under development)

Source: Courtesy of Professor Yusuke Miyao, Graduate School of Information Science and Technology, The University of Tokyo

series, Anthropic's Claude series, and Google's Gemini series). Some local models now offer sufficient performance for advanced data processing on standard consumer laptops, enabling "in-house" measurement and analysis environments without recurring API fees or extensive reliance on large-scale data centers with substantial environmental footprints.

3.2. Applicability to the Measurement of Human Security

Given the current state of digital technology, this subsection outlines concrete possibilities for measuring human security without undue speculation. First, the use of open data discussed in the previous section is likely to accelerate further. With appropriate prompts, an AI agent can retrieve relevant data from the expanding pool of web-accessible open datasets without manual browsing. It is also feasible for AI systems to conduct quantitative analyses

autonomously or to compute a Human Security Index (HSI) under specified aggregation procedures (e.g., normalization, averaging, or factor analysis). Moreover, visualization of results via charts, maps, and dashboards can increasingly be carried out by individuals without advanced programming expertise or significant organizational resources.

More importantly, AI supports not only efficient acquisition and processing of existing data but also low-cost, automated data generation. AI systems can identify events of interest—such as conflicts, disasters, food crises, or human rights violations—from streams of online articles, posts, reports, and images and extract structured information (e.g., event type, actors, damages, time, and location). Although still under development, the Institute for Digital Observatory (IDO) at the University of Tokyo, with which the author is affiliated, is building such a system in collaboration with experts in AI and natural language processing (Figure 2). As illustrated, detailed information on armed conflict events is

extracted from news texts delivered by agencies and newspapers selected by specialists in international relations, comparative politics, and area studies,¹⁷ using large language models, and the resulting event locations are mapped globally for specified periods. Armed conflict is an initial focus because high-granularity benchmark datasets such as UCDP-GED and ACLED are relatively abundant and can be used to validate extraction accuracy. Whereas existing datasets mobilize large teams—on the order of 200 experts in the case of ACLED—to manually code events from text, this system aims to achieve near-real-time data generation through automation.

The IDO is currently expanding this automated data generation pipeline to domains where high-granularity datasets are less developed, including protest activity, human rights violations, and political regime change. In combination with existing open data, the project further aims not only to detect past events but also to anticipate unknown events and develop systems that generate natural-language explanations of associated risks and impacts. Although current IDO efforts are oriented toward understanding and forecasting risks to global supply chains and are not designed specifically as human security monitoring, the overlap in relevant risk events is substantial. From both technical and methodological perspectives, the transferability of these technologies to human security measurement is therefore highly plausible. Ultimately, the objective is to realize observation systems capable of capturing, at high granularity and in near real time, the diverse threats confronting vulnerable populations in specific locations.

Conclusion

This article has argued that the expansion of open data and AI-driven technological innovation can substantially empower quantitative measurement and analysis of human security. In particular, it has outlined a path toward mitigating

the difficult trade-off between achieving the granularity and temporal frequency implied by a human security paradigm centered on individuals—and supporting such observation at scale in a sustainable manner. As data digitalization and open access continue to consolidate, and as advances in AI and the growing availability of open-source local models reduce operational costs, researchers may increasingly be able to overcome methodological and technical constraints that earlier indexing efforts could not transcend.

At the same time, significant challenges and caveats remain. Even within the scope of this article, both functional and legal issues arise, including hallucination—the generation of plausible but false information—and the legal complexities associated with using copyrighted news content in AI-assisted pipelines. Moreover, AI-based data generation requires sustained attention to information reliability (including the proliferation of “fake news”) and to reporting bias in media coverage—the selective reporting of events that are politically salient or attention-grabbing—even when inputs are restricted to reputable agencies, as in initiatives associated with the IDO. While multimodal approaches (e.g., integrating satellite imagery) offer one potential countermeasure, technical fixes alone have inherent limits. Regardless of how far automation advances, continuous human oversight, expert verification, and rigorous validation will remain indispensable.

A further longstanding bottleneck in human security measurement concerns how to incorporate the subjective perceptions and lived experiences of those who are the objects of measurement. Progress is being made through the shift toward online survey infrastructure and the availability of open survey data (e.g., DHS and Afrobarometer). Novel approaches have also begun to appear, such as collecting disaster-related narratives via Google Maps (Uchio 2024). Nevertheless, systematic understanding of subjective views cannot, at present, rely solely on digital means. Physical site visits, field observation, and direct engagement with affected populations remain essential.

Indeed, as digitally mediated observation expands rapidly, ground-truth data collected in the field may gain even greater value as a means of validating and complementing digitally observed data. Developing robust approaches for hybridizing digital and non-digital data will therefore remain a

¹⁷ In the development stage, news articles from nearly 40 news agencies and newspapers are used, retrieved via Factiva, an API service provided by Dow Jones & Company (<https://www.dowjones.com/business-intelligence/factiva/>; accessed August 30, 2025).

central challenge for future work on measuring human security.¹⁸

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¹⁸ For an overview collating many concrete examples of such hybridization, see Salganik (2017), especially Chapter 3.

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